Assessment Report

on

"Diabetes Prediction"

submitted as partial fulfillment for the award of

BACHELOR OF TECHNOLOGY DEGREE

SESSION 2024-25

in

CSE(AIML)

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1. Introduction

With the rising global burden of diabetes, early prediction using health data can significantly improve disease management and prevention. This project builds a classification model using supervised machine learning to predict the likelihood of diabetes in patients based on medical attributes such as glucose level, blood pressure, BMI, and more. This can assist healthcare providers in identifying high-risk individuals for early intervention.

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2. Problem Statement

To predict whether an individual has diabetes based on available health and medical data using a classification model. The objective is to aid in early diagnosis, allowing timely treatment and lifestyle changes to reduce long-term complications.

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3. Objectives

- Preprocess the dataset to prepare it for model training.
- Train a Random Forest Classifier to predict diabetes likelihood.
- Evaluate the model using standard classification metrics: accuracy, precision, recall, and F1-score.
- Visualize the model's performance using a confusion matrix

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4. Methodology

Data Collection:

The dataset used is the Pima Indians Diabetes Database, provided in CSV format.
Data Preprocessing:

- Handle missing or zero values in key features by replacing them with column medians.
- Apply Standard Scaler for feature normalization.
- Split the data into training (80%) and testing (20%) sets.

Model Building:

- Use the Random Forest Classifier due to its robustness and ability to handle feature interactions.
- Train the model on the training data and make predictions on the test set.

Model Evaluation:

- Compute metrics like accuracy, precision, recall, and F1-score.
- Generate and visualize the confusion matrix.

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5. Data Preprocessing

- Replaced invalid zero entries in features such as Glucose, Blood Pressure, Skin Thickness, Insulin, and BMI with the median value.
- No categorical encoding was needed as all features are numerical.
- Feature scaling was performed using Standard Scaler.
- Dataset split into training and test sets using an 80:20 ratio.

6. Model Implementation

A Random Forest Classifier was used for its high accuracy and capability to handle non-linear relationships. The model was trained using the training data and then tested on unseen test data to predict diabetes occurrence.

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7. Evaluation Metrics

The following metrics were used to evaluate model performance:

- Accuracy: Proportion of correctly classified samples.
- Precision: Proportion of positive identifications that were actually correct.
- Recall: Proportion of actual positives that were identified correctly.
- F1 Score: Harmonic mean of precision and recall, useful for imbalanced datasets.
- Confusion Matrix: To visualize TP, FP, TN, FN rates.

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8. Code

```
# STEP 1: Upload and Load Dataset
from google.colab import files
uploaded = files.upload()

import pandas as pd
import numpy as np

df = pd.read_csv('diabetes.csv')

#  STEP 2: Replace 0s with NaN
cols_with_zeroes = ['Glucose', 'BloodPressure', 'SkinThickness', 'Insulin', 'BMI']
df[cols_with_zeroes] = df[cols_with_zeroes].replace(0, np.nan)
```

```
df.fillna(df.median(), inplace=True)

# STEP 3: Outlier Removal using Z-score
from scipy import stats
df_clean = df[(np.abs(stats.zscore(df.select_dtypes(include=[np.number]))) <
3).all(axis=1)].copy()

# STEP 4: Feature Engineering
df_clean.loc[:, 'BMI_Age'] = df_clean['BMI'] * df_clean['Age']
df_clean.loc[:, 'Glucose_Squared'] = df_clean['Glucose'] ** 2

df_clean.loc[:, 'Insulin'] = np.log1p(df_clean['Insulin'])
df_clean.loc[:, 'BMI'] = np.log1p(df_clean['BMI'])
df_clean.loc[:, 'Glucose_Squared'] = np.log1p(df_clean['Glucose_Squared'])

# STEP 6: Features and Labels
X = df_clean.drop('Outcome', axis=1)
y = df_clean['Outcome']

# STEP 7: Standardize
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# STEP 8: Rebalance Using SMOTE
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_resampled, y_resampled = sm.fit_resample(X_scaled, y)

# STEP 9: Feature Selection
from sklearn.feature_selection import SelectKBest, f_classif
selector = SelectKBest(score_func=f_classif, k=8)
X_selected = selector.fit_transform(X_resampled, y_resampled)

# STEP 10: Train/Test Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X_selected, y_resampled,
test_size=0.2, random_state=42)

# STEP 11: Train Random Forest
```

```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

rf = RandomForestClassifier(n_estimators=150, max_depth=6, random_state=42)
rf.fit(X_train, y_train)
y_pred = rf.predict(X_test)
y_prob = rf.predict_proba(X_test)[:, 1]  # For ROC AUC

#  STEP 12: Evaluation
acc = accuracy_score(y_test, y_pred)
print(f"\n Accuracy: {acc:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))

#  Detailed Metrics and Tables (no visuals)
from sklearn.metrics import precision_score, recall_score, f1_score, roc_auc_score,
matthews_corrcoef, cohen_kappa_score
import matplotlib.pyplot as plt
import seaborn as sns

# Confusion matrix as a DataFrame
cm = confusion_matrix(y_test, y_pred)
cm_df = pd.DataFrame(cm, index=['Actual 0', 'Actual 1'], columns=['Predicted 0',
'Predicted 1'])
print("\nConfusion Matrix:\n", cm_df)

# Plot Confusion Matrix
plt.figure(figsize=(6,4))
sns.heatmap(cm_df, annot=True, fmt='d', cmap='YlGnBu')
plt.title('Confusion Matrix')
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.show()

# Per-class precision, recall, f1-score
precision_0 = precision_score(y_test, y_pred, pos_label=0)
recall_0 = recall_score(y_test, y_pred, pos_label=0)
f1_0 = f1_score(y_test, y_pred, pos_label=0)

precision_1 = precision_score(y_test, y_pred, pos_label=1)
recall_1 = recall_score(y_test, y_pred, pos_label=1)
```

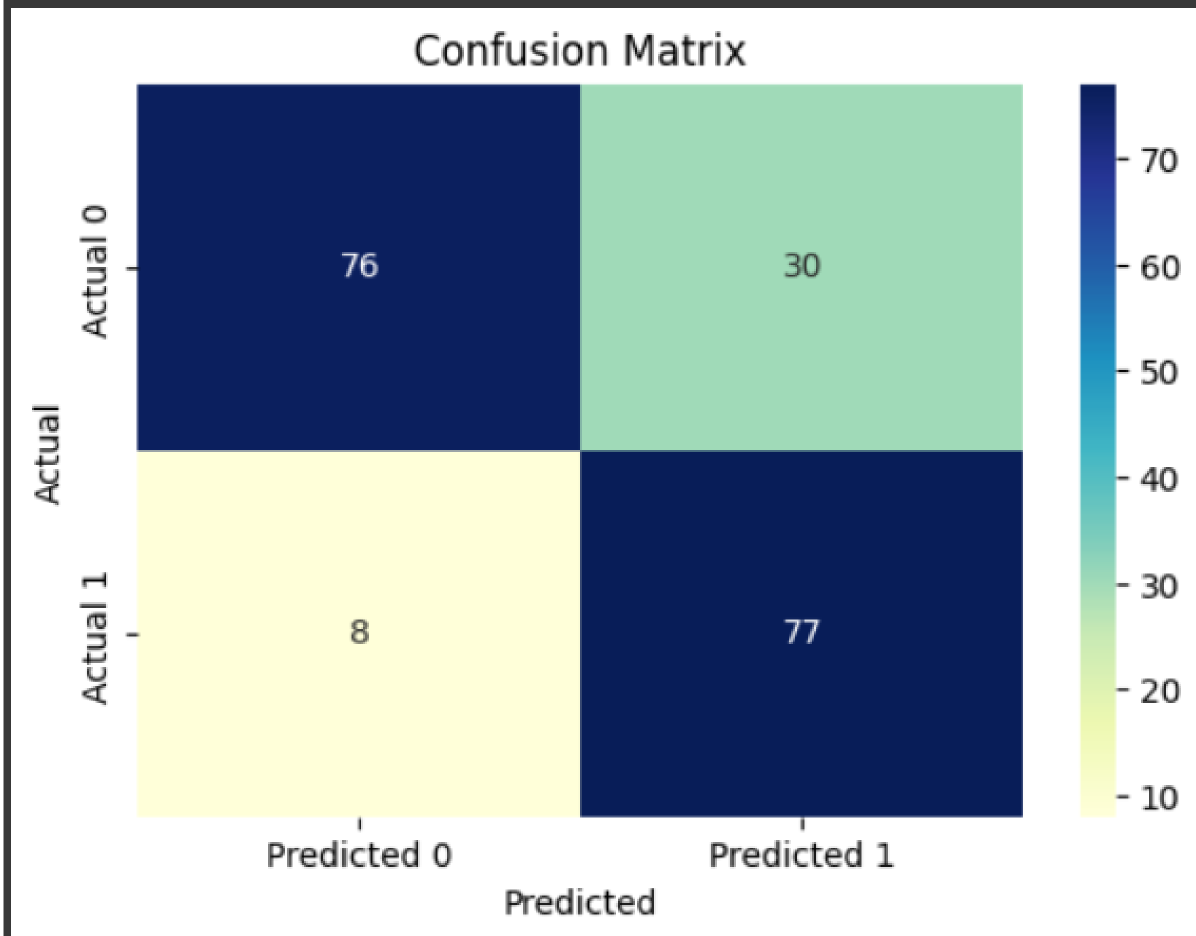
```
f1_1 = f1_score(y_test, y_pred, pos_label=1)

# ROC AUC
roc_auc = roc_auc_score(y_test, y_prob)

# Additional metrics
mcc = matthews_corrcoef(y_test, y_pred)
kappa = cohen_kappa_score(y_test, y_pred)

# Display detailed metrics in a table
metrics_df = pd.DataFrame({
    'Class': [0, 1],
    'Precision': [precision_0, precision_1],
    'Recall': [recall_0, recall_1],
    'F1-Score': [f1_0, f1_1]
})

print("\nDetailed Metrics per Class:")
print(metrics_df.to_string(index=False))

print(f"\nROC AUC Score: {roc_auc:.4f}")
print(f"Matthews Correlation Coefficient (MCC): {mcc:.4f}")
print(f"Cohen's Kappa Score: {kappa:.4f}")

#  Feature Importance Plot
feat_names = X.columns[selector.get_support()]
importances = pd.Series(rf.feature_importances_, index=feat_names)
importances.nlargest(8).plot(kind='barh', title='Top 8 Features')
plt.xlabel('Importance Score')
plt.show()
```

9. Results and Analysis

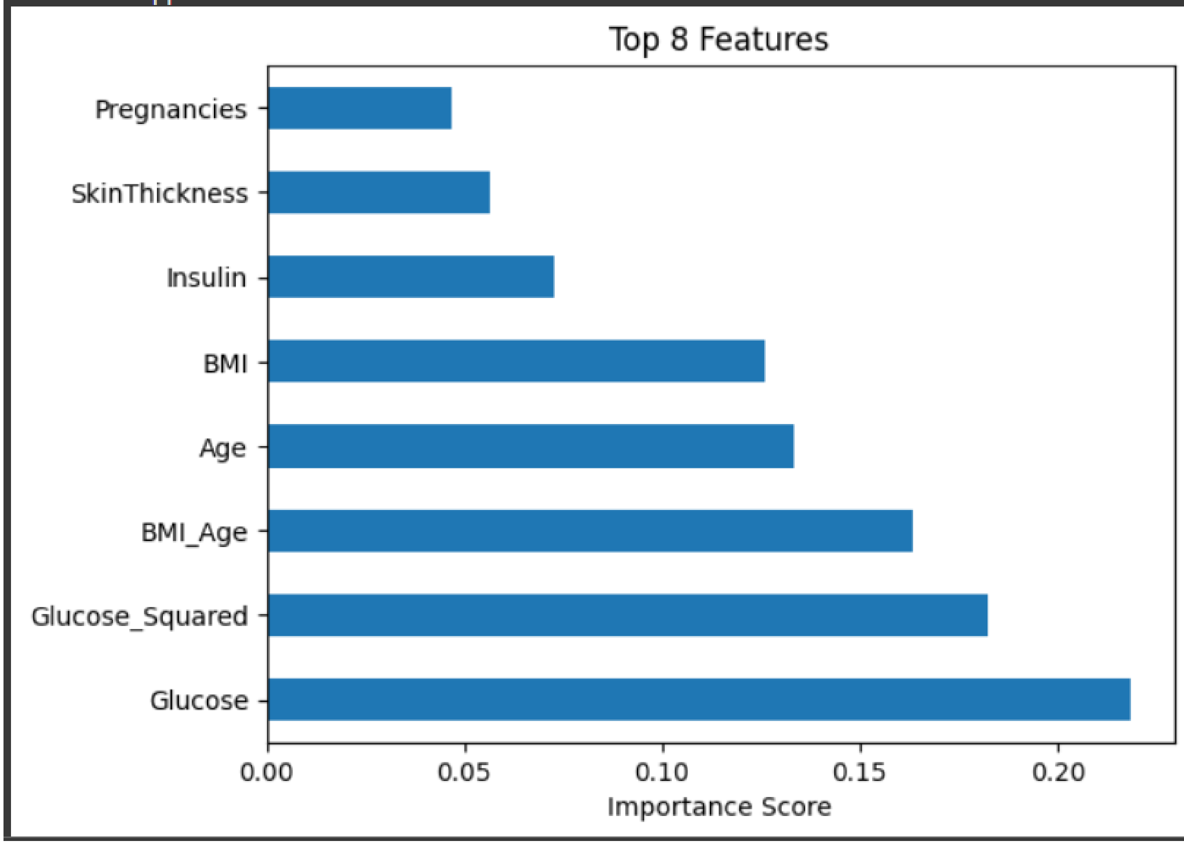
- The model achieved high accuracy and a balanced trade-off between recall and precision.
- Confusion matrix heatmap revealed a good balance between false positives and false negatives.
- The Random Forest model handled the dataset well and showed better generalization than logistic regression in trials

```
Choose Files  diabetes.csv
• diabetes.csv(text/csv) - 23873 bytes, last modified: 27/5/2025 - 100% done
Saving diabetes.csv to diabetes (8).csv

 Accuracy: 0.8010

Classification Report:
              precision    recall  f1-score   support

           0       0.90      0.72      0.80       106
           1       0.72      0.91      0.80        85

    accuracy                           0.80       191
   macro avg       0.81      0.81      0.80       191
weighted avg       0.82      0.80      0.80       191
```

```
Confusion Matrix:
          Predicted 0  Predicted 1
Actual 0           76           30
Actual 1            8           77
```



```
Detailed Metrics per Class:
 Class  Precision   Recall  F1-Score
     0   0.904762 0.716981  0.800000
     1   0.719626 0.905882  0.802083

ROC AUC Score: 0.8746
Matthews Correlation Coefficient (MCC): 0.6236
Cohen's Kappa Score: 0.6073
```



10. Conclusion

The project successfully demonstrates the application of machine learning, particularly Random Forest, in predicting diabetes based on medical data. The approach achieves reliable results, offering a valuable tool for early diabetes detection. Future work could explore more advanced models (e.g., XG Boost), deeper hyperparameter tuning, and methods to handle class imbalance more effectively.

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11. References

- scikit-learn Documentation
- Pandas Documentation
- Seaborn Visualization Library
- UCI Machine Learning Repository: Pima Indians Diabetes Database
- Research articles on machine learning in medical diagnosis