Breast Cancer Prediction Model



MAHATMA EDUCATION SOCIETY'S

PILLAI COLLEGE OF ARTS, COMMERCE & SCIENCE (Autonomous)

NEW PANVEL

PROJECT REPORT ON

"Breast Cancer Risk Prediction Model"

IN PARTIAL FULFILLMENT OF

MASTER OF DATA ANALYTICS

SEMESTER III- 2024-25

PROJECT GUIDE

Name: Omkar Sherkhane

SUBMITTED BY: Shreya Bhattacharjee

ROLL NO: 6861

Mahatma Education Society's PILLAI COLLEGE OF ARTS, COMMERCE & SCIENCE (Autonomous) Re-accredited "A" Grade by NAAC (3rd Cycle)



Project Completion Certificate THIS IS TO CERTIFY THAT

Shreya Bhattacharjee

of M.Sc. Data Analytics Part - II has completed the project titled Breast Cancer Prediction Model of subject Machine Learning under our guidance and supervision during the academic year 2024-25 in the department of Master of Data Analytics.

Project Guide Course Coordinator Head of the Department

Introduction:

Breast cancer is one of the most prevalent and life-threatening diseases affecting women worldwide. Early detection and accurate diagnosis are crucial in improving the chances of successful treatment and survival. The Breast Cancer Prediction Model is a machine learning-based application developed to aid in the early detection of breast cancer by predicting the likelihood of a patient having malignant (cancerous) or benign (non-cancerous) tumors based on their medical features.

This project leverages advanced classification algorithms to analyze medical data and provide reliable predictions, which can assist healthcare professionals in making informed decisions. The model is trained on the Breast Cancer Wisconsin (Diagnostic) dataset, a widely-used dataset in the medical research community that contains detailed measurements of cell nuclei present in breast cancer biopsies.

The predictive model is deployed within an easy-to-use web application, built using the Flask framework. This web interface allows users to input specific medical features related to breast cancer, and it returns predictions along with informative messages and visual aids to help interpret the results.

The Breast Cancer Prediction Model demonstrates the potential of machine learning in healthcare, showcasing how technology can be harnessed to enhance diagnostic accuracy and support early intervention strategies. By providing a user-friendly platform for breast cancer prediction, this project aims to contribute to the ongoing efforts to improve breast cancer outcomes and save lives through early detection.

Technologies Used for the Breast Cancer Prediction Model

1. Python

- **Description**: A high-level programming language known for its readability andversatility.
- **Role**: Used for data processing, model training, and application development. Python's extensive libraries facilitate machine learning and web development.

2. Scikit-learn

- **Description**: A powerful machine learning library for Python.
- **Role**: Provides tools for building and training the predictive model. It includes various algorithms for classification, such as support vector machines, decision trees, and ensemble methods.

3. Flask

- **Description**: A lightweight web framework for Python.
- **Role**: Used to build the web application that allows users to interact with the predictive model. Flask handles web requests, routing, and rendering of HTML templates.

4. Pickle

- **Description**: A Python module for serializing and describilizing Python objects.
- Role: Used to save the trained machine learning model to a file (model.pkl) and loadit into the application for making predictions.

5. HTML/CSS

- **Description**: Standard technologies for creating and styling web pages.
- **Role**: HTML is used for structuring the content of the web application, while CSS is used for styling and visual design, including layout and color schemes.

6. Bootstrap

- **Description**: A front-end framework for developing responsive and mobile-first websites.
- **Role**: Provides pre-designed components and styles to create a responsive and visually appealing user interface. Bootstrap simplifies the design process and ensures compatibility across various devices.

7. Jinja2

- **Description**: A templating engine for Python, used with Flask.
- **Role**: Allows dynamic generation of HTML pages by embedding Python code within HTML templates. It helps in rendering data and results from the Flask application into the web pages.

8. NumPy

- **Description**: A fundamental package for scientific computing with Python.
- **Role**: Provides support for large multi-dimensional arrays and matrices. Used to handle and manipulate the input features for prediction.

9. Pandas

- **Description**: A data manipulation and analysis library for Python.
- **Role**: Facilitates data cleaning, transformation, and analysis. It is particularly useful for preprocessing the dataset before training the model.

10. Matplotlib & Seaborn

- **Description**: Libraries for data visualization in Python.
- **Role**: Used to create plots and visualizations that help in analyzing the data and understanding model performance.

CODE AND OUTPUT

```
import numpy as np
import pandas as pd
```

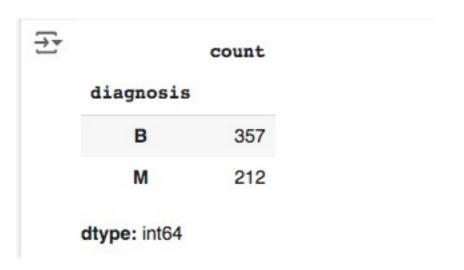
```
breast=pd.read_csv('/content/breast cancer.csv')
breast.head()
```

| | id | diagnosis | radius_mean | texture_mean | perimeter_mean | area_mean | smoothness_mean | compactness_mean | concavity_mean | concave points_mean | texture_v |
|---|----------|-----------|-------------|--------------|----------------|-----------|-----------------|------------------|----------------|------------------------|---------------|
| 0 | 842302 | М | 17.99 | 10.38 | 122.80 | 1001.0 | 0.11840 | 0.27760 | 0.3001 | 0.14710 | |
| 1 | 842517 | М | 20.57 | 17.77 | 132.90 | 1326.0 | 0.08474 | 0.07864 | 0.0869 | 0.07017 | |
| 2 | 84300903 | М | 19.69 | 21.25 | 130.00 | 1203.0 | 0.10960 | 0.15990 | 0.1974 | 0.12790 | |
| 3 | 84348301 | М | 11.42 | 20.38 | 77.58 | 386.1 | 0.14250 | 0.28390 | 0.2414 | 0.10520 | |
| 4 | 84358402 | М | 20.29 | 14.34 | 135.10 | 1297.0 | 0.10030 | 0.13280 | 0.1980 | 0.10430 | |

5 rows x 33 columns

```
breast.shape (569,33)
```

breast['diagnosis'].value_counts()



breast.info()

RangeIndex: 569 entries, 0 to 568 Data columns (total 33 columns):

| Data | columns (total 33 columns): | | | | | | | |
|------|-----------------------------|----------------|---------|--|--|--|--|--|
| # | Column | Non-Null Count | Dtype | | | | | |
| | | | | | | | | |
| 0 | id | 569 non-null | int64 | | | | | |
| 1 | diagnosis | 569 non-null | object | | | | | |
| 2 | radius_mean | 569 non-null | float64 | | | | | |
| 3 | texture_mean | 569 non-null | float64 | | | | | |
| 4 | perimeter_mean | 569 non-null | float64 | | | | | |
| 5 | area_mean | 569 non-null | float64 | | | | | |
| 6 | smoothness_mean | 569 non-null | float64 | | | | | |
| 7 | compactness_mean | 569 non-null | float64 | | | | | |
| 8 | concavity_mean | 569 non-null | float64 | | | | | |
| 9 | concave points_mean | 569 non-null | float64 | | | | | |
| 10 | symmetry_mean | 569 non-null | float64 | | | | | |
| 11 | fractal_dimension_mean | 569 non-null | float64 | | | | | |
| 12 | radius_se | 569 non-null | float64 | | | | | |
| 13 | texture_se | 569 non-null | float64 | | | | | |
| 14 | perimeter_se | 569 non-null | float64 | | | | | |
| 15 | area_se | 569 non-null | float64 | | | | | |
| 16 | smoothness_se | 569 non-null | float64 | | | | | |
| 17 | compactness_se | 569 non-null | float64 | | | | | |
| 18 | concavity_se | 569 non-null | float64 | | | | | |
| 19 | concave points_se | 569 non-null | float64 | | | | | |
| 20 | symmetry_se | 569 non-null | float64 | | | | | |
| 21 | fractal_dimension_se | 569 non-null | float64 | | | | | |
| 22 | radius_worst | 569 non-null | float64 | | | | | |
| 23 | texture_worst | 569 non-null | float64 | | | | | |
| 24 | perimeter worst | 569 non-null | float64 | | | | | |

breast.isnull().sum()



| | 0 |
|------------------------|---|
| id | 0 |
| diagnosis | 0 |
| radius_mean | 0 |
| texture_mean | 0 |
| perimeter_mean | 0 |
| area_mean | 0 |
| smoothness_mean | 0 |
| compactness_mean | 0 |
| concavity_mean | 0 |
| concave points_mean | 0 |
| symmetry_mean | 0 |
| fractal_dimension_mean | 0 |
| radius_se | 0 |
| texture_se | 0 |

```
# Convert 'diagnosis' column to numerical
representation
breast['diagnosis'] = breast['diagnosis'].map({'M': 1,
    'B': 0})
# Now calculate correlations
breast.corr()
```

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| | id | diagnosis | radius_mean | texture_mean |
|------------------|-----------|-----------|-------------|--------------|
| id | 1.000000 | 0.039769 | 0.074626 | 0.099770 |
| diagnosis | 0.039769 | 1.000000 | 0.730029 | 0.415185 |
| radius_mean | 0.074626 | 0.730029 | 1.000000 | 0.323782 |
| texture_mean | 0.099770 | 0.415185 | 0.323782 | 1.000000 |
| perimeter_mean | 0.073159 | 0.742636 | 0.997855 | 0.329533 |
| area_mean | 0.096893 | 0.708984 | 0.987357 | 0.321086 |
| smoothness_mean | -0.012968 | 0.358560 | 0.170581 | -0.023389 |
| compactness_mean | 0.000096 | 0.596534 | 0.506124 | 0.236702 |
| concavity_mean | 0.050080 | 0.696360 | 0.676764 | 0.302418 |

breast.drop('Unnamed: 32', axis=1, inplace=True)

breast.describe()

| | id | diagnosis | radius_mean | texture_mean | perimeter_mean | area_mean | |
|---------------------|--------------|------------|-------------|--------------|----------------|-------------|--|
| count | 5.690000e+02 | 569.000000 | 569.000000 | 569.000000 | 569.000000 | 569.000000 | |
| mean | 3.037183e+07 | 0.372583 | 14.127292 | 19.289649 | 91.969033 | 654.889104 | |
| std | 1.250206e+08 | 0.483918 | 3.524049 | 4.301036 | 24.298981 | 351.914129 | |
| min | 8.670000e+03 | 0.000000 | 6.981000 | 9.710000 | 43.790000 | 143.500000 | |
| 25% | 8.692180e+05 | 0.000000 | 11.700000 | 16.170000 | 75.170000 | 420.300000 | |
| 50% | 9.060240e+05 | 0.000000 | 13.370000 | 18.840000 | 86.240000 | 551.100000 | |
| 75% | 8.813129e+06 | 1.000000 | 15.780000 | 21.800000 | 104.100000 | 782.700000 | |
| max | 9.113205e+08 | 1.000000 | 28.110000 | 39.280000 | 188.500000 | 2501.000000 | |
| 8 rows × 32 columns | | | | | | | |

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()

```
breast['diagnosis'] =
le.fit_transform(breast['diagnosis'])
```

Splitting Data into Training and Testing Sets

```
from sklearn.model_selection import train_test_split
# Split the data into training and testing sets
X = breast.drop('diagnosis', axis=1)
y = breast['diagnosis']
X_train, X_test, y_train, y_test = train_test_split(X,
y, test_size=0.2, random_state=42)
```

Featule Scaling

```
from sklearn.preprocessing import StandardScaler
# Scale the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Exploiatoiy Data Analysis (EDA)

```
import seaborn as sns
import matplotlib.pyplot as plt

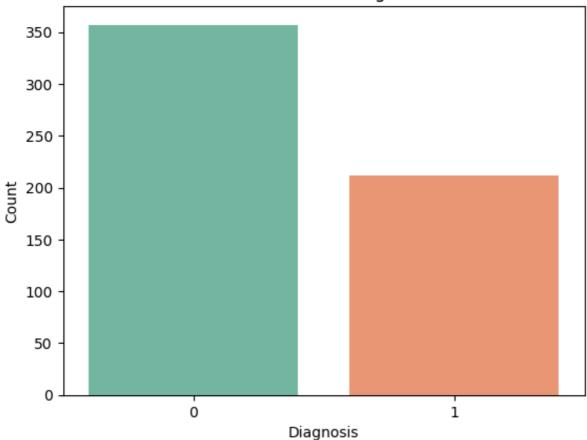
# Assuming 'breast' is a DataFrame and 'diagnosis' is
the target variable

# Set a specific palette to differentiate the bars
sns.countplot(x=breast['diagnosis'], palette='Set2')
plt.title('Distribution of Diagnosis')
```

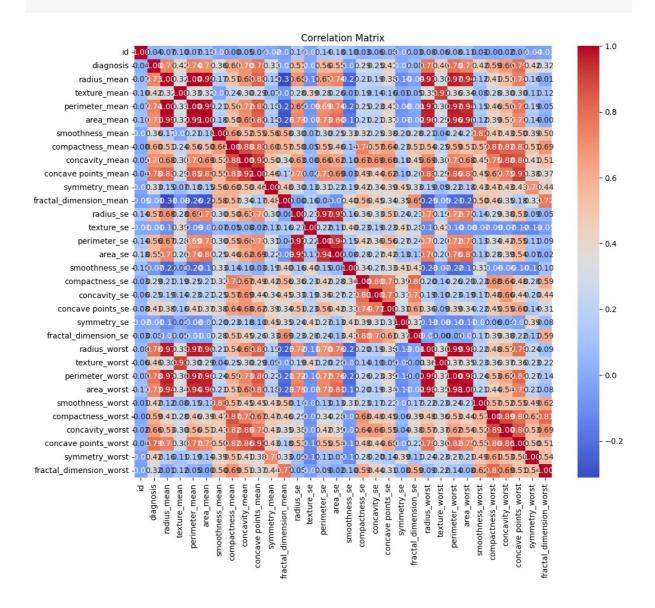
```
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```

```
plt.xlabel('Diagnosis')
plt.ylabel('Count')
plt.show()
```

Distribution of Diagnosis

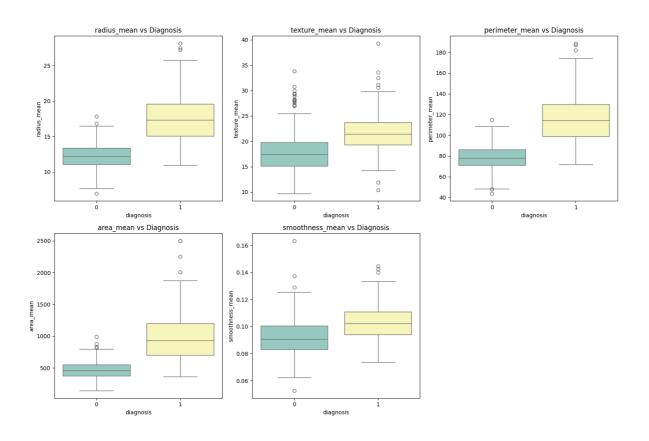


```
# Correlation Heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(breast.corr(), annot=True, cmap='coolwarm',
fmt=".2f")
plt.title('Correlation Matrix')
plt.show()
```



```
# Box Plots for Selected Features
features_to_plot = ['radius_mean', 'texture_mean',
'perimeter_mean', 'area_mean', 'smoothness_mean']
plt.figure(figsize=(15, 10))
for i, feature in enumerate(features_to_plot, 1):
    plt.subplot(2, 3, i)
```

```
sns.boxplot(x='diagnosis', y=feature, data=breast,
palette='Set3')
  plt.title(f'{feature} vs Diagnosis')
plt.tight_layout()
plt.show()
```



```
# Pairplot for Selected Features
selected_features = ['radius_mean', 'texture_mean',
   'perimeter_mean', 'area_mean']
sns.pairplot(breast[selected_features + ['diagnosis']],
hue='diagnosis', palette='husl')
plt.show()
```



perimeter_mean

area_mean

Visualize the correlation matrix
breast.corr()

texture_mean

radius_mean

| id | diagnosis | radius_mean | texture_mean |
|----|-----------|-------------|--------------|
|----|-----------|-------------|--------------|

| id | 1.000000 | 0.039769 | 0.074626 | 0.099770 |
|------------------|-----------|----------|----------|-----------|
| diagnosis | 0.039769 | 1.000000 | 0.730029 | 0.415185 |
| radius_mean | 0.074626 | 0.730029 | 1.000000 | 0.323782 |
| texture_mean | 0.099770 | 0.415185 | 0.323782 | 1.000000 |
| perimeter_mean | 0.073159 | 0.742636 | 0.997855 | 0.329533 |
| area_mean | 0.096893 | 0.708984 | 0.987357 | 0.321086 |
| smoothness_mean | -0.012968 | 0.358560 | 0.170581 | -0.023389 |
| compactness_mean | 0.000096 | 0.596534 | 0.506124 | 0.236702 |

l'íaining Model

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

# Train the logistic regression model
lr = LogisticRegression()
lr.fit(X_train, y_train)

# Evaluate the performance on the testing set
y_pred_lr = lr.predict(X_test)
accuracy_lr = accuracy_score(y_test, y_pred_lr)
print('Accuracy:', accuracy_lr)
```

Accuracy: 0.9736842105263158

```
input_text = (-0.23717126, -0.64487029, -0.11382239, -
0.57427777, -0.60294971,
```

```
1.0897546, 0.91543814, 0.41448279, 0.09311633,
1.78465117,
    2.11520208, 0.28454765, -0.31910982, 0.2980991,
0.01968238,
    -0.47096352, 0.45757106, 0.28733283, -0.23125455,
0.26417944,
    0.66325388, 0.12170193, 0.42656325, 0.36885508,
0.02065602,
    1.39513782, 2.0973271, 2.01276347, 0.61938913,
2.9421769,
    3.15970842)
np df = np.asarray(input text)
# Use 'lr' instead of 'lg' to make the prediction
predictiont = lr.predict(np df.reshape(1,-1))
if prediciont[0] == 1:
    print("Cancrous")
else:
print("Not Cancrous")
```

Cancrous

Píediction System

Saving a Machine Learning Model with Pickle

```
import pickle

pickle.dump(lr, open('model.pkl','wb')) # Now pickle
the 'lg' object
```

FLASK CODE

App.py

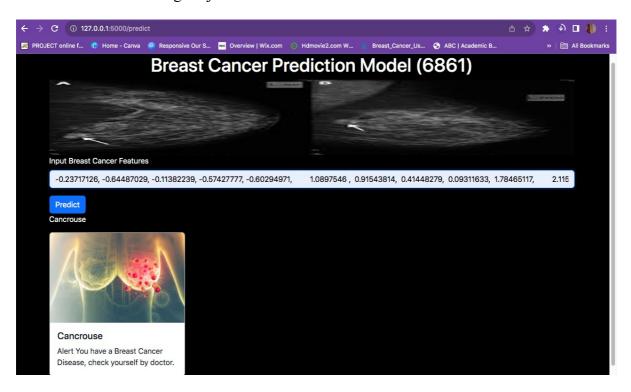
```
from flask import Flask, render_template, request
import numpy as np
import pandas as pd
import pickle
# loading model
model = pickle.load(open('model.pkl', 'rb'))
# flask app
app = Flask(__name__)
@app.route('/')
def home():
    return render template('index.html')
@app.route('/predict', methods=['POST'])
def predict():
    features = request.form['feature']
    features = features.split(',')
    np features = np.asarray(features, dtype=np.float32)
    # prediction
    pred = model.predict(np_features.reshape(1, -1))
    message = ['Cancrouse' if pred[0] == 1 else 'Not Cancrouse']
    # print(message[0])
    return render template('index.html', message=message)
if name
          == '<u>__main__</u>':
    app.run (debug=True)
```

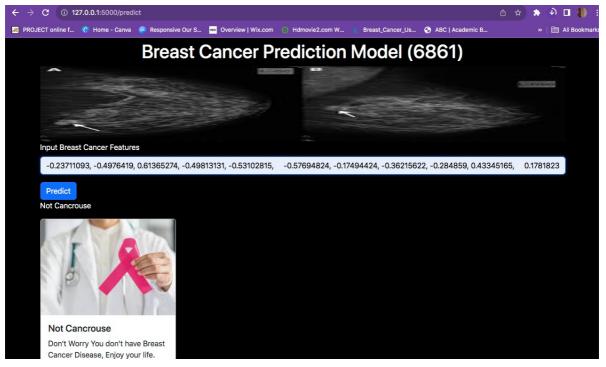
INDEX.HTML

```
<!doctype html>
<html lang="en">
  <head>
    <meta charset="utf-8">
    <meta name="viewport" content="width=device-width, initial-scale=1">
    <title>CA 2 FOR MACHINE LEARNING 6861</title>
    <link href="https://cdn.jsdelivr.net/npm/bootstrap@5.3.0-</pre>
alpha3/dist/css/bootstrap.min.css" rel="stylesheet" integrity="sha384-
KK94CHFLLe+nY2dmCWGMq91rCGa5qtU4mk92HdvYe+M/SXH301p5ILy+dN9+nJOZ"
crossorigin="anonymous">
  </head>
  <body style="background:black; color:white;">
  <div class="container my-3 mt-3">
      <h1 style="text-align:center">Breast Cancer Prediction Model
(6861) < /h1>
      <img style="width:100%; height:160px" src="{{ url for('static',</pre>
filename='images.jpg') }}" alt="My Image">
          <form action="/predict" method="POST">
            <div class="mb-3">
              <label for="text" class="form-label">Input Breast Cancer
Features</label>
              <input type="text" class="form-control" id="number"</pre>
name="feature" aria-describedby="emailHelp">
            </div>
            <button type="submit" class="btn btn-primary">Predict</button>
      </form>
         {% for i in message %}
       { {i} } 
          {% if i=='Not Cancrouse' %}
            <div class="card my-3 mt-3" style="width: 18rem;">
              <img src="{{url for('static', filename='img2.jpg')}}"</pre>
class="card-img-top" alt="...">
              <div class="card-body">
                <h5 class="card-title">Not Cancrouse</h5>
                Don't Worry You don't have Breast
Cancer Disease, Enjoy your life.
              </div>
            </div>
          {% else %}
            <div class="card my-3 mt-3" style="width: 18rem;">
              <img src="{{url for('static', filename='img1.jpg')}}"</pre>
class="card-img-top" alt="...">
              <div class="card-body">
                <h5 class="card-title">Cancrouse</h5>
                Alert You have a Breast Cancer
Disease, check yourself by doctor.
              </div>
            </div>
          {% endif %}
        {% endfor %}
</div>
```

Output







Conclusion:

The cancer prediction system employs logistic regression to assess key features and predict the likelihood of cancer presence. Achieving an accuracy of approximately 97.37%, the model demonstrates high reliability and precision in generating predictions from input data. This robust performance highlights its potential as an effective tool for early cancer detection, aiding in timely diagnosis and intervention. The system's accuracy underscores its capability to support healthcare professionals in making informed decisions, ultimately contributing to improved patient outcomes and proactive healthcare management.