In [1]:
```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
import numpy as np
import pandas as pd
import tensorflow as tf
from tensorflow import keras
from sklearn.model_selection import train_test_split, StratifiedKFold
from sklearn.preprocessing import StandardScaler
from sklearn.utils.class_weight import compute_class_weight
from sklearn.metrics import accuracy_score, precision_score, recall_score, 
import matplotlib.pyplot as plt
import seaborn as sns
```

```
/Users/mengjiayu/opt/anaconda3/lib/python3.8/site-packages/pandas/core/computation/expressions.py:20: UserWarning: Pandas requires version '2.7.3' or newer of 'numexpr' (version '2.7.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
```

In [2]:
```
df = pd.read_csv('output_dataset.csv')
```

In [4]:
```
whole = df[['Total Bilirubin', 'Alkphos Alkaline Phosphotase',
'Sgpt Alamine Aminotransferase', 'Sgot Aspartate Aminotransferase',
'Total Protiens', 'ALB Albumin', 'A/G Ratio Albumin and Globulin Ratio',
'Bilirubin Ratio', 'SGOT/SGPT Ratio', 'Protien Ratio', 'Result']]
```

In [5]:
```
whole
```

Out[5]:

	Total Bilirubin	Alkphos Alkaline Phosphotase	Sgpt Alamine Aminotransferase	Sgot Aspartate Aminotransferase	Total Protiens	ALB Albumin	Alb... Gl...
0	0.530628	187.0	2.833213	2.944439	6.8	3.3	
1	2.476538	690.0	4.174387	4.615121	7.5	3.2	
2	2.116256	490.0	4.110874	4.234107	7.0	3.3	
3	0.693147	182.0	2.772589	3.044522	6.8	3.4	
4	1.589235	195.0	3.332205	4.094345	7.3	2.4	
...	...	...	...	...	...	...	
30686	1.163151	610.0	2.890372	3.367296	7.3	2.6	
30687	1.360977	482.0	3.135494	3.555348	7.0	2.4	
30688	2.054124	542.0	4.762174	4.204693	6.4	3.1	
30689	1.064711	231.0	2.833213	4.025352	4.6	1.8	
30690	1.410987	253.0	4.394449	6.007239	6.8	3.9	

30691 rows × 11 columns

In [ ]:

In [ ]:

In [6]:
```
# Prepare features and target variable
feature_cols = ['Total Bilirubin', 'Alkphos Alkaline Phosphotase',
                'Sgpt Alamine Aminotransferase', 'Sgot Aspartate Aminotrans
                'Total Protiens', 'ALB Albumin', 'A/G Ratio Albumin and Glol
                'Bilirubin Ratio', 'SGOT/SGPT Ratio', 'Protien Ratio']

X = df[feature_cols]
y = df['Result']

# Convert target labels: 2 → 0 (Non-Disease), 1 → 1 (Disease)
y = (y == 1).astype(int)

# Train-test split (80:20)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, ran

# Standardize Numeric Features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Compute Correct Class Weights
class_weights = compute_class_weight('balanced', classes=np.array([0, 1]), y
class_weights_dict = {0: class_weights[0], 1: class_weights[1]}  # Ensure o

# Function to Build FNN Model
def build_fnn_model(hidden_units=128, dropout_rate=0.3, learning_rate=0.001
    model = keras.Sequential([
        keras.layers.Dense(hidden_units, activation='relu', input_shape=(X_
        keras.layers.BatchNormalization(),
        keras.layers.Dropout(dropout_rate),
        keras.layers.Dense(hidden_units // 2, activation='relu'),
        keras.layers.Dense(hidden_units // 4, activation='relu'),
        keras.layers.Dense(1, activation='sigmoid')  # Binary classificatio
    ])

    model.compile(optimizer=keras.optimizers.Adam(learning_rate=learning_ra
                  loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model

# Hyperparameter tuning with Stratified K-Fold Cross Validation
best_model = None
best_score = 0
kf = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

for units in [64, 128, 256]:  # Wider range of neurons
    for dropout in [0.1, 0.3, 0.5]:  # More dropout variations
        for lr in [0.001, 0.0005, 0.0001]:  # Test higher and lower learnin
            fold_scores = []

            for train_idx, val_idx in kf.split(X_train, y_train):
                X_train_fold, X_val_fold = X_train[train_idx], X_train[val_
                y_train_fold, y_val_fold = y_train.iloc[train_idx], y_train

                model = build_fnn_model(hidden_units=units, dropout_rate=dr

                # Add Early Stopping to prevent overfitting
                early_stopping = keras.callbacks.EarlyStopping(monitor='val_

                history = model.fit(X_train_fold, y_train_fold, epochs=50, b
                                    validation_data=(X_val_fold, y_val_fold
                                    class_weight=class_weights_dict)
```

```
                val_loss, val_acc = model.evaluate(X_val_fold, y_val_fold, v
                fold_scores.append(val_acc)

            avg_score = np.mean(fold_scores)
            print(f"Units: {units}, Dropout: {dropout}, LR: {lr} -> Avg Val

            if avg_score > best_score:
                best_score = avg_score
                best_model = model  # Save the best model dynamically

# Train the best model on full training data
print("\n Best Model Found - Training on Full Training Data...")
final_model = best_model

history = final_model.fit(X_train, y_train, epochs=50, batch_size=32, verbos
                          callbacks=[keras.callbacks.EarlyStopping(monitor=
                          class_weight=class_weights_dict)
```

```
Units: 64, Dropout: 0.1, LR: 0.001 -> Avg Val Accuracy: 0.9695
Units: 64, Dropout: 0.1, LR: 0.0005 -> Avg Val Accuracy: 0.9744
Units: 64, Dropout: 0.1, LR: 0.0001 -> Avg Val Accuracy: 0.8991
Units: 64, Dropout: 0.3, LR: 0.001 -> Avg Val Accuracy: 0.9457
Units: 64, Dropout: 0.3, LR: 0.0005 -> Avg Val Accuracy: 0.9375
Units: 64, Dropout: 0.3, LR: 0.0001 -> Avg Val Accuracy: 0.8414
Units: 64, Dropout: 0.5, LR: 0.001 -> Avg Val Accuracy: 0.8733
Units: 64, Dropout: 0.5, LR: 0.0005 -> Avg Val Accuracy: 0.8753
Units: 64, Dropout: 0.5, LR: 0.0001 -> Avg Val Accuracy: 0.7628
Units: 128, Dropout: 0.1, LR: 0.001 -> Avg Val Accuracy: 0.9869
Units: 128, Dropout: 0.1, LR: 0.0005 -> Avg Val Accuracy: 0.9841
Units: 128, Dropout: 0.1, LR: 0.0001 -> Avg Val Accuracy: 0.9621
Units: 128, Dropout: 0.3, LR: 0.001 -> Avg Val Accuracy: 0.9845
Units: 128, Dropout: 0.3, LR: 0.0005 -> Avg Val Accuracy: 0.9810
Units: 128, Dropout: 0.3, LR: 0.0001 -> Avg Val Accuracy: 0.9359
Units: 128, Dropout: 0.5, LR: 0.001 -> Avg Val Accuracy: 0.9709
Units: 128, Dropout: 0.5, LR: 0.0005 -> Avg Val Accuracy: 0.9652
Units: 128, Dropout: 0.5, LR: 0.0001 -> Avg Val Accuracy: 0.8713
Units: 256, Dropout: 0.1, LR: 0.001 -> Avg Val Accuracy: 0.9846
Units: 256, Dropout: 0.1, LR: 0.0005 -> Avg Val Accuracy: 0.9873
Units: 256, Dropout: 0.1, LR: 0.0001 -> Avg Val Accuracy: 0.9862
Units: 256, Dropout: 0.3, LR: 0.001 -> Avg Val Accuracy: 0.9857
Units: 256, Dropout: 0.3, LR: 0.0005 -> Avg Val Accuracy: 0.9865
Units: 256, Dropout: 0.3, LR: 0.0001 -> Avg Val Accuracy: 0.9803
Units: 256, Dropout: 0.5, LR: 0.001 -> Avg Val Accuracy: 0.9845
Units: 256, Dropout: 0.5, LR: 0.0005 -> Avg Val Accuracy: 0.9815
Units: 256, Dropout: 0.5, LR: 0.0001 -> Avg Val Accuracy: 0.9583

 Best Model Found - Training on Full Training Data...
Epoch 1/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0613 - acc
uracy: 0.9805 - val_loss: 0.0478 - val_accuracy: 0.9879
Epoch 2/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0527 - acc
uracy: 0.9828 - val_loss: 0.0529 - val_accuracy: 0.9860
Epoch 3/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0588 - acc
uracy: 0.9808 - val_loss: 0.0527 - val_accuracy: 0.9871
Epoch 4/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0503 - acc
uracy: 0.9835 - val_loss: 0.0550 - val_accuracy: 0.9847
Epoch 5/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0485 - acc
uracy: 0.9837 - val_loss: 0.0540 - val_accuracy: 0.9879
Epoch 6/50
768/768 [==============================] - 1s 2ms/step - loss: 0.0421 - acc
uracy: 0.9860 - val_loss: 0.0631 - val_accuracy: 0.9871
```

In [ ]:

```
# Units: 256, Dropout: 0.1, LR: 0.0005 -> Avg Val Accuracy: 0.9873
```

In [7]:

```
final_model.summary()
```

```
Model: "sequential_99"
_________________________________________________________________
 Layer (type)                Output Shape              Param #   
=================================================================
 dense_396 (Dense)           (None, 256)               2816      
                                                                 
 batch_normalization_99 (Ba  (None, 256)               1024      
 tchNormalization)                                               
                                                                 
 dropout_99 (Dropout)        (None, 256)               0         
                                                                 
 dense_397 (Dense)           (None, 128)               32896     
                                                                 
 dense_398 (Dense)           (None, 64)                8256      
                                                                 
 dense_399 (Dense)           (None, 1)                 65        
                                                                 
=================================================================
Total params: 45057 (176.00 KB)
Trainable params: 44545 (174.00 KB)
Non-trainable params: 512 (2.00 KB)
_________________________________________________________________
```

In [8]:
```python
# Save the Final Model
final_model.save("fnn_model.h5")
```

```
/Users/mengjiayu/opt/anaconda3/lib/python3.8/site-packages/keras/src/engin
e/training.py:3000: UserWarning: You are saving your model as an HDF5 file
via `model.save()`. This file format is considered legacy. We recommend usi
ng instead the native Keras format, e.g. `model.save('my_model.keras')`.
  saving_api.save_model(
```

In [14]:
```python
# Get Final Training Accuracy (Last Epoch)
train_accuracy = history.history['accuracy'][-1]

# Get Mean Cross-Validation Accuracy from Best Model
cv_accuracy = best_score

accuracy_df = pd.DataFrame({
    "Metric": ["Train Accuracy", "Mean CV Accuracy"],
    "Value": [train_accuracy, cv_accuracy]
})

accuracy_df
```

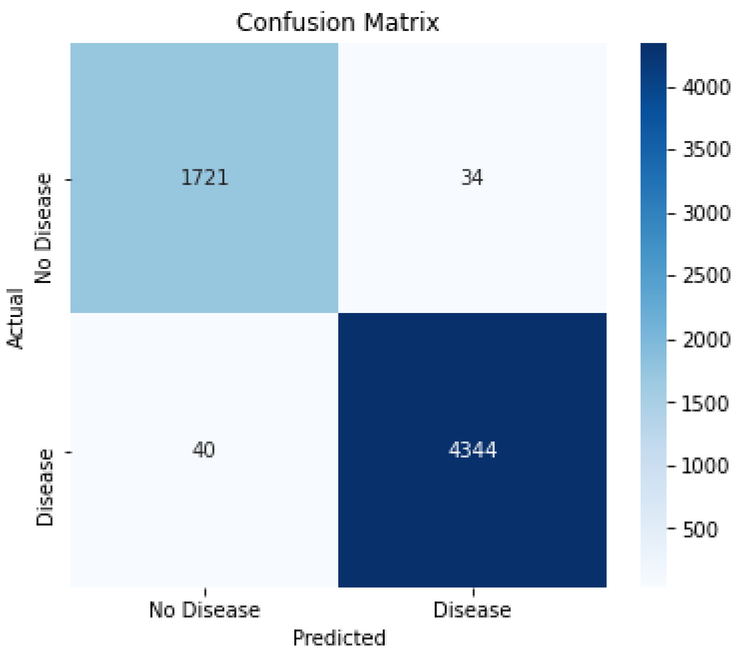
Out[14]:

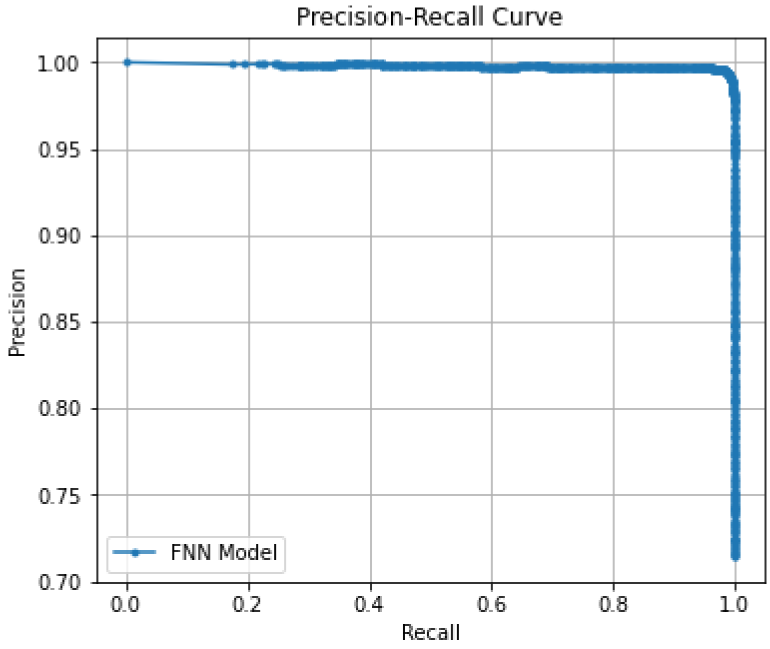
	Metric	Value
0	Train Accuracy	0.986030
1	Mean CV Accuracy	0.987251

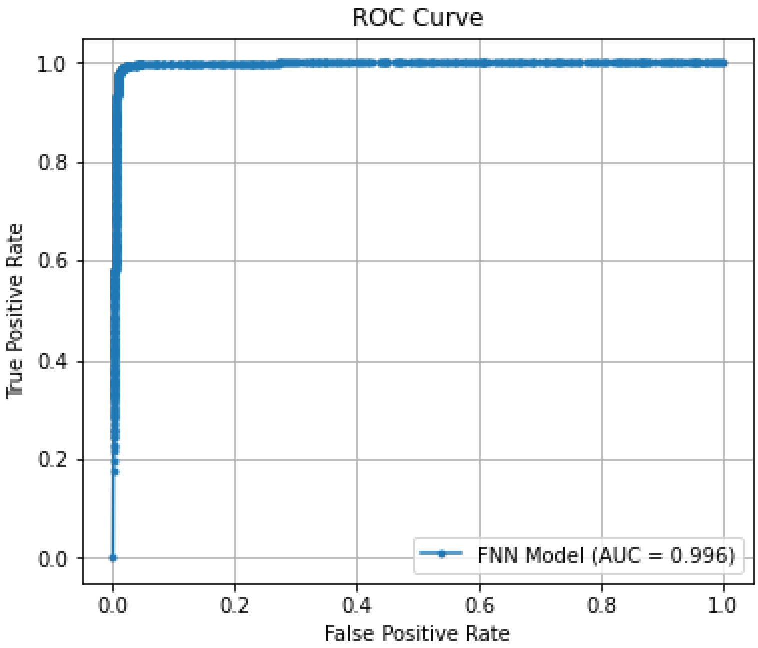
In [9]:
```python
# Model Testing (Predictions)
y_pred_prob = final_model.predict(X_test)  # Get probabilities
y_pred = (y_pred_prob > 0.5).astype(int)  # Convert probabilities to class 

# Model Evaluation
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
f1 = f1_score(y_test, y_pred)
roc_auc = roc_auc_score(y_test, y_pred_prob)

# Confusion Matrix
conf_matrix = confusion_matrix(y_test, y_pred)
```

```
# Print Evaluation Results in Tabular Form
metrics_df = pd.DataFrame({
    "Metric": ["Accuracy", "Precision", "Recall", "F1 Score", "ROC-AUC"],
    "Value": [accuracy, precision, recall, f1, roc_auc]
})
print("\n Model Evaluation Metrics:")
print(metrics_df)

# Classification Report
print("\n Classification Report:")
print(classification_report(y_test, y_pred))

# Plot Metrics Curves (Loss & Accuracy)
plt.figure(figsize=(12,5))
plt.subplot(1,2,1)
plt.plot(history.history['loss'], label='Train Loss')
plt.plot(history.history['val_loss'], label='Validation Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.title('Training vs. Validation Loss')
plt.legend()

plt.subplot(1,2,2)
plt.plot(history.history['accuracy'], label='Train Accuracy')
plt.plot(history.history['val_accuracy'], label='Validation Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.title('Training vs. Validation Accuracy')
plt.legend()
plt.show()

# Confusion Matrix Heatmap
plt.figure(figsize=(6,5))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['N
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()

# Precision-Recall Curve
precision_vals, recall_vals, _ = precision_recall_curve(y_test, y_pred_prob

plt.figure(figsize=(6,5))
plt.plot(recall_vals, precision_vals, marker='.', label="FNN Model")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.title("Precision-Recall Curve")
plt.legend()
plt.grid()
plt.show()

# ROC Curve
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)

plt.figure(figsize=(6,5))
plt.plot(fpr, tpr, marker='.', label=f"FNN Model (AUC = {roc_auc:.3f})")
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ROC Curve")
plt.legend()
plt.grid()
plt.show()
```

```
192/192 [==============================] - 0s 713us/step

 Model Evaluation Metrics:
      Metric     Value
0   Accuracy  0.987946
1  Precision  0.992234
2     Recall  0.990876
3   F1 Score  0.991554
4    ROC-AUC  0.996445

 Classification Report:
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1755
           1       0.99      0.99      0.99      4384

    accuracy                           0.99      6139
   macro avg       0.98      0.99      0.99      6139
weighted avg       0.99      0.99      0.99      6139
```







In [15]:
```
# Extract final training accuracy
train_accuracy = history.history['accuracy'][-1]
print(f"Final Training Accuracy: {train_accuracy:.4f}")
# Evaluate model on the test set
test_loss, test_accuracy = final_model.evaluate(X_test, y_test, verbose=0)
print(f"Test Accuracy: {test_accuracy:.4f}")
```

```
Final Training Accuracy: 0.9860
Test Accuracy: 0.9879
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:
```
'''# Load the saved model
from tensorflow.keras.models import load_model

loaded_model = load_model("fnn_model.h5")
```

```
loaded_model.summary()
'''
```