MINI PROJECT

1.Problem Statement:Which model is suitable best for Insurance Dataset

In [2]:
```
import pandas as pd
import numpy as np
from sklearn import preprocessing,svm
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import RidgeCV
from sklearn.linear_model import Lasso
from sklearn.linear_model import LassoCV
from sklearn.linear_model import ElasticNet
from sklearn import metrics
```

Data Collection

Read the Data

In [3]:

```
df=pd.read_csv(r"C:\Users\DELL E5490\Downloads\insurance.csv")
df
```

Out[3]:

	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
...	...	...	...	...	...	...	...
1333	50	male	30.970	3	no	northwest	10600.54830
1334	18	female	31.920	0	no	northeast	2205.98080
1335	18	female	36.850	0	no	southeast	1629.83350
1336	21	female	25.800	0	no	southwest	2007.94500
1337	61	female	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

2.Data Cleaning and Preprocessing

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1338 entries, 0 to 1337
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   age       1338 non-null   int64  
 1   sex       1338 non-null   object 
 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   charges   1338 non-null   float64
dtypes: float64(2), int64(2), object(3)
memory usage: 73.3+ KB
```

In [5]:
```
df.columns
```

Out[5]:
```
Index(['age', 'sex', 'bmi', 'children', 'smoker', 'region', 'charges'], dtype='object')
```

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

Out[6]:

	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 [7]:
```
df.tail()
```

Out[7]:

	age	sex	bmi	children	smoker	region	charges
1333	50	male	30.97	3	no	northwest	10600.5483
1334	18	female	31.92	0	no	northeast	2205.9808
1335	18	female	36.85	0	no	southeast	1629.8335
1336	21	female	25.80	0	no	southwest	2007.9450
1337	61	female	29.07	0	yes	northwest	29141.3603

In [8]:
```
df.shape
```

Out[8]:
```
(1338, 7)
```

In [9]:
```
df.describe()
```

Out[9]:

	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

To find Duplicate Values

In [10]:
```
df.duplicated().sum()
```

Out[10]: 1

To find Unique Values

In [11]:

```
df['age'].unique()
df['children'].unique()
df['bmi'].unique()

```

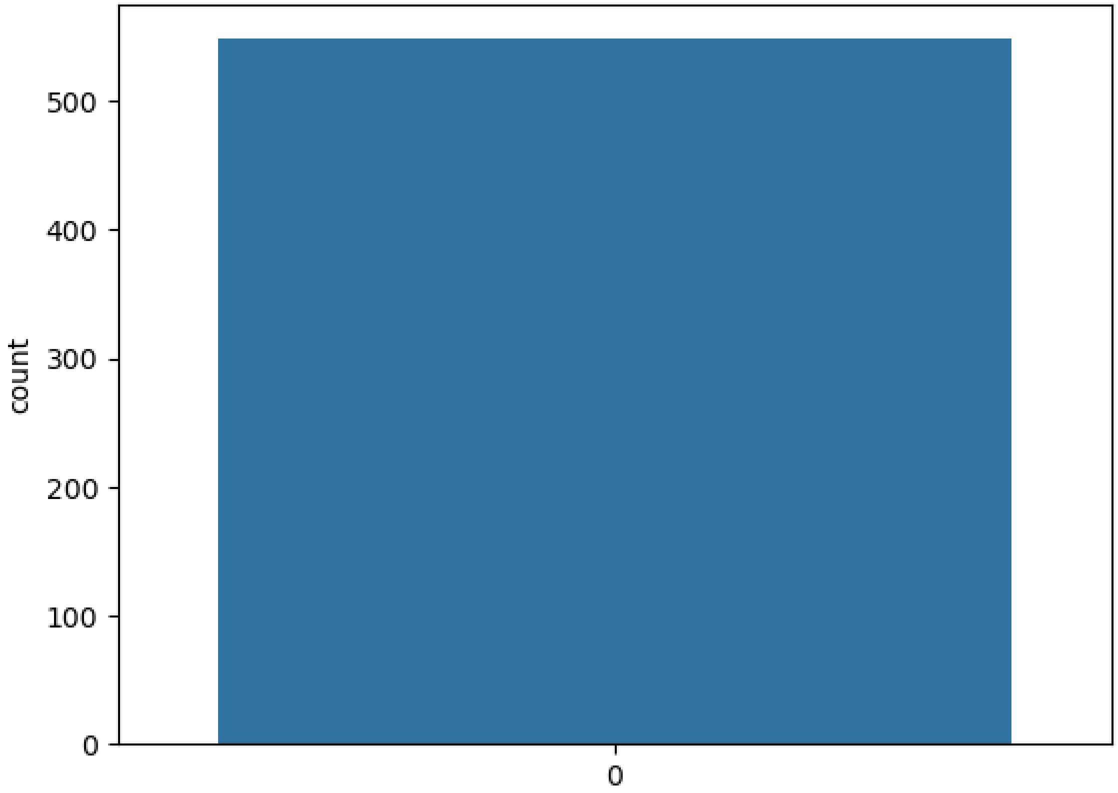
Out[11]:
```
array([27.9  , 33.77 , 33.   , 22.705, 28.88 , 25.74 , 33.44 , 27.74 ,
       29.83 , 25.84 , 26.22 , 26.29 , 34.4  , 39.82 , 42.13 , 24.6  ,
       30.78 , 23.845, 40.3  , 35.3  , 36.005, 32.4  , 34.1  , 31.92 ,
       28.025, 27.72 , 23.085, 32.775, 17.385, 36.3  , 35.6  , 26.315,
       28.6  , 28.31 , 36.4  , 20.425, 32.965, 20.8  , 36.67 , 39.9  ,
       26.6  , 36.63 , 21.78 , 30.8  , 37.05 , 37.3  , 38.665, 34.77 ,
       24.53 , 35.2  , 35.625, 33.63 , 28.   , 34.43 , 28.69 , 36.955,
       31.825, 31.68 , 22.88 , 37.335, 27.36 , 33.66 , 24.7  , 25.935,
       22.42 , 28.9  , 39.1  , 36.19 , 23.98 , 24.75 , 28.5  , 28.1  ,
       32.01 , 27.4  , 34.01 , 29.59 , 35.53 , 39.805, 26.885, 38.285,
       37.62 , 41.23 , 34.8  , 22.895, 31.16 , 27.2  , 26.98 , 39.49 ,
       24.795, 31.3  , 38.28 , 19.95 , 19.3  , 31.6  , 25.46 , 30.115,
       29.92 , 27.5  , 28.4  , 30.875, 27.94 , 35.09 , 29.7  , 35.72 ,
       32.205, 28.595, 49.06 , 27.17 , 23.37 , 37.1  , 23.75 , 28.975,
       31.35 , 33.915, 28.785, 28.3  , 37.4  , 17.765, 34.7  , 26.505,
       22.04 , 35.9  , 25.555, 28.05 , 25.175, 31.9  , 36.   , 32.49 ,
       25.3  , 29.735, 38.83 , 30.495, 37.73 , 37.43 , 24.13 , 37.145,
       39.52 , 24.42 , 27.83 , 36.85 , 39.6  , 29.8  , 29.64 , 28.215,
       37.   , 33.155, 18.905, 41.47 , 30.3  , 15.96 , 33.345, 37.7  ,
       27.835, 29.2  , 26.41 , 30.69 , 41.895, 30.9  , 32.2  , 32.11 ,
       31.57 , 26.2  , 30.59 , 32.8  , 18.05 , 39.33 , 32.23 , 24.035,
       36.08 , 22.3  , 26.4  , 31.8  , 26.73 , 23.1  , 23.21 , 33.7  ,
       33.25 , 24.64 , 33.88 , 38.06 , 41.91 , 31.635, 36.195, 17.8  ,
       24.51 , 22.22 , 38.39 , 29.07 , 22.135, 26.8  , 30.02 , 35.86 ,
       20.9  , 17.29 , 34.21 , 25.365, 40.15 , 24.415, 25.2  , 26.84 ,
       24.32 , 42.35 , 19.8  , 32.395, 30.2  , 29.37 , 34.2  , 27.455,
       27.55 , 20.615, 24.3  , 31.79 , 21.56 , 28.12 , 40.565, 27.645,
       31.2  , 26.62 , 48.07 , 36.765, 33.4  , 45.54 , 28.82 , 22.99 ,
       27.7  , 25.41 , 34.39 , 22.61 , 37.51 , 38.   , 33.33 , 34.865,
       33.06 , 35.97 , 31.4  , 25.27 , 40.945, 34.105, 36.48 , 33.8  ,
       36.7  , 36.385, 34.5  , 32.3  , 27.6  , 29.26 , 35.75 , 23.18 ,
       25.6  , 35.245, 43.89 , 20.79 , 30.5  , 21.7  , 21.89 , 24.985,
       32.015, 30.4  , 21.09 , 22.23 , 32.9  , 24.89 , 31.46 , 17.955,
       30.685, 43.34 , 39.05 , 30.21 , 31.445, 19.855, 31.02 , 38.17 ,
       20.6  , 47.52 , 20.4  , 38.38 , 24.31 , 23.6  , 21.12 , 30.03 ,
       17.48 , 20.235, 17.195, 23.9  , 35.15 , 35.64 , 22.6  , 39.16 ,
       27.265, 29.165, 16.815, 33.1  , 26.9  , 33.11 , 31.73 , 46.75 ,
       29.45 , 32.68 , 33.5  , 43.01 , 36.52 , 26.695, 25.65 , 29.6  ,
       38.6  , 23.4  , 46.53 , 30.14 , 30.   , 38.095, 28.38 , 28.7  ,
       33.82 , 24.09 , 32.67 , 25.1  , 32.56 , 41.325, 39.5  , 34.3  ,
       31.065, 21.47 , 25.08 , 43.4  , 25.7  , 27.93 , 39.2  , 26.03 ,
```

```
30.25 , 28.93 , 35.7  , 35.31 , 31.   , 44.22 , 26.07 , 25.8  ,
39.425, 40.48 , 38.9  , 47.41 , 35.435, 46.7  , 46.2  , 21.4  ,
23.8  , 44.77 , 32.12 , 29.1  , 37.29 , 43.12 , 36.86 , 34.295,
23.465, 45.43 , 23.65 , 20.7  , 28.27 , 35.91 , 29.   , 19.57 ,
31.13 , 21.85 , 40.26 , 33.725, 29.48 , 32.6  , 37.525, 23.655,
37.8  , 19.   , 21.3  , 33.535, 42.46 , 38.95 , 36.1  , 29.3  ,
39.7  , 38.19 , 42.4  , 34.96 , 42.68 , 31.54 , 29.81 , 21.375,
40.81 , 17.4  , 20.3  , 18.5  , 26.125, 41.69 , 24.1  , 36.2  ,
40.185, 39.27 , 34.87 , 44.745, 29.545, 23.54 , 40.47 , 40.66 ,
36.6  , 35.4  , 27.075, 28.405, 21.755, 40.28 , 30.1  , 32.1  ,
23.7  , 35.5  , 29.15 , 27.   , 37.905, 22.77 , 22.8  , 34.58 ,
27.1  , 19.475, 26.7  , 34.32 , 24.4  , 41.14 , 22.515, 41.8  ,
26.18 , 42.24 , 26.51 , 35.815, 41.42 , 36.575, 42.94 , 21.01 ,
24.225, 17.67 , 31.5  , 31.1  , 32.78 , 32.45 , 50.38 , 47.6  ,
25.4  , 29.9  , 43.7  , 24.86 , 28.8  , 29.5  , 29.04 , 38.94 ,
44.   , 20.045, 40.92 , 35.1  , 29.355, 32.585, 32.34 , 39.8  ,
24.605, 33.99 , 28.2  , 25.   , 33.2  , 23.2  , 20.1  , 32.5  ,
37.18 , 46.09 , 39.93 , 35.8  , 31.255, 18.335, 42.9  , 26.79 ,
39.615, 25.9  , 25.745, 28.16 , 23.56 , 40.5  , 35.42 , 39.995,
34.675, 20.52 , 23.275, 36.29 , 32.7  , 19.19 , 20.13 , 23.32 ,
45.32 , 34.6  , 18.715, 21.565, 23.   , 37.07 , 52.58 , 42.655,
21.66 , 32.   , 18.3  , 47.74 , 22.1  , 19.095, 31.24 , 29.925,
20.35 , 25.85 , 42.75 , 18.6  , 23.87 , 45.9  , 21.5  , 30.305,
44.88 , 41.1  , 40.37 , 28.49 , 33.55 , 40.375, 27.28 , 17.86 ,
33.3  , 39.14 , 21.945, 24.97 , 23.94 , 34.485, 21.8  , 23.3  ,
36.96 , 21.28 , 29.4  , 27.3  , 37.9  , 37.715, 23.76 , 25.52 ,
27.61 , 27.06 , 39.4  , 34.9  , 22.   , 30.36 , 27.8  , 53.13 ,
39.71 , 32.87 , 44.7  , 30.97 ])
```

3.Data Visualize : Visualize the unique counts

In [12]:
```
sns.countplot(df['bmi'].unique())
```

Out[12]: <Axes: ylabel='count'>



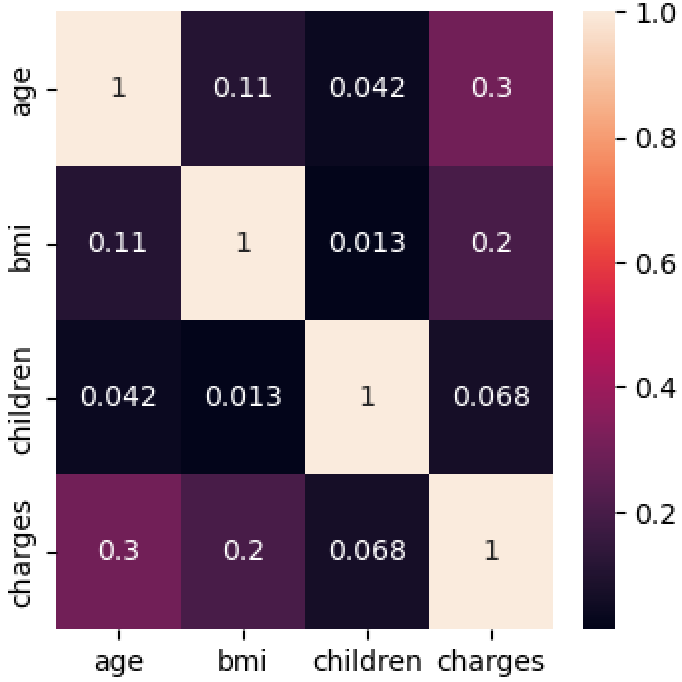
Find the Null values

In [13]:
```
df.isnull().sum()
```

Out[13]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

In [14]:
```
Insuranced=df[['age','bmi','children','charges']]
plt.figure(figsize=(4,4))
sns.heatmap(Insuranced.corr(),annot=True)
```

Out[14]: <Axes: >



To Check The Null values

In [15]:
```
df.replace(np.nan,'0',inplace=True)

```

In [16]:
```
df.isnull().sum()
```

Out[16]:
```
age         0
sex         0
bmi         0
children    0
smoker      0
region      0
charges     0
dtype: int64
```

Feature Scaling:To Split the data into train and test data

In [17]:
```
x=np.array(df['age']).reshape(-1,1)
y=np.array(df['charges']).reshape(-1,1)
```

In [18]:
```
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))

```

```
0.1124787316394128
```

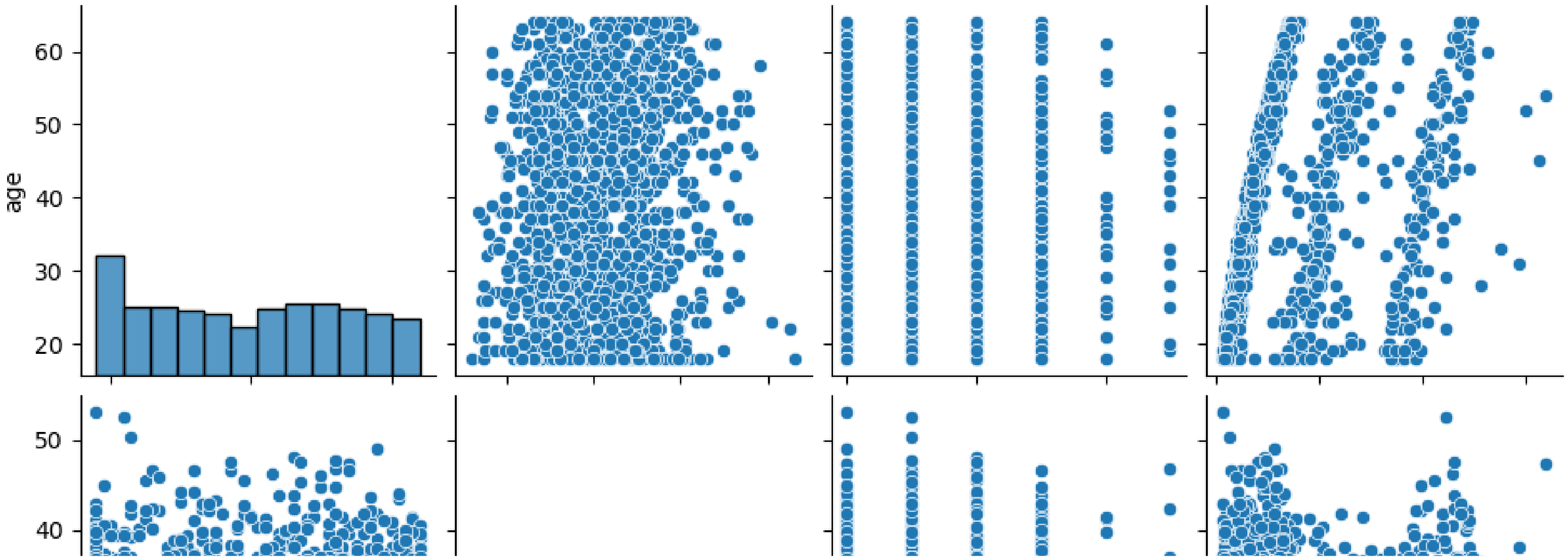
In the Linear Regression is not suitable for this model because of accuracy is very less

Logistisc Regression

In [38]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.preprocessing import StandardScaler
```

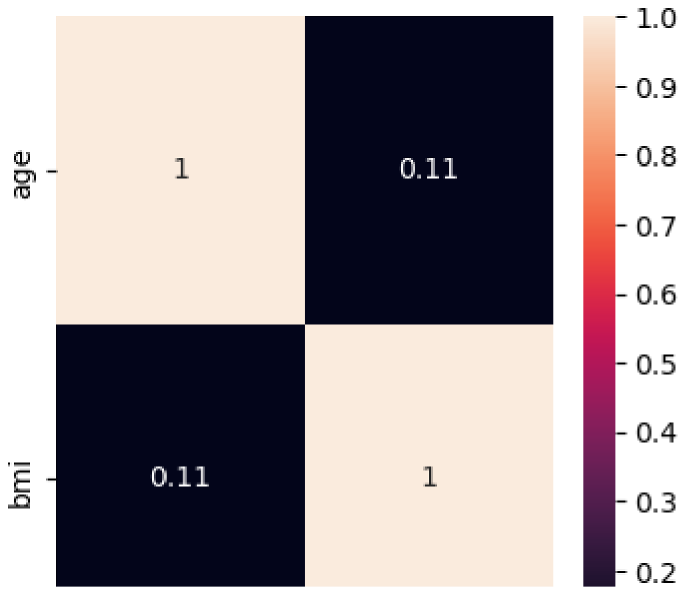
In [21]:
```
sns.pairplot(df)
```

Out[21]:
```
<seaborn.axisgrid.PairGrid at 0x250bfe043d0>
```



In [39]:
```
Insuranced=df[['age','bmi']]
plt.figure(figsize=(4,4))
sns.heatmap(Insuranced.corr(),annot=True)
```

Out[39]: <Axes: >



In [40]:
```
x = df.iloc[:,:-1].values
y = df.iloc[:,1].values
```

In [41]:
```
#Split the train and test dataset
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size = 0.2)
```

In [42]:
```
ml = LogisticRegression()
```

In [43]:
```
x=np.array(df['smoker']).reshape(-1,1)
x=np.array(df['age']).reshape(-1,1)
df.dropna(inplace=True)
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25,random_state=1)
from sklearn.linear_model import LogisticRegression
lr=LogisticRegression(max_iter=10000)
```

In [44]:
```
lr.fit(x_train,y_train)
```

Out[44]:
```
LogisticRegression(max_iter=10000)
```

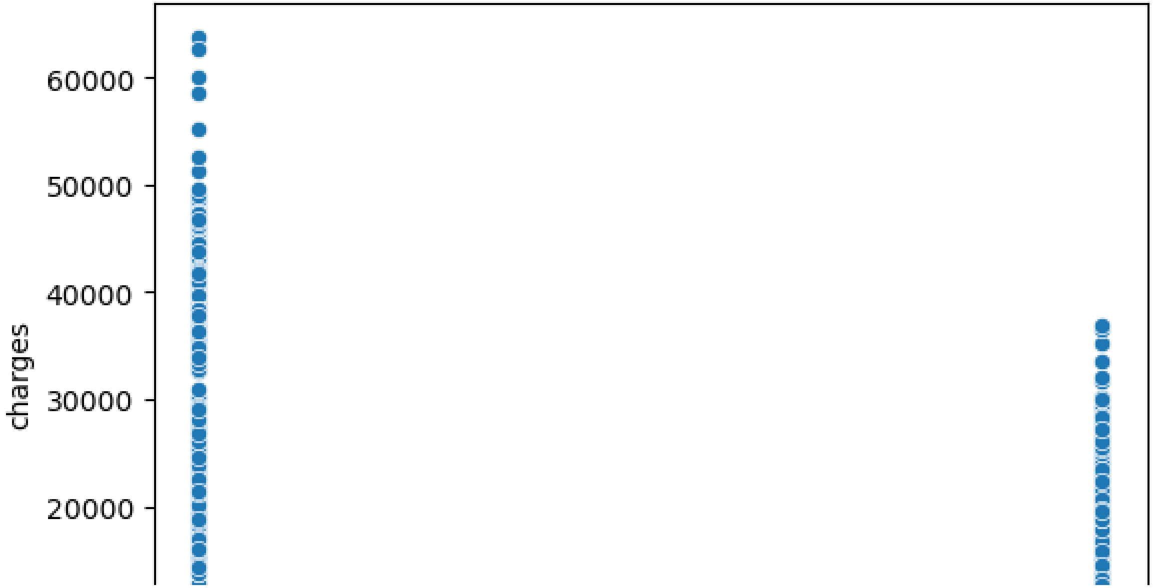
In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
On GitHub, the HTML representation is unable to render, please try loading this page with nbviewer.org.

In [45]:
```
score=lr.score(x_test,y_test)
print(score)
```

```
0.48059701492537316
```

In [46]:
```
sns.scatterplot(data=df,x='smoker',y='charges')
```

Out[46]: <Axes: xlabel='smoker', ylabel='charges'>



Decesion Tree

In [47]:
```
# Decision Tree
from sklearn.tree import DecisionTreeClassifier
clf=DecisionTreeClassifier()
clf.fit(x_train,y_train)
```

Out[47]: DecisionTreeClassifier()

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 [48]:
```
score=clf.score(x_test,y_test)
print(score)
```

0.36716417910447763

Random Forest

In [49]:
```
#random forest
from sklearn.ensemble import RandomForestClassifier
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
```

Out[49]:
```
RandomForestClassifier()
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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In [50]:
```
params={'max_depth':[2,3,5,10,20],
'min_samples_leaf':[5,10,20,50,100,200],
'n_estimators':[10,25,30,50,100,200]}
```

In [51]:
```
from sklearn.model_selection import GridSearchCV
grid_search=GridSearchCV(estimator=rfc,param_grid=params,cv=2,scoring="accuracy")
```

In [54]:
```
grid_search.fit(x_train,y_train)
```

Out[54]:
```
GridSearchCV(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 [55]:
```
grid_search.best_score_
```

Out[55]: 0.5134591375018887

In [56]:
```
rf_best=grid_search.best_estimator_
rf_best
```

Out[56]:
```
RandomForestClassifier(max_depth=2, min_samples_leaf=100, n_estimators=10)
```

In a Jupyter environment, please rerun this cell to show the HTML representation or trust the notebook.
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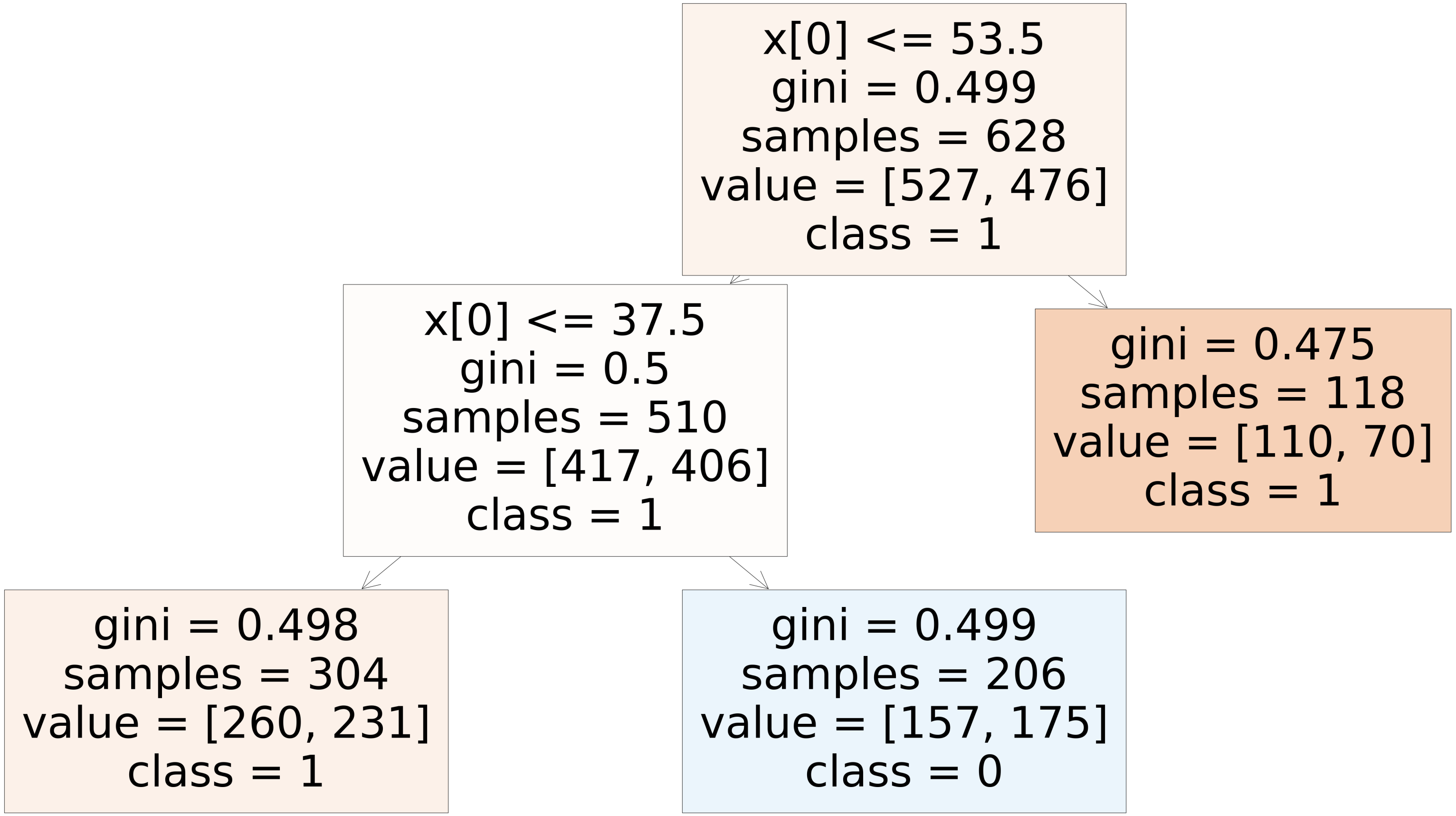
In [57]:
```
from sklearn.tree import plot_tree
plt.figure(figsize=(80,40))
plot_tree(rf_best.estimators_[4],class_names=['1','0'],filled=True);
```



In [58]:
```
score=rfc.score(x_test,y_test)
print(score)
```

```
0.36716417910447763
```

In [59]:
```
convert={"sex":{'male':1,'female':2}}
df=df.replace(convert)
df
```

Out[59]:

	age	sex	bmi	children	smoker	region	charges
0	19	2	27.900	0	yes	southwest	16884.92400
1	18	1	33.770	1	no	southeast	1725.55230
2	28	1	33.000	3	no	southeast	4449.46200
3	33	1	22.705	0	no	northwest	21984.47061
4	32	1	28.880	0	no	northwest	3866.85520
...	...	...	...	...	...	...	...
1333	50	1	30.970	3	no	northwest	10600.54830
1334	18	2	31.920	0	no	northeast	2205.98080
1335	18	2	36.850	0	no	southeast	1629.83350
1336	21	2	25.800	0	no	southwest	2007.94500
1337	61	2	29.070	0	yes	northwest	29141.36030

1338 rows × 7 columns

In [60]:
```
from sklearn.metrics import r2_score
```

In [61]:
```
import pickle
```

In [62]:
```
filename="Prediction"
pickle.dump(rfc,open(filename,'wb'))
```

Conclusion

for the above different types of models we getaccuracy based on the accuracy We can predict thewhich model is better for this dataset .When wecomparing the above accuracies Logistic regressionis getting more accuracy among all the models.So, thegiven dataset is best fit for LogisticRegression

In [ ]:

```

```