Early Stage Detection, Classification and Prediction of Alzheimer Disease

In [1]:
```
#Necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import scale
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, cross_val_score, cross_val_predict
# from sklearn.metrics import mean_squared_error
from sklearn import model_selection
import sys
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
from xgboost import XGBClassifier
import xgboost as xgb
```

In [2]:
```
# ALZHEIMER_FEATURES_FILE_NAME = "alzheimer.csv"
```

In [3]:
```
import pandas as pd

data=pd.read_csv("alzheimer.csv")
```

In [4]:
```
data.columns
```

Out[4]:
```
Index(['Group', 'M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'CDR', 'eTIV', 'nWBV',
       'ASF'],
      dtype='object')
```

In [5]:
```
data.head(5)
```

Out[5]:

	Group	M/F	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	Nondemented	M	87	14	2.0	27.0	0.0	1987	0.696	0.883
1	Nondemented	M	88	14	2.0	30.0	0.0	2004	0.681	0.876
2	Demented	M	75	12	NaN	23.0	0.5	1678	0.736	1.046
3	Demented	M	76	12	NaN	28.0	0.5	1738	0.713	1.010
4	Demented	M	80	12	NaN	22.0	0.5	1698	0.701	1.034

Dataset Information

Group: Whether demented, non demented or converted(growing from non-demented to demented)

M/F: Gender of patient

Age: Age of Patient

EDUC: Education Level

SES: Socio Economic Status

MMSE: Mini Mental State Examination

CDR: Clinical Dementia Rating

eTIV: estimated InterCranial Volume

nWBV: normalize Whole brain volume

ASF: Atlas scaling factor

In [6]:
```
print(data.shape)
```

```
(373, 10)
```

In [7]:
```
print(data.columns)
```

```
Index(['Group', 'M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'CDR', 'eTIV', 'nWBV',
       'ASF'],
      dtype='object')
```

In [8]:
```
print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 373 entries, 0 to 372
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Group   373 non-null    object 
 1   M/F     373 non-null    object 
 2   Age     373 non-null    int64  
 3   EDUC    373 non-null    int64  
 4   SES     354 non-null    float64
 5   MMSE    371 non-null    float64
 6   CDR     373 non-null    float64
 7   eTIV    373 non-null    int64  
 8   nWBV    373 non-null    float64
 9   ASF     373 non-null    float64
dtypes: float64(5), int64(3), object(2)
memory usage: 29.3+ KB
None
```

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

Out[9]:

	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
count	373.000000	373.000000	354.000000	371.000000	373.000000	373.000000	373.000000	373.000000
mean	77.013405	14.597855	2.460452	27.342318	0.290885	1488.128686	0.729568	1.195461
std	7.640957	2.876339	1.134005	3.683244	0.374557	176.139286	0.037135	0.138092
min	60.000000	6.000000	1.000000	4.000000	0.000000	1106.000000	0.644000	0.876000
25%	71.000000	12.000000	2.000000	27.000000	0.000000	1357.000000	0.700000	1.099000
50%	77.000000	15.000000	2.000000	29.000000	0.000000	1470.000000	0.729000	1.194000
75%	82.000000	16.000000	3.000000	30.000000	0.500000	1597.000000	0.756000	1.293000
max	98.000000	23.000000	5.000000	30.000000	2.000000	2004.000000	0.837000	1.587000

In [10]:
```
print(data.describe().T)
```

```
      count         mean         std       min       25%       50%       75%  \
Age   373.0    77.013405    7.640957    60.000    71.000    77.000    82.000
EDUC  373.0    14.597855    2.876339     6.000    12.000    15.000    16.000
SES   354.0     2.460452    1.134005     1.000     2.000     2.000     3.000
MMSE  371.0    27.342318    3.683244     4.000    27.000    29.000    30.000
CDR   373.0     0.290885    0.374557     0.000     0.000     0.000     0.500
eTIV  373.0  1488.128686  176.139286  1106.000  1357.000  1470.000  1597.000
nWBV  373.0     0.729568    0.037135     0.644     0.700     0.729     0.756
ASF   373.0     1.195461    0.138092     0.876     1.099     1.194     1.293

           max
Age     98.000
EDUC    23.000
SES      5.000
MMSE    30.000
CDR      2.000
eTIV  2004.000
nWBV     0.837
ASF      1.587
```

In [11]:
```
print(data["M/F"].value_counts())
```

```
F    213
M    160
Name: M/F, dtype: int64
```

In [12]:
```
print(data.corr())
```

```
           Age      EDUC       SES      MMSE       CDR      eTIV      nWBV  \
Age   1.000000 -0.027886 -0.046857  0.055612 -0.026257  0.042348 -0.518359
EDUC -0.027886  1.000000 -0.722647  0.194884 -0.153121  0.257015 -0.012200
SES  -0.046857 -0.722647  1.000000 -0.149219  0.076160 -0.261575  0.090095
MMSE  0.055612  0.194884 -0.149219  1.000000 -0.686519 -0.032084  0.341912
CDR  -0.026257 -0.153121  0.076160 -0.686519  1.000000  0.022819 -0.344819
eTIV  0.042348  0.257015 -0.261575 -0.032084  0.022819  1.000000 -0.210122
nWBV -0.518359 -0.012200  0.090095  0.341912 -0.344819 -0.210122  1.000000
ASF  -0.035067 -0.241752  0.255576  0.040052 -0.029340 -0.988877  0.213476

           ASF
Age  -0.035067
EDUC -0.241752
SES   0.255576
MMSE  0.040052
CDR  -0.029340
eTIV -0.988877
nWBV  0.213476
ASF   1.000000

C:\Users\titik\AppData\Local\Temp\ipykernel_15808\3359323643.py:1: FutureWarning: The default value of numer
ic_only in DataFrame.corr is deprecated. In a future version, it will default to False. Select only valid co
lumns or specify the value of numeric_only to silence this warning.
  print(data.corr())
```

In [13]:
```
print(data.isnull().sum())
```

```
Group     0
M/F       0
Age       0
EDUC      0
SES      19
MMSE      2
CDR       0
eTIV      0
nWBV      0
ASF       0
dtype: int64
```

In [14]:
```
data.dropna(inplace=True)
```

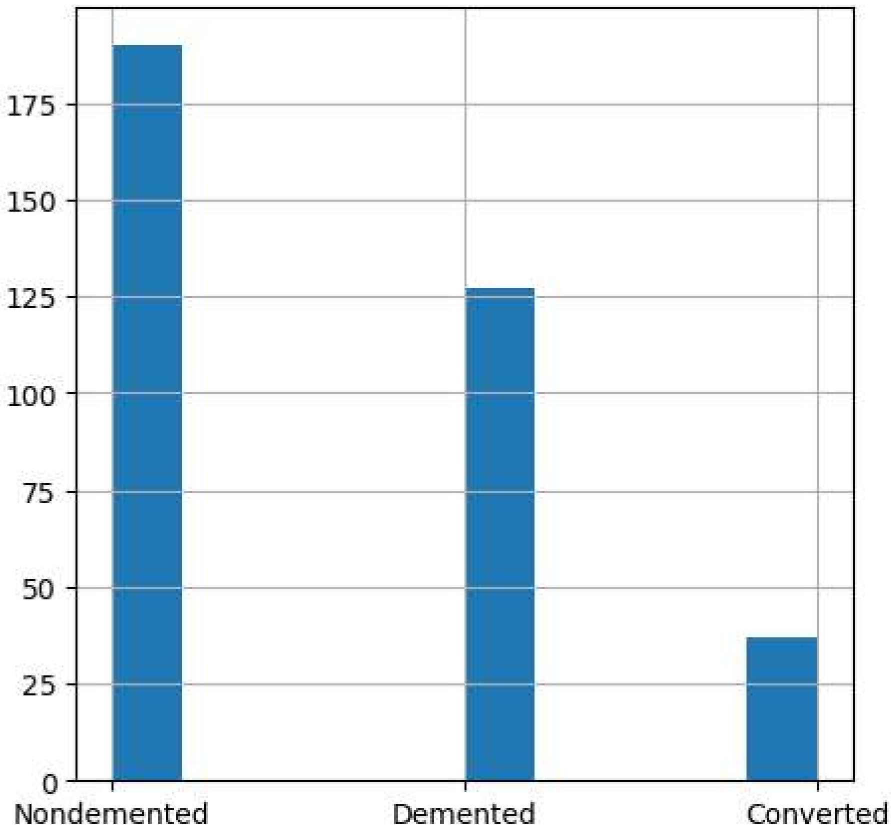
In [15]:
```
data.shape
```

Out[15]:
```
(354, 10)
```

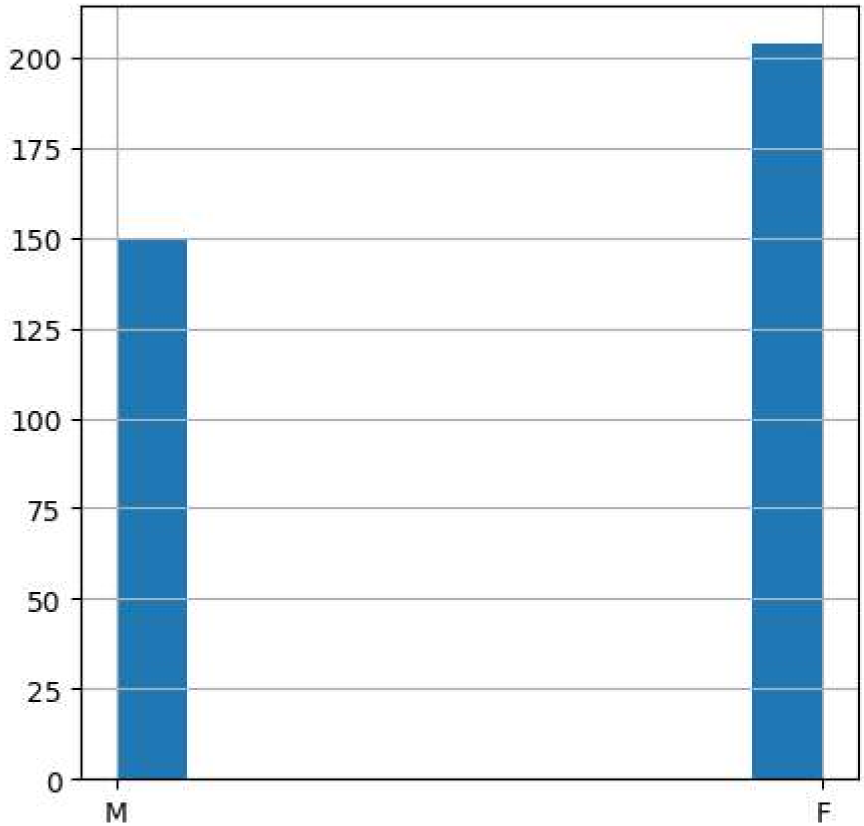
Visualizations

Histograms

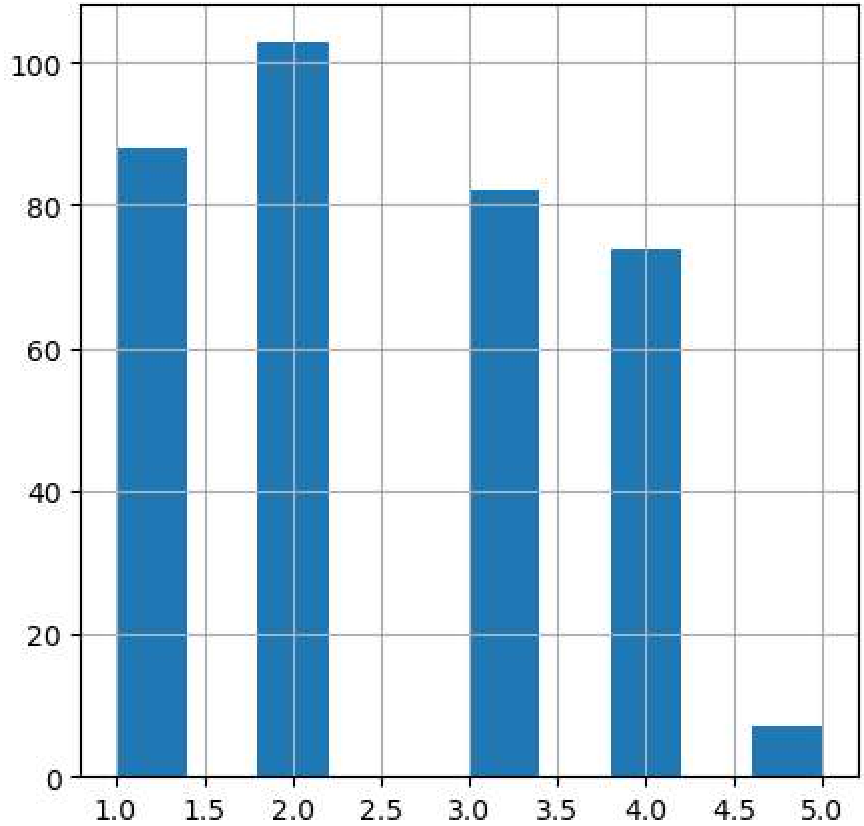
In [16]:
```
ax=data["Group"].hist(figsize=(5,5))
plt.show()
```



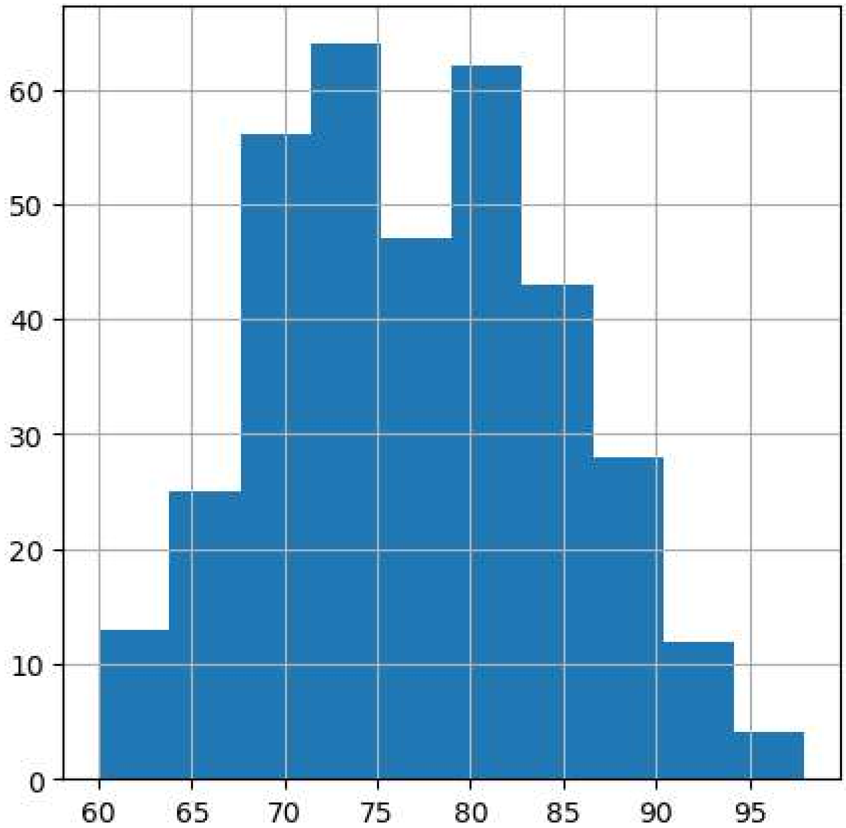
In [17]:
```
# For gender
data["M/F"].hist(figsize=(5,5))
plt.show()
```



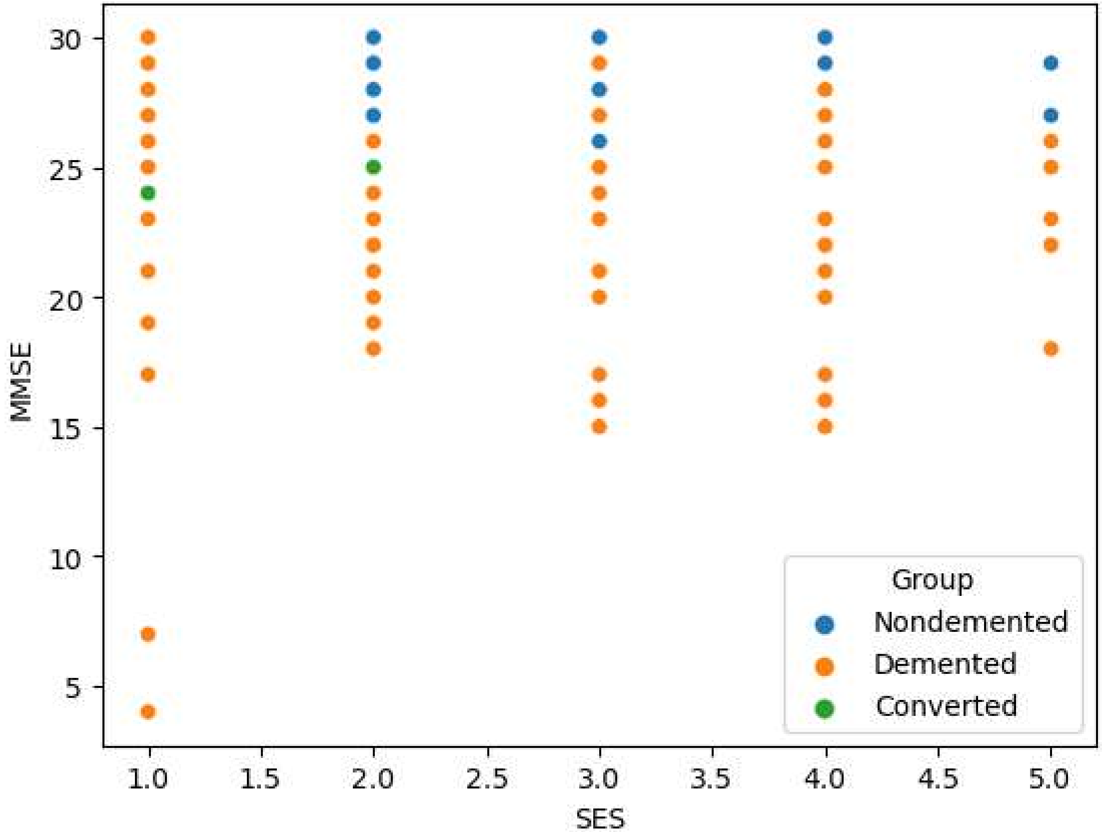
In [18]:
```
data["SES"].hist(figsize=(5,5))
plt.show()
```

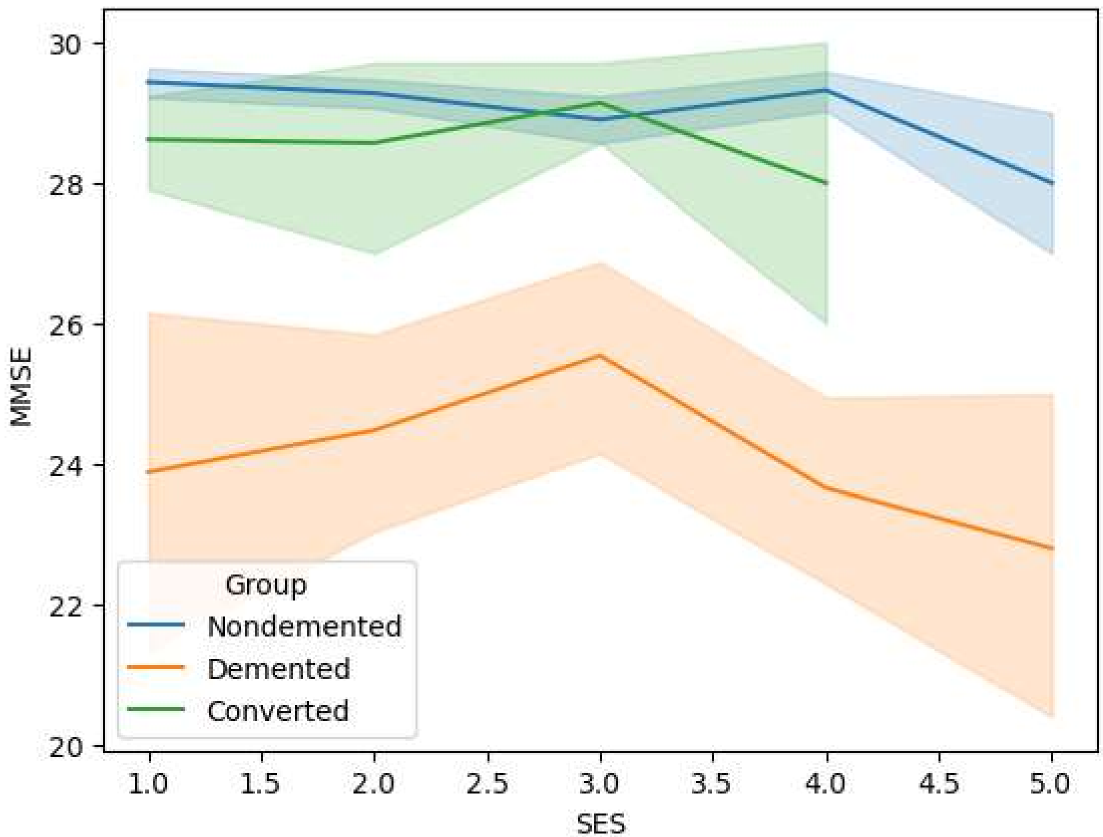


In [19]:
```
# For Age
data["Age"].hist(figsize=(5,5))
plt.show()
```



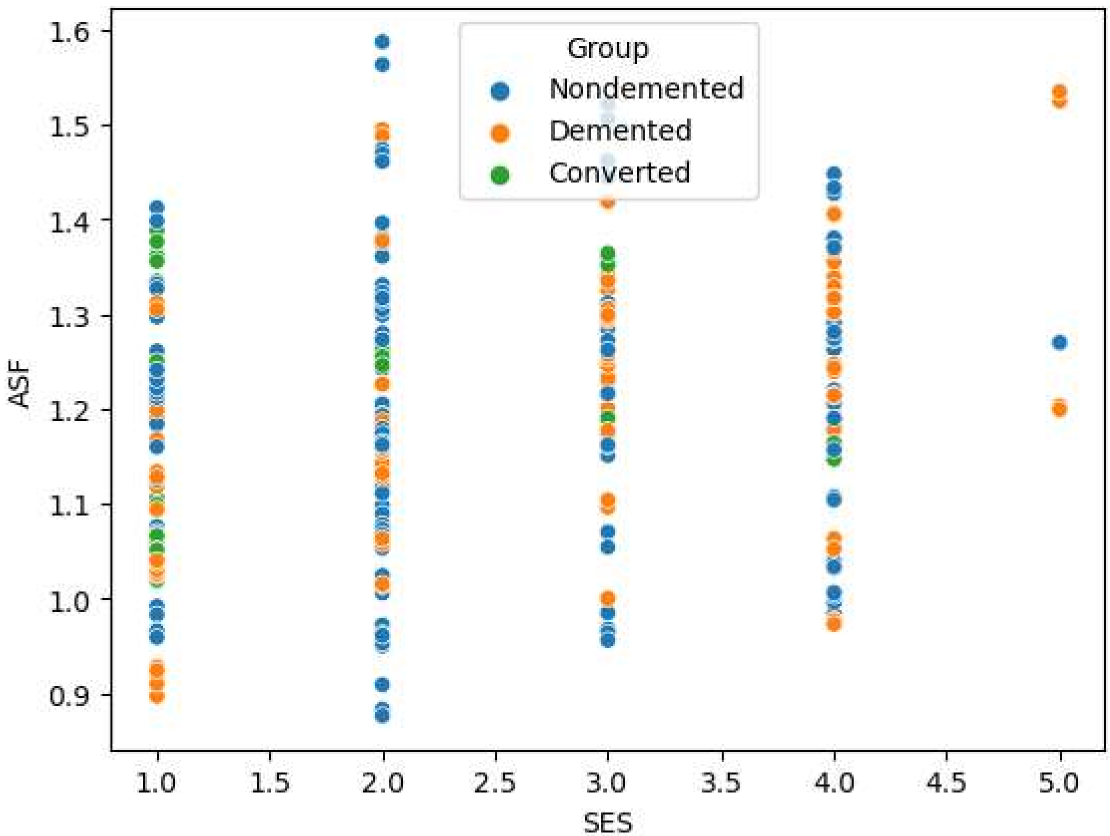
In [20]:
```
# scatter plot
sns.scatterplot(x="SES",y="MMSE",hue="Group",data=data)
plt.show()
sns.lineplot(x="SES", y="MMSE",hue="Group", data=data)
plt.show()
```

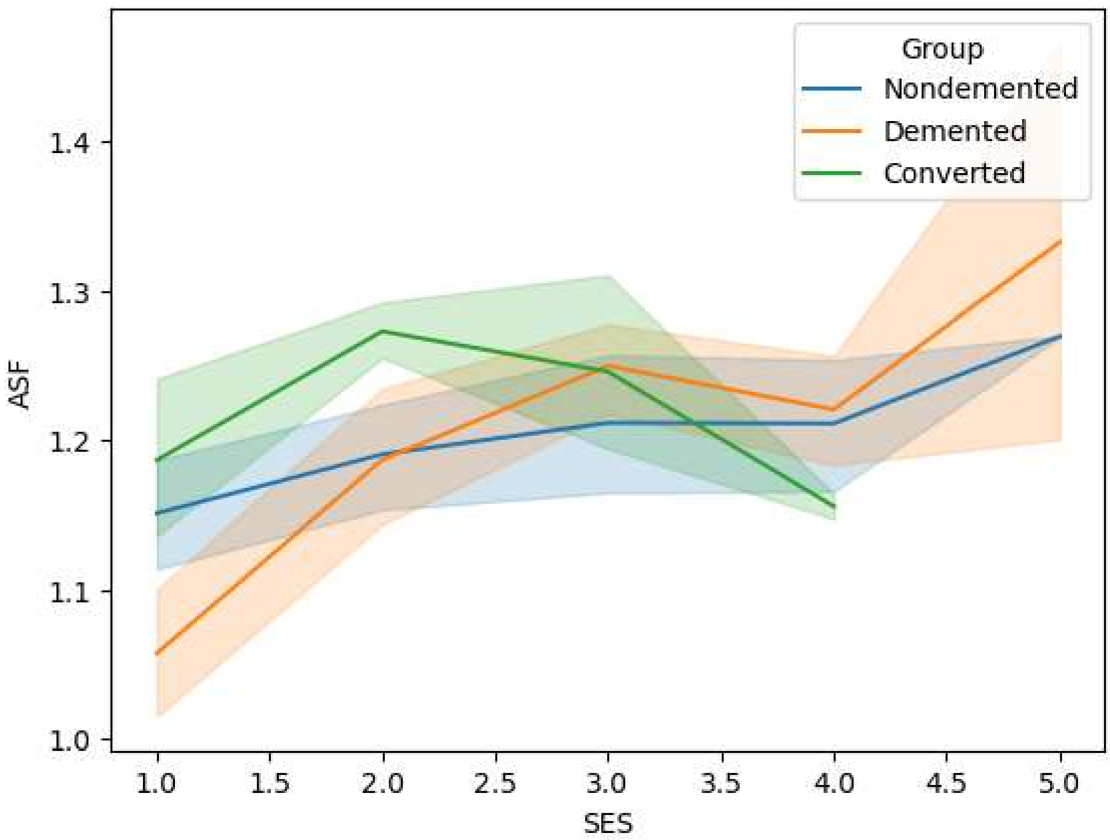




MMSE
SES
30
28
26
24
22
20
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
Group
Nondemented
Demented
Converted

In [21]:
```
sns.scatterplot(x="SES",y="ASF",hue="Group",data=data)
plt.show()
sns.lineplot(x="SES", y="ASF",hue="Group", data=data)
plt.show()
```





In [22]:
```
Features = ["MMSE","eTIV","nWBV","ASF"]
```

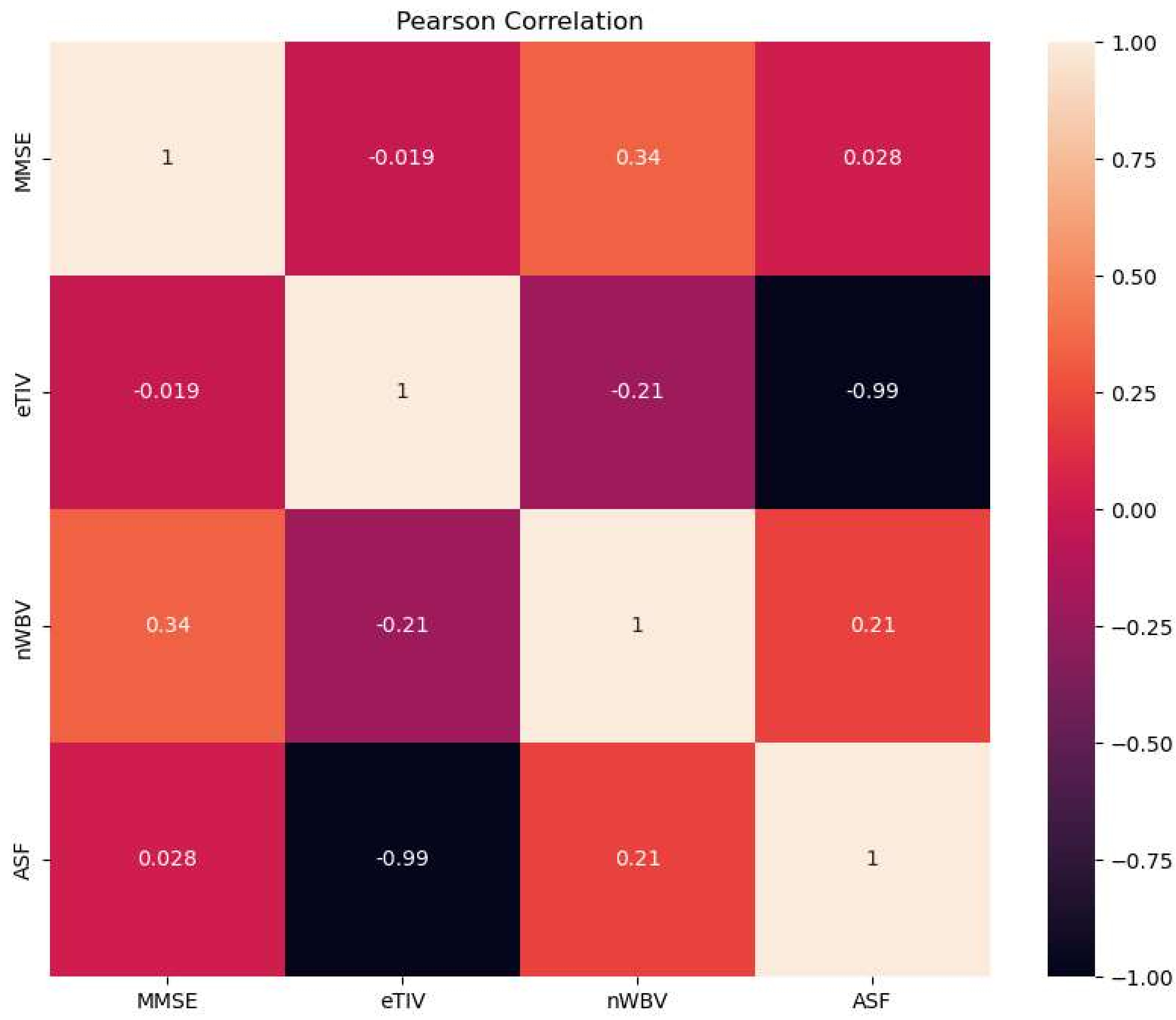
Correlation

In [23]:
```
corrPearson = data[Features].corr(method="pearson")
```

In [24]:

```
fig = plt.figure(figsize=(10,8))
sns.heatmap(corrPearson,annot=True, vmin=-1, vmax=+1)

plt.title("Pearson Correlation")
plt.show()
```



Pearson Correlation
MMSE
eTIV
nWBV
ASF
1
-0.019
0.34
0.028
-0.019
1
-0.21
-0.99
0.34
-0.21
1
0.21
0.028
-0.99
0.21
1
MMSE
eTIV
nWBV
ASF
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−0.75
−1.00

In [25]:
```
data.columns = ['Group', 'Gender', 'Age', 'EDUC', 'SES', 'MMSE', 'CDR', 'eTIV', 'nWBV', 'ASF']
```

In [26]:
```
#categorical to numerical
Columns = ["Group","Gender"]
encode = LabelEncoder()
for i in Columns:
    print(data[i].value_counts())
    print("----")
    data[i] = encode.fit_transform(data[i])
    print(data[i].value_counts())
```

```
Nondemented    190
Demented       127
Converted       37
Name: Group, dtype: int64
----
2    190
1    127
0     37
Name: Group, dtype: int64
F    204
M    150
Name: Gender, dtype: int64
----
0    204
1    150
Name: Gender, dtype: int64
```

In [27]:
```
data.Gender = data.Gender.replace("M", 0)
data.Gender = data.Gender.replace("F", 1)
data.Group = data.Group.replace("Converted", 0)
data.Group = data.Group.replace("Demented", 1)
data.Group = data.Group.replace("Nondemented", 2)

print(data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 354 entries, 0 to 372
Data columns (total 10 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   Group   354 non-null    int32  
 1   Gender  354 non-null    int32  
 2   Age     354 non-null    int64  
 3   EDUC    354 non-null    int64  
 4   SES     354 non-null    float64
 5   MMSE    354 non-null    float64
 6   CDR     354 non-null    float64
 7   eTIV    354 non-null    int64  
 8   nWBV    354 non-null    float64
 9   ASF     354 non-null    float64
dtypes: float64(5), int32(2), int64(3)
memory usage: 27.7 KB
None
```

In [28]:
```
#replacing null values
data["SES"].fillna(data["SES"].mean(), inplace=True)
data["MMSE"].fillna(data["MMSE"].mean(), inplace=True)
print(data.isnull().sum())
```

```
Group     0
Gender    0
Age       0
EDUC      0
SES       0
MMSE      0
CDR       0
eTIV      0
nWBV      0
ASF       0
dtype: int64
```

Train_test

In [29]:
```
#splitting data into dependant and independant grps
x = data.drop("Group",axis=1)
y = data["Group"]

xTrain, xTest, yTrain, yTest = train_test_split(x,y,test_size=0.20,random_state=42)
```

DECISION TREE

Decision trees are a type of machine-learning algorithm that can be used for both classification and regression tasks.

They are represented as tree structures, where each internal node represents a feature, each branch represents a decision rule, and each leaf node represents a prediction.

The algorithm works by recursively splitting the data into smaller and smaller subsets based on the feature values.

At each node, the algorithm chooses the feature that best splits the data into groups with different target values.

Why decision tree rather than any other:

Unlike most Machine Learning algorithms, it works effectively with non-linear data. And since our dataset it from medical background, the data here are complex.

In [30]:
```
data
```

Out[30]:

	Group	Gender	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	2	1	87	14	2.0	27.0	0.0	1987	0.696	0.883
1	2	1	88	14	2.0	30.0	0.0	2004	0.681	0.876
5	2	0	88	18	3.0	28.0	0.0	1215	0.710	1.444
6	2	0	90	18	3.0	27.0	0.0	1200	0.718	1.462
7	2	1	80	12	4.0	28.0	0.0	1689	0.712	1.039
...	...	...	...	...	...	...	...	...	...	...
368	1	1	82	16	1.0	28.0	0.5	1693	0.694	1.037
369	1	1	86	16	1.0	26.0	0.5	1688	0.675	1.040
370	2	0	61	13	2.0	30.0	0.0	1319	0.801	1.331
371	2	0	63	13	2.0	30.0	0.0	1327	0.796	1.323
372	2	0	65	13	2.0	30.0	0.0	1333	0.801	1.317

In [31]:
```
import warnings
warnings.filterwarnings('ignore')
#DECISION TREE
#Before Tuning
print("Results from Decision Tree Classifier before tuning")
Deci_Tree = DecisionTreeClassifier().fit(xTrain,yTrain)
predict = Deci_Tree.predict(xTest)

#accuracy score
print("Accuracy Score: ", accuracy_score(yTest,predict))

#cross validation
CV = cross_val_score(Deci_Tree,xTest,yTest,cv=10).mean()
print("Cross Validation score : ",CV);

print("=============Results from Decision Tree Classifier after tuning=============")
Deci_Tree_Tuned = DecisionTreeClassifier(max_depth=1,min_samples_split=2).fit(xTrain,yTrain)
predict_tuned = Deci_Tree_Tuned.predict(xTest)
print("Accuracy Score: ", accuracy_score(yTest,predict_tuned))
CVtuned = cross_val_score(Deci_Tree_Tuned,xTest,yTest,cv=10).mean()
print("Cross Validaition Score: ",CVtuned)
```

```
Results from Decision Tree Classifier before tuning
Accuracy Score:  0.8450704225352113
Cross Validation score :  0.8321428571428571
=============Results from Decision Tree Classifier after tuning=============
Accuracy Score:  0.8732394366197183
Cross Validaition Score:  0.8732142857142856
```

XGBoost Algorithms

XGBoost is a robust machine-learning algorithm that can help you understand your data and make better decisions.

In [32]:

```
#XGBoost
#Before tuning
print("Results from XGB Classifier before tuning")
xgbc = XGBClassifier(verbose=False).fit(xTrain, yTrain)
predict = xgbc.predict(xTest)
print("Accuracy Score: ", accuracy_score(yTest, predict))
CV = cross_val_score(xgbc, xTest, yTest, cv=10).mean()
print("Cross Validation Score: ", CV)

print("==============Results from XGB Classifier after tuning==============")
xgbc_tuned = XGBClassifier( max_depth=6, min_samples_split=2, n_estimators=100, subsample=0.8).fit(xTrain, yTr
predict_tuned = xgbc_tuned.predict(xTest)
print("Accuracy Score: ", accuracy_score(yTest, predict_tuned))
CVtuned = cross_val_score(xgbc_tuned,xTest,yTest,cv=10).mean()
print("Cross Validation Score: ", CVtuned)
```

```
Results from XGB Classifier before tuning
Accuracy Score:  0.8873239436619719
Cross Validation Score:  0.8464285714285713
==============Results from XGB Classifier after tuning==============
Accuracy Score:  0.8873239436619719
Cross Validation Score:  0.8464285714285713
```

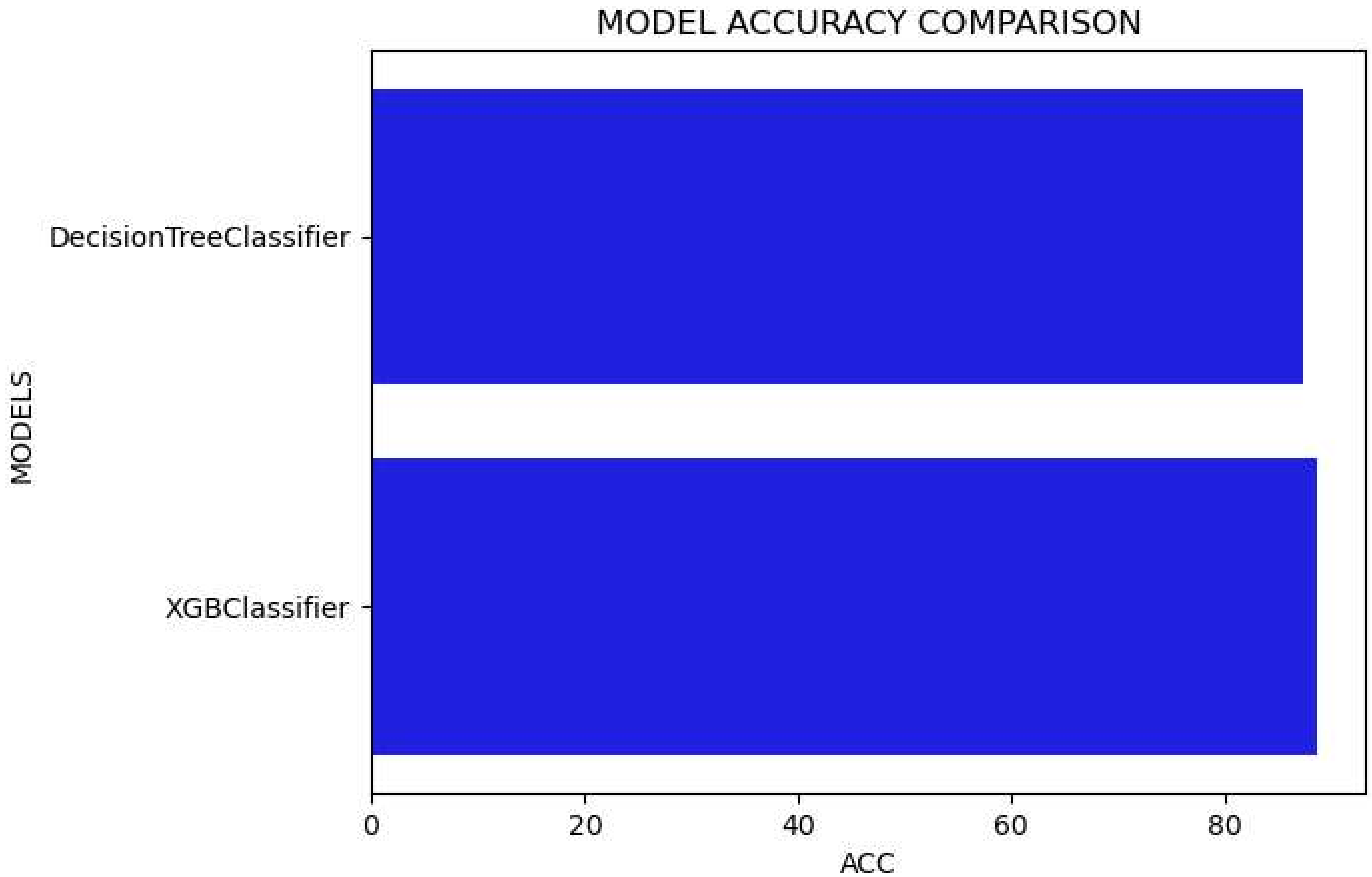
In [33]:

```
models = [Deci_Tree_Tuned,xgbc]
r = pd.DataFrame(columns=["MODELS","ACC"])

for model in models:
    name = model.__class__.__name__
    predict = model.predict(xTest)
    accuracy = accuracy_score(yTest, predict)
    print("-" * 28)
    print(name + ": ")
    print(f"Accuracy: {accuracy}")
    result = pd.DataFrame([[name,accuracy*100]],columns=["MODELS","ACC"])
    r = r.append(result)

sns.barplot(x="ACC",y="MODELS",data=r,color="b")
plt.xlabel("ACC")
plt.title("MODEL ACCURACY COMPARISON")
plt.show()
```

```
----------------------------
DecisionTreeClassifier:
Accuracy: 0.8732394366197183
----------------------------
XGBClassifier:
Accuracy: 0.8873239436619719
```



MODEL ACCURACY COMPARISON
DecisionTreeClassifier
XGBClassifier
MODELS
0
20
40
60
80
ACC

Most accurate is XGBclassifier

In [34]:
```python
user_input={
    'Gender': int(input("Enter Gender:")),
    'Age':int(input("Enter Age:")),
    'EDUC':int(input("Enter EDUC:")),
    'SES':float(input("Enter SES:")),
    'MMSE':float(input("Enter MMSE:")),
    'CDR':float(input("Enter CDR:")),
    'eTIV':int(input("Enter eTIV:")),
    'nWBV':float(input("Enter nWBV:")),
    'ASF':float(input("Enter ASF:"))
}
#create a dataframe from user input
user_data=pd.DataFrame([user_input])
x = data.drop("Group",axis=1)
y = data["Group"]
xTrain, xTest, yTrain, yTest = train_test_split(x,y,test_size=0.20,random_state=42)
model = XGBClassifier(verbose=False)
model.fit(xTrain, yTrain)
predict = model.predict(user_data)
#if you also want to predict the probability you can use predict_proba

if predict==[1]:
    print(predict)
else:
    print(predict)
    print('\n')
    user_prob=model.predict_proba(user_data)
    print('\n')
    print(f'probability percentage of AD : {user_prob[0][1] *100:.2f}%')

#0  67  16  3.000000    25.0    0.1 1787    0.926   0.873....output[2] non demented
#1  87  14  2.000000    27.0    0.0 1987    0.696   0.883....output[2] non demented
#1  75  12  2.460452    23.0    0.5 1678    0.736   1.046....output[1] demented
#0  92  14  1   27  0.5 1423    0.696   1.234...output[0]...converted

#working for all the cases above
```

```
Enter Gender:0
Enter Age:92
Enter EDUC:14
Enter SES:1
Enter MMSE:27
Enter CDR:0.5
Enter eTIV:1423
Enter nWBV:0.696
Enter ASF:1.234
[0]
```

```
probability percentage of AD : 1.88%
```

In [ ]:

```
```

In [ ]:

```
```