Importing Required Modules

```
1 import warnings
2 warnings.filterwarnings('ignore')

1 import numpy as np
2 import pandas as pd

1 from sklearn.svm import SVR
2 from sklearn.tree import DecisionTreeRegressor
3 from sklearn.tree import DecisionTreeRegressor, GradientBoostingRegressor
4 from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
5 from sklearn.ensemble import PolynomialFeatures
5 from sklearn.metrics import mean_squared_error, r2_score
6 from xgboost import XGBRegressor
7 from sklearn.neighbors import KNeighborsRegressor
8 from sklearn.neural_network import MLPRegressor
```

→ Mounting Google Drive

```
1 from google.colab import drive
2 drive.mount('/content/drive')

Mounted at /content/drive

1 import seaborn as sns
2 import matplotlib.pyplot as plt
3 import plotly.express as px
```

Reading data from csv files

Note: If does not works, one download the same datasets (csv files) manually from the links:

- Link 1 Kaggle
- Link 2 Google Drive
- Link 3 Our World India

```
1 df1=pd.read_csv("/content/prevalence-by-mental-and-substance-use-disorder _AI.csv")
2 df2=pd.read_csv("/content/mental-and-substance-use-as-share-of-disease -AI.csv")
```

▼ Data Exploration

```
1 df1.head()
                               Prevalence -
                              Schizophrenia disorder - disorders - disorders - disorders - disorders - disorders -
                                                Age: Age-
                                                                           Age: Age-
                                                                                                                    (Percent)
                                                                                                                     0.444036
    0 Afghanistan AFG 1990
                                   0.228979
                                                 0.721207
                                                               0.131001
                                                                            4.835127
                                                                                          0.454202
                                                                                                        5.125291
    2 Afghanistan AFG 1992
                                    0.227328
                                                                            4.801434
                                                                                                                      0.445501
                                                 0.718418
                                                               0.121832
                                                                                          0.441190
                                                                                                        5.106558
    4 Afghanistan AFG 1994
                                   0.225567
                                                 0.717012
                                                                            4.784923
                                                                                                        5.099424
                                                                                                                      0.445779
                                                               0.114547
                                                                                          0.431822
```



1 df2.head()

 Entity
 Code
 Year
 DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent)

 0
 Afghanistan
 AFG
 1990
 1.696670

 1
 Afghanistan
 AFG
 1991
 1.734281

 2
 Afghanistan
 AFG
 1992
 1.791189

 3
 Afghanistan
 AFG
 1993
 1.776779

 4
 Afghanistan
 AFG
 1994
 1.712986

Merging the two datasets into one

```
1 data=pd.merge(df1,df2)
2 data.head(10)
```

```
Prevalence - Bipolar disorders - Sex: Both - Age: Age- standardized (Percent)

Afghanistan AFG 1991

Prevalence - Bipolar disorder - Sex: Both - Age: Age- standardized (Percent)

Prevalence - Bipolar disorders - Sex: Both - Age: Age- standardized (Percent)

O Afghanistan AFG 1991

O .228979

O .228120

O .719952

O .719952

Prevalence - Bipolar disorders - Sex: Both - Anxiety disorders - Sex: Both - Age: Age- standardized (Percent)

O .719952

O .
```

▼ Filtering out the null data or unlabelled data

```
1 data.isnull().sum()
                                                                                                        0
   Entity
                                                                                                       690
   Code
   Year
   Prevalence - Schizophrenia - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Bipolar disorder - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Eating disorders - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Anxiety disorders - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Drug use disorders - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Depressive disorders - Sex: Both - Age: Age-standardized (Percent)
   Prevalence - Alcohol use disorders - Sex: Both - Age: Age-standardized (Percent)
                                                                                                        0
   DALYs (Disability-Adjusted Life Years) - Mental disorders - Sex: Both - Age: All Ages (Percent)
   dtype: int64
1 data.drop("Code",axis=1,inplace=True)
```

▼ Filtered data

1 data.head(10)

	Entity	Year	Prevalence - Schizophrenia - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Bipolar disorder - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Eating disorders - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Anxiety disorders - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Drug use disorders - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Depressive disorders - Sex: Both - Age: Age- standardized (Percent)	Prevalence - Alcohol use disorders - Sex: Both - Age: Age- standardized (Percent)	(Disal Al Life - disol Sex: A
0	Afghanistan	1990	0.228979	0.721207	0.131001	4.835127	0.454202	5.125291	0.444036	1
1	Afghanistan	1991	0.228120	0.719952	0.126395	4.821765	0.447112	5.116306	0.444250	1
2	Afghanistan	1992	0.227328	0.718418	0.121832	4.801434	0.441190	5.106558	0.445501	1
3	Afghanistan	1993	0.226468	0.717452	0.117942	4.789363	0.435581	5.100328	0.445958	1
4	Afghanistan	1994	0.225567	0.717012	0.114547	4.784923	0.431822	5.099424	0.445779	1
5	Afghanistan	1995	0.224713	0.716686	0.111129	4.780851	0.428578	5.098495	0.445422	1
6	Afghanistan	1996	0.223690	0.716388	0.107786	4.777272	0.426393	5.100580	0.444837	1
7	Afghanistan	1997	0.222424	0.716143	0.103931	4.775242	0.423720	5.105474	0.443938	1
8	Afghanistan	1998	0.221129	0.716139	0.100343	4.777377	0.422491	5.113707	0.442665	1
9	Afghanistan	1999	0.220065	0.716323	0.097946	4.782067	0.421215	5.120480	0.441428	1

→ Filtered dataset size

1 data.size, data.shape (68400, (6840, 10))

▼ Renaming columns as per our convenience

1 data.set_axis(["Country","Year","Schizophrenia","Bipolar_disorder","Eating_disorder","Anxiety","drug_usage","depression","alcohol","mental_fitness"], axis="columns", inplace=True)

1 data.head()

	Country	Year	Schizophrenia	Bipolar_disorder	Eating_disorder	Anxiety	drug_usage	depression	alcohol	mental_fitn
0	Afghanistan	1990	0.228979	0.721207	0.131001	4.835127	0.454202	5.125291	0.444036	1.696
1	Afghanistan	1991	0.228120	0.719952	0.126395	4.821765	0.447112	5.116306	0.444250	1.734
2	Afghanistan	1992	0.227328	0.718418	0.121832	4.801434	0.441190	5.106558	0.445501	1.791
3	Afghanistan	1993	0.226468	0.717452	0.117942	4.789363	0.435581	5.100328	0.445958	1.776
4	Afghanistan	1994	0.225567	0.717012	0.114547	4.784923	0.431822	5.099424	0.445779	1.712

Visual Analysis

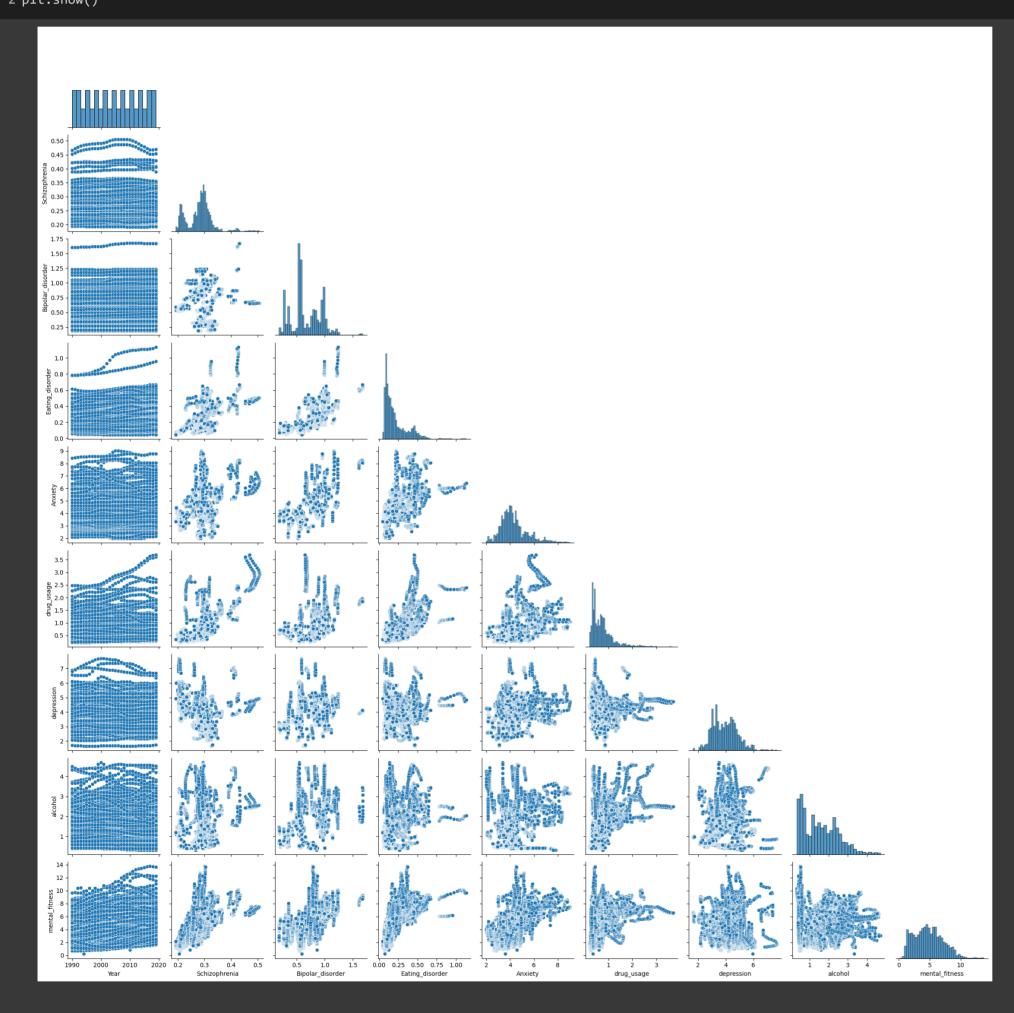
The correlation heatmap of diseases and mental fitness

```
1 plt.figure(figsize=(12,6))
2 sns.heatmap(data.corr(),annot=True,cmap='Blues')
3 plt.plot()
```



▼ Pairplot of each feature

1 sns.pairplot(data,corner=True)
2 plt.show()



Mean of mental fitness column of the data dataframe

1 mean=data['mental_fitness'].mean()

2 mear

4.8180618117506135

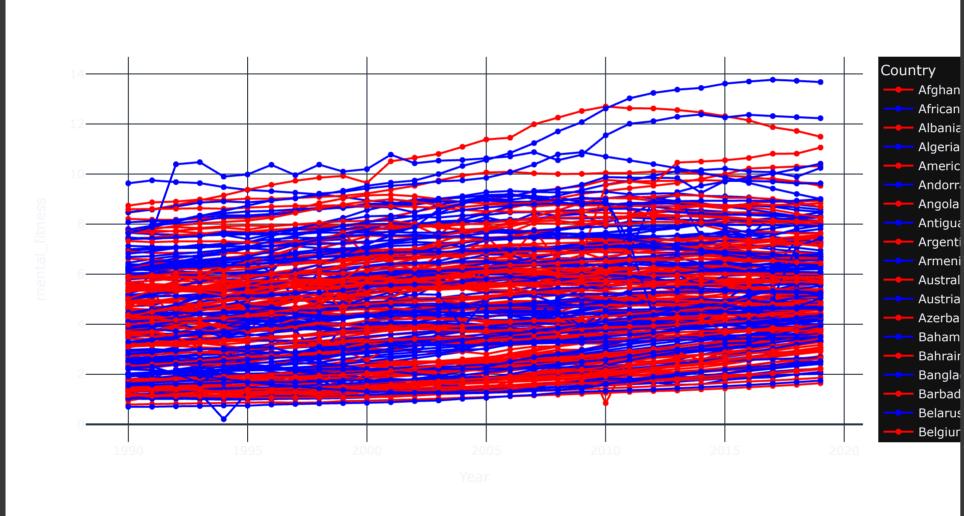
→ Pie Chart

```
1 fig=px.pie(data, values="mental_fitness", names="Year")
2 fig.show()

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```

Year wise variation in mental fitness in different countries

```
1 fig=px.line(data, x="Year", y="mental_fitness", color="Country", markers=True, color_discrete_sequence=["red","blue"], template="plotly_dark")
2 fig.show()
```



→ Describing our data i.e. dataframe object

Fitting the data for further processing

dtypes: float64(8), int64(1), object(1)

memory usage: 587.8+ KB

```
1 from sklearn.preprocessing import LabelEncoder
2 l=LabelEncoder()
3 for i in df.columns:
4     if df[i].dtype == 'object':
5         df[i]=l.fit_transform(df[i])

1 df.shape
(6840, 10)
```

Splitting our dataset into two halves i.e. testing and training set

```
1 X = df.drop('mental_fitness',axis=1)
2 y = df['mental_fitness']
3
4 from sklearn.model_selection import train_test_split
5 xtrain, xtest, ytrain, ytest = train_test_split(X, y, test_size=0.2, random_state=2)

1 print("xtrain :", xtrain.shape)
2 print("xtest :", xtest.shape)
3 print("ytrain :", ytrain.shape)
4 print("ytest :", xtest.shape)

xtrain : (5472, 9)
xtest : (1368, 9)
ytrain : (5472,)
ytest : (1368, 9)
```

Using Random Forest Algorithm

```
from sklearn.ensemble import RandomForestRegressor
    from sklearn.metrics import mean_squared_error, r2_score
    rf = RandomForestRegressor()
    rf.fit(xtrain, ytrain)
6 # model evaluation for training set
    ytrain_pred = rf.predict(xtrain)
8 mse = mean_squared_error(ytrain, ytrain_pred)
    rmse = (np.sqrt(mse))
10 r2 = r2_score(ytrain, ytrain_pred)
11 print("The model performance for training set")
12 print("----")
13 print(f'MSE is {mse}')
    print(f'RMSE is {rmse}')
    print(f'R2 score is {r2}')
    print()
17
# model evaluation for testing set
19 ytest_pred = rf.predict(xtest)
20 mse = mean_squared_error(ytest, ytest_pred)
21  rmse = (np.sqrt(mean_squared_error(ytest, ytest_pred)))
    r2 = r2_score(ytest, ytest_pred)
23
24 print("The model performance for testing set")
    print("----<u>----</u>")
26 print(f'MSE is {mse}')
27 print(f'RMSE is {rmse}')
28 print(f'R2 score is {r2}')
    The model performance for training set
    MSE is 0.005259863595446224
    RMSE is 0.07252491706611063
    R2 score is 0.9990211243170465
    The model performance for testing set
```

Using Linear Regression Algorithm

MSE is 0.03115675220203062 RMSE is 0.17651275365262029 R2 score is 0.9935230811549247

```
1 from sklearn.linear_model import Ridge, Lasso, ElasticNet, LinearRegression, BayesianRidge
2 model = LinearRegression()
3 model.fit(xtrain, ytrain)

* LinearRegression
LinearRegression()
```

Using pre-trained model

```
1 y_pred = model.predict(xtest)
```

1. Ridge Regression

```
1 model = Ridge(alpha=0.5)
2 model.fit(xtrain, ytrain)
3 y_pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
6 rmse = np.sqrt(mse)
7 print("The model Performance for testing set")
8 print("--------")
9 print(f"MSE is {mse}")
10 print(f"MSE is {mse}")
11 print(f"R2 score is {r2}")

The model Performance for testing set

MSE is 1.1393226139229882
```

2. Lasso Regression

RMSE is 1.0673905629726113 R2 score is 0.7631556697280758

```
1 model = Lasso(alpha=0.5)
2 model.fit(xtrain, ytrain)
3 y_pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
6 rmse = np.sqrt(mse)
```

```
7/17/23, 12:15 PM
                                                                                        mental-fitness-tracker.ipynb - Colaboratory
    7 print("The model Performance for testing set")
    8 print("----")
    9 print(f"MSE is {mse}")
   10 print(f"RMSE is {rmse}")
   11 print(f"R2 score is {r2}")
        The model Performance for testing set
        MSE is 2.7702717436599804
        RMSE is 1.6644133331777837
        R2 score is 0.4241111799412294
    3. Elastic Net Regression
    1 model = ElasticNet(alpha=0.5, l1_ratio=0.5)
    2 model.fit(xtrain, ytrain)
    3 y_pred = model.predict(xtest)
    4 mse = mean_squared_error(ytest, y_pred)
    5 r2 = r2_score(ytest, y_pred)
    6 rmse = np.sqrt(mse)
    7 print("The model Performance for testing set")
    8 print("----")
    9 print(f"MSE is {mse}")
   10 print(f"RMSE is {rmse}")
   11 print(f"R2 score is {r2}")
        The model Performance for testing set
        MSE is 2.740266404991704
        RMSE is 1.6553750043394106
        R2 score is 0.4303487409749741
    4. Decision Tree Regression
    1 model = DecisionTreeRegressor()
    2 model.fit(xtrain, ytrain)
    3 y_pred = model.predict(xtest)
    4 mse = mean_squared_error(ytest, y_pred)
    5 r2 = r2_score(ytest, y_pred)
    6 rmse = np.sqrt(mse)
    7 print("The model Performance for testing set")
    8 print("-----")
    9 print(f"MSE is {mse}")
   10 print(f"RMSE is {rmse}")
   11 print(f"R2 score is {r2}")
        The model Performance for testing set
        MSE is 0.08630921976031734
        RMSE is 0.2937843082268305
        R2 score is 0.9820578920310921
    5. Random Forest Regression
    1 model = RandomForestRegressor()
    2 model.fit(xtrain, ytrain)
       y_pred = model.predict(xtest)
    4 mse = mean_squared_error(ytest, y_pred)
    5 r2 = r2_score(ytest, y_pred)
    6 rmse = np.sqrt(mse)
    7 print("The model Performance for testing set")
    8 print("----")
       print(f"MSE is {mse}")
   10 print(f"RMSE is {rmse}")
   print(f"R2 score is {r2}")
        The model Performance for testing set
        MSE is 0.030616600459818923
        RMSE is 0.17497599966800853
        R2 score is 0.9936353688213556
    6. Polynomial Regression
    1 features = PolynomialFeatures(degree=2)
    2 xpoly = features.fit_transform(xtrain)
    3 model = LinearRegression()
    4 model.fit(xpoly, ytrain)
    5 xtest_poly = features.transform(xtest)
    6 y_pred = model.predict(xtest_poly)
    7 mse = mean_squared_error(ytest, y_pred)
    8 r2 = r2_score(ytest, y_pred)
    9 rmse = np.sqrt(mse)
   10 print("The model Performance for testing set")
   11 print("----")
   12 print(f"MSE is {mse}")
   13 print(f"RMSE is {rmse}")
   14 print(f"R2 score is {r2}")
        The model Performance for testing set
        MSE is 0.5365987525787108
        RMSE is 0.7325290114246061
        R2 score is 0.8884509351204317
    7. Support Vector Regression
```

```
1 model = SVR()
2 model.fit(xtrain, ytrain)
3 y_pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
6 rmse = np.sqrt(mse)
7 print("The model Performance for testing set")
8 print("-----")
9 print(f"MSE is {mse}")
```

```
mental-fitness-tracker.ipynb - Colaboratory
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
     The model Performance for testing set
    MSE is 4.7911713917240055
    RMSE is 2.1888744577348436
    R2 score is 0.0040031105995593785
 8. XGBoost Regression
 1 model = XGBRegressor()
 2 model.fit(xtrain, ytrain)
 3 y pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
 5 r2 = r2_score(ytest, y_pred)
 6 rmse = np.sqrt(mse)
 7 print("The model Performance for testing set")
 8 print("----")
9 print(f"MSE is {mse}")
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
     The model Performance for testing set
    MSE is 0.04225689361124382
    RMSE is 0.2055648160830151
    R2 score is 0.9912155648062968
 9. K - Nearest Neighbour Regression
 1 model = KNeighborsRegressor()
 2 model.fit(xtrain, ytrain)
 3 y_pred = model.predict(xtest)
 4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
 6 rmse = np.sqrt(mse)
 7 print("The model Performance for testing set")
 8 print("----")
 9 print(f"MSE is {mse}")
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
     The model Performance for testing set
    MSE is 1.0049803438106724
    RMSE is 1.0024870791240514
    R2 score is 0.7910829702162167
10. Bayesian Ridge Regression
 1 model = BayesianRidge()
 2 model.fit(xtrain, ytrain)
 3 y_pred = model.predict(xtest)
 4 mse = mean_squared_error(ytest, y_pred)
 5 r2 = r2_score(ytest, y_pred)
 6 rmse = np.sqrt(mse)
 7 print("The model Performance for testing set")
 8 print("----")
9 print(f"MSE is {mse}")
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
    The model Performance for testing set
    MSE is 1.135667232782995
    RMSE is 1.0656768894852675
    R2 score is 0.7639155566006879
11. Neural Network Regression
1 model = MLPRegressor(max_iter=1000)
 2 model.fit(xtrain, ytrain)
3 y_pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
6 rmse = np.sqrt(mse)
 7 print("The model Performance for testing set")
8 print("-----")
9 print(f"MSE is {mse}")
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
     The model Performance for testing set
    MSE is 2.0379544186653145
    RMSE is 1.42756940940373
    R2 score is 0.5763465558262661
12. Gradient Boosting Regression
 1 model = GradientBoostingRegressor()
 2 model.fit(xtrain, ytrain)
 3 y_pred = model.predict(xtest)
4 mse = mean_squared_error(ytest, y_pred)
5 r2 = r2_score(ytest, y_pred)
 6 rmse = np.sqrt(mse)
 7 print("The model Performance for testing set")
 8 print("-----")
9 print(f"MSE is {mse}")
10 print(f"RMSE is {rmse}")
11 print(f"R2 score is {r2}")
     The model Performance for testing set
    MSE is 0.24536599739628345
```

RMSE is 0.49534432205919493 R2 score is 0.9489928975211638

Results Visualization

```
1 # dictionary which stores model performance like <model-name: accuracy>
2 models_performance = {"Random Forests": 0.9938472950788096,
                        "Elastic Net": 0.4303487409749741,
                        "Polynomail": 0.8884509351204317,
                        "Decision Trees": 0.984631488977419,
                         "Lasso Regression": 0.4241111799412294,
                         "Support Vector Machine": 0.0040031105995593785,
                         "XGBoost Regression": 0.9912155648062968,
                         "K - Nearest Neighbour": 0.7910829702162167,
10
                        "Bayesian Ridge Regression": 0.7639155566006879,
11
                         "Neural Networks": 0.7281529631080045,
12
                        "Gradient Boosting": 0.9490628375125112}
13
14 for key, value in models_performance.items():
      models_performance[key] = round(value * 100, 3)
```

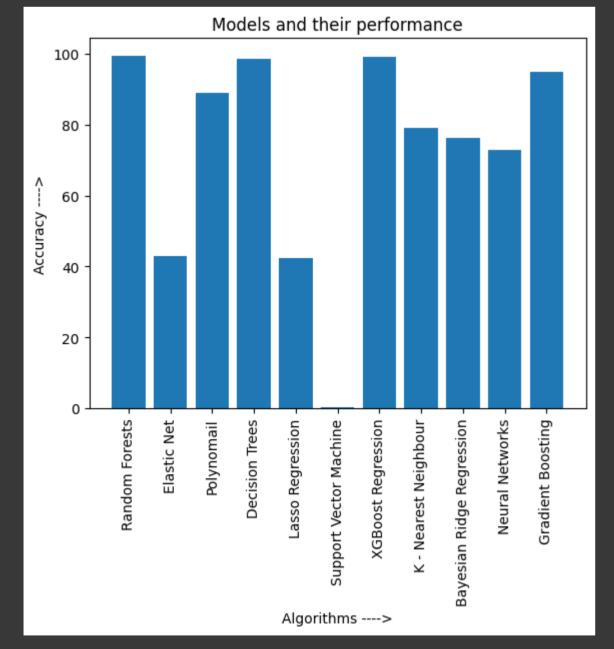
1 print(models_performance)

{'Random Forests': 99.385, 'Elastic Net': 43.035, 'Polynomail': 88.845, 'Decision Trees': 98.463, 'Lasso Regression': 42.411, 'Support Vector Machine': 0.4, 'XGBoost Regression': 99.122,

```
1 def get_key_with_max_and_min_value(dict_data):
      max_value = min_value = dict_data[list(dict_data.keys())[0]]
      max_key = min_key = list(dict_data.keys())[0]
      for key, value in dict_data.items():
          if value > max_value:
              max_value = value
8
              max_key = key
          elif value < min_value:</pre>
10
              min_value = value
11
              min_key = key
12
13
      return max_key, min_key
14
15
16 max_key, min_key = get_key_with_max_and_min_value(models_performance)
17 print("The algorithm with the maximum accuracy is:", max_key)
18 print("The key with the minimum accuracy is:", min_key)
```

- Bar graph

```
1 import matplotlib.pyplot as plt
2 plt.bar(models_performance.keys(), models_performance.values())
3 plt.title("Models and their performance")
4 plt.xticks(rotation=90)
5 plt.xlabel("Algorithms ---->")
6 plt.ylabel("Accuracy ---->")
7 plt.show()
```



The algorithm with the maximum accuracy is: Random Forests
The key with the minimum accuracy is: Support Vector Machine

Summary

Algorithm	Mean Squared Error (MSE)	Root Mean Squared Error (RMSE)	R^2
Random Forests	0.031286265113436774	0.1768792387857794	99.385%
Elastic Net Regression	2.740266404991704	1.6553750043394106	43.035%
PLoynomail Regression	0.5365987525787108	0.7325290114246061	88.845%
Decision Trees	0.07392911677576598	0.27189909300283804	98.463%
Lasso Regression	2.7702717436599804	1.6644133331777837	42.411%
Support Vector Machine (SVM)	4.7911713917240055	2.1888744577348436	0.4%
XGBoost Regression	0.04225689361124382	0.2055648160830151	99.122%

Algorithm

K-Nearest Neighbour (KNN)

Bayesian Ridge Regression

```
1.1435473826125222
      Neural Networks
                           1.30770061627995
                                                                     72.815%
                          0.24502955609887844
                                                0.49500460209868596
                                                                     94.906%
      Gradient Boosting
1 np.random.seed(range(0,100))
print("Hi!\nWelcome to Mental Fitness Tracker!\nFill the detail to check your mental fitness!")
    country=1.fit_transform([input("Enter Your country Name : ")])
4 year=int(input("Enter the Year : "))
5 schi=(float(input("Enter your Schizophrenia rate in % (it not enter 0) : ")))
    bipo_dis=(float(input("Enter your Bipolar disorder rate in % (it not enter 0) : ")))
    eat_dis=(float(input("Enter your Eating disorder rate in % (it not enter 0) : ")))
8 anx=(float(input("Enter your Anxiety rate in % (it not enter 0) : ")))
    drug_use=(float(input("Enter your Drug Usage rate in per year % (it not enter 0) : ")))
10 depr=(float(input("Enter your Depression rate in % (it not enter 0) : ")))
    alch=(float(input("Enter your Alcohol Consuming rate per year in % (it not enter 0) : ")))
11
12
prediction=rf.predict([[country,year,schi,bipo_dis,eat_dis,anx,drug_use,depr,alch]])
    print(f"Your Mental Fitness is {prediction[0]/10:.3%}")
```

```
Hi!
Welcome to Mental Fitness Tracker!
Fill the detail to check your mental fitness!
Enter Your country Name: India
Enter the Year: 2012
Enter your Schizophrenia rate in % (it not enter 0): 3
Enter your Bipolar disorder rate in % (it not enter 0): 23
Enter your Eating disorder rate in % (it not enter 0): 54
Enter your Anxiety rate in % (it not enter 0): 64
Enter your Drug Usage rate in per year % (it not enter 0): 78
Enter your Depression rate in % (it not enter 0): 65
Enter your Alcohol Consuming rate per year in % (it not enter 0): 97
Your Mental Fitness is 96.746%
```

Mean Squared Error (MSE) Root Mean Squared Error (RMSE) \mathbb{R}^2

1.0024870791240514

1.0656768894852675

79.108%

76.392%

1.0049803438106724

1.135667232782995