TTDS: Machine Learning project

Accuracy Improved Decision Tree Algorithm

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib as plt
from matplotlib import pyplot
import matplotlib.pyplot as plt
```

In [2]:
```
data=pd.read_csv("D:/DataSets/diabetes.csv")
```

In [3]:
```
data
```

Out[3]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
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
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

Dataset Extension

In [4]:
```
# Generate synthetic data by doubling the 'label' values
data_synthetic = data.copy()

# Concatenate the original and synthetic DataFrames
df = pd.concat([data, data_synthetic], ignore_index=True)

# Display the extended DataFrame
df
```

Out[4]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
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
...	...	...	...	...	...	...	...	...	...
1531	10	101	76	48	180	32.9	0.171	63	0
1532	2	122	70	27	0	36.8	0.340	27	0
1533	5	121	72	23	112	26.2	0.245	30	0
1534	1	126	60	0	0	30.1	0.349	47	1
1535	1	93	70	31	0	30.4	0.315	23	0

1536 rows × 9 columns

In [5]:
```
df.head(10)
```

Out[5]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
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
5	5	116	74	0	0	25.6	0.201	30	0
6	3	78	50	32	88	31.0	0.248	26	1
7	10	115	0	0	0	35.3	0.134	29	0
8	2	197	70	45	543	30.5	0.158	53	1
9	8	125	96	0	0	0.0	0.232	54	1

In [6]:
```
df.tail()
```

Out[6]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
1531	10	101	76	48	180	32.9	0.171	63	0
1532	2	122	70	27	0	36.8	0.340	27	0
1533	5	121	72	23	112	26.2	0.245	30	0
1534	1	126	60	0	0	30.1	0.349	47	1
1535	1	93	70	31	0	30.4	0.315	23	0

In [7]:
```
df.dtypes
```

Out[7]:
```
preg              int64
glucose           int64
bp_diastolic      int64
skin_triceps      int64
insulin           int64
bmi             float64
pedigree        float64
age               int64
label             int64
dtype: object
```

Descriptive Satistics:

In [8]:
```
print("Number of Row in the Dataset:", df.shape[0])
print("Number of Columns in the Dataset:", df.shape[1])
```

```
Number of Row in the Dataset: 1536
Number of Columns in the Dataset: 9
```

In [9]:
```
df.head(10)
```

Out[9]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
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
5	5	116	74	0	0	25.6	0.201	30	0
6	3	78	50	32	88	31.0	0.248	26	1
7	10	115	0	0	0	35.3	0.134	29	0
8	2	197	70	45	543	30.5	0.158	53	1
9	8	125	96	0	0	0.0	0.232	54	1

In [10]:
```
df.tail()
```

Out[10]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
1531	10	101	76	48	180	32.9	0.171	63	0
1532	2	122	70	27	0	36.8	0.340	27	0
1533	5	121	72	23	112	26.2	0.245	30	0
1534	1	126	60	0	0	30.1	0.349	47	1
1535	1	93	70	31	0	30.4	0.315	23	0

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1536 entries, 0 to 1535
Data columns (total 9 columns):
 #   Column        Non-Null Count  Dtype  
---  ------        --------------  -----  
 0   preg          1536 non-null   int64  
 1   glucose       1536 non-null   int64  
 2   bp_diastolic  1536 non-null   int64  
 3   skin_triceps  1536 non-null   int64  
 4   insulin       1536 non-null   int64  
 5   bmi           1536 non-null   float64
 6   pedigree      1536 non-null   float64
 7   age           1536 non-null   int64  
 8   label         1536 non-null   int64  
dtypes: float64(2), int64(7)
memory usage: 108.1 KB
```

In [12]:
```
df.describe().T
```

Out[12]:

	count	mean	std	min	25%	50%	75%	max
preg	1536.0	3.845052	3.368480	0.000	1.00000	3.0000	6.00000	17.00
glucose	1536.0	120.894531	31.962202	0.000	99.00000	117.0000	140.25000	199.00
bp_diastolic	1536.0	69.105469	19.349501	0.000	62.00000	72.0000	80.00000	122.00
skin_triceps	1536.0	20.536458	15.947021	0.000	0.00000	23.0000	32.00000	99.00
insulin	1536.0	79.799479	115.206457	0.000	0.00000	30.5000	127.25000	846.00
bmi	1536.0	31.992578	7.881592	0.000	27.30000	32.0000	36.60000	67.10
pedigree	1536.0	0.471876	0.331221	0.078	0.24375	0.3725	0.62625	2.42
age	1536.0	33.240885	11.756400	21.000	24.00000	29.0000	41.00000	81.00
label	1536.0	0.348958	0.476796	0.000	0.00000	0.0000	1.00000	1.00

In [13]:
```
#check label value count
data.label.value_counts()
```

Out[13]:
```
0    500
1    268
Name: label, dtype: int64
```

Missing Values:

In [14]:
```
df.isnull().sum()
```

Out[14]:
```
preg            0
glucose         0
bp_diastolic    0
skin_triceps    0
insulin         0
bmi             0
pedigree        0
age             0
label           0
dtype: int64
```

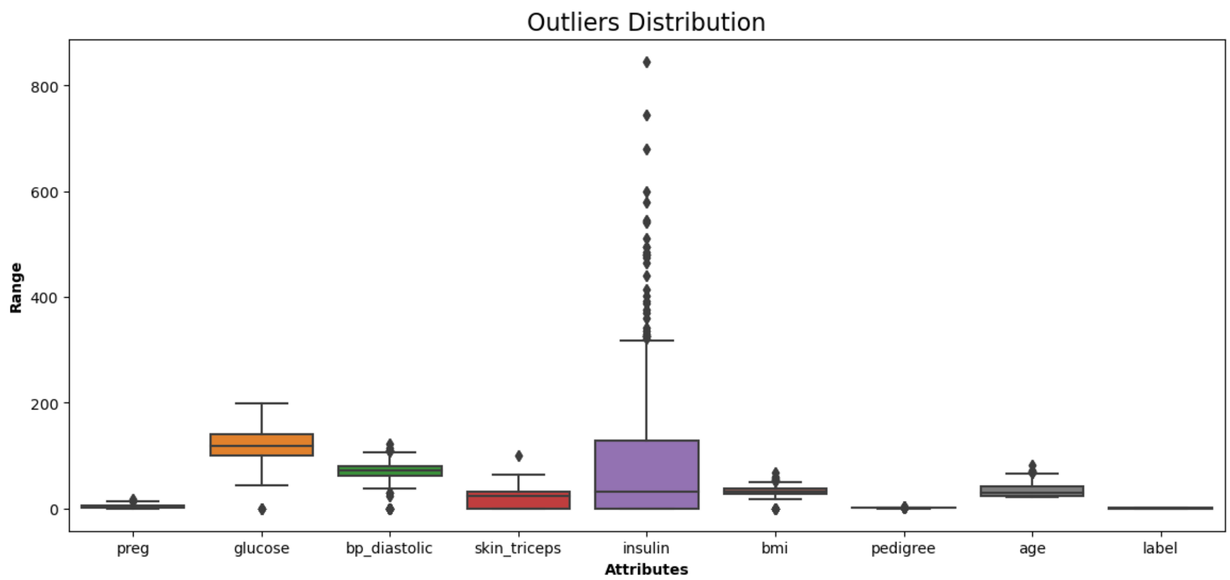
In [15]:
```
#check missing Values in the Dataset
missing_data=df.isnull()
for column in missing_data.columns.values.tolist():
    print(column)
    print(missing_data[column].value_counts())
    print("")
```

```
preg
False    1536
Name: preg, dtype: int64

glucose
False    1536
Name: glucose, dtype: int64

bp_diastolic
False    1536
Name: bp_diastolic, dtype: int64

skin_triceps
False    1536
Name: skin_triceps, dtype: int64

insulin
False    1536
Name: insulin, dtype: int64

bmi
False    1536
Name: bmi, dtype: int64

pedigree
False    1536
Name: pedigree, dtype: int64

age
False    1536
Name: age, dtype: int64

label
False    1536
Name: label, dtype: int64
```

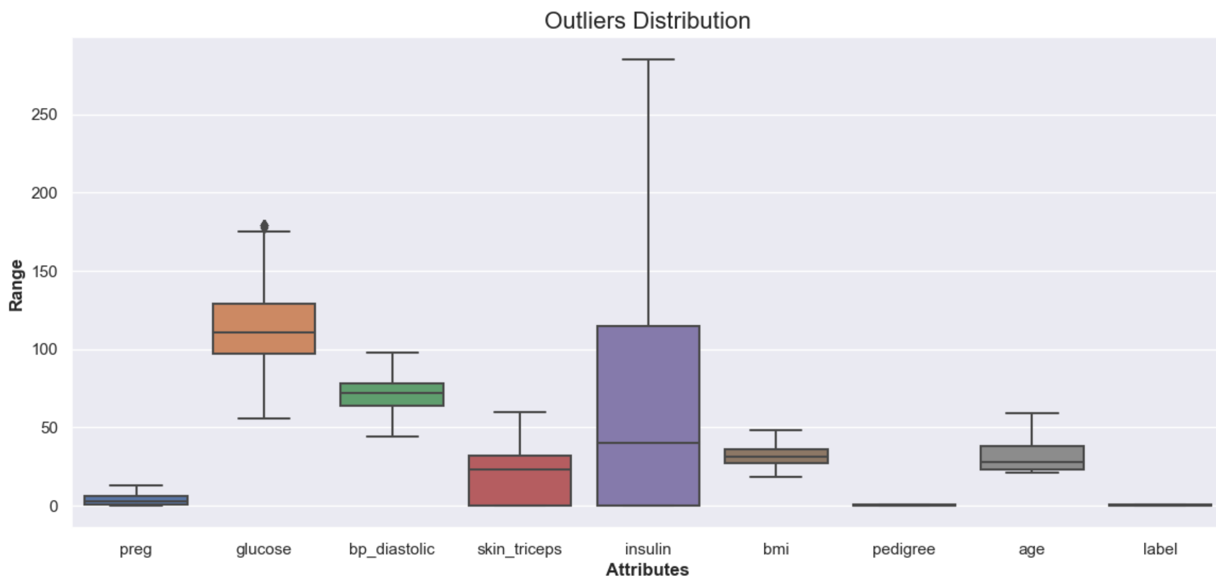
No missing values found in the dataset, therefore data doesn't need to be drop or replace.

Outliers Analysis

In [16]:
```
def show_boxplot(df):
    plt.rcParams['figure.figsize'] = [14,6]
    sns.boxplot(data = df, orient="v")
    plt.title("Outliers Distribution", fontsize = 16)
    plt.ylabel("Range", fontweight = 'bold')
    plt.xlabel("Attributes", fontweight = 'bold')
show_boxplot(df)
```



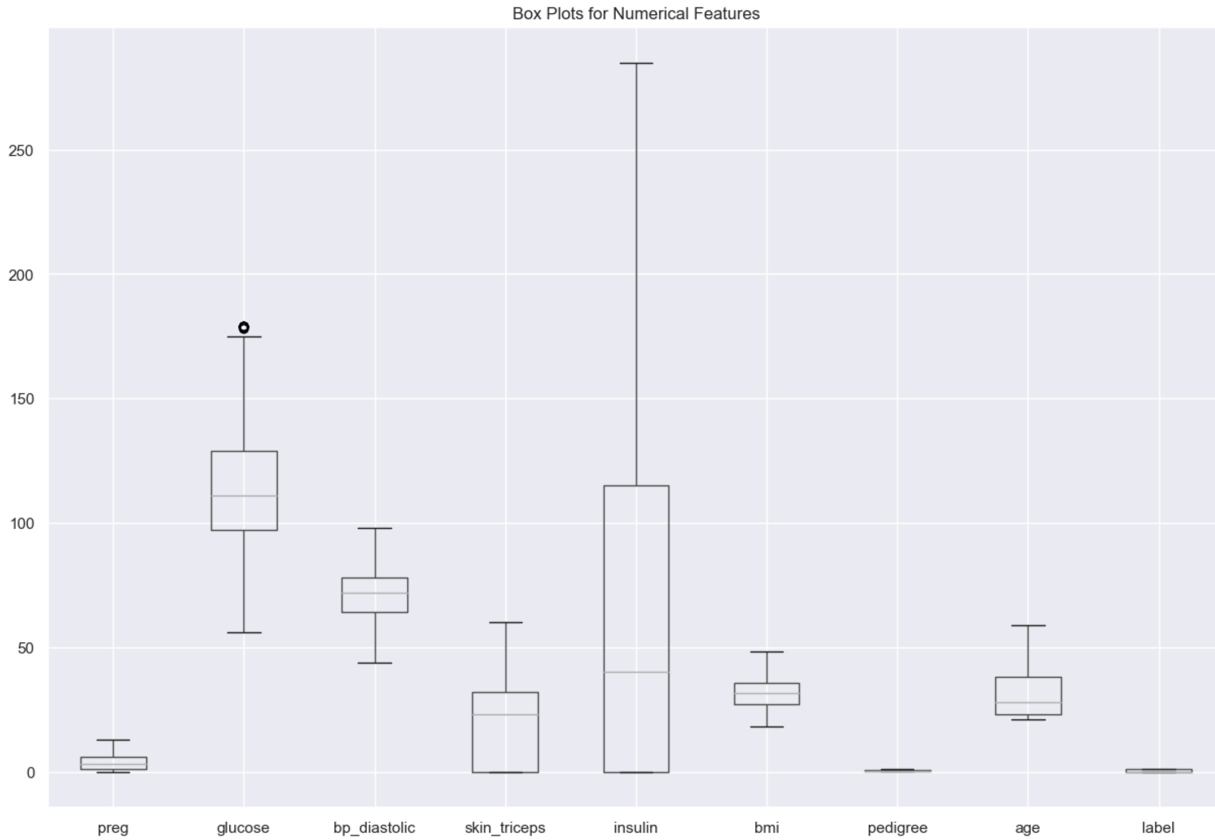
In [86]:
```
#Function 1st time
def remove_outliers(data):

    df = data.copy()

    for col in list(df.columns):
        Q1 = df[str(col)].quantile(0.25)
        Q3 = df[str(col)].quantile(0.75)
        IQR = Q3 - Q1
        # Define the lower and upper bounds to filter outliers
        lower_bound = Q1 - 1.5 * IQR
        upper_bound = Q3 + 1.5 * IQR

        df = df[(df[str(col)] >= lower_bound) & (df[str(col)] <= upper_bound)]

    return df
without_outliers = remove_outliers(df)
show_boxplot(without_outliers)
```



NOTE: Outliers completely removed, after function has been run two to three times.

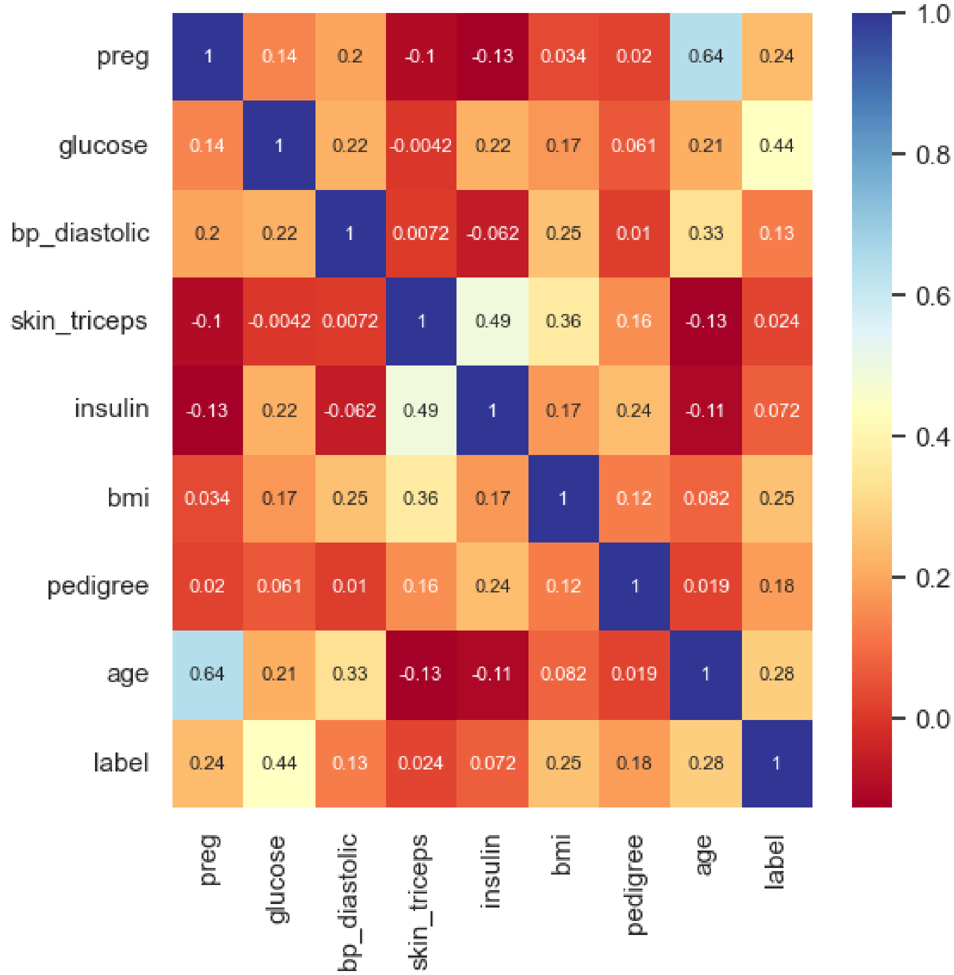
In [87]:
```
df=without_outliers
```

In [90]:
```
# Box plots for numerical features
plt.figure(figsize=(15, 10))
df.boxplot()
plt.title('Box Plots for Numerical Features')
plt.show()
```

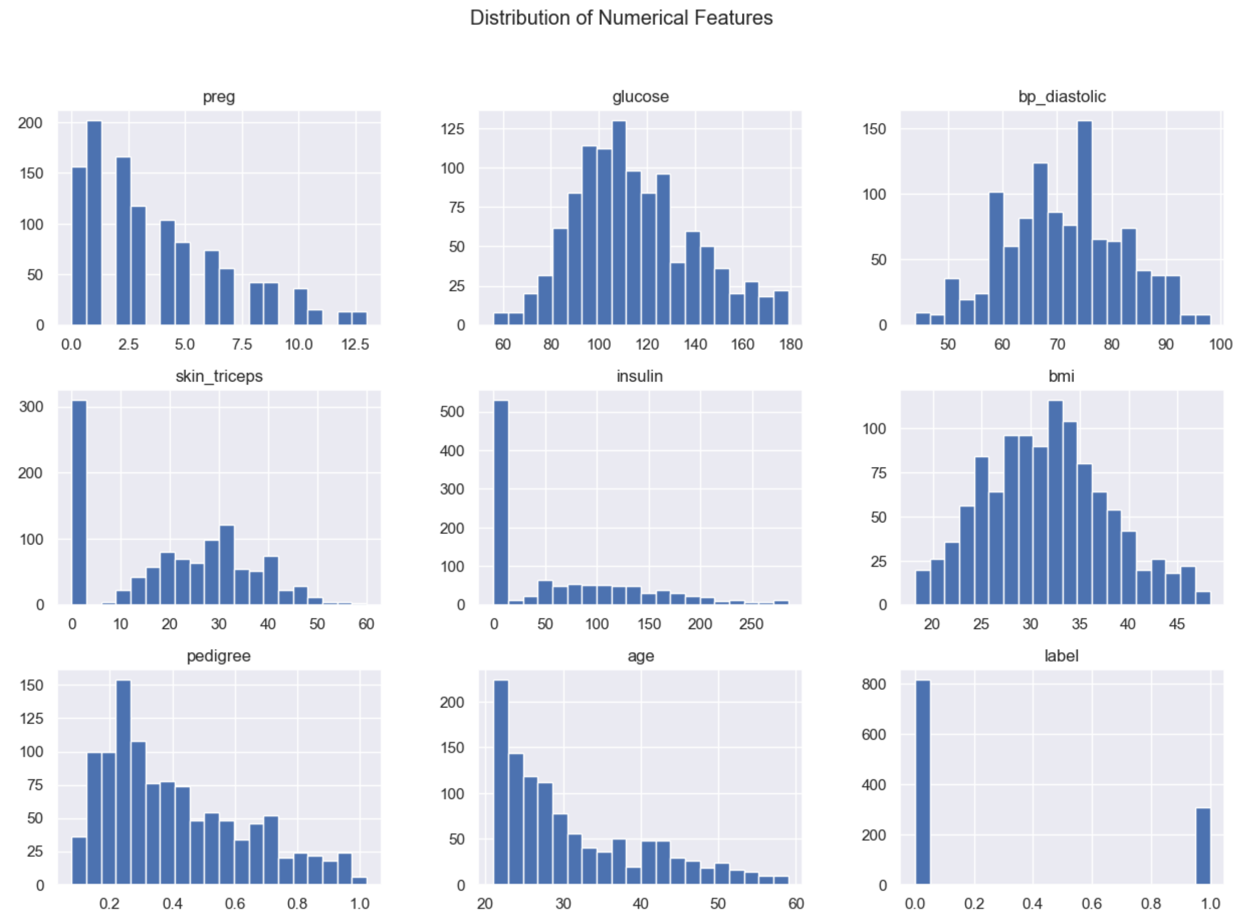


HeatMap

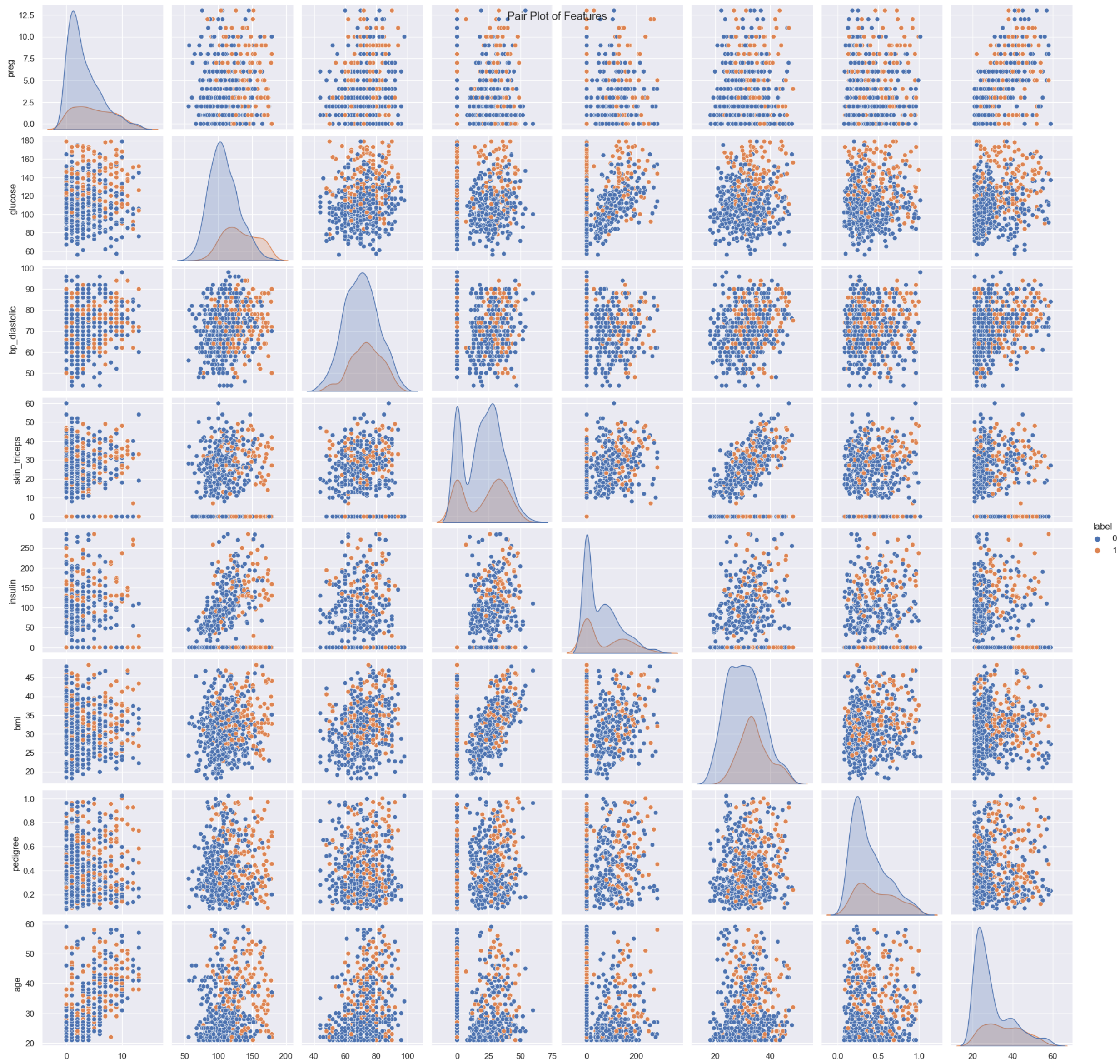
In [89]:
```
#get correlations of each features in dataset
corrmat = df.corr()
top_corr_features = corrmat.index
plt.figure(figsize=(6,6))
#plot heat map
sns.heatmap(df[top_corr_features].corr(),annot=True,cmap="RdYlBu", annot_kws={"fontsize": 8});
```



In [88]:
```
# Distribution of numerical features
df.hist(bins=20, figsize=(15, 10))
plt.suptitle('Distribution of Numerical Features')
plt.show()
```



In [119]:
```
# Pair plot
sns.pairplot(df, hue='label')
plt.suptitle('Pair Plot of Features')
plt.show()
```



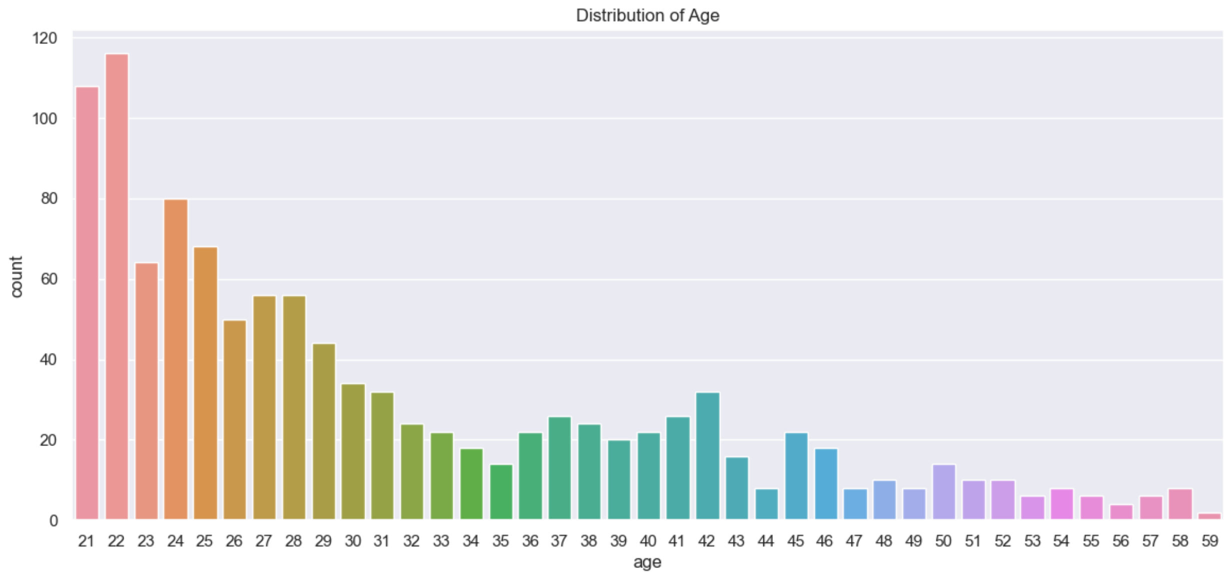
In [120]:
```
df.corr()
```

Out[120]:

	preg	glucose	bp_diastolic	skin_triceps	insulin	bmi	pedigree	age	label
preg	1.000000	0.139553	0.195395	-0.100111	-0.125753	0.034058	0.019659	0.640850	0.241720
glucose	0.139553	1.000000	0.217810	-0.004162	0.220023	0.170383	0.060741	0.213677	0.439359
bp_diastolic	0.195395	0.217810	1.000000	0.007192	-0.061532	0.253796	0.010113	0.330009	0.126285
skin_triceps	-0.100111	-0.004162	0.007192	1.000000	0.489710	0.363690	0.156150	-0.127629	0.024426
insulin	-0.125753	0.220023	-0.061532	0.489710	1.000000	0.174412	0.244436	-0.108542	0.072008
bmi	0.034058	0.170383	0.253796	0.363690	0.174412	1.000000	0.123642	0.082336	0.251246
pedigree	0.019659	0.060741	0.010113	0.156150	0.244436	0.123642	1.000000	0.018783	0.181338
age	0.640850	0.213677	0.330009	-0.127629	-0.108542	0.082336	0.018783	1.000000	0.284521
label	0.241720	0.439359	0.126285	0.024426	0.072008	0.251246	0.181338	0.284521	1.000000

Distribution of categorical features

In [122]:
```
# Distribution of categorical features
sns.countplot(x='age', data=df)
plt.title('Distribution of Age')
plt.show()
```



In [92]:
```
print(df.shape[0])
print(df.shape[1])
```

```
1122
9
```

In [93]:
```
df.label.value_counts()
```

Out[93]:
```
0    816
1    306
Name: label, dtype: int64
```

In [94]:
```
df.columns
```

Out[94]:
```
Index(['preg', 'glucose', 'bp_diastolic', 'skin_triceps', 'insulin', 'bmi',
       'pedigree', 'age', 'label'],
      dtype='object')
```

In [95]:
```
cols=list(df.columns)
cols
```

Out[95]:
```
['preg',
 'glucose',
 'bp_diastolic',
 'skin_triceps',
 'insulin',
 'bmi',
 'pedigree',
 'age',
 'label']
```

In [96]:
```
df.shape
```
Out[96]:
```
(1122, 9)
```

In [97]:
```
feature_cols=cols[0:8]
print(feature_cols)
```
```
['preg', 'glucose', 'bp_diastolic', 'skin_triceps', 'insulin', 'bmi', 'pedigree', 'age']
```

In [98]:
```
feature_cols=['preg', 'glucose', 'bp_diastolic', 'skin_triceps', 'insulin', 'bmi', 'pedigree',
print(feature_cols)
```
```
['preg', 'glucose', 'bp_diastolic', 'skin_triceps', 'insulin', 'bmi', 'pedigree', 'age']
```

Data Train-Test split

In [99]:
```
#Library Call for data split in two portion Train and Test:
from sklearn.model_selection import train_test_split
```

In [100]:
```
#dataframe
x=df[feature_cols]  #feature
#series
y=df.label
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size =0.20, random_state=0)
```

In [101]:
```
#Total size of the Training dataset:
print("[XY_Train] dataset Shape:", x_train.shape)

#Total size of the Testing dataset:
print("[XY_Test] dataset Shape:", x_test.shape)
```
```
[XY_Train] dataset Shape: (897, 8)
[XY_Test] dataset Shape: (225, 8)
```

In [102]:
```
#get total number of 0 in the actual dataset
count0=df["label"][df.label==0].count()
print("Total Number of 0's in Label:", count0)
```
```
Total Number of 0's in Label: 816
```

In [103]:
```
#get total number of 1 in the actual dataset
count1=df["label"][df.label==1].count()
print("Total Number of 1's in Label:", count1)
```
```
Total Number of 1's in Label: 306
```

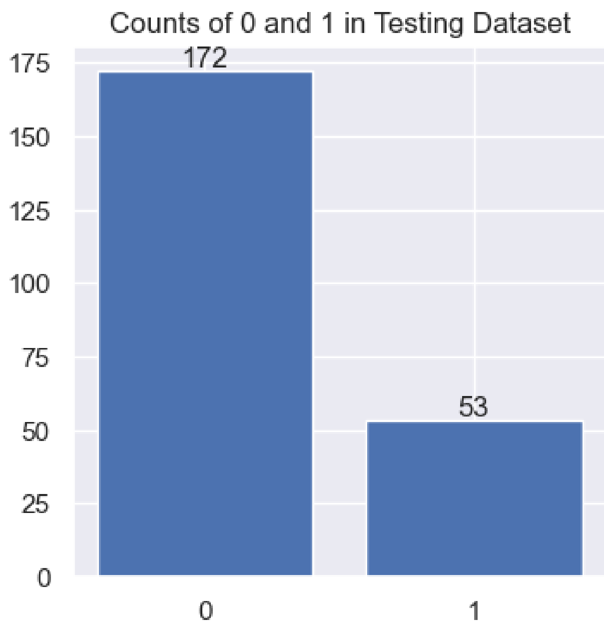
In [104]:
```
#Checking the number of 0's in Training portion of the Dataset:
print("[Y_Train] Total number of [0] in dataset :", len(y_train[y_train==0]))

#Checking the number of 1's in Training portion of the Dataset:
print("[Y_Train] Total number of [1] in dataset :", len(y_train[y_train==1]))
```
```
[Y_Train] Total number of [0] in dataset : 644
[Y_Train] Total number of [1] in dataset : 253
```

In [105]:
```
#Checking the number of 0's in Testing portion of the Dataset:
print("[Y_Test] Total number of [0] in dataset :", len(y_test[y_test==0]))

#Checking the number of 1's in Testing portion of the Dataset:
print("[Y_Test] Total number of [1] in dataset :", len(y_test[y_test==1]))
```

```
[Y_Test] Total number of [0] in dataset : 172
[Y_Test] Total number of [1] in dataset : 53
```

In [106]:
```
# get total number of 0 in the training dataset
Trcount0 = y_train[y_train==0].count()

# get total number of 1 in the training dataset
Trcount1 = y_train[y_train==1].count()

# Plotting the bar chart
label = ['0', '1']
counts = [Trcount0, Trcount1]

plt.figure(figsize=(4,4))
plt.title('Counts of 0 and 1 in Training Dataset')
plt.bar(label, counts)

# Add annotations to the bars
for i, count in enumerate(counts):
    plt.text(i, count, str(count), ha='center', va='bottom')

plt.show()
```

In [107]:
```
# get total number of 0 in the testing dataset
Trcount0 = y_test[y_test==0].count()

# get total number of 1 in the testing dataset
Trcount1 = y_test[y_test==1].count()

# Plotting the bar chart
label = ['0', '1']
counts = [Trcount0, Trcount1]

plt.figure(figsize=(4,4))
plt.title('Counts of 0 and 1 in Testing Dataset')
plt.bar(label, counts)

# Add annotations to the bars
for i, count in enumerate(counts):
    plt.text(i, count, str(count), ha='center', va='bottom')

plt.show()
```



Decision Tree Lib Call

In [108]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [109]:
```
# Create Decision Tree classifer object
dpth=4
clf = DecisionTreeClassifier(criterion="entropy", max_depth=dpth)
```

In [110]:
```
# Train Classifer
model = clf.fit(x_train, y_train)
```

Model

In [111]:
```
#Predict the response for test dataset
y_pred = clf.predict(x_test)
```

In [112]:
```
y=pd.DataFrame({"Origional": y_test, "Predicted": y_pred})
y.head()
```

Out[112]:

	Origional	Predicted
1069	1	0
1271	0	0
548	0	1
1396	0	0
704	0	0

In [113]:
```
y.sample(10)
```

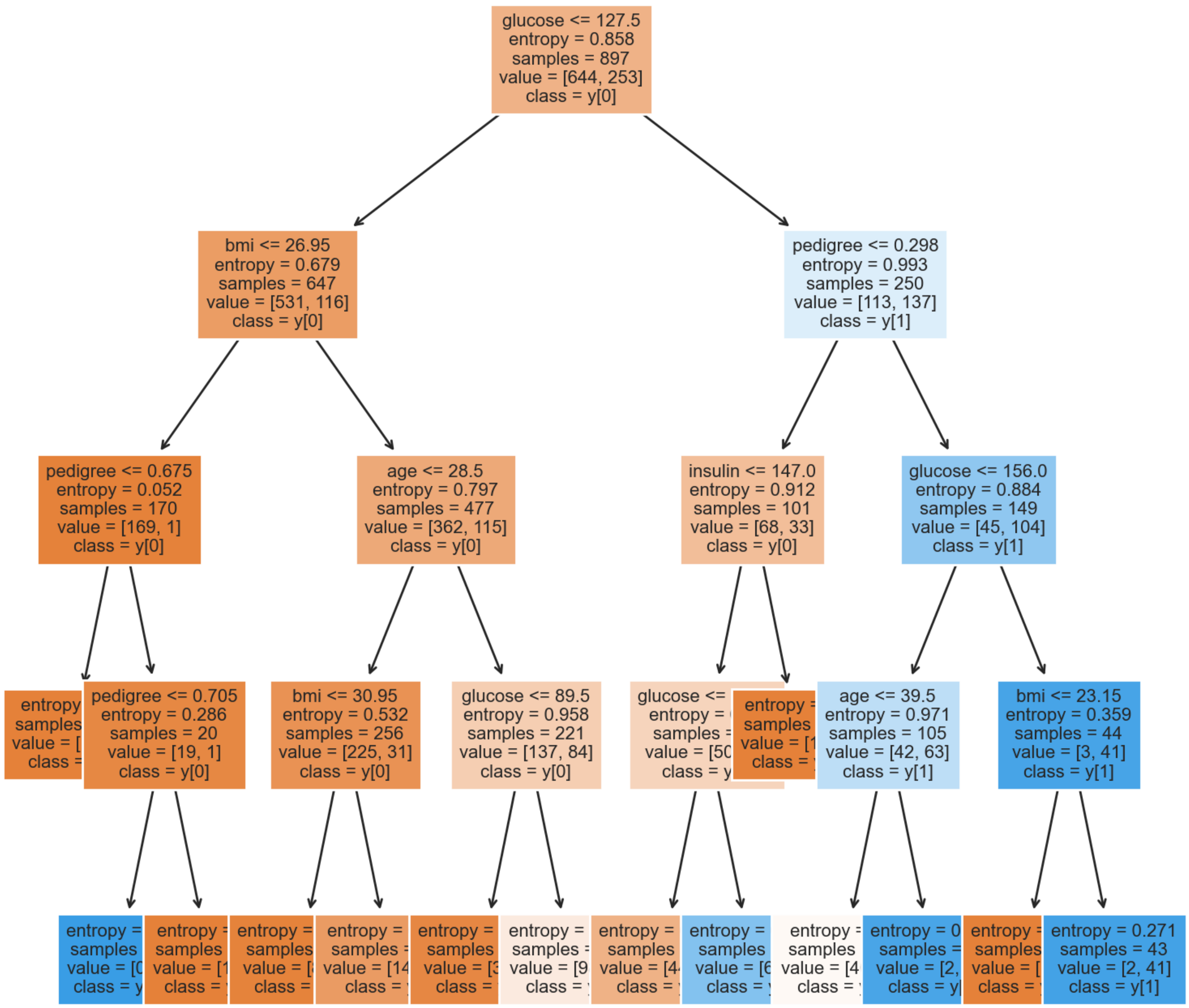
Out[113]:

	Origional	Predicted
641	0	0
219	1	0
721	0	0
1376	0	0
1439	0	0
470	0	0
443	1	0
1315	0	0
3	0	0
531	0	0

Decision Tree Plot

In [114]:
```
import matplotlib.pyplot as plt
from sklearn import tree
```

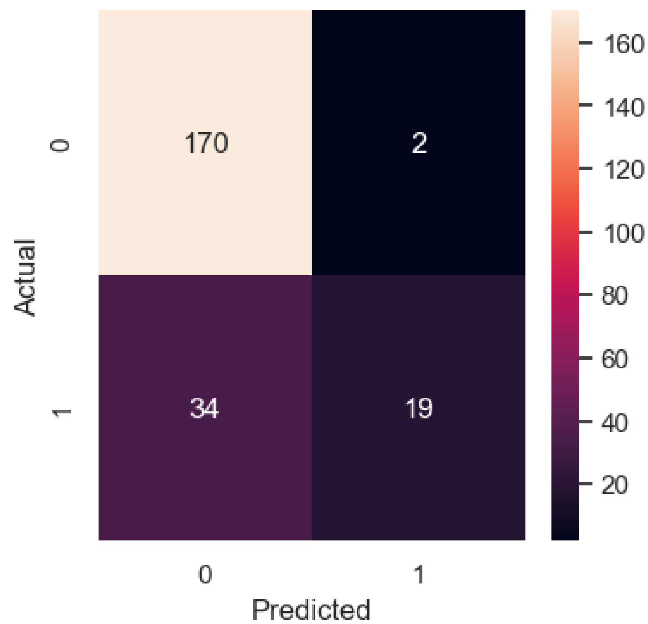
In [115]:
```
# Plot the decision tree with customizations
plt.figure(figsize=(9, 9), dpi=200)
plt.title("Decision Tree Visualization")
tree.plot_tree(clf, filled=True, feature_names=x_train.columns, class_names=True, fontsize=8,

plt.show()
```



Confusion Matrics

In [116]:
```
# calculate accuracy
from sklearn import metrics

result = metrics.confusion_matrix(y_test, y_pred)
print("Confusion Matrix:")
print(result)

def plt1():
    import seaborn as sns; sns.set()
    plt.figure(figsize=(4,4))
    c_mtrx = pd.crosstab(y_test, y_pred, rownames=['Actual'], colnames=['Predicted'])
    sns.heatmap(c_mtrx, annot=True, fmt = '.3g')

plt1()
```

```
Confusion Matrix:
[[170   2]
 [ 34  19]]
```



Accuracy Calculation

In [117]:
```
#[row, column]
#(Actual, Predict)
TP = result[1, 1]
TN = result[0, 0]
FP = result[0, 1]
FN = result[1, 0]
```

In [118]:
```
def EvClsMdl(res):
    print('Metrics computed from a confusion matrix')
    print("Accuracy:\t", metrics.accuracy_score(y_test, y_pred))
    print("Sensitivity:\t", metrics.recall_score(y_test, y_pred))
    print("Specificity:\t",TN / (TN + FP))
    print("Precision:\t", metrics.precision_score(y_test, y_pred))
    print("Classification Eerror:", 1 - metrics.accuracy_score(y_test, y_pred))
    print("False_Positive_Rate:", 1 - TN / (TN + FP))
    print('###########################################')
EvClsMdl(result)
```

```
Metrics computed from a confusion matrix
Accuracy:        0.84
Sensitivity:     0.3584905660377358
Specificity:     0.9883720930232558
Precision:       0.9047619047619048
Classification Eerror: 0.16000000000000003
False_Positive_Rate: 0.011627906976744207
###########################################
```

In [ ]:

In [ ]:

In [ ]: