Importing Libraries

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

Importing Dataset

```
dfx = pd.read_csv('Test1.csv')
```

```
dfx
```

	Unnamed: 0	Insurance_Type	Diagnosed	Living_situation	Housing_Utilities	Housing_Rent_Mortgag
0	0	Medicaid and Medicare Insurance Plan	Yes	Live alone in my own home	sometimes	sometime
1	1	Medicaid Insurance Plan	No	Live in a household with other people	rarely	Neve
2	2	Medicaid Insurance Plan	Yes	Live in a household with other people	often	ofte
3	3	Medicaid and Medicare Insurance Plan	Yes	Live in a household with other people	often	ofte
4	4	Medicaid Insurance Plan	No	Live in a household with other people	often	Alway
...	...	...	...	...	...	..
408	408	Medicaid and Medicare Insurance Plan	No	Live alone in my own home	Always	ofte
409	409	Medicaid and Medicare Insurance Plan	No	Live in a household with other people	sometimes	rarel
410	410	Medicaid and Medicare Insurance Plan	No	Live in a household with other people	rarely	rarel
411	411	Medicaid and Medicare Insurance Plan	No	Live in a household with other people	often	ofte
412	412	Medicaid and Medicare Insurance Plan	No	Live alone in my own home	sometimes	rarel

413 rows × 24 columns

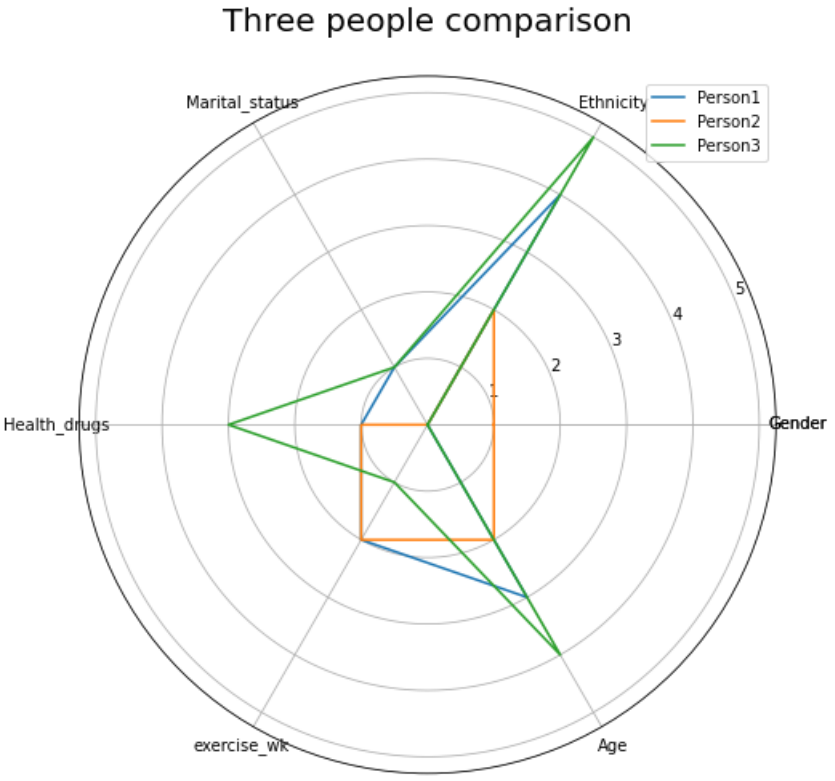
Radar Chart

```
Category = ['Gender','Ethnicity',
         'Marital_status','Health_drugs','exercise_wk','Age'
         ]
Category = [*Category, Category[0]]

Person1 = [0,4,1,1,2,3]
Person2 = [1,2,0,1,2,2]
Person3 = [0,5,1,3,1,4]
Person1 = [*Person1, Person1[0]]
Person2 = [*Person2, Person2[0]]
Person3 = [*Person3, Person3[0]]

label_loc = np.linspace(start=0, stop=2 * np.pi, num=len(Person1))

plt.figure(figsize=(8, 8))
plt.subplot(polar=True)
plt.plot(label_loc, Person1, label='Person1')
plt.plot(label_loc, Person2, label='Person2')
plt.plot(label_loc, Person3, label='Person3')
plt.title('Three people comparison', size=20, y=1.05)
lines, labels = plt.thetagrids(np.degrees(label_loc), labels=Category)
plt.legend()
plt.show()
```




```
dfx.isnull().sum()
```

```
Unnamed: 0                0
Insurance_Type            0
Diagnosed                 0
Living_situation          0
Housing_Utilities         0
Housing_Rent_Mortgage     0
Empl_status               0
Empl_#hrs               270
Empl_job_security       289
Edu_level                 0
Health_drugs            158
```

```
exercise_wk              158
Gender                     0
Age                        0
Location                   0
Ethnicity                  0
Marital_status             0
Income                     0
Housing_security           0
Health_literacy            0
Transportation             1
Community_saftey           0
Food_security              0
Social_engagement          0
dtype: int64
```

Filling all the nulls with the most occurred value

```
dfx = dfx.apply(lambda x:x.fillna(x.value_counts().index[0]))
```

```
dfx.drop(['Unnamed: 0'], axis=1, inplace=True)
```

Labelling all the non numeric categorical data using Label Encoder

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
Categ = ['Insurance_Type','Diagnosed','Income','Living_situation','Empl_#hrs','Housing_Utilities',
         'Housing_Rent_Mortgage','Empl_status','Edu_level','Gender','Location','Ethnicity',
         'Marital_status','Empl_job_security','Health_drugs','exercise_wk','Age'
         ]
dfx[Categ] = dfx[Categ].apply(le.fit_transform)
```

```
print( list (le.classes_) )
```

```
[' 35 - 44 year', '25 - 34 years', '45 - 54 years', '55 - 64 years', '65 or older years']
```

```
dfx.dtypes
```

```
Insurance_Type             int64
Diagnosed                  int64
Living_situation           int64
Housing_Utilities          int64
Housing_Rent_Mortgage      int64
Empl_status                int64
Empl_#hrs                  int64
Empl_job_security          int64
Edu_level                  int64
Health_drugs               int64
exercise_wk                int64
Gender                     int64
Age                        int64
Location                   int64
Ethnicity                  int64
Marital_status             int64
Income                     int64
Housing_security         float64
Health_literacy          float64
Transportation           float64
Community_saftey         float64
Food_security            float64
Social_engagement        float64
dtype: object
```

```
print({col: {n: cat for n, cat in enumerate(dfx[col].astype('category').cat.categories)}
     for col in dfx})
```

```
{'Insurance_Type': {0: 0, 1: 1}, 'Diagnosed': {0: 0, 1: 1}, 'Living_situation': {0: 0, 1: 1, 2: 2,
```

```
dfx.head(10)
```

	Insurance_Type	Diagnosed	Living_situation	Housing_Utilities	Housing_Rent_Mortgage	Empl_stat
0	1	1	2	4	4	
1	0	0	0	3	1	
2	0	1	0	2	2	
3	1	1	0	2	2	
4	0	0	0	2	0	
5	0	1	2	1	0	
6	0	0	2	1	1	
7	1	0	0	4	4	
8	0	0	0	4	4	
9	0	1	0	3	3	

10 rows × 23 columns

```
[0,2,1,0,6,1,4,1,1,4,0,0,3,5,2,3,2.00,1.0,1.00,2.2,3.00,3.00]
```

```
[0, 2, 1, 0, 6, 1, 4, 1, 1, 4, 0, 0, 3, 5, 2, 3, 2.0, 1.0, 1.0, 2.2, 3.0, 3.0]
```

```
dir(dfx)
```

```
['Age',
 'Community_saftey',
 'Diagnosed',
 'Edu_level',
 'Empl_job_security',
 'Empl_status',
 'Ethnicity',
 'Food_security',
 'Gender',
 'Health_drugs',
 'Health_literacy',
 'Housing_Rent_Mortgage',
 'Housing_Utilities',
 'Housing_security',
 'Income',
 'Insurance_Type',
 'Living_situation',
 'Location',
 'Marital_status',
 'Social_engagement',
 'T',
 'Transportation',
 '_AXIS_LEN',
 '_AXIS_ORDERS',
 '_AXIS_REVERSED',
 '_AXIS_TO_AXIS_NUMBER',
 '_HANDLED_TYPES',
 '__abs__',
 '__add__',
 '__and__',
 '__annotations__',
 '__array__',
 '__array_priority__',
 '__array_ufunc__',
 '__array_wrap__',
 '__bool__',
 '__class__',
 '__contains__',
```

```
 '__copy__',
 '__deepcopy__',
 '__delattr__',
 '__delitem__',
 '__dict__',
 '__dir__',
 '__divmod__',
 '__doc__',
 '__eq__',
 '__finalize__',
 '__floordiv__',
 '__format__',
 '__ge__',
 '__getattr__',
 '__getattribute__',
 '__getitem__',
 '__getstate__',
 '__gt__',
 '__hash__',
 '  iadd  ',
```

```
d1 = dfx.drop_duplicates('Insurance_Type').set_index('Insurance_Type')
print(d1)
```

```
                  Diagnosed  Living_situation  Housing_Utilities  \
Insurance_Type
1                         1                 2                  4
0                         0                 0                  3

                  Housing_Rent_Mortgage  Empl_status  Empl_#hrs  \
Insurance_Type
1                                     4            2          1
0                                     1            6          1

                  Empl_job_security  Edu_level  Health_drugs  exercise_wk  ...  \
Insurance_Type                                                              ...
1                                 4          5             1            3  ...
0                                 4          4             1            2  ...

                  Location  Ethnicity  Marital_status  Income  Housing_security  \
Insurance_Type
1                        3          5               5       6              3.25
0                        1          5               2       1              1.75

                  Health_literacy  Transportation  Community_saftey  \
Insurance_Type
1                             1.0             2.5               2.0
0                             2.0             2.5               1.2

                  Food_security  Social_engagement
Insurance_Type
1                          2.25               2.75
0                          1.75               3.00

[2 rows x 22 columns]
```

```
dfx['Age'].unique()
```

```
array([1, 0, 2, 3, 4])
```

EDA

```
# correlation heatmap for all features
corr = dfx.corr()
mask = np.zeros_like(corr, dtype=np.bool)
mask[np.triu_indices_from(mask)] = True
sns.heatmap(corr, mask = mask, annot=True)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3: DeprecationWarning: `np.bool` is a
Deprecated in NumPy 1.20; for more details and guidance: https://numpy.org/devdocs/release/1.20.0-r
  This is separate from the ipykernel package so we can avoid doing imports until
```


```
targetdf = dfx.groupby('Diagnosed').apply(np.mean).head()
targetdf.style.background_gradient(cmap='Reds')
```

Diagnosed	Insurance_Type	Diagnosed	Living_situation	Housing_Utilities	Housing_Rent_Mortgage	E
0	0.246835	0.000000	0.886076	1.987342	1.765823	
1	0.462745	1.000000	1.043137	1.784314	1.862745	

Data seems to be equally distributed and balanced corresponding to target variable

```
#Array to store results of different models
Model= []
Results = []
```

Modelling

```
dataset = dfx.copy()
data = dataset.sample(frac=0.80, random_state=786)
data_unseen = dataset.drop(data.index).reset_index(drop=True)
print('Data for Modeling: ' + str(data.shape))
print('Unseen Data For Predictions: ' + str(data_unseen.shape))
```

```
Data for Modeling: (330, 23)
Unseen Data For Predictions: (83, 23)
```

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(dfx.drop(columns=['Diagnosed'],axis=1),
                                                    dfx['Diagnosed'],test_size=0.2, random_state=42)
```

```
from sklearn.metrics import confusion_matrix, accuracy_score
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report
lr1 = LogisticRegression()
lr1.fit(X_train, y_train)
predictions = lr1.predict(X_test)

# print classification report
print(classification_report(y_test, predictions))
```

```
                  precision    recall  f1-score   support

               0       0.52      0.43      0.47        28
               1       0.73      0.80      0.77        55

        accuracy                           0.67        83
       macro avg       0.63      0.61      0.62        83
    weighted avg       0.66      0.67      0.67        83
```

```
accuracy_score(y_test, predictions)
```

```
0.6746987951807228
```

```
Results.append(accuracy_score(y_test, predictions))
```

```
Model.append('LR')
```

Decision Tree

```
from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion = 'entropy', random_state = 0)
classifier.fit(X_train, y_train)
```

```
DecisionTreeClassifier(criterion='entropy', random_state=0)
```

```
predictions = classifier.predict(X_test)
```

```
# print classification report
print(classification_report(y_test, predictions))
```

```
                  precision    recall  f1-score   support

               0       0.82      0.82      0.82        28
               1       0.91      0.91      0.91        55

        accuracy                           0.88        83
       macro avg       0.87      0.87      0.87        83
    weighted avg       0.88      0.88      0.88        83
```

```
Results.append(accuracy_score(y_test, predictions))
Model.append('DecTree')
```

Gradient Boosting

```
from sklearn.ensemble import GradientBoostingClassifier
gbclf = GradientBoostingClassifier(random_state=42)
gbclf.fit(X_train,y_train)
```

```
GradientBoostingClassifier(random_state=42)
```

```
param_grid = {
    'learning_rate': [0.1,0.2],
    'max_depth': [6],
    'subsample': [0.5,0.7,1],
    'n_estimators': [100]
}
```

```
from sklearn.metrics import accuracy_score, classification_report
```

```
from sklearn.model_selection import GridSearchCV

grid_clf = GridSearchCV(gbclf,param_grid,scoring='roc_auc',cv=None,n_jobs=1)
grid_clf.fit(X_train,y_train)

best_parameters = grid_clf.best_params_

print('Grid search found the following optimal parameters: ')
for param_name in sorted(best_parameters.keys()):
    print('%s: %r' % (param_name,best_parameters[param_name]))

training_preds = grid_clf.predict(X_train)
test_preds = grid_clf.predict(X_test)
training_accuracy = accuracy_score(y_train,training_preds)
test_accuracy = accuracy_score(y_test,test_preds)

print('')
print('Training Accuracy: {:.4}%'.format(training_accuracy*100))
print('Validation Accuracy: {:.4}%'.format(test_accuracy*100))
```

```
Grid search found the following optimal parameters:
learning_rate: 0.1
max_depth: 6
n_estimators: 100
subsample: 1

Training Accuracy: 100.0%
Validation Accuracy: 91.57%
```

```
print(classification_report(y_test, test_preds), '\n\n')
```

```
                  precision    recall  f1-score   support

               0       0.89      0.86      0.87        28
               1       0.93      0.95      0.94        55

        accuracy                           0.92        83
       macro avg       0.91      0.90      0.90        83
    weighted avg       0.92      0.92      0.92        83
```

```
Results.append(accuracy_score(y_test, test_preds))
Model.append('GBC')
```

```
from sklearn.metrics import confusion_matrix

#Generate the confusion matrix
cf_matrix = confusion_matrix(y_test, test_preds)

print(cf_matrix)
```

```
[[24  4]
 [ 3 52]]
```

Random forest

```
from sklearn.ensemble import RandomForestClassifier
modelRf = RandomForestClassifier(n_estimators = 10, criterion = 'entropy', random_state = 0)
modelRf.fit(X_train, y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10, random_state=0)
```

```
y_pred = modelRf.predict(X_test)
```

```
print('True:', y_test.values[0:25])
print('False:', y_pred[0:25])
```

```
True: [1 0 1 1 1 0 1 1 1 0 0 0 1 1 1 0 1 0 1 1 1 1 0 1 1]
False: [1 1 1 1 0 1 1 1 1 0 0 0 1 1 1 0 1 1 1 1 1 1 0 1 1]
```

```
import collections
collections.Counter(y_pred)
```

```
Counter({0: 24, 1: 59})
```

```
from sklearn.metrics import confusion_matrix, accuracy_score
cm = confusion_matrix(y_test, y_pred)
print(cm)
accuracy_score(y_test, y_pred)
```

```
[[21  7]
 [ 3 52]]
0.8795180722891566
```

```
Results.append(accuracy_score(y_test, y_pred))
Model.append('RF')
```

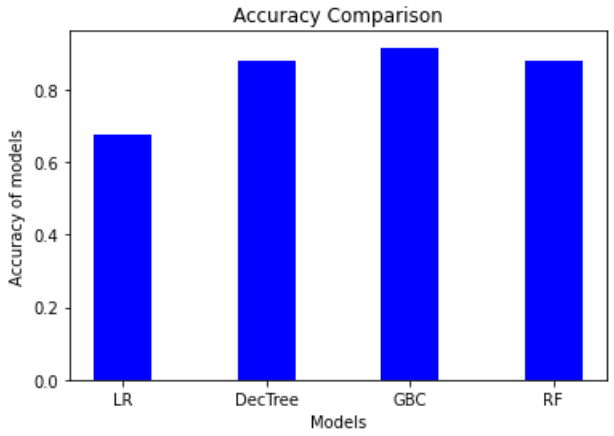
```
feature_scores = pd.Series(modelRf.feature_importances_, index=X_train.columns).sort_values(ascending=Fa
print(feature_scores)
```

```
exercise_wk              0.238445
Health_drugs             0.089996
Social_engagement        0.068936
Age                      0.058217
Transportation           0.052227
Food_security            0.045908
Community_saftey         0.044062
Housing_security         0.041522
Empl_status              0.039843
Housing_Utilities        0.038143
Health_literacy          0.037139
Marital_status           0.036904
Insurance_Type           0.033962
Income                   0.033090
Location                 0.027659
Ethnicity                0.024940
Edu_level                0.019901
Living_situation         0.018941
Housing_Rent_Mortgage    0.015504
Gender                   0.013254
Empl_job_security        0.012026
Empl_#hrs                0.009382
dtype: float64
```

Compare & visualize all the implemented models

```
# creating the bar plot
plt.bar(Model, Results, color ='blue',
        width = 0.4)
```

```
plt.xlabel("Models")
plt.ylabel("Accuracy of models")
plt.title("Accuracy Comparison")
plt.show()
```



GBC is giving us best accuracy among all hence we will be going ahead with this model only for final results.

Input by User

```
import pickle
pickle.dump(gbclf,open('modelGBC.pkl','wb'))
```

```
def get_result_Rf(args_list):

    model = pickle.load(open('modelGBC.pkl', 'rb'))
    cent = model.predict_proba(args_list)*100
    prediction = model.predict(args_list)
    value = round(cent[0][prediction[0]], 2)
    print(prediction)
    if prediction == 1:
        #result = "Chances of getting diagnosed with chronic condition is {0}% ".format(value)
        result = "Chances of getting diagnosed with chronic condition is very high "
    else:
        #result="Chances of not getting diagnosed with chronic condition is {0}%".format(value)
        result = "Chances of getting diagnosed with chronic condition is very Low "
    return result
```

```
input1 = [1,2,4,4,2,1,4,5,1,3,1,1,3,5,5,6,3.25,1.0,2.50,2.0,2.25,2.75]
input1 = np.reshape(input1, (-1, 22))
output1 = get_result_Rf(input1)
print(output1)
```

```
[1]
Chances of getting diagnosed with chronic condition is very high
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feat
  "X does not have valid feature names, but"
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feat
  "X does not have valid feature names, but"
```

```
input1 = [0,0,3,1,6,1,4,4,1,2,0,0,1,5,2,1,1.75,2.0,2.50,1.2,1.75,3.00]
input1 = np.reshape(input1, (-1, 22))
output1 = get_result_Rf(input1)
print(output1)
```

```
[0]
```

```
Chances of getting diagnosed with chronic condition is very Low
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feat
  "X does not have valid feature names, but"
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have valid feat
  "X does not have valid feature names, but"
```

✓ 0s completed at 11:18 AM