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ARITIFICAL INTELLIGENCE

PROJECT

AI-BASED DIABETES PREDICTION SYSTEM-PHASE 2

INTRODUCTION:

An AI-based diabetes prediction system is to develop a model that can accurately predict the likelihood of an individual developing diabetes based on their demographic, lifestyle, and health factors. The system should be able to analyze large amounts of data, including medical records, genetic information, and lifestyle choices, to provide personalized predictions. The goal is to assist healthcare professionals in identifying individuals who are at high risk of developing diabetes, allowing for early intervention and prevention strategies. The system should also be user-friendly and easily accessible to both healthcare professionals and individuals looking to assess their own risk of diabetes.

DATA SOURCE:

A data source for Diabetes prediction system using Artificial intelligence

Dataset link: **https://www.kaggle.com/datasets/mathchi/diabetes-data-set**

PROGRAM:

```
In [1]:  import pandas as pd
         import numpy as np
         from sklearn.preprocessing import StandardScaler
         from sklearn.linear_model  import LogisticRegression
         from sklearn.model_selection import train_test_split
         from sklearn.metrics import accuracy_score, confusion_matrix
         import matplotlib.pyplot as plt
         import seaborn as sns

In[2]:    data = pd.read_csv("/kaggle/input/diabetes-data-set/diabetes.csv")
          data.head()

Out[2]:
```

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

In [3]: `data.describe()`

Out [3]:

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
count	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000	768.000000
mean	3.845052	120.894531	69.105469	20.536458	79.799479	31.992578	0.471876	33.240885	0.348958
std	3.369578	31.972618	19.355807	15.952218	115.244002	7.884160	0.331329	11.760232	0.476951
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.078000	21.000000	0.000000
25%	1.000000	99.000000	62.000000	0.000000	0.000000	27.300000	0.243750	24.000000	0.000000
50%	3.000000	117.000000	72.000000	23.000000	30.500000	32.000000	0.372500	29.000000	0.000000
75%	6.000000	140.250000	80.000000	32.000000	127.250000	36.600000	0.626250	41.000000	1.000000
max	17.00000	199.000000	122.00000	99.00000	846.0000	67.100000	2.420000	81.00000	1.000000

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
	0		0	0	00			0	

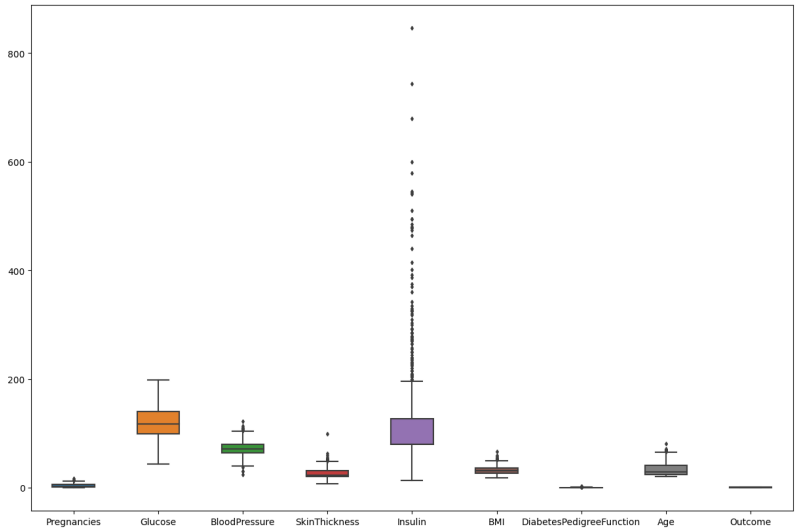
```
In [4]: data.isnull().sum()
 Out [ 4 ]:
 Pregnancies                 0
 Glucose                     0
 BloodPressure               0
 SkinThickness               0
 Insulin                     0
 BMI                         0
 DiabetesPedigreeFunction    0
 Age                         0
 Outcome                     0
 dtype: int64

In [5]:
#here few misconception is there lke BMI can not be zero, BP can't be zero, glucose,
insuline can't be zero so lets try to fix it
# now replacing zero values with the mean of the column
data['BMI'] = data['BMI'].replace(0,data['BMI'].mean())
data['BloodPressure'] = data['BloodPressure'].replace(0,data['BloodPressure'].mean())
data['Glucose'] = data['Glucose'].replace(0,data['Glucose'].mean())
data['Insulin'] = data['Insulin'].replace(0,data['Insulin'].mean())
data['SkinThickness'] = data['SkinThickness'].replace(0,data['SkinThickness'].mean())
```

In [6]:

```
#now we have dealt with the 0 values and data looks better. But, there still are outliers
present in some columns.lets visualize it
fig, ax = plt.subplots(figsize=(15,10))
sns.boxplot(data=data, width= 0.5,ax=ax,  fliersize=3)
```

Out [6]:

```
<Axes: >
```



In [7]:

```
Data.head()
```

Out [7]:

Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome	
0	6	148.0	72.0	35.000000	79.799479	33.6	0.627	50	1
1	1	85.0	66.0	29.000000	79.799479	26.6	0.351	31	0
2	8	183.0	64.0	20.536458	79.799479	23.3	0.672	32	1
3	1	89.0	66.0	23.000000	94.000000	28.1	0.167	21	0
4	0	137.0	40.0	35.000000	168.000000	43.1	2.288	33	1

In [8]:

```
#segregate the dependent and independent variable
X = data.drop(columns = ['Outcome'])
y = data['Outcome']
```

In [9]:
```
  # separate dataset into train and test
  X_train, X_test, y_train, y_test =
train_test_split(X,y,test_size=0.25,random_state=0)
  X_train.shape, X_test.shape
```

Out[9]:
```
  ((576, 8), (192, 8))
```

In [10]:
```
  import pickle
  ##standard Scaling- Standardization
  def scaler_standard(X_train, X_test):
    #scaling the data
    scaler = StandardScaler()
    X_train_scaled = scaler.fit_transform(X_train)
    X_test_scaled = scaler.transform(X_test)

    #saving the model
    file = open('standardScalar.pkl','wb')
    pickle.dump(scaler,file)
    file.close()

    return X_train_scaled, X_test_scaled
```

In [11]:
```
   X_train_scaled, X_test_scaled = scaler_standard(X_train, X_test)
```

In [12]:
```
   X_train_scaled
```

Out[12]:
```
    array([[ 1.50755225, -1.09947934, -0.89942504, ..., -1.45561965,
        -0.98325882, -0.04863985],
       [-0.82986389, -0.1331471 , -1.23618124, ...,  0.09272955,
        -0.62493647, -0.88246592],
       [-1.12204091, -1.03283573,  0.61597784, ..., -0.03629955,
         0.39884168, -0.5489355 ],
       ...,
       [ 0.04666716, -0.93287033, -0.64685789, ..., -1.14021518,
        -0.96519215, -1.04923114],
       [ 2.09190629, -1.23276654,  0.11084355, ..., -0.36604058,
        -0.5075031 ,  0.11812536],
       [ 0.33884418,  0.46664532,  0.78435594, ..., -0.09470985,
         0.51627505,  2.953134  ]])
```

In [13]:
```
   log_reg = LogisticRegression()

   log_reg.fit(X_train_scaled,y_train)
```

Out[13]:

☑ LogisticRegression

```
LogisticRegression()
```

In [14]:
```
  ## Hyperparameter Tuning
  ## GridSearch CV
  from sklearn.model_selection import GridSearchCV
  import numpy as np
  import warnings
```

```
  warnings.filterwarnings('ignore')
  # parameter grid
  parameters = {
    'penalty' : ['l1','l2'],
    'C'       : np.logspace(-3,3,7),
    'solver'  : ['newton-cg', 'lbfgs', 'liblinear'],
}
```

In [15]:

```
  logreg = LogisticRegression()
  clf = GridSearchCV(logreg,                    # model
                     param_grid = parameters,   # hyperparameters
                     scoring='accuracy',        # metric for scoring
                     cv=10)                     # number of folds

  clf.fit(X_train_scaled,y_train)
```

Out[15]:

GridSearchCV

estimator: LogisticRegression

LogisticRegression

In [16]:

```
  clf.best_params_
```

Out[16]:

```
{'C': 1.0, 'penalty': 'l2', 'solver': 'liblinear'}
```

In [17]:

```
   clf.best_score_
```

Out[17]:

```
0.763793103448276
```

let's see how well our model performs on the test data set.

In [18]:

```
  y_pred = clf.predict(X_test_scaled)
```

accuracy = accuracy_score(y_test,y_pred) accuracy

In [19]:

```
  conf_mat = confusion_matrix(y_test,y_pred)
  conf_mat
```

Out[19]:

```
array([[117,  13],
       [ 26,  36]])
```

In [20]:

```
   true_positive = conf_mat[0][0]
   false_positive = conf_mat[0][1]
   false_negative = conf_mat[1][0]
   true_negative = conf_mat[1][1]
```

In [21]:

```
   Accuracy = (true_positive + true_negative) / (true_positive
+false_positive +      false_negative + true_negative)
   Accuracy
```

Out[21]:

```
0.796875
```

```
In [22]:
Precision = true_positive/(true_positive+false_positive)
Precision
```

```
Out[22]:
0.9
```

```
In [23]:
Recall = true_positive/(true_positive+false_negative)
Recall
```

```
Out[23]:
0.8181818181818182
```

```
In [24]:
F1_Score = 2*(Recall * Precision) / (Recall + Precision)
F1_Score
```

```
Out[24]:
0.8571428571428572
```

```
In [25]:
linkcode
import pickle
file = open('modelForPrediction.pkl','wb')
pickle.dump(log_reg,file)
file.close()
```

CONCLUSION:

In conclusion, the development of an AI-based diabetes prediction system holds significant potential for improving healthcare outcomes related to diabetes. By leveraging artificial intelligence techniques, such as machine learning and data analysis, the system can provide accurate risk assessments and enable early intervention and prevention strategies.

The AI-based diabetes prediction system offers several advantages. Firstly, it can assist healthcare professionals in identifying individuals at high risk of developing diabetes, allowing for targeted interventions and personalized care plans. Secondly, it can contribute to reducing healthcare costs by focusing resources on prevention and early detection, which can help mitigate the long-term complications associated with diabetes. Additionally, the system can empower individuals to take proactive steps towards managing their health and making informed lifestyle choices.