Assessment Report

on

"Diagnose Diabetes"

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BACHELOR OF TECHNOLOGY

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in

CSEAIML

By

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Introduction

Diabetes is one of the most common and serious chronic diseases affecting millions worldwide. Early detection is critical for managing symptoms, preventing complications, and improving the quality of life of those affected. However, manual diagnosis often takes time and resources. With the rise of data science and machine learning, we can leverage medical data to predict the likelihood of diabetes in a more efficient and automated way.

In this project, we use the Pima Indians Diabetes Dataset, which contains records from female patients of Pima Indian heritage aged 21 years or older. Each record includes attributes such as the number of pregnancies, glucose concentration, blood pressure, skin thickness, insulin level, BMI, diabetes pedigree function, and age. The target variable is Outcome, where 1 indicates diabetes and 0 indicates no diabetes.

This report outlines the step-by-step approach for analyzing the data, preprocessing it, building machine learning models, and evaluating their performance.

Methodology

The project follows the complete machine learning pipeline, as detailed below:

1. **Data Collection**:
    - The dataset was provided in CSV format titled 2. Diagnose Diabetes.csv.
    - It contains 768 rows and 9 columns.
2. **Data Preprocessing**:
    - Some features had zero values that are not physically possible (e.g., BMI = 0), which were treated as missing values.
    - Columns with such values (Glucose, BloodPressure, SkinThickness, Insulin, and BMI) were corrected by replacing 0s with NaN.
    - All missing values were filled with the **median** of their respective columns.
3. **Exploratory Data Analysis (EDA)**:
    - We generated **heatmaps** to analyze correlation between variables.
    - **Distribution plots** and **count plots** were used to understand the spread of data and class imbalance.
    - Important findings:
        - Glucose, BMI, and Age showed a strong correlation with the target variable.
        - Around 35% of the patients in the dataset were diagnosed with diabetes (Outcome = 1).
4. **Feature Scaling**:
    - Since models like Logistic Regression perform better with normalized data, we used StandardScaler to scale all features.
5. **Model Building**:
    - The data was split into training and testing sets (80:20 ratio).

- Two machine learning models were trained:
  - **Logistic Regression** – a linear model used for binary classification.
  - **Random Forest Classifier** – an ensemble method that builds multiple decision trees for better accuracy.

6. **Evaluation**:
   - Both models were evaluated using:
     - **Accuracy Score**
     - **Classification Report** (Precision, Recall, F1-score)
     - **Confusion Matrix**
   - Visualization of confusion matrices was done using heatmaps.

Code

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix,
classification_report, accuracy_score, precision_score,
recall_score
import seaborn as sns
import matplotlib.pyplot as plt

# For file upload in Google Colab
from google.colab import files
import io

# Upload the dataset file
uploaded = files.upload()

# Load the uploaded CSV file
for file_name in uploaded.keys():
    data = pd.read_csv(io.BytesIO(uploaded[file_name]))

# Check the first few rows
data.head()
```

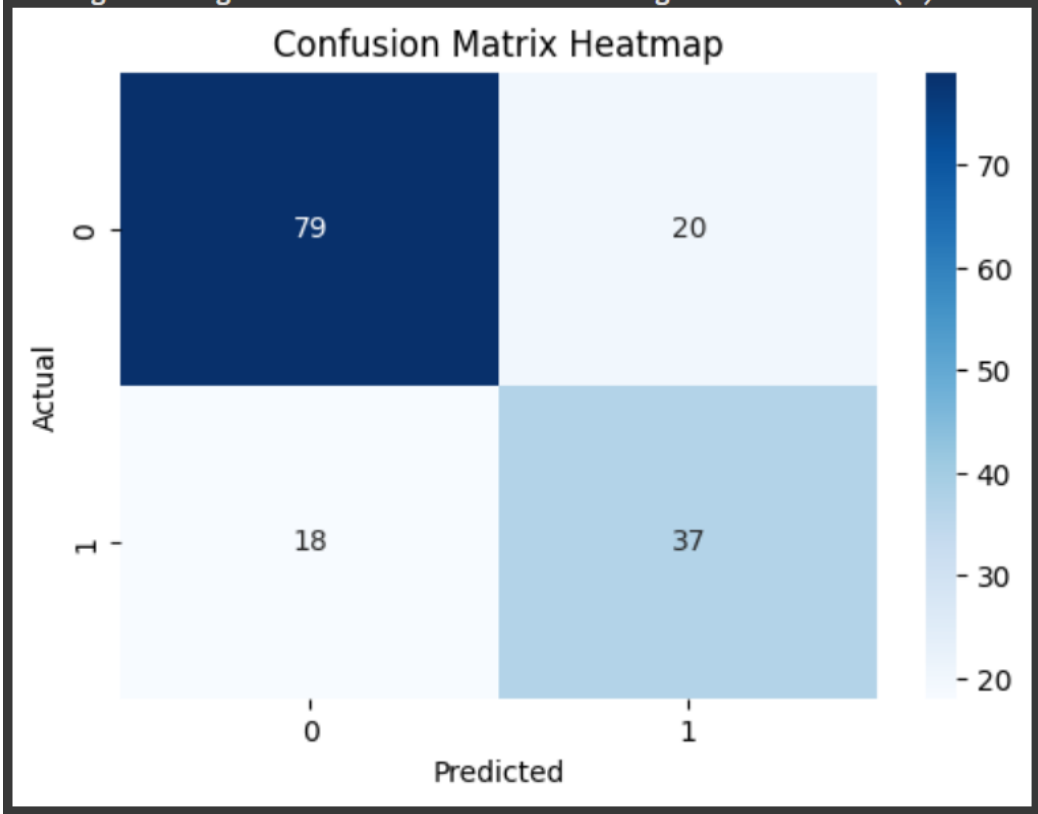
```
# Define features and target
X = data.drop('Outcome', axis=1)
y = data['Outcome']

# Split the data into train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

# Initialize and fit a Logistic Regression model
model = LogisticRegression(random_state=42)
model.fit(X_train_scaled, y_train)

# Make predictions
y_pred = model.predict(X_test_scaled)

# Calculate confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot heatmap of confusion matrix
plt.figure(figsize=(6,4))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues')
```

```
plt.title('Confusion Matrix Heatmap')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Calculate evaluation metrics
accuracy = accuracy_score(y_test, y_pred)
precision = precision_score(y_test, y_pred)
recall = recall_score(y_test, y_pred)
report = classification_report(y_test, y_pred)

# Print metrics
print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print("\nClassification Report:\n", report)
```

Output

- **2. Diagnose Diabetes.csv**(text/csv) - 23873 bytes, last modified: 4/18/2025 - 100% done

```
Saving 2. Diagnose Diabetes.csv to 2. Diagnose Diabetes (1).csv
```




```
Accuracy: 0.7532
Precision: 0.6491
Recall: 0.6727
```

```
Classification Report:
              precision    recall  f1-score   support

           0       0.81      0.80      0.81        99
           1       0.65      0.67      0.66        55

    accuracy                           0.75       154
   macro avg       0.73      0.74      0.73       154
weighted avg       0.76      0.75      0.75       154
```

References / Credits

- Dataset: Pima Indians Diabetes Dataset from Kaggle
- Python Libraries:
  - pandas for data manipulation
  - numpy for numerical operations
  - matplotlib & seaborn for visualization
  - scikit-learn for machine learning models
- Image & Screenshot Tools: Windows Snipping Tool / Screenshot tool