Optimizing Early Diabetes Detection: A Comparative Analysis of Traditional Machine Learning Baseline and Enhanced Deep Learning Models

###Diabetes Detection Tool

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Section 1: Explore Data

In this section, we explore the data and check for any missing values in the dataset that may need to be addressed and any features consisting of values that may pose redundancy.

```
# Importing libraries
import pandas as pd
import numpy as np
import tensorflow as tf

np.random.seed(42)
tf.random.set_seed(42)

from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
!ls /content/drive/MyDrive/DS402MLProj/
```

```
402MLProj.ipynb  diabetesDataset.csv
```

```
data =
pd.read_csv('/content/drive/MyDrive/DS402MLProj/diabetesDataset.csv')
data.iloc[500:]
```

```
     Age  Gender Polyuria Polydipsia sudden weight loss weakness
Polyphagia  \
500   66    Male      Yes         No                Yes       No
No
501   67    Male       No         No                 No       No
Yes
502   70    Male      Yes         No                 No       No
Yes
503   44    Male       No         No                 No       No
No
504   38    Male       No         No                 No       No
No
505   35    Male       No         No                 No       No
No
506   61    Male       No         No                 No      Yes
```

```
No
507   60    Male         No           No                    Yes        No
No
508   58    Male         No           No                     No       Yes
No
509   54    Male         No           No                     No        No
No
510   67    Male         No           No                     No       Yes
No
511   66    Male         No           No                     No       Yes
Yes
512   43    Male         No           No                     No        No
No
513   62  Female        Yes          Yes                    Yes       Yes
No
514   54  Female        Yes          Yes                    Yes       Yes
Yes
515   39  Female        Yes          Yes                    Yes        No
Yes
516   48  Female        Yes          Yes                    Yes       Yes
Yes
517   58  Female        Yes          Yes                    Yes       Yes
Yes
518   32  Female         No           No                     No       Yes
No
519   42    Male         No           No                     No        No
No

    Genital thrush visual blurring Itching Irritability delayed
healing  \
500            Yes              No     Yes          Yes
No
501             No             Yes      No           No
No
502             No             Yes     Yes           No
Yes
503             No              No      No           No
No
504             No              No      No           No
No
505             No              No      No           No
No
506            Yes              No     Yes           No
Yes
507             No              No      No           No
No
508             No              No     Yes           No
Yes
509             No              No      No           No
```

```
No
510                No                No     Yes             No
Yes
511                No               Yes     Yes             No
Yes
512                No                No      No             No
No
513                No               Yes      No             No
No
514                No                No      No             No
No
515                No                No     Yes             No
Yes
516                No                No     Yes            Yes
Yes
517                No               Yes      No             No
No
518                No               Yes     Yes             No
Yes
519                No                No      No             No
No

    partial paresis muscle stiffness Alopecia Obesity     class
500              No                No      Yes      No  Positive
501              No               Yes       No      No  Negative
502             Yes               Yes      Yes      No  Negative
503              No                No       No      No  Negative
504              No                No       No      No  Negative
505              No                No       No      No  Negative
506              No                No      Yes      No  Negative
507              No                No       No     Yes  Negative
508              No               Yes      Yes      No  Negative
509              No                No       No      No  Negative
510              No                No      Yes      No  Negative
511             Yes               Yes      Yes      No  Negative
512              No                No      Yes      No  Negative
513             Yes                No       No     Yes  Positive
514             Yes                No       No      No  Positive
515             Yes                No       No      No  Positive
516             Yes                No       No      No  Positive
517             Yes               Yes       No     Yes  Positive
518              No                No      Yes      No  Negative
519              No                No       No      No  Negative
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 520 entries, 0 to 519
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype
```

```
---  ------              --------------  -----
 0   Age                 520 non-null    int64
 1   Gender              520 non-null    object
 2   Polyuria            520 non-null    object
 3   Polydipsia          520 non-null    object
 4   sudden weight loss  520 non-null    object
 5   weakness            520 non-null    object
 6   Polyphagia          520 non-null    object
 7   Genital thrush      520 non-null    object
 8   visual blurring     520 non-null    object
 9   Itching             520 non-null    object
 10  Irritability        520 non-null    object
 11  delayed healing     520 non-null    object
 12  partial paresis     520 non-null    object
 13  muscle stiffness    520 non-null    object
 14  Alopecia            520 non-null    object
 15  Obesity             520 non-null    object
 16  class               520 non-null    object
dtypes: int64(1), object(16)
memory usage: 69.2+ KB
```

```
data.columns
```

```
Index(['Age', 'Gender', 'Polyuria', 'Polydipsia', 'sudden weight
loss',
       'weakness', 'Polyphagia', 'Genital thrush', 'visual blurring',
       'Itching', 'Irritability', 'delayed healing', 'partial
paresis',
       'muscle stiffness', 'Alopecia', 'Obesity', 'class'],
      dtype='object')
```

```
# Number of columns in the dataframe
len(data.columns)
```

```
17
```

```
# Here we print our columns
print(data.iloc[:, 1:6])
print(data.iloc[:, 6:11])
print(data.iloc[:, 11:16])
print(data.iloc[:, 16:])
```

```
     Gender Polyuria Polydipsia sudden weight loss weakness
0      Male       No        Yes                 No      Yes
1      Male       No         No                 No      Yes
2      Male      Yes         No                 No      Yes
3      Male       No         No                Yes      Yes
4      Male      Yes        Yes                Yes      Yes
..      ...      ...        ...                ...      ...
515  Female      Yes        Yes                Yes       No
516  Female      Yes        Yes                Yes      Yes
```

```
517  Female       Yes         Yes                     Yes       Yes
518  Female        No          No                      No       Yes
519    Male        No          No                      No        No

[520 rows x 5 columns]
    Polyphagia Genital thrush visual blurring Itching Irritability
0           No             No              No     Yes           No
1           No             No             Yes      No           No
2          Yes             No              No     Yes           No
3          Yes            Yes              No     Yes           No
4          Yes             No             Yes     Yes          Yes
..         ...            ...             ...     ...          ...
515        Yes             No              No     Yes           No
516        Yes             No              No     Yes          Yes
517        Yes             No             Yes      No           No
518         No             No             Yes     Yes           No
519         No             No              No      No           No

[520 rows x 5 columns]
    delayed healing partial paresis muscle stiffness Alopecia Obesity
0               Yes              No              Yes      Yes     Yes
1                No             Yes               No      Yes      No
2               Yes              No              Yes      Yes      No
3               Yes              No               No       No      No
4               Yes             Yes              Yes      Yes     Yes
..              ...             ...              ...      ...     ...
515             Yes             Yes               No       No      No
516             Yes             Yes               No       No      No
517              No             Yes              Yes       No     Yes
518             Yes              No               No      Yes      No
519              No              No               No       No      No

[520 rows x 5 columns]
        class
0    Positive
1    Positive
2    Positive
3    Positive
4    Positive
..        ...
515  Positive
516  Positive
517  Positive
518  Negative
519  Negative

[520 rows x 1 columns]

# identifying columns with binary values
cols = ['Gender', 'Polyuria', 'Polydipsia', 'sudden weight loss',
```

```
       'weakness', 'Polyphagia', 'Genital thrush', 'visual blurring',
       'Itching', 'Irritability', 'delayed healing', 'partial
paresis',
       'muscle stiffness', 'Alopecia', 'Obesity', 'class']

for i in cols:
  unique_vals = data[i].unique()
  print(unique_vals)
```

```
['Male' 'Female']
['No' 'Yes']
['Yes' 'No']
['No' 'Yes']
['Yes' 'No']
['No' 'Yes']
['No' 'Yes']
['No' 'Yes']
['Yes' 'No']
['No' 'Yes']
['Yes' 'No']
['No' 'Yes']
['Yes' 'No']
['Yes' 'No']
['Yes' 'No']
['Positive' 'Negative']
```

Section 2: Feature Engineering

In this section we perform feature engineering on our dataset. Here we begin with performing one-hot encoding to convert our binary categorical features into numerical features.

```
cat_col = ['Gender', 'Polyuria', 'Polydipsia', 'sudden weight loss',
       'weakness', 'Polyphagia', 'Genital thrush', 'visual blurring',
       'Itching', 'Irritability', 'delayed healing', 'partial
paresis',
       'muscle stiffness', 'Alopecia', 'Obesity', 'class']

data = pd.get_dummies(data, columns = cat_col, drop_first = True)
data
```

```
     Age  Gender_Male  Polyuria_Yes  Polydipsia_Yes  sudden weight
loss_Yes  \
0     40            1             0               1
0
1     58            1             0               0
0
2     41            1             1               0
0
3     45            1             0               0
```

```
1
4    60            1             1              1
1
..   ...          ...           ...            ...
...
515   39            0             1              1
1
516   48            0             1              1
1
517   58            0             1              1
1
518   32            0             0              0
0
519   42            1             0              0
0

     weakness_Yes  Polyphagia_Yes  Genital thrush_Yes  visual
blurring_Yes  \
0               1               0                   0
0
1               1               0                   0
1
2               1               1                   0
0
3               1               1                   1
0
4               1               1                   0
1
..            ...             ...                 ...
...
515             0               1                   0
0
516             1               1                   0
0
517             1               1                   0
1
518             1               0                   0
1
519             0               0                   0
0

     Itching_Yes  Irritability_Yes  delayed healing_Yes  partial
paresis_Yes  \
0              1                 0                    1
0
1              0                 0                    0
1
2              1                 0                    1
0
```

```
3              1                 0                    1
0
4              1                 1                    1
1
..           ...               ...                  ...
...
515            1                 0                    1
1
516            1                 1                    1
1
517            0                 0                    0
1
518            1                 0                    1
0
519            0                 0                    0
0

     muscle stiffness_Yes  Alopecia_Yes  Obesity_Yes  class_Positive
0                       1             1            1               1
1                       0             1            0               1
2                       1             1            0               1
3                       0             0            0               1
4                       1             1            1               1
..                    ...           ...          ...             ...
515                     0             0            0               1
516                     0             0            0               1
517                     1             0            1               1
518                     0             1            0               0
519                     0             0            0               0

[520 rows x 17 columns]
```

```
data.columns
```

```
Index(['Age', 'Gender_Male', 'Polyuria_Yes', 'Polydipsia_Yes',
       'sudden weight loss_Yes', 'weakness_Yes', 'Polyphagia_Yes',
       'Genital thrush_Yes', 'visual blurring_Yes', 'Itching_Yes',
       'Irritability_Yes', 'delayed healing_Yes', 'partial
paresis_Yes',
       'muscle stiffness_Yes', 'Alopecia_Yes', 'Obesity_Yes',
       'class_Positive'],
      dtype='object')
```

```
# here we shuffle our data to make it more meaningful
data = data.sample(n = len(data))
data = data.reset_index(drop = True)
data
```

```
     Age  Gender_Male  Polyuria_Yes  Polydipsia_Yes  sudden weight
loss_Yes  \
```

```
0     72            1             1              0
0
1     40            0             1              1
0
2     57            1             1              1
0
3     41            1             1              1
1
4     45            0             0              0
0
..   ...          ...           ...            ...
...
515   35            0             0              1
1
516   58            1             0              1
1
517   40            0             1              1
1
518   57            1             1              1
1
519   90            0             0              1
1

     weakness_Yes  Polyphagia_Yes  Genital thrush_Yes  visual
blurring_Yes  \
0               0               1                   0
1
1               1               1                   0
0
2               1               1                   1
0
3               1               1                   1
1
4               0               1                   0
1
..            ...             ...                 ...
...
515             1               0                   0
0
516             1               1                   0
1
517             1               0                   0
1
518             1               1                   0
1
519             0               0                   1
1

     Itching_Yes  Irritability_Yes  delayed healing_Yes  partial
```

```
paresis_Yes  \
0              1                 0                   1
1
1              1                 0                   0
1
2              0                 0                   1
1
3              1                 1                   0
0
4              1                 0                   0
1
..           ...               ...                 ...
...
515            1                 0                   1
1
516            1                 0                   0
1
517            0                 0                   1
1
518            0                 0                   0
1
519            1                 0                   0
0

     muscle stiffness_Yes  Alopecia_Yes  Obesity_Yes  class_Positive
0                       1             1            0               0
1                       0             0            0               1
2                       0             0            0               1
3                       0             0            1               1
4                       0             0            0               1
..                    ...           ...          ...             ...
515                     1             0            0               1
516                     0             1            1               1
517                     1             0            0               1
518                     0             0            0               1
519                     1             1            0               1

[520 rows x 17 columns]
```

Engineering Features Summary

```
cols_num = data.select_dtypes(include=['number']).shape[1]
cols_cat = data.select_dtypes(exclude=['number']).shape[1]

print('Total number of features:', len(data.columns))
print('Numerical Features:', cols_num)
print('Categorical Features:', cols_cat)
```

```
Total number of features: 17
Numerical Features: 17
Categorical Features: 0
```

Section 3: Splitting Data for Training, Validation & Testing

In this section we split our data into 70% training, 15% validation & 15% test data by fractions.

```
# here we store 30% of the data as validation and test data combined
df_val_test = data.sample(frac = 0.30)

# here we split the data_valid_test into 50-50 valid and test data
df_val = df_val_test.sample(frac = 0.5)
df_test = df_val_test.drop(df_val.index)

# here we use the remaining data 50% as the training data
df_train = data.drop(df_val_test.index)

df_train.shape

(364, 17)

df_val.shape

(78, 17)

df_test.shape

(78, 17)
```

Here we preprocess our data as per training the baseline and further for the deep learning model

```
X_train = df_train.drop('class_Positive', axis = 1)
y_train = df_train['class_Positive']

X_val = df_val.drop('class_Positive', axis = 1)
y_val = df_val['class_Positive']

X_test = df_test.drop('class_Positive', axis = 1)
y_test = df_test['class_Positive']

# this code describes the shape of the training, validation, testing
sets
print('Training shapes:',X_train.shape, y_train.shape)
print('Validation shapes:',X_val.shape, y_val.shape)
print('Test shapes:',X_test.shape, y_test.shape)

Training shapes: (364, 16) (364,)
Validation shapes: (78, 16) (78,)
Test shapes: (78, 16) (78,)
```

Section 4: Feature Scaling & Baseline Model: Logistic Regression

In this section we conduct our initial prediction analysis implementing logistic regression as the baseline model.

```
# Here we import our libraries for baseline and further processing of
the data
import pandas as pd
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression

# Here we perform feature scaling as some basline models, in our case
logistic regression, are sensitive to scale of input features
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_val = scaler.transform(X_val)
X_test = scaler.transform(X_test)

# Now we train our baseline model with the training data
bmodel = LogisticRegression(random_state = 42)

bmodel.fit(X_train, y_train)
```

```
LogisticRegression(random_state=42)
```

```
# Now we use the trained model to perform predictions on our
validation set
y_val_pred = bmodel.predict(X_val)

# Now we evaluate our model using the following functions
from sklearn.metrics import roc_auc_score, accuracy_score,
precision_score, recall_score
def calc_specificity(y_actual, y_pred, thresh):
    # calculates specificity
    return sum((y_pred < thresh) & (y_actual == 0)) /sum(y_actual ==0)

def print_report(y_actual, y_pred, thresh):

    auc = roc_auc_score(y_actual, y_pred)
    accuracy = accuracy_score(y_actual, (y_pred > thresh))
    recall = recall_score(y_actual, (y_pred > thresh))
    precision = precision_score(y_actual, (y_pred > thresh))
    specificity = calc_specificity(y_actual, y_pred, thresh)
    print('AUC:%.3f'%auc)
    print('accuracy:%.3f'%accuracy)
    print('recall:%.3f'%recall)
    print('precision:%.3f'%precision)
    print('specificity:%.3f'%specificity)
```

```python
    print(' ')
    return auc, accuracy, recall, precision, specificity

# Here we set our threshold and call the model evaluation functions to
determine the performance of the model with the validation set
thresh = 0.5
y_train_preds = bmodel.predict_proba(X_train)[:,1]
y_val_preds = bmodel.predict_proba(X_val)[:,1]

print('Logistic Regression')
print('Training:')
bmodel_train_auc, bmodel_train_accuracy, bmodel_train_recall, \
    bmodel_train_precision, bmodel_train_specificity =
print_report(y_train, y_train_preds, thresh)
print('Validation:')
bmodel_valid_auc, bmodel_valid_accuracy, bmodel_valid_recall, \
    bmodel_valid_precision, bmodel_valid_specificity =
print_report(y_val ,y_val_preds, thresh)
```

```
Logistic Regression
Training:
AUC:0.986
accuracy:0.945
recall:0.963
precision:0.946
specificity:0.917

Validation:
AUC:0.943
accuracy:0.897
recall:0.896
precision:0.935
specificity:0.900
```

```python
# Now we use the trained model to perform predictions on our test set
y_test_pred = bmodel.predict(X_test)

# Here we call the model evaluation functions to determine the
performance of the model with the test set
y_test_preds = bmodel.predict_proba(X_test)[:,1]

print('Logistic Regression')
print('Test:')
bmodel_valid_auc, bmodel_valid_accuracy, bmodel_valid_recall, \
    bmodel_valid_precision, bmodel_valid_specificity =
print_report(y_test, y_test_preds, thresh)
```

```
Logistic Regression
Test:
AUC:0.966
```

```
accuracy:0.923
recall:0.925
precision:0.961
specificity:0.920
```

```
features = ['Age', 'Gender_Male', 'Polyuria_Yes', 'Polydipsia_Yes',
       'sudden weight loss_Yes', 'weakness_Yes', 'Polyphagia_Yes',
       'Genital thrush_Yes', 'visual blurring_Yes', 'Itching_Yes',
       'Irritability_Yes', 'delayed healing_Yes', 'partial
paresis_Yes',
       'muscle stiffness_Yes', 'Alopecia_Yes', 'Obesity_Yes']

# Here we perform feature importance over our regression model to
identify the priority features for our model
feature_importances = pd.DataFrame(bmodel.coef_[0],
                                   index = features,

columns=['importance']).sort_values('importance',

ascending=False)

feature_importances.head()
```

```
                     importance
Polydipsia_Yes         1.871165
Polyuria_Yes           1.623144
Irritability_Yes       1.152463
Genital thrush_Yes     0.932349
partial paresis_Yes    0.706734
```

Section 5: Design & Implement Deep Learning Model: Feed-Forward Neural Network

```
from tensorflow import keras

model = keras.Sequential([
    keras.layers.Input(shape=(16,)),    # Input layer with 16 features
    keras.layers.Dense(50, activation='relu'),  # We implement the
model with 2 hidden layers, with 50 neurons and 30 neaurons
respectively
    keras.layers.Dense(30, activation='relu'),  # We implement the
model with ReLU activation
    keras.layers.Dense(1, activation='sigmoid')  # Output layer with 1
neuron and sigmoid activation for binary classification
])

# Here we compile our model with the optimizer and further parameters
model.compile(optimizer='Adam',  # We use Adam optimizer
              loss='binary_crossentropy',  # For our binary
```

```
classification data we implement with Binary cross-entropy loss
              metrics=['accuracy'])  # Here we track accuracy of each
run

# Here we train our Feed-forward Neural Network Model
model.fit(X_train, y_train, epochs=15, validation_data=(X_val, y_val))
```

```
Epoch 1/15
12/12 [==============================] - 2s 33ms/step - loss: 0.6530 -
accuracy: 0.6703 - val_loss: 0.6034 - val_accuracy: 0.7949
Epoch 2/15
12/12 [==============================] - 0s 7ms/step - loss: 0.5281 -
accuracy: 0.8846 - val_loss: 0.5105 - val_accuracy: 0.8205
Epoch 3/15
12/12 [==============================] - 0s 8ms/step - loss: 0.4419 -
accuracy: 0.9093 - val_loss: 0.4443 - val_accuracy: 0.8205
Epoch 4/15
12/12 [==============================] - 0s 11ms/step - loss: 0.3723 -
accuracy: 0.9258 - val_loss: 0.3892 - val_accuracy: 0.8974
Epoch 5/15
12/12 [==============================] - 0s 7ms/step - loss: 0.3155 -
accuracy: 0.9258 - val_loss: 0.3435 - val_accuracy: 0.9231
Epoch 6/15
12/12 [==============================] - 0s 7ms/step - loss: 0.2711 -
accuracy: 0.9258 - val_loss: 0.3112 - val_accuracy: 0.9359
Epoch 7/15
12/12 [==============================] - 0s 13ms/step - loss: 0.2373 -
accuracy: 0.9313 - val_loss: 0.2888 - val_accuracy: 0.9231
Epoch 8/15
12/12 [==============================] - 0s 8ms/step - loss: 0.2101 -
accuracy: 0.9341 - val_loss: 0.2750 - val_accuracy: 0.9231
Epoch 9/15
12/12 [==============================] - 0s 8ms/step - loss: 0.1895 -
accuracy: 0.9396 - val_loss: 0.2654 - val_accuracy: 0.9231
Epoch 10/15
12/12 [==============================] - 0s 8ms/step - loss: 0.1714 -
accuracy: 0.9396 - val_loss: 0.2581 - val_accuracy: 0.9231
Epoch 11/15
12/12 [==============================] - 0s 7ms/step - loss: 0.1563 -
accuracy: 0.9396 - val_loss: 0.2555 - val_accuracy: 0.8718
Epoch 12/15
12/12 [==============================] - 0s 8ms/step - loss: 0.1436 -
accuracy: 0.9505 - val_loss: 0.2541 - val_accuracy: 0.8718
Epoch 13/15
12/12 [==============================] - 0s 8ms/step - loss: 0.1324 -
accuracy: 0.9588 - val_loss: 0.2542 - val_accuracy: 0.8718
Epoch 14/15
12/12 [==============================] - 0s 9ms/step - loss: 0.1223 -
accuracy: 0.9615 - val_loss: 0.2516 - val_accuracy: 0.8590
Epoch 15/15
```

```
12/12 [==============================] - 0s 8ms/step - loss: 0.1144 -
accuracy: 0.9615 - val_loss: 0.2508 - val_accuracy: 0.8590

<keras.src.callbacks.History at 0x7fd9f0cb4a30>
```

```
# Here we perform predictions on our test data with the trained model
y_pred = model.predict(X_test)
```

```
3/3 [==============================] - 0s 4ms/step
```

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

```
3/3 [==============================] - 0s 5ms/step - loss: 0.1519 -
accuracy: 0.9231
Test Loss: 0.15193887054920197, Test Accuracy: 0.9230769276618958
```

Section 6: Model Evaluation Analysis

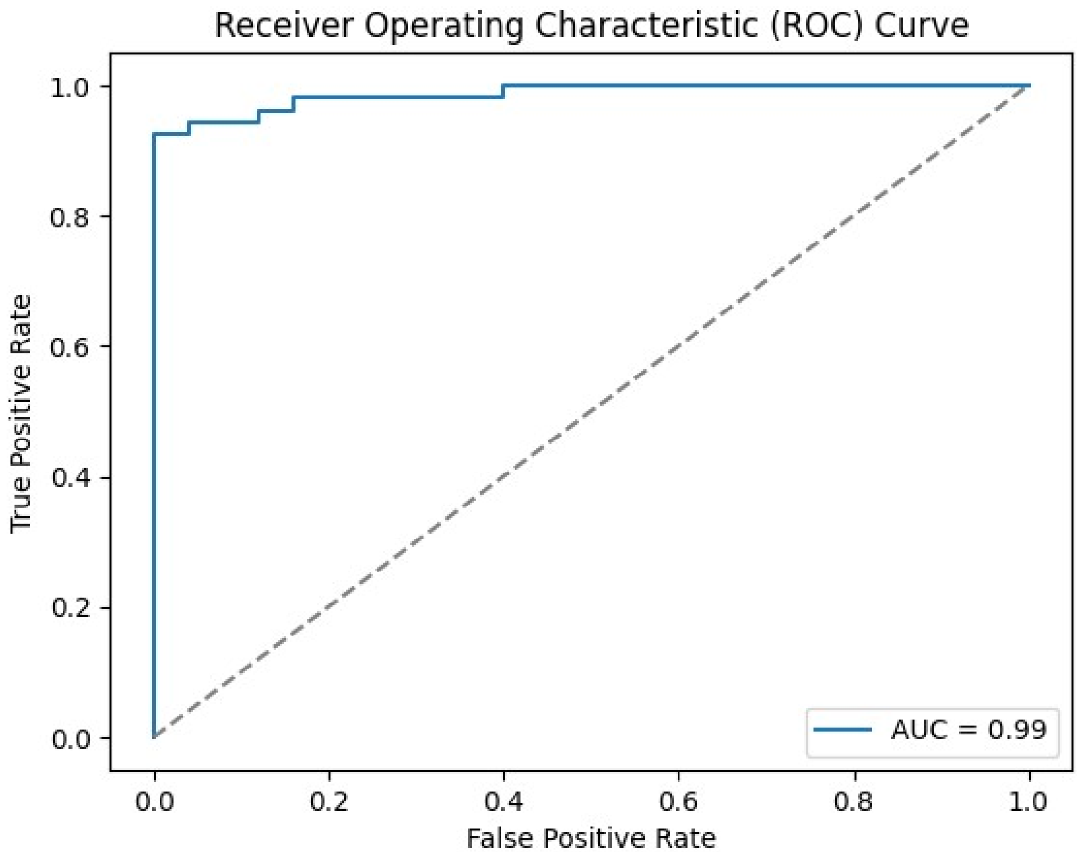
In this section we conduct analysis on our model to determine the accurate results of the model using analysis techniques including F-1 Score, Recall, Precision, AUC score, and AUC-ROC curve.

```
from sklearn.metrics import precision_score, recall_score, f1_score,
accuracy_score, confusion_matrix, roc_auc_score

y_train_preds_nn = model.predict(X_train)
y_val_preds_nn = model.predict(X_val)
y_test_preds_nn = model.predict(X_test)

y_train_preds_binary = (y_train_preds_nn > 0.5).astype(int)
y_val_preds_binary = (y_val_preds_nn > 0.5).astype(int)
y_test_preds_binary = (y_test_preds_nn > 0.5).astype(int)

# Here we determine precision, recall, f1-score, AUC, and accuracy
based on the training data performance of the model
precision_train = precision_score(y_train, y_train_preds_binary)
recall_train = recall_score(y_train, y_train_preds_binary)
f1_train = f1_score(y_train, y_train_preds_binary)
accuracy_train = accuracy_score(y_train, y_train_preds_binary)
auc_train = roc_auc_score(y_train, y_train_preds_nn)

# Here we determine precision, recall, f1-score, AUC, and accuracy
based on the validation data performance of the model
precision_val = precision_score(y_val, y_val_preds_binary)
recall_val = recall_score(y_val, y_val_preds_binary)
f1_val = f1_score(y_val, y_val_preds_binary)
accuracy_val = accuracy_score(y_val, y_val_preds_binary)
auc_val = roc_auc_score(y_val, y_val_preds_nn)
```

```python
# Here we determine precision, recall, f1-score, AUC, and accuracy based on the testing data performance of the model
precision_test = precision_score(y_test, y_test_preds_binary)
recall_test = recall_score(y_test, y_test_preds_binary)
f1_test = f1_score(y_test, y_test_preds_binary)
accuracy_test = accuracy_score(y_test, y_test_preds_binary)
auc_test = roc_auc_score(y_test, y_test_preds_nn)

print('Training Set Metrics:')
print(f'Precision: {precision_train:.4f}')
print(f'Recall: {recall_train:.4f}')
print(f'F1-score: {f1_train:.4f}')
print(f'Accuracy: {accuracy_train:.4f}')
print(f'AUC: {auc_train:.4f}')
print('Confusion Matrix:')
print(confusion_matrix(y_train, y_train_preds_binary))

print('\nValidation Set Metrics:')
print(f'Precision: {precision_val:.4f}')
print(f'Recall: {recall_val:.4f}')
print(f'F1-score: {f1_val:.4f}')
print(f'Accuracy: {accuracy_val:.4f}')
print(f'AUC: {auc_val:.4f}')
print('Confusion Matrix:')
print(confusion_matrix(y_val, y_val_preds_binary))

print('\nTest Set Metrics:')
print(f'Precision: {precision_test:.4f}')
print(f'Recall: {recall_test:.4f}')
print(f'F1-score: {f1_test:.4f}')
print(f'Accuracy: {accuracy_test:.4f}')
print(f'AUC: {auc_test:.4f}')
print('Confusion Matrix:')
print(confusion_matrix(y_test, y_test_preds_binary))

# # Additionaly we compute the confusion matrix
# cm = confusion_matrix(y_test, y_test_preds_binary)
# print('Confusion Matrix:')
# print(cm)
```

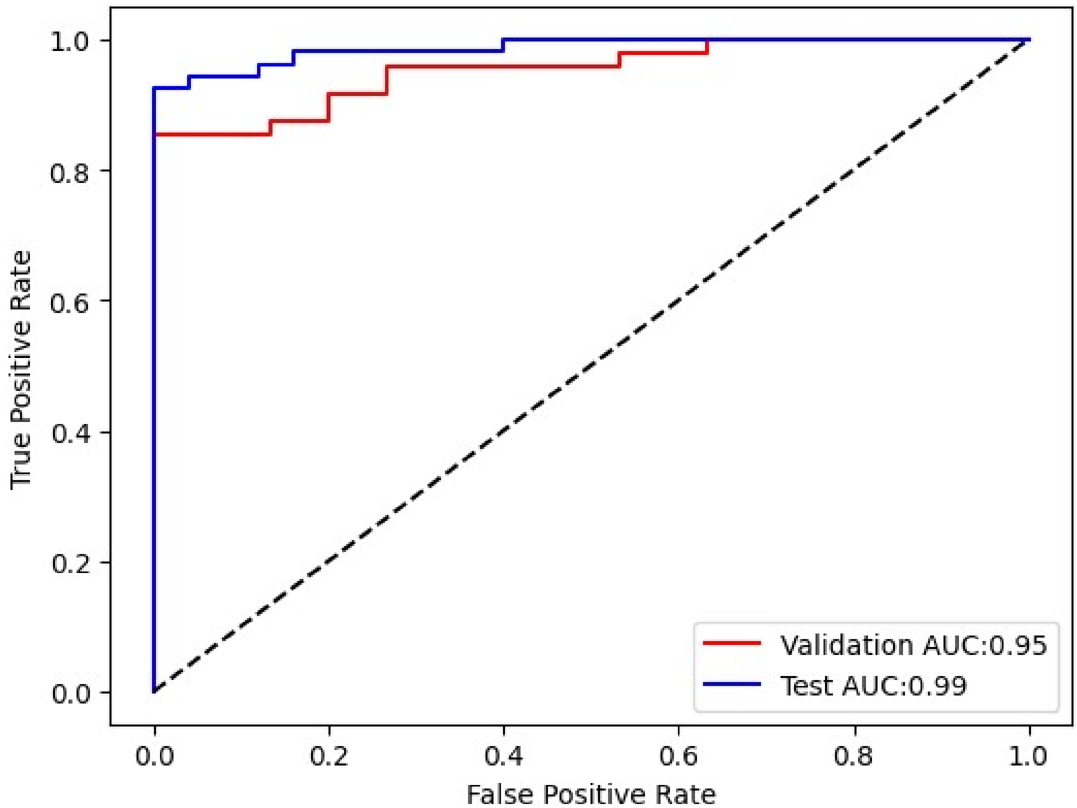
```
12/12 [==============================] - 0s 2ms/step
3/3 [==============================] - 0s 3ms/step
3/3 [==============================] - 0s 6ms/step
Training Set Metrics:
Precision: 0.9680
Recall: 0.9680
F1-score: 0.9680
Accuracy: 0.9615
AUC: 0.9939
Confusion Matrix:
```

```
[[138   7]
 [  7 212]]

Validation Set Metrics:
Precision: 0.9111
Recall: 0.8542
F1-score: 0.8817
Accuracy: 0.8590
AUC: 0.9535
Confusion Matrix:
[[26  4]
 [ 7 41]]

Test Set Metrics:
Precision: 0.9434
Recall: 0.9434
F1-score: 0.9434
Accuracy: 0.9231
AUC: 0.9864
Confusion Matrix:
[[22  3]
 [ 3 50]]

from sklearn.metrics import roc_curve, auc
import matplotlib.pyplot as plt

fpr, tpr, thresholds = roc_curve(y_test, y_pred)
roc_auc = auc(fpr, tpr)

plt.plot(fpr, tpr, label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], linestyle='--', color='gray')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```




```
from sklearn.metrics import roc_curve

y_val_pred = model.predict(X_val)

fpr_val, tpr_val, thresholds_val = roc_curve(y_val, y_val_pred)
auc_val = roc_auc_score(y_val, y_val_pred)

fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_pred)
auc_test = roc_auc_score(y_test, y_pred)

print('Validation AUC:%.2f'%auc_val)
print('Test AUC:%.2f'%auc_test)

plt.plot(fpr_val, tpr_val, 'r-',label ='Validation AUC:%.2f'%auc_val)
plt.plot(fpr_test, tpr_test, 'b-',label ='Test AUC:%.2f'%auc_test)
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
3/3 [==============================] - 0s 4ms/step
Validation AUC:0.95
Test AUC:0.99
```




```
from sklearn.metrics import roc_curve

y_train_pred = model.predict(X_train)

fpr_train, tpr_train, thresholds_train = roc_curve(y_train,
y_train_pred)
auc_train = roc_auc_score(y_train, y_train_pred)

fpr_val, tpr_val, thresholds_val = roc_curve(y_val, y_val_pred)
auc_val = roc_auc_score(y_val, y_val_pred)

fpr_test, tpr_test, thresholds_test = roc_curve(y_test, y_pred)
auc_test = roc_auc_score(y_test, y_pred)

print('Training AUC:%.2f'%auc_train)
print('Validation AUC:%.2f'%auc_val)
print('Test AUC:%.2f'%auc_test)

plt.plot(fpr_train, tpr_train, 'g-',label ='Training AUC:
%.2f'%auc_train)
```

```
plt.plot(fpr_val, tpr_val, 'r-',label ='Validation AUC:%.2f'%auc_val)
plt.plot(fpr_test, tpr_test, 'b-',label ='Test AUC:%.2f'%auc_test)
plt.plot([0,1],[0,1],'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.legend()
plt.show()
```

```
12/12 [==============================] - 0s 3ms/step
Training AUC:0.99
Validation AUC:0.95
Test AUC:0.99
```