Course Project on Machine Learning

Project Guide - Prof. Jitendra Singh Thakur Sir

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Problem Name - Early Stage Alzheimer Disease Detection

Dataset source - Kaggle

- Alzheimer's disease (AD) is a neurodegenerative disorder of uncertain cause and pathogenesis that primarily affects older adults and is the most common cause of dementia.
- The earliest clinical manifestation of AD is selective memory impairment and while treatments are available to ameliorate some symptoms, there is no cure currently available.
- Studies have suggested that MRI features may predict rate of decline of AD and may guide therapy in the future.
- However in order to reach that stage clinicians and researchers will have to make use of machine learning techniques that can accurately predict progress of a patient from mild cognitive impairment to dementia.

to dementia.

The Clinical Dementia Rating or CDR is a numeric scale used to quantify the severity of symptoms of dementia (i.e. its 'stage').

CDR Rating	Symptoms
0	none
0.5	very mild
1	mild
2	moderate
3	severe

---

1. Import Necessary Libraries

In [1]:
```
import numpy as np
import pandas as pd
import sklearn

import seaborn as sns
from matplotlib import pyplot as plt

import warnings
warnings.filterwarnings('ignore')

"""if you face any 'module not found' or library missing issues"""
"""please install it executing the following command in a new jupyter-cell it
""" !pip install {module-name} such as !pip install seaborn"""
```

Out[1]:
```
' !pip install {module-name} such as !pip install seaborn'
```

2. Import dataset

In [2]:
```
data_long = pd.read_csv('oasis_longitudinal.csv')
```

In [3]:
```
data_long.head()
```

Out[3]:

	Subject ID	MRI ID	Group	Visit	MR Delay	M/F	Hand	Age	EDUC	SES	MMSE	CDR
0	OAS2_0001	OAS2_0001_MR1	Nondemented	1	0	M	R	87	14	2.0	27.0	0.0
1	OAS2_0001	OAS2_0001_MR2	Nondemented	2	457	M	R	88	14	2.0	30.0	0.0
2	OAS2_0002	OAS2_0002_MR1	Demented	1	0	M	R	75	12	NaN	23.0	0.5
3	OAS2_0002	OAS2_0002_MR2	Demented	2	560	M	R	76	12	NaN	28.0	0.5
4	OAS2_0002	OAS2_0002_MR3	Demented	3	1895	M	R	80	12	NaN	22.0	0.5

COLUMN DESCRIPTORS

COL	FULL-FORMS
EDUC	Years of education
SES	Socioeconomic Status
MMSE	Mini Mental State Examination (http://www.dementiatoday.com/wp-content/uploads/2012/06/MiniMentalStateExamination.pdf)
CDR	Clinical Dementia Rating (http://knightadrc.wustl.edu/cdr/PDFs/CDR_Table.pdf)
eTIV	Estimated Total Intracranial Volume (https://link.springer.com/article/10.1007/s12021-015-9266-5)
nWBV	Normalize Whole Brain Volume (https://www.ncbi.nlm.nih.gov/pubmed/11547042)
ASF	Atlas Scaling Factor (http://www.sciencedirect.com/science/article/pii/S1053811904003271)

In [4]:
```
data_long.Group.unique()
```

Out[4]:
```
array(['Nondemented', 'Demented', 'Converted'], dtype=object)
```

In [5]:
```
data_long.groupby('Group')['CDR'].count()
```

Out[5]:
```
Group
Converted       37
Demented       146
Nondemented    190
Name: CDR, dtype: int64
```

Drop unnecessary columns - MRI Id and Visit columns do not help in predicting anything

In [6]:
```
data_long.drop(['MRI ID'], axis=1, inplace=True)
data_long.drop(['Visit'], axis=1, inplace=True)
data_long.drop(['Subject ID'], axis=1, inplace=True)
```

---

3. Handling Missing Data

In [7]:
```
"""store all column names in data_columns list"""
data_columns = data_long.columns

"""store length of dataset"""
data_len = len(data_long)
```

In [8]:
```
"""function to get missing values information of the dataset"""
def get_missing_info(data_long, data_columns):
    temp = []
    for col in data_columns:
        info = {}
        info['column_name'] = col
        info['num_of_missing_values'] = data_len - data_long[col].count()
        info['sample_data'] = data_long[col][0]
        info['datatype'] = data_long[col].dtypes
        temp.append(info)

    # create dataframe to show missing values
    missing_df = pd.DataFrame(data=temp)

    # only store the rows where missing values > 0
    missing_df = missing_df[missing_df.num_of_missing_values > 0]
    return missing_df

"""call function"""
get_missing_info(data_long, data_columns)
```

Out[8]:

	column_name	num_of_missing_values	sample_data	datatype
6	SES	19	2	float64
7	MMSE	2	27	float64

So we have to fill in the missing values in 'SSE' & 'MMSE' columns. Since the values to be imputed are not much we can use ffill method to fill values.

In [9]:
```
data_long = data_long.fillna(method='ffill')
```

In [10]:
```
"""calling the function again to test whether missing values are filled"""
get_missing_info(data_long, data_columns)
```

Out[10]:

column_name	num_of_missing_values	sample_data	datatype

Since no rows gets displayed above therefore now there is now column with any missing value.

In [11]:
```
data_long.describe()
```

Out[11]:

	MR Delay	Age	EDUC	SES	MMSE	CDR	eTIV	nWE
count	373.000000	373.000000	373.000000	373.000000	373.000000	373.000000	373.000000	373.00000
mean	595.104558	77.013405	14.597855	2.455764	27.335121	0.290885	1488.128686	0.72956
std	635.485118	7.640957	2.876339	1.134171	3.674641	0.374557	176.139286	0.03713
min	0.000000	60.000000	6.000000	1.000000	4.000000	0.000000	1106.000000	0.64400
25%	0.000000	71.000000	12.000000	2.000000	27.000000	0.000000	1357.000000	0.70000
50%	552.000000	77.000000	15.000000	2.000000	29.000000	0.000000	1470.000000	0.72900
75%	873.000000	82.000000	16.000000	3.000000	30.000000	0.500000	1597.000000	0.75600
max	2639.000000	98.000000	23.000000	5.000000	30.000000	2.000000	2004.000000	0.83700

4. Handling Categorical Data

In [12]:
```
for col in data_columns:
    if data_long[col].dtypes == "object":
        print(col, end=" - ")
        print(data_long[col].unique())
```

```
Group - ['Nondemented' 'Demented' 'Converted']
M/F - ['M' 'F']
Hand - ['R']
```

We have three categorical columns to fix - 'Group' | 'M/F' | 'Hand'

In [13]:
```
"""Since the column Hand has only one value 'R' for all the rows, we can drop
data_long.drop(['Hand'], axis=1, inplace=True)
```

We will also convert different CDR ratings to categorical variable A,B,C,D because it is a classification problem

In [14]:
```
data_long['CDR'].replace(to_replace=0.0, value='A', inplace=True)
data_long['CDR'].replace(to_replace=0.5, value='B', inplace=True)
data_long['CDR'].replace(to_replace=1.0, value='C', inplace=True)
data_long['CDR'].replace(to_replace=2.0, value='D', inplace=True)
```

Applying Label Encoder to convert all categorical columns to numerical columns

In [15]:
```
from sklearn.preprocessing import LabelEncoder

f = LabelEncoder()
data_long['M/F'] = f.fit_transform(data_long['M/F'])
data_long['CDR'] = f.fit_transform(data_long['CDR'])


"""WE ALSO SEE THAT ATTRIBUTES 'GROUP' AND 'CDR' ESSENTIALLY MEAN THE SAME.""
"""THEREFORE WE WILL DROP 'GROUP' AS THERE IS NO POINT IN USING THAT FOR CLAS

data_long.drop('Group', axis=1, inplace=True)
```

Notice that all columns (previously categorical such as M/F) are now changed to numerical columns (including CDR)

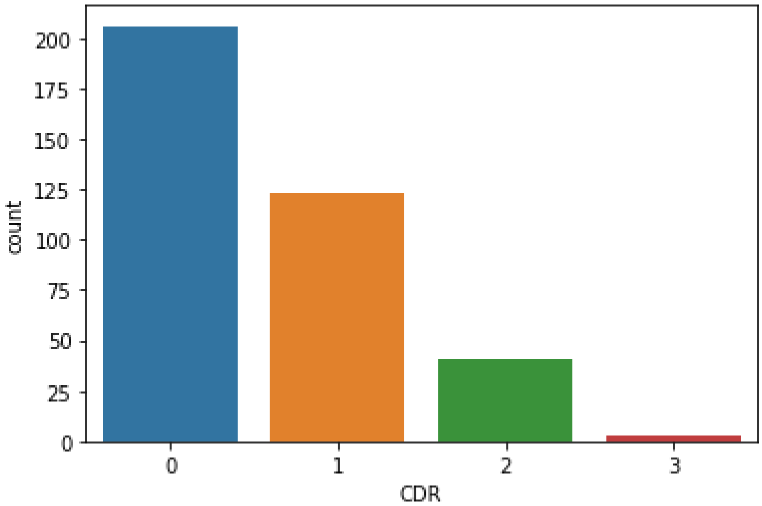
In [16]:
```
data_long.head()
```

Out[16]:

	MR Delay	M/F	Age	EDUC	SES	MMSE	CDR	eTIV	nWBV	ASF
0	0	1	87	14	2.0	27.0	0	1987	0.696	0.883
1	457	1	88	14	2.0	30.0	0	2004	0.681	0.876
2	0	1	75	12	2.0	23.0	1	1678	0.736	1.046
3	560	1	76	12	2.0	28.0	1	1738	0.713	1.010
4	1895	1	80	12	2.0	22.0	1	1698	0.701	1.034

In [17]:
```
"""Plotting count of patients with CDR values; where 0 = no alzheimers & 3 =
sns.countplot(data_long.CDR)
```

Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb094cc30f0>



5. Feature Engineering

In [18]:
```
"""count of patients with different CDR ratings"""
data_long.groupby('CDR')['MMSE'].count()
```

Out[18]:
```
CDR
0    206
1    123
2     41
3      3
Name: MMSE, dtype: int64
```

We observed that the values for CDR == 1,2,3 are very less as compared to count of values for CDR == 0.
Therefore, we can combine the CDR classes 1,2,3 into one class.
Hence, we will have two values for CDR now - 0 == Non-Demented and 1 == Demented.

In [19]:
```
for i in range(len(data_long)):
    rating = data_long.CDR[i]

    """if CDR rating = 1 or 2 or 3 we group them"""
    if rating > 0:
        data_long['CDR'].iloc[i] = 1
```

MMSE value observation

In [20]:
```
data_long.groupby('CDR')['MMSE'].max()
```

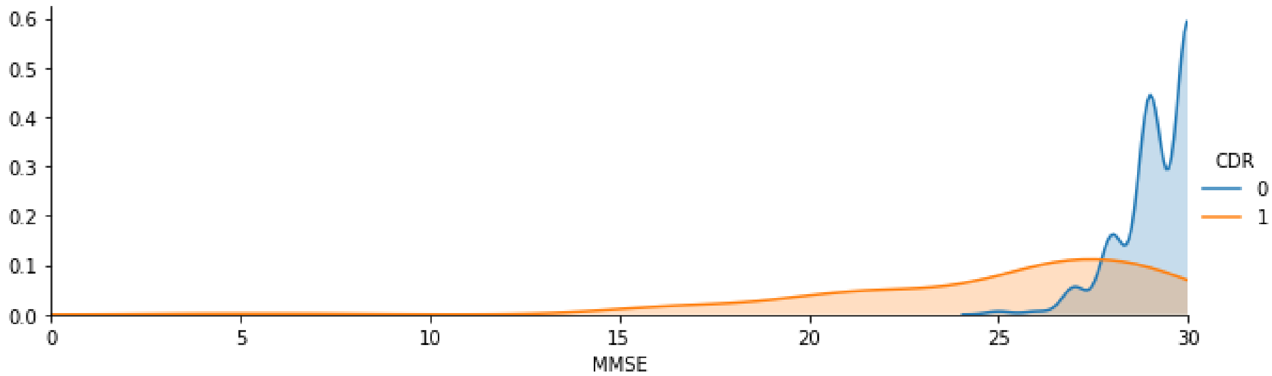
Out[20]:
```
CDR
0    30.0
1    30.0
Name: MMSE, dtype: float64
```

In [21]:
```
data_long.groupby('CDR')['MMSE'].min()
```

Out[21]:
```
CDR
0    25.0
1     4.0
Name: MMSE, dtype: float64
```

In [22]:
```
facet= sns.FacetGrid(data_long, hue="CDR", aspect=3)
facet.map(sns.kdeplot,'MMSE',shade= True)
facet.set(xlim=(0, data_long['MMSE'].max()))
facet.add_legend()
```

Out[22]:
```
<seaborn.axisgrid.FacetGrid at 0x7fb093861390>
```



MMSE - The Mini-Mental State Examination or Folstein test is a 30-point questionnaire that is used extensively in clinical and research settings to measure cognitive impairment/dementia.

We also observe that the values for MMSE highly affect the CDR value. The higher the value of MMSE, higher the chances of patient being undemented.

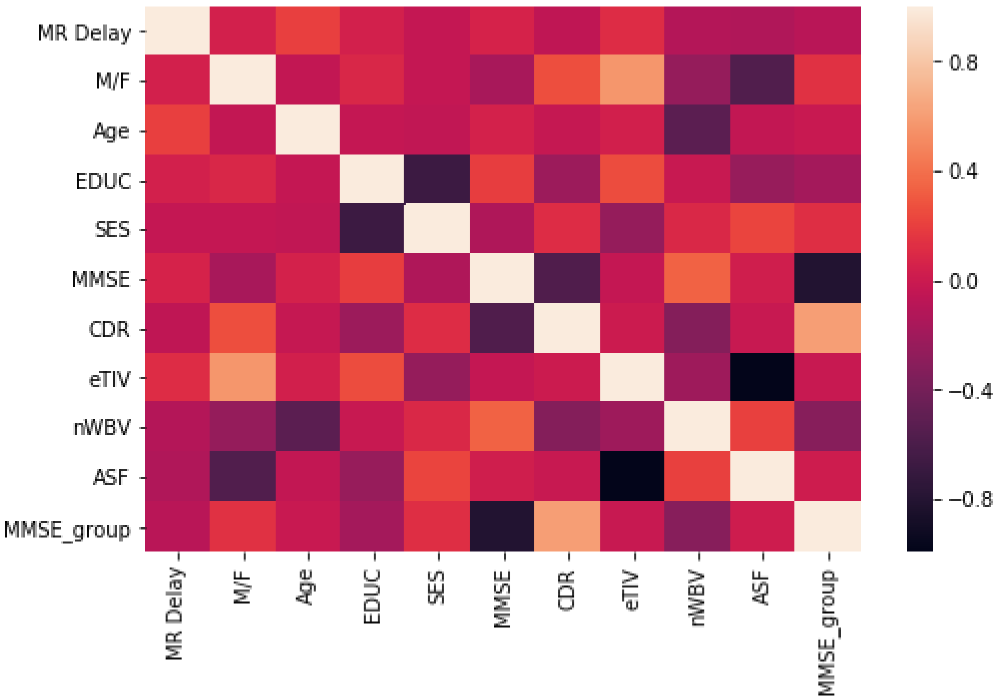
Therefore, we can introduce a new variable called 'MMSE_group' in our data to distribute values of MMSE into bins.

In [23]:
```
data_long['MMSE_group'] = ""

for i in range(len(data_long)):
    mmse = data_long.MMSE[i]
    if mmse >= 27 and mmse <= 30:
        data_long['MMSE_group'][i] = 0
    else:
        data_long['MMSE_group'][i] = 1

data_long['MMSE_group'] = pd.to_numeric(data_long['MMSE_group'])
```

Correlation Analysis

In [24]:
```
corr_matrix = data_long.corr()

from pylab import rcParams
# set figure size
rcParams['figure.figsize'] = 8, 5

# plotting corr_matrix using sns library
sns.heatmap(corr_matrix)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb093803f60>



In [25]:
```
"""Correlation values of columns with the target column 'CDR'"""

print("Correlation values of columns with the target column CDR")
corr_matrix['CDR']
```

```
Correlation values of columns with the target column CDR
```

Out[25]:
```
MR Delay     -0.053279
M/F           0.265416
Age          -0.020659
EDUC         -0.217428
SES           0.118466
MMSE         -0.571461
CDR           1.000000
eTIV          0.008015
nWBV         -0.325932
ASF          -0.013254
MMSE_group    0.605809
Name: CDR, dtype: float64
```

We observe that columns MMSE, MMSE_group, nWBV are the top correlated features with target column CDR from the dataset

In [26]:
```
"""since eTIV has correlation value of 0.008 --> it is not related with CDR."
"""Hence, we will drop this feature as it becomes unnecessary for our model."

data_long.drop('eTIV', axis=1, inplace=True)
```

6. Model Training

In [27]:
```
# install scikit-plot if not already installed
# !pip install -q scikit-plot
```

In [28]:
```
"""we use joblib to save and load the ml models"""
import joblib

"""we use scikitplot to plot the confusion matrix"""
import scikitplot as skplt

from sklearn.metrics import classification_report
```

Splitting Dataset

In [29]:
```
from sklearn.model_selection import train_test_split

train, test = train_test_split(data_long, test_size = 0.25, random_state=10)
```

In [30]:
```
print("Number of rows in training set = ", len(train))
print("Number of rows in test set = ", len(test))
```

```
Number of rows in training set =  279
Number of rows in test set =  94
```

We have to predict CDR

In [31]:
```
print(data_long.columns)
```

```
Index(['MR Delay', 'M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'CDR', 'nWBV', 'AS
F',
       'MMSE_group'],
      dtype='object')
```

In [32]:
```
X_train = train[['MR Delay', 'M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'nWBV', 'AS
y_train = train.CDR

X_test = test[['MR Delay', 'M/F', 'Age', 'EDUC', 'SES', 'MMSE', 'nWBV', 'ASF'
y_test = test.CDR
```

In [33]:
```
print("X_train.shape - ", X_train.shape)
print("y_train.shape - ", y_train.shape)
print("X_test.shape - ", X_test.shape)
print("y_test.shape - ", y_test.shape)
```

```
X_train.shape -  (279, 8)
y_train.shape -  (279,)
X_test.shape -  (94, 8)
y_test.shape -  (94,)
```

Scaling our data

Algorithm	Distance Dependent?	Scaling Required
1. Logistic Regression	No	No
2. Decision Tree	No	No
3. Random Forest	No	No
4. KNN	Yes	Yes
5. SVM	Yes	Yes

In [34]:
```
from sklearn.preprocessing import StandardScaler

# Define the scaler
scaler = StandardScaler().fit(X_train)

# Scale the train set
X_scaled_train = scaler.transform(X_train)

# Scale the test set
X_scaled_test = scaler.transform(X_test)
```

```
In [35]: """we will store accuracies of every classifier in a dictionary to display at
accuracy_dict = {}
```

6.1 Logistic Regression

```
In [36]: from sklearn.linear_model import LogisticRegression
lr_classifier = LogisticRegression(solver='liblinear')
lr_classifier.fit(X_train, y_train)
```

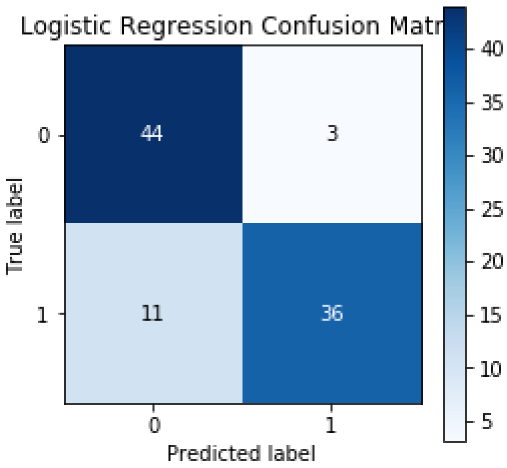
```
Out[36]: LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='liblinear', tol=0.0001, verbos
e=0,
                   warm_start=False)
```

```
In [37]: lr_classifier = joblib.load('lr_model.sav')
lr_prediction = lr_classifier.predict(X_test)

lr_accuracy = lr_classifier.score(X_test, y_test)
lr_accuracy = round(lr_accuracy, 4)*100

accuracy_dict['LogisticRegression'] = lr_accuracy
print('Accuracy of prediction - ', lr_accuracy)
```

```
Accuracy of prediction -  85.11
```

```
In [38]: """CONFUSION MATRIX"""
skplt.metrics.plot_confusion_matrix(y_test, lr_prediction, figsize=(4,4),
                                    title="Logistic Regression Confusion Matri
```

```
Out[38]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb0916083c8>
```



Classification Report

In [39]:
```
print(classification_report(y_test, lr_prediction))
```

```
              precision    recall  f1-score   support

           0       0.80      0.94      0.86        47
           1       0.92      0.77      0.84        47

    accuracy                           0.85        94
   macro avg       0.86      0.85      0.85        94
weighted avg       0.86      0.85      0.85        94
```

6.2 Decision Tree

In [40]:
```
from sklearn.tree import DecisionTreeClassifier
dt_classifier = DecisionTreeClassifier(max_depth=6)
dt_classifier.fit(X_train, y_train)
```

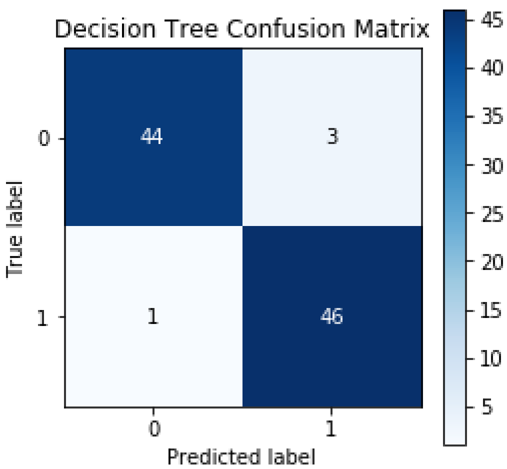
Out[40]:
```
DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='gini',
                       max_depth=6, max_features=None, max_leaf_nodes=None,
                       min_impurity_decrease=0.0, min_impurity_split=None,
                       min_samples_leaf=1, min_samples_split=2,
                       min_weight_fraction_leaf=0.0, presort='deprecated',
                       random_state=None, splitter='best')
```

In [41]:
```
dt_classifier = joblib.load('dt_model.sav')
dt_prediction = dt_classifier.predict(X_test)

dt_accuracy = dt_classifier.score(X_test, y_test)
dt_accuracy = round(dt_accuracy, 4)*100

accuracy_dict['DecisionTree'] = dt_accuracy
print('Accuracy of prediction - ', dt_accuracy)
```

```
Accuracy of prediction -  95.74000000000001
```

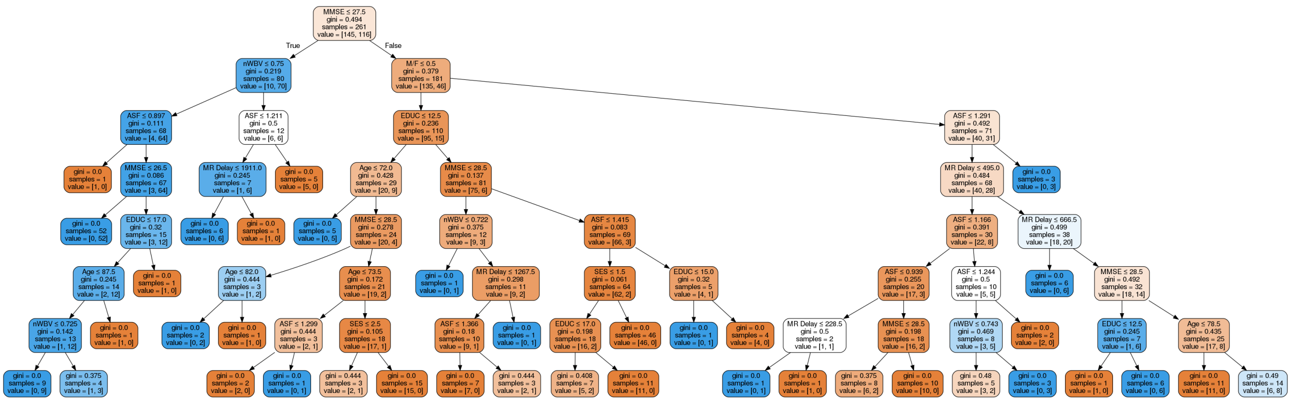
In [42]:
```
"""CONFUSION MATRIX"""
skplt.metrics.plot_confusion_matrix(y_test, dt_prediction, figsize=(4,4),
                                    title="Decision Tree Confusion Matrix")
```

Out[42]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb09027eb38>
```



Visualizing the Decision Tree

In [43]:
```python
from sklearn import tree
import graphviz
import pydotplus

dot_data = tree.export_graphviz(dt_classifier, feature_names=X_test.columns,
                                filled=True, rounded=True, special_characters=

pydot_graph = pydotplus.graph_from_dot_data(dot_data)
pydot_graph.write_png('alzheimer_decision_tree.png')
pydot_graph.set_size('"5,5!"')
```



For better visual please check the project folder for decision tree image named - 'alzheimer_decision_tree.png' or click the link below -

https://drive.google.com/file/d/14mhukEF1k_mxXRU1fnrCiDWPxUUo_mvj/view?usp=sharing (https://drive.google.com/file/d/14mhukEF1k_mxXRU1fnrCiDWPxUUo_mvj/view?usp=sharing)

Classification Report

In [44]:
```python
print(classification_report(y_test, dt_prediction))
```

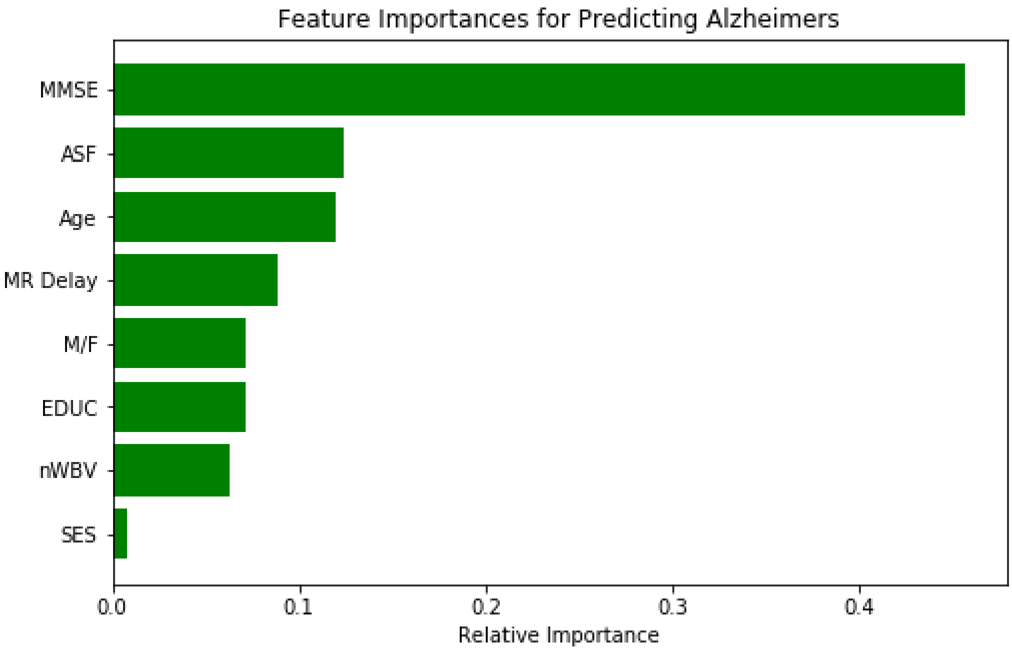
```
              precision    recall  f1-score   support

           0       0.98      0.94      0.96        47
           1       0.94      0.98      0.96        47

    accuracy                           0.96        94
   macro avg       0.96      0.96      0.96        94
weighted avg       0.96      0.96      0.96        94
```

6.3 Random Forest

In [45]:
```
from sklearn.ensemble import RandomForestClassifier
rf_classifier = RandomForestClassifier(n_estimators=300, max_depth=6)
rf_classifier.fit(X_train, y_train)

rf_classifier = joblib.load('dt_model.sav')
rf_prediction = rf_classifier.predict(X_test)
rf_accuracy = rf_classifier.score(X_test, y_test)
rf_accuracy = round(rf_accuracy, 4)*100
accuracy_dict['RandomForest'] = rf_accuracy
print('Accuracy of prediction - ', rf_accuracy)
```

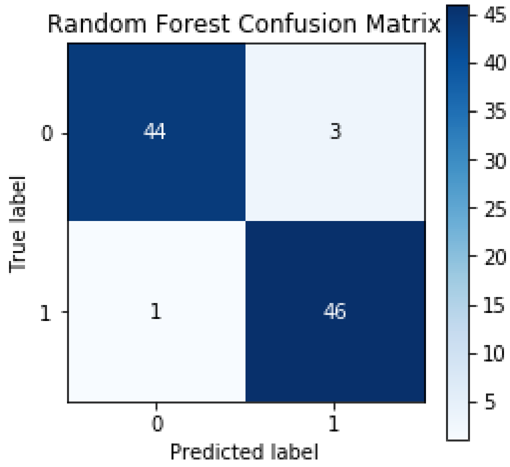
```
Accuracy of prediction -  95.74000000000001
```

In [46]:
```
features = X_test.columns
importances = rf_classifier.feature_importances_
indices = np.argsort(importances)

plt.title('Feature Importances for Predicting Alzheimers')
plt.barh(range(len(indices)), importances[indices], color='g', align='center'
plt.yticks(range(len(indices)), [features[i] for i in indices])
plt.xlabel('Relative Importance')
plt.show()
```



In [47]:
```python
"""CONFUSION MATRIX"""
skplt.metrics.plot_confusion_matrix(y_test, rf_prediction, figsize=(4,4),
                                    title="Random Forest Confusion Matrix")
```

Out[47]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb08f34ca90>
```



Classification Report

In [48]:
```python
print(classification_report(y_test, rf_prediction))
```

```
              precision    recall  f1-score   support

           0       0.98      0.94      0.96        47
           1       0.94      0.98      0.96        47

    accuracy                           0.96        94
   macro avg       0.96      0.96      0.96        94
weighted avg       0.96      0.96      0.96        94
```

6.4 KNN

In [49]:
```python
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier(n_neighbors=7)
knn.fit(X_scaled_train, y_train)
```

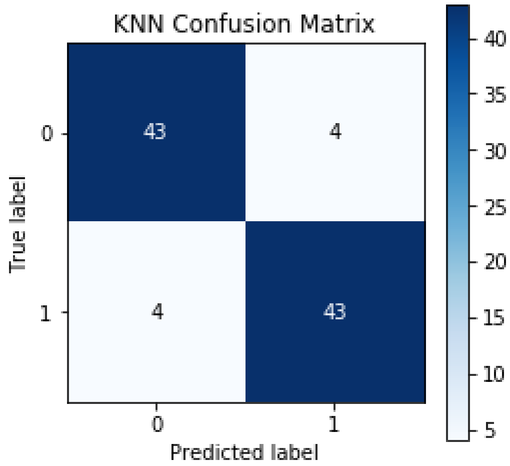
Out[49]:
```
KNeighborsClassifier(algorithm='auto', leaf_size=30, metric='minkowski',
                     metric_params=None, n_jobs=None, n_neighbors=7, p=2,
                     weights='uniform')
```

In [50]:
```python
knn = joblib.load('knn_model.sav')
knn_prediction = knn.predict(X_scaled_test)

knn_accuracy = knn.score(X_scaled_test, y_test)
knn_accuracy = round(knn_accuracy, 4)*100

accuracy_dict['KNN'] = knn_accuracy
print('Accuracy of prediction - ', knn_accuracy)
```

```
Accuracy of prediction -  91.49000000000001
```

In [51]:
```
"""CONFUSION MATRIX"""
skplt.metrics.plot_confusion_matrix(y_test, knn_prediction, figsize=(4,4),
                                    title="KNN Confusion Matrix")
```

Out[51]: <matplotlib.axes._subplots.AxesSubplot at 0x7fb08f367978>



Classification Report

In [52]:
```
print(classification_report(y_test, knn_prediction))
```

```
              precision    recall  f1-score   support

           0       0.91      0.91      0.91        47
           1       0.91      0.91      0.91        47

    accuracy                           0.91        94
   macro avg       0.91      0.91      0.91        94
weighted avg       0.91      0.91      0.91        94
```

6.5 SVM

In [53]:
```
from sklearn.svm import SVC

svc=SVC(kernel="linear", C=0.3)
svc.fit(X_scaled_train, y_train)
```

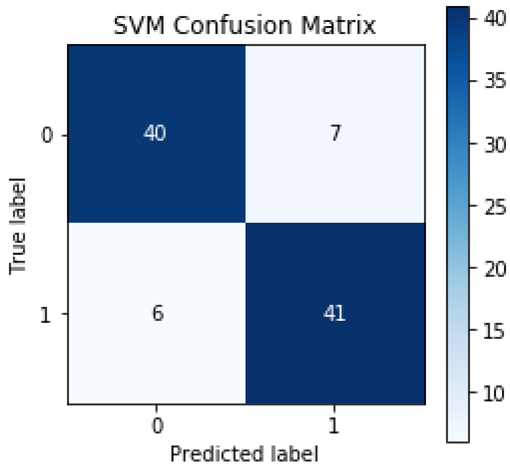
Out[53]:
```
SVC(C=0.3, break_ties=False, cache_size=200, class_weight=None, coef0=0.0,
    decision_function_shape='ovr', degree=3, gamma='scale', kernel='linear',
    max_iter=-1, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)
```

In [54]:
```
svc = joblib.load('svc_model.sav')
svc_prediction = svc.predict(X_scaled_test)

svc_accuracy = svc.score(X_scaled_test, y_test)
svc_accuracy = round(svc_accuracy, 4)*100

accuracy_dict['SVC'] = svc_accuracy
print('Accuracy of prediction - ', svc_accuracy)
```

```
Accuracy of prediction -  86.17
```

In [55]:
```
"""CONFUSION MATRIX"""
skplt.metrics.plot_confusion_matrix(y_test, svc_prediction, figsize=(4,4),
                                    title="SVM Confusion Matrix")
```

Out[55]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb08f090a58>
```



Classification Report

In [56]:
```
print(classification_report(y_test, svc_prediction))
```

```
              precision    recall  f1-score   support

           0       0.87      0.85      0.86        47
           1       0.85      0.87      0.86        47

    accuracy                           0.86        94
   macro avg       0.86      0.86      0.86        94
weighted avg       0.86      0.86      0.86        94
```

7. Results

In [57]:
```
"""We create a new dataframe results_df to store values from all the classifi

results_df = pd.DataFrame()
results_df['actual_label'] = y_test
results_df['logistic_label'] = lr_prediction
results_df['decision_tree_label'] = dt_prediction
results_df['random_forest_label'] = rf_prediction
results_df['knn_label'] = knn_prediction
results_df['svm_label'] = svc_prediction
results_df = results_df.reset_index(drop=True)
```

Ensemble of all the five models above and take mode for each data point in the test set

In [58]:
```
import statistics
results_df['ensemble'] = ""

for i in range(len(results_df)):
    logistic = results_df.logistic_label[i]
    dtree = results_df.decision_tree_label[i]
    rforest = results_df.random_forest_label[i]
    knn = results_df.knn_label[i]
    svm = results_df.svm_label[i]
    acc_list = [logistic, svm, dtree, rforest, knn]
    results_df['ensemble'][i] = statistics.mode(acc_list)
```

Confusion Matrix for Ensembled results -

In [59]:
```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(list(results_df.actual_label), list(results_df.ensemble
cm
```

Out[59]:
```
array([[45,  2],
       [ 2, 45]])
```

Ensemble Model Accuracy -

In [60]:
```
correct = cm[0][0] + cm[1][1]
ensemble_acc = round((correct/cm.sum()),4)*100
print(ensemble_acc)
```

```
95.74000000000001
```

THE FOLLOWING TABLE SHOWS THE ACTUAL CDR VALUE AND THE VALUES PREDICTED BY VARIOUS CLASSIFIERS.

In [61]:
```python
results_df.head()
```

Out[61]:

	actual_label	logistic_label	decision_tree_label	random_forest_label	knn_label	svm_label	ensemble
0	1	0	1	1	1	1	1
1	1	0	1	1	1	1	1
2	1	1	1	1	1	1	1
3	1	0	0	0	0	0	0
4	1	1	1	1	1	1	1

8. Results

Final Accuracy -

In [62]:
```python
"""Accuracy dataframe - """
accuracy_df = pd.DataFrame(data = [accuracy_dict])
accuracy_df['ensemble_acc'] = ensemble_acc
```

In [63]:
```python
accuracy_df
```

Out[63]:

	LogisticRegression	DecisionTree	RandomForest	KNN	SVC	ensemble_acc
0	85.11	95.74	95.74	91.49	86.17	95.74

9. Uniqueness of our Approach and Conclusion

- In this project, the prominent section was FEATURE ENGINEERING where from existing attributes, we calculated a derived attribute MMSE-group.
- This calculation of derived attribute was possible because we studied literature on attributes present in the dataset. Eventually, our work on feature engineering significantly boosted our accuracy results.
- The high accuracy of the ML models establishes the fact that it can make a significant contribution in the clinical environment.

In [64]:
```python
"""Thank You!"""
"""Author - Satakshi Dubey | 0201cs171063 """
```

Out[64]: 'Author - Satakshi Dubey | 0201cs171063 '