Srushti Shah
191071902
Final Year B. Tech. CE
Data Mining and Warehouse

Experiment No. 6

AIM: Study of predictive algorithms.

THEORY:

In short, predictive modeling is a statistical technique using machine learning and data mining to predict and forecast likely future outcomes with the aid of historical and existing data. It works by analyzing current and historical data and projecting what it learns on a model generated to forecast likely outcomes. Predictive modeling can be used to predict just about anything, from TV ratings and a customer's next purchase to credit risks and corporate earnings.

A predictive model is not fixed; it is validated or revised regularly to incorporate changes in the underlying data. In other words, it's not a one-and-done prediction. Predictive models make assumptions based on what has happened in the past and what is happening now. If incoming, new data shows changes in what is happening now, the impact on the likely future outcome must be recalculated, too. For example, a software company could model historical sales data against marketing expenditures across multiple regions to create a model for future revenue based on the impact of the marketing spend.

Most predictive models work fast and often complete their calculations in real time. That's why banks and retailers can, for example, calculate the risk of an online mortgage or credit card application and accept or decline the request almost instantly based on that prediction.

Some predictive models are more complex, such as those used in computational biology and quantum computing; the resulting outputs take longer to compute than a credit card application but are done much more quickly than was possible in the past thanks to advances in technological capabilities, including computing power.

The top five predictive analytics models are:

1. **Classification model:** Considered the simplest model, it categorizes data for simple and direct query response. An example use case would be to answer the question “Is this a fraudulent transaction?”
2. **Clustering model:** This model nests data together by common attributes. It works by grouping things or people with shared characteristics or behaviors and plans strategies for each group at a larger scale. An example is in determining credit risk for a loan applicant based on what other people in the same or a similar situation did in the past.
3. **Forecast model:** This is a very popular model, and it works on anything with a numerical value based on learning from historical data. For example, in answering how much lettuce a restaurant should order next week or how many calls a customer support agent should be able to handle per day or week, the system looks back to historical data.
4. **Outliers model:** This model works by analyzing abnormal or outlying data points. For example, a bank might use an outlier model to identify fraud by asking whether a transaction is outside of the customer’s normal buying habits or whether an expense in a given category is normal or not. For example, a $1,000 credit card charge for a washer and dryer in the cardholder’s preferred big box store would not be alarming, but $1,000 spent on designer clothing in a location where the customer has never charged other items might be indicative of a breached account.
5. **Time series model:** This model evaluates a sequence of data points based on time. For example, the number of stroke patients admitted to the hospital in the last four months is used to predict how many patients the hospital might expect to admit next week, next month or the rest of the year. A single metric measured and compared over time is thus more meaningful than a simple average.

IMPLEMENTATION AND OUTPUT:

Description:

The objective of the dataset is to predict whether or not a patient has diabetes, based on certain diagnostic measurements included in the dataset. The datasets consists of several medical predictor variables and one target variable, Outcome. Predictor variables includes the number of pregnancies the patient has had, their BMI, insulin level, age, and so on.

Dataset url : https://www.kaggle.com/uciml/pima-indians-diabetes-database

Step 0: Import libraries and Dataset

In [2]:

```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

In [3]:

```
# Importing dataset
dataset = pd.read_csv('diabetes.csv')
```

Step 1: Descriptive Statistics

In [4]:

```
# Preview data
dataset.head()
```

Out[4]:

	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
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 [5]:

```
# Dataset dimensions - (rows, columns)
dataset.shape
```

Out[5]:

```
(768, 9)
```

In [6]:

```
# Features data-type
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 768 entries, 0 to 767
Data columns (total 9 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   Pregnancies               768 non-null    int64
 1   Glucose                   768 non-null    int64
 2   BloodPressure             768 non-null    int64
 3   SkinThickness             768 non-null    int64
```

```
 4   Insulin                   768 non-null    int64
 5   BMI                       768 non-null    float64
 6   DiabetesPedigreeFunction  768 non-null    float64
 7   Age                       768 non-null    int64
 8   Outcome                   768 non-null    int64
dtypes: float64(2), int64(7)
memory usage: 54.1 KB
```

In [7]:

```
# Statistical summary
dataset.describe().T
```

Out[7]:

	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.0000	6.00000	17.00
Glucose	768.0	120.894531	31.972618	0.000	99.00000	117.0000	140.25000	199.00
BloodPressure	768.0	69.105469	19.355807	0.000	62.00000	72.0000	80.00000	122.00
SkinThickness	768.0	20.536458	15.952218	0.000	0.00000	23.0000	32.00000	99.00
Insulin	768.0	79.799479	115.244002	0.000	0.00000	30.5000	127.25000	846.00
BMI	768.0	31.992578	7.884160	0.000	27.30000	32.0000	36.60000	67.10
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.3725	0.62625	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.0000	41.00000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.0000	1.00000	1.00

In [8]:

```
# Count of null values
dataset.isnull().sum()
```

Out[8]:

```
Pregnancies                 0
Glucose                     0
BloodPressure               0
SkinThickness               0
Insulin                     0
BMI                         0
DiabetesPedigreeFunction    0
Age                         0
Outcome                     0
dtype: int64
```

Observations:

1. There are a total of 768 records and 9 features in the dataset.
2. Each feature can be either of integer or float dataype.
3. Some features like Glucose, Blood pressure , Insulin, BMI have zero values which represent missing data.
4. There are zero NaN values in the dataset.
5. In the outcome column, 1 represents diabetes positive and 0 represents diabetes negative.

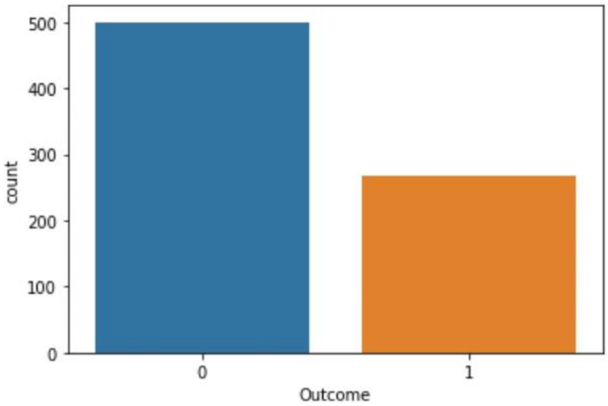
Step 2: Data Visualization

In [9]:

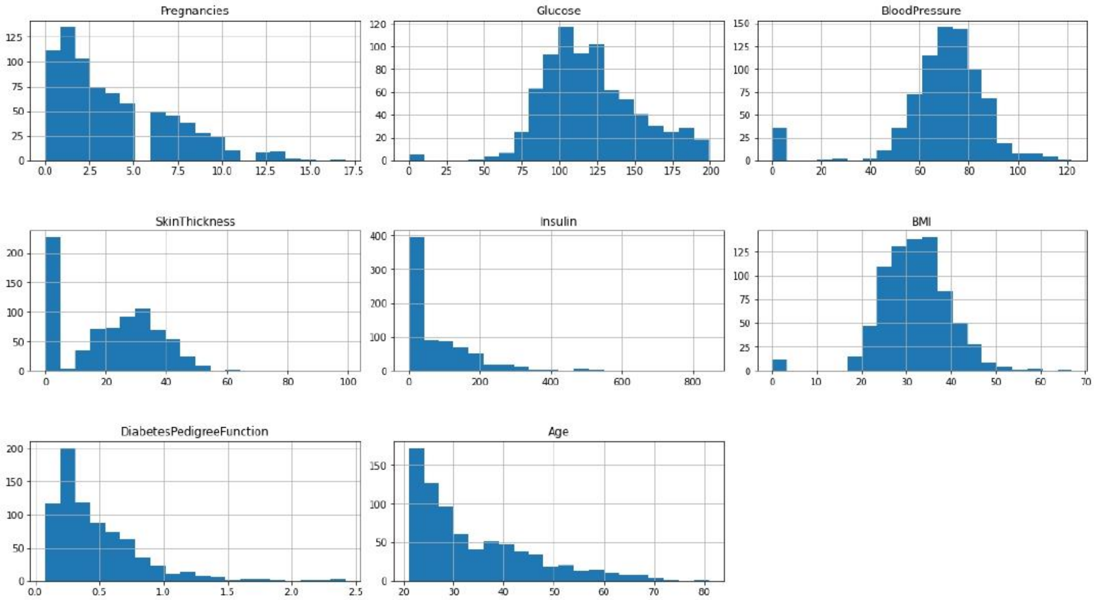
```
# Outcome countplot
sns.countplot(x = 'Outcome',data = dataset)
```

Out[9]:

```
<AxesSubplot:xlabel='Outcome', ylabel='count'>
```



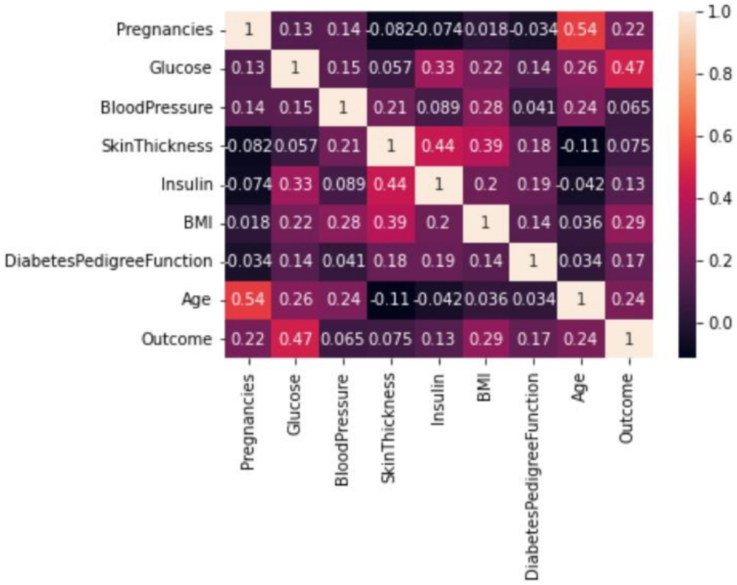

```
In [10]:
# Histogram of each feature
import itertools

col = dataset.columns[:8]
plt.subplots(figsize = (20, 15))
length = len(col)

for i, j in itertools.zip_longest(col, range(length)):
    plt.subplot((length/2), 3, j + 1)
    plt.subplots_adjust(wspace = 0.1,hspace = 0.5)
    dataset[i].hist(bins = 20)
    plt.title(i)
plt.show()
```




```
In [12]:
# Pairplot
sns.pairplot(data = dataset, hue = 'Outcome')
plt.show()
```

In [13]:

```python
# Heatmap
sns.heatmap(dataset.corr(), annot = True)
plt.show()
```



Observations:

1. The countplot tells us that the dataset is imbalanced, as number of patients who don't have diabetes is more than those who do.
2. From the correaltion heatmap, we can see that there is a high correlation between Outcome and [Glucose,BMI,Age,Insulin]. We can select these features to accept input from the user and predict the outcome.

Step 3: Data Preprocessing

In [14]:
```
dataset_new = dataset
```

In [15]:
```
# Replacing zero values with NaN
dataset_new[["Glucose", "BloodPressure", "SkinThickness", "Insulin", "BMI"]] = dataset_new[["Gl
```

In [16]:
```
# Count of NaN
dataset_new.isnull().sum()
```

Out[16]:
```
Pregnancies                   0
Glucose                       5
BloodPressure                35
SkinThickness               227
Insulin                     374
BMI                          11
DiabetesPedigreeFunction      0
Age                           0
Outcome                       0
dtype: int64
```

In [17]:
```
# Replacing NaN with mean values
dataset_new["Glucose"].fillna(dataset_new["Glucose"].mean(), inplace = True)
dataset_new["BloodPressure"].fillna(dataset_new["BloodPressure"].mean(), inplace = True)
dataset_new["SkinThickness"].fillna(dataset_new["SkinThickness"].mean(), inplace = True)
dataset_new["Insulin"].fillna(dataset_new["Insulin"].mean(), inplace = True)
dataset_new["BMI"].fillna(dataset_new["BMI"].mean(), inplace = True)
```

In [18]:
```python
# Statistical summary
dataset_new.describe().T
```

Out[18]:

	count	mean	std	min	25%	50%	75%	max
Pregnancies	768.0	3.845052	3.369578	0.000	1.00000	3.000000	6.000000	17.00
Glucose	768.0	121.686763	30.435949	44.000	99.75000	117.000000	140.250000	199.00
BloodPressure	768.0	72.405184	12.096346	24.000	64.00000	72.202592	80.000000	122.00
SkinThickness	768.0	29.153420	8.790942	7.000	25.00000	29.153420	32.000000	99.00
Insulin	768.0	155.548223	85.021108	14.000	121.50000	155.548223	155.548223	846.00
BMI	768.0	32.457464	6.875151	18.200	27.50000	32.400000	36.600000	67.10
DiabetesPedigreeFunction	768.0	0.471876	0.331329	0.078	0.24375	0.372500	0.626250	2.42
Age	768.0	33.240885	11.760232	21.000	24.00000	29.000000	41.000000	81.00
Outcome	768.0	0.348958	0.476951	0.000	0.00000	0.000000	1.000000	1.00

In [19]:
```python
# Feature scaling using MinMaxScaler
from sklearn.preprocessing import MinMaxScaler
sc = MinMaxScaler(feature_range = (0, 1))
dataset_scaled = sc.fit_transform(dataset_new)
```

In [20]:
```python
dataset_scaled = pd.DataFrame(dataset_scaled)
```

In [21]:
```python
# Selecting features - [Glucose, Insulin, BMI, Age]
X = dataset_scaled.iloc[:, [1, 4, 5, 7]].values
Y = dataset_scaled.iloc[:, 8].values
```

In [22]:
```python
# Splitting X and Y
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size = 0.20, random_state = 42,
```

In [23]:
```python
# Checking dimensions
print("X_train shape:", X_train.shape)
print("X_test shape:", X_test.shape)
print("Y_train shape:", Y_train.shape)
print("Y_test shape:", Y_test.shape)
```

```
X_train shape: (614, 4)
X_test shape: (154, 4)
Y_train shape: (614,)
Y_test shape: (154,)
```

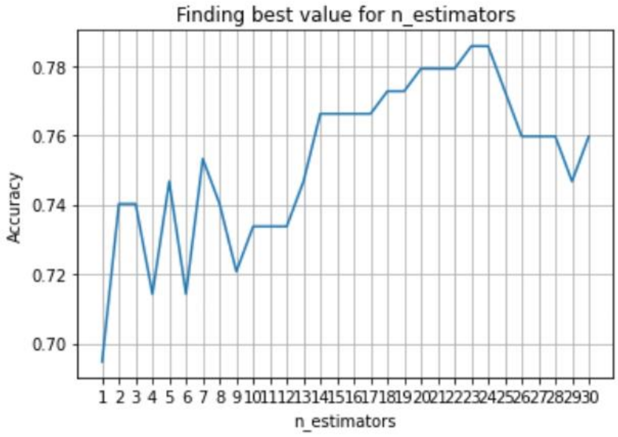
Step 4: Data Modelling

In [24]:
```python
# Logistic Regression Algorithm
from sklearn.linear_model import LogisticRegression
logreg = LogisticRegression(random_state = 42)
logreg.fit(X_train, Y_train)
```

Out[24]:
```
LogisticRegression(random_state=42)
```

In [25]:
```python
# Plotting a graph for n_neighbors
from sklearn import metrics
```

```
from sklearn.neighbors import KNeighborsClassifier

X_axis = list(range(1, 31))
acc = pd.Series()
x = range(1,31)

for i in list(range(1, 31)):
    knn_model = KNeighborsClassifier(n_neighbors = i)
    knn_model.fit(X_train, Y_train)
    prediction = knn_model.predict(X_test)
    acc = acc.append(pd.Series(metrics.accuracy_score(prediction, Y_test)))
plt.plot(X_axis, acc)
plt.xticks(x)
plt.title("Finding best value for n_estimators")
plt.xlabel("n_estimators")
plt.ylabel("Accuracy")
plt.grid()
plt.show()
print('Highest value: ',acc.values.max())
```




```
Highest value:  0.7857142857142857
```

In [26]:

```
# K nearest neighbors Algorithm
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 24, metric = 'minkowski', p = 2)
knn.fit(X_train, Y_train)
```

Out[26]:

```
KNeighborsClassifier(n_neighbors=24)
```

In [27]:

```
# Support Vector Classifier Algorithm
from sklearn.svm import SVC
svc = SVC(kernel = 'linear', random_state = 42)
svc.fit(X_train, Y_train)
```

Out[27]:

```
SVC(kernel='linear', random_state=42)
```

In [28]:

```
# Naive Bayes Algorithm
from sklearn.naive_bayes import GaussianNB
nb = GaussianNB()
nb.fit(X_train, Y_train)
```

Out[28]:

```
GaussianNB()
```

In [29]:

```
# Decision tree Algorithm
from sklearn.tree import DecisionTreeClassifier
dectree = DecisionTreeClassifier(criterion = 'entropy', random_state = 42)
dectree.fit(X_train, Y_train)
```

Out[29]:

```
DecisionTreeClassifier(criterion='entropy', random_state=42)
```

In [30]:

```
# Random forest Algorithm
from sklearn.ensemble import RandomForestClassifier
ranfor = RandomForestClassifier(n_estimators = 11, criterion = 'entropy', random_state = 42)
ranfor.fit(X_train, Y_train)
```

Out[30]:

```
RandomForestClassifier(criterion='entropy', n_estimators=11, random_state=42)
```

In [31]:

```
# Making predictions on test dataset
Y_pred_logreg = logreg.predict(X_test)
Y_pred_knn = knn.predict(X_test)
Y_pred_svc = svc.predict(X_test)
Y_pred_nb = nb.predict(X_test)
Y_pred_dectree = dectree.predict(X_test)
Y_pred_ranfor = ranfor.predict(X_test)
```

Step 5: Model Evaluation

In [32]:

```
# Evaluating using accuracy_score metric
from sklearn.metrics import accuracy_score
accuracy_logreg = accuracy_score(Y_test, Y_pred_logreg)
accuracy_knn = accuracy_score(Y_test, Y_pred_knn)
accuracy_svc = accuracy_score(Y_test, Y_pred_svc)
accuracy_nb = accuracy_score(Y_test, Y_pred_nb)
accuracy_dectree = accuracy_score(Y_test, Y_pred_dectree)
accuracy_ranfor = accuracy_score(Y_test, Y_pred_ranfor)
```

In [33]:

```
# Accuracy on test set
print("Logistic Regression: " + str(accuracy_logreg * 100))
print("K Nearest neighbors: " + str(accuracy_knn * 100))
print("Support Vector Classifier: " + str(accuracy_svc * 100))
print("Naive Bayes: " + str(accuracy_nb * 100))
print("Decision tree: " + str(accuracy_dectree * 100))
print("Random Forest: " + str(accuracy_ranfor * 100))
```

```
Logistic Regression: 72.07792207792207
K Nearest neighbors: 78.57142857142857
Support Vector Classifier: 73.37662337662337
Naive Bayes: 71.42857142857143
Decision tree: 68.18181818181817
Random Forest: 75.97402597402598
```

In [34]:

```
#From the above comparison, we can observe that K Nearest neighbors gets the highest accuracy c
```

In [35]:

```
# Confusion matrix
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test, Y_pred_knn)
cm
```

Out[35]:

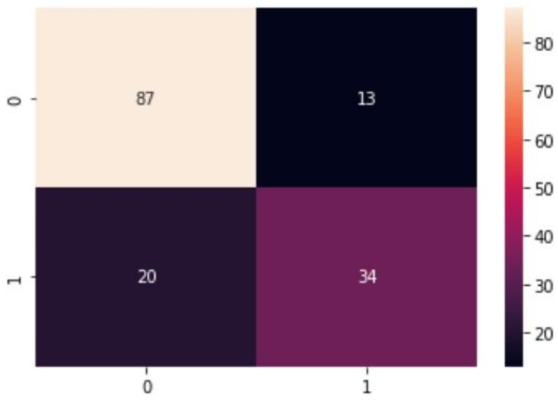
```
array([[87, 13],
       [20, 34]], dtype=int64)
```

In [36]:

```
# Heatmap of Confusion matrix
sns.heatmap(pd.DataFrame(cm), annot=True)
```

Out[36]:

```
<AxesSubplot:>
```



In [37]:

```
# Classification report
from sklearn.metrics import classification_report
print(classification_report(Y_test, Y_pred_knn))
```

```
              precision    recall  f1-score   support

         0.0       0.81      0.87      0.84       100
         1.0       0.72      0.63      0.67        54

    accuracy                           0.79       154
   macro avg       0.77      0.75      0.76       154
weighted avg       0.78      0.79      0.78       154
```

CONCLUSION: Thus, from this experiment I implemented various predictive algorithms for predicting the outcome of a hypotheses based on the existing and historical data that is given.