INSURANCE Dataset

PROBLEM STATEMENT: Which model is suitable for insurance dataset

Import Libraries

```
In [1]: import numpy as np
    import pandas as pd
    from sklearn import preprocessing
    import matplotlib.pyplot as plt
    import seaborn as sns
    from sklearn.model_selection import train_test_split
    from sklearn.tree import DecisionTreeClassifier
    from sklearn.linear_model import LogisticRegression
    from sklearn.preprocessing import StandardScaler
    from sklearn.linear_model import LinearRegression
```

In [2]: df=pd.read_csv(r"C:\Users\DELL\Downloads\insurance (1).csv")
df

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		age	sex	bmi	children	smoker	region	charges
	0	19	female	27.900	0	yes	southwest	16884.92400
	1	18	ma l e	33.770	1	no	southeast	1725.55230
	2	28	ma l e	33.000	3	no	southeast	4449.46200
	3	33	ma l e	22.705	0	no	northwest	21984.47061
	4	32	ma l e	28.880	0	no	northwest	3866.85520
133	33	50	ma l e	30.970	3	no	northwest	10600.54830
133	34	18	female	31.920	0	no	northeast	2205.98080
133	35	18	female	36.850	0	no	southeast	1629.83350
133	36	21	female	25.800	0	no	southwest	2007.94500
133	37	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

Data cleaning & Preprocessing

In [3]: df.head()

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	age	sex	bmi	children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92400
1	18	male	33.770	1	no	southeast	1725.55230
2	28	male	33.000	3	no	southeast	4449.46200
3	33	male	22.705	0	no	northwest	21984.47061
4	32	male	28.880	0	no	northwest	3866.85520

In [36]: df.tail()

Out[36]:

	age	sex	bmi	children	smoker	region	charges
1333	50	1	30.97	3	no	2	10600.5483
1334	18	2	31.92	0	no	3	2205.9808
1335	18	2	36.85	0	no	1	1629.8335
1336	21	2	25.80	0	no	0	2007.9450
1337	61	2	29.07	0	yes	2	29141.3603

In [4]: df.shape

Out[4]: (1338, 7)

In [5]: df.describe()

Out[5]:

	age	bmi	children	charges
count	1338.000000	1338.000000	1338.000000	1338.000000
mean	39.207025	30.663397	1.094918	13270.422265
std	14.049960	6.098187	1.205493	12110.011237
min	18.000000	15.960000	0.000000	1121.873900
25%	27.000000	26.296250	0.000000	4740.287150
50%	39.000000	30.400000	1.000000	9382.033000
75%	51.000000	34.693750	2.000000	16639.912515
max	64.000000	53.130000	5.000000	63770.428010

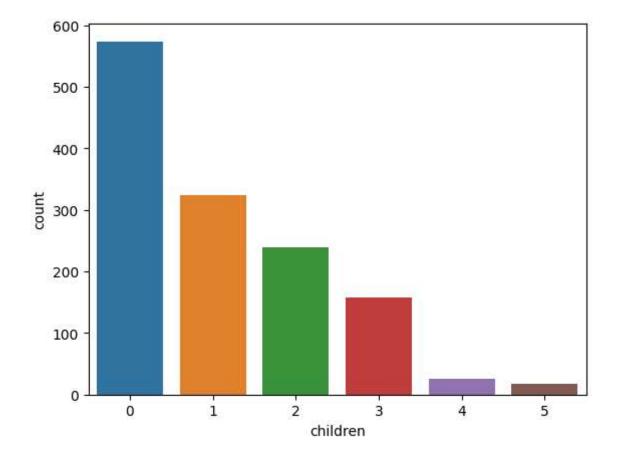
```
In [6]: df.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 1338 entries, 0 to 1337
         Data columns (total 7 columns):
              Column
                         Non-Null Count Dtvpe
          0
                         1338 non-null
                                          int64
              age
          1
                         1338 non-null
                                          object
              sex
          2
              bmi
                         1338 non-null
                                          float64
          3
              children 1338 non-null
                                          int64
          4
              smoker
                         1338 non-null
                                          object
          5
              region
                         1338 non-null
                                          object
          6
                         1338 non-null
                                          float64
              charges
         dtypes: float64(2), int64(2), object(3)
         memory usage: 73.3+ KB
        convert={"sex":{"male":1,"female":2}}
In [7]:
         df=df.replace(convert)
         print(df)
                                   children smoker
               age
                             bmi
                                                        region
                                                                     charges
                     sex
         0
                19
                       2
                          27.900
                                          0
                                                     southwest
                                                                 16884.92400
                                                yes
         1
                18
                       1
                          33.770
                                          1
                                                     southeast
                                                                  1725.55230
                                                 no
         2
                          33.000
                28
                       1
                                          3
                                                 no
                                                     southeast
                                                                  4449.46200
         3
                33
                          22.705
                                          0
                                                     northwest
                                                                 21984.47061
                                                 no
                          28.880
                                          0
         4
                32
                                                 no
                                                     northwest
                                                                  3866.85520
                             . . .
                                         . . .
                                                . . .
         . . .
                50
                          30.970
                                                     northwest
                                                                 10600.54830
         1333
                       1
                                          3
                                                 no
         1334
                18
                       2
                          31.920
                                          0
                                                     northeast
                                                                  2205.98080
                                                 no
         1335
                18
                       2
                          36.850
                                          0
                                                     southeast
                                                                  1629.83350
                                                 no
         1336
                21
                       2
                          25.800
                                                     southwest
                                                                  2007.94500
                                                 no
         1337
                61
                          29.070
                                                ves
                                                     northwest
                                                                 29141.36030
         [1338 rows x 7 columns]
        convert={"region":{"southwest":0,"southeast":1,"northwest":2,"northeast":3}}
In [8]:
         df=df.replace(convert)
         print(df)
                             bmi
                                   children smoker
                                                     region
               age
                     sex
                                                                  charges
         0
                19
                       2
                          27.900
                                          0
                                                yes
                                                          0
                                                              16884.92400
         1
                          33.770
                                          1
                18
                       1
                                                          1
                                                               1725.55230
                                                 no
         2
                28
                       1
                          33.000
                                          3
                                                 no
                                                          1
                                                               4449.46200
         3
                33
                       1
                          22.705
                                          0
                                                          2
                                                              21984.47061
                                                 no
         4
                32
                       1
                          28.880
                                          0
                                                          2
                                                               3866.85520
                                                 no
                              . . .
                                                . . .
         . . .
         1333
                50
                       1
                          30.970
                                          3
                                                           2
                                                              10600.54830
                                                 no
                       2 31.920
         1334
                                          0
                                                          3
                                                               2205.98080
                18
                                                 no
         1335
                18
                       2 36.850
                                          0
                                                 no
                                                          1
                                                               1629.83350
         1336
                21
                       2
                          25.800
                                          0
                                                               2007.94500
                                                 no
                                                          0
         1337
                       2
                          29.070
                61
                                          0
                                                yes
                                                          2
                                                              29141.36030
         [1338 rows x 7 columns]
```

```
In [9]: x=["age","sex","bmi","children","region","charges"]
y=["yes","No"]
all_inputs=df[x]
all_classes=df["smoker"]
```

Data Visualisation

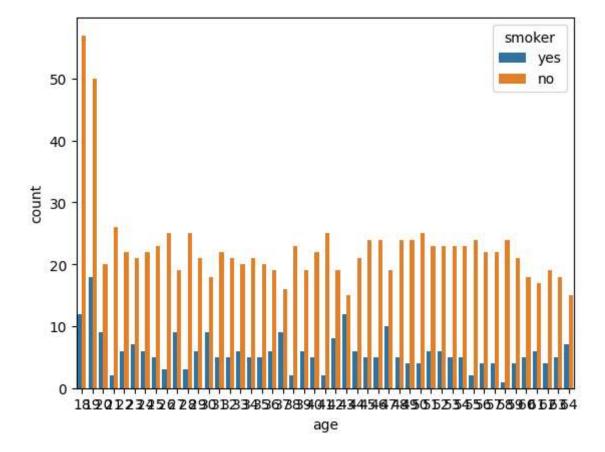
```
In [28]: sns.countplot(x="children", data=df)
```

Out[28]: <Axes: xlabel='children', ylabel='count'>



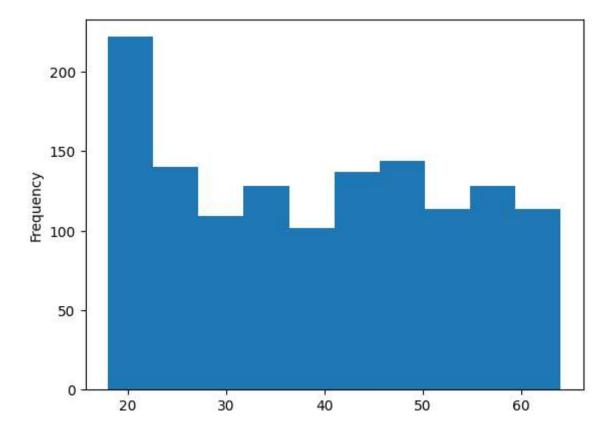
```
In [29]: sns.countplot(x="age",hue="smoker",data=df)
```

Out[29]: <Axes: xlabel='age', ylabel='count'>



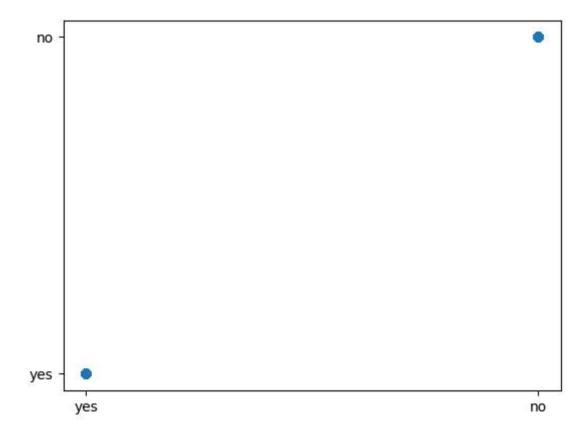
In [30]: df["age"].plot.hist()

Out[30]: <Axes: ylabel='Frequency'>



```
In [42]: predictions=clt.predict(x_train)
   plt.scatter(y_train,predictions)
```

Out[42]: <matplotlib.collections.PathCollection at 0x2de1f4359d0>



Linear Regression

```
In [11]: feature=df.columns[0:3]
    target=df.columns[-1]
    x=df[feature].values
    y=df[target].values
Thus [12]: x the in x test x the in x test the in test solit(x x test size=0.25)
```

```
In [12]: x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
    regr=LinearRegression()
    regr.fit(x_train,y_train)
    print(regr.score(x_test,y_test))
```

0.02843532430351725

Logistic Regression

```
In [31]: lg = LogisticRegression()
    lg.fit(x_train,y_train)
    print(lg.score(x_test,y_test))
    print(lg.score(x_train,y_train))

0.9552238805970149
```

Decision Tree

0.9202392821535393

```
In [15]: x_train,x_test,y_train,y_test=train_test_split(all_inputs,all_classes,test_size
```

```
In [16]: clt=DecisionTreeClassifier(random_state=0)
    clt.fit(x_train,y_train)
```

Out[16]: DecisionTreeClassifier(random_state=0)

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

```
In [17]: score=clt.score(x_test,y_test)
print(score)
```

0.9492537313432836

RANDOM FOREST

```
In [22]: from sklearn.ensemble import RandomForestClassifier
    rfc=RandomForestClassifier()
    rfc.fit(x_train,y_train)
    score=rfc.score(x_test,y_test)
    score1=rfc.score(x_train,y_train)
    print(score,score1)

0.9701492537313433 1.0
```

```
In [23]: rf=RandomForestClassifier()
```

```
In [25]: from sklearn.model_selection import GridSearchCV
    grid_search=GridSearchCV(estimator=rf,param_grid=params,cv=2,scoring="accuracy'
    grid_search.fit(x_train,y_train)
Out[25]: GridSearchCV(cv=2, estimator=RandomForestClassifier(),
```

ridSearchCV(cv=2, estimator=RandomForestClassifier(),

param_grid={'max_depth': [2, 3, 5, 10, 20],

'min_samples_leaf': [5, 10, 20, 50, 100, 200],

'n_estimators': [10, 25, 30, 50, 100, 200]},

scoring='accuracy')

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.

On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

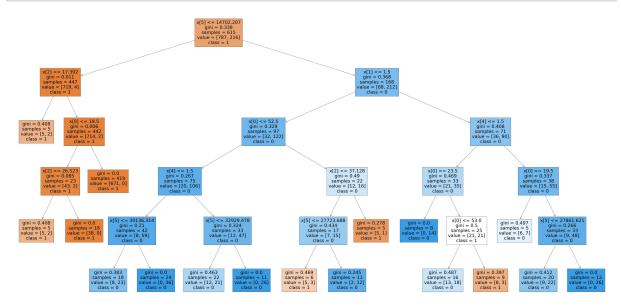
```
In [26]: grid_search.best_score_
```

Out[26]: 0.9531435137692742

```
In [27]: rf_best=grid_search.best_estimator_
print(rf_best)
```

RandomForestClassifier(max_depth=5, min_samples_leaf=5, n_estimators=30)

```
In [32]: from sklearn.tree import plot_tree
    plt.figure(figsize=(80,40))
    plot_tree(rf_best.estimators_[5],class_names=["1","0"],filled=True);
```



```
Out[34]: array([0.03427488, 0.0059298, 0.04189636, 0.01141585, 0.008755
                 0.89772811])
In [35]:
          imp_df=pd.DataFrame({"Varname":x_train.columns,"Imp":rf_best.feature_importance
          imp df.sort values(by="Imp",ascending=False)
Out[35]:
             Varname
                          Imp
           5
              charges
                      0.897728
           2
                      0.041896
                  bmi
                 age
                      0.034275
                     0.011416
           3
              children
                     0.008755
                region
                  sex 0.005930
```

CONCLUSION: Based on the accuracy scores of all models that were implemented we can conclude that "Logistic Regression" is the best model for the given dataset.