The goal of this project is to build a **Classification Tree** to predict whether or not an individual is obese.

We use the **Estimation of Obesity Levels Based On Eating Habits and Physical Condition** dataset from the UCI Machine Learning Repository.

Import Modules

In [1]:
```
# Import pandas for data handling
import pandas as pd

# Import numpy for numerical operations
import numpy as np

# Import matplotlib for plotting
import matplotlib.pyplot as plt

# Import scikit-learn for decision tree and model evaluation tools
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import balanced_accuracy_score
```

Load the Dataset

In [2]:
```
# Fetch dataset as pandas dataframe
df = pd.read_csv('ObesityDataSet_raw_and_data_sinthetic.csv')

df.head()
```

Out[2]:

	Gender	Age	Height	Weight	family_history_with_overweight	FAVC	FCVC	NCP	CAEC	SMOKE	CH2O	SCC	FAF	TUE	CALC	
0	Female	21.0	1.62	64.0	yes	no	2.0	3.0	Sometimes	no	2.0	no	0.0	1.0	no	Pu
1	Female	21.0	1.52	56.0	yes	no	3.0	3.0	Sometimes	yes	3.0	yes	3.0	0.0	Sometimes	Pu
2	Male	23.0	1.80	77.0	yes	no	2.0	3.0	Sometimes	no	2.0	no	2.0	1.0	Frequently	Pu
3	Male	27.0	1.80	87.0	no	no	3.0	3.0	Sometimes	no	2.0	no	2.0	0.0	Frequently	
4	Male	22.0	1.78	89.8	no	no	2.0	1.0	Sometimes	no	2.0	no	0.0	0.0	Sometimes	Pu

This data contains the following variables:

Variable	Description
Gender	
Age	
Height	
Weight	
family_history_with_overweight	Has a family member suffered or suffers from overweight?
FAVC	Do you eat high caloric food frequently?
FCVC	Do you usually eat vegetables in your meals
NCP	How many main meals do you have daily?
CAEC	Do you eat any food between meals?
SMOKE	Do you smoke?
CH2O	How much water do you drink daily?
SCC	Do you monitor the calories you eat daily?
FAF	How often do you have physical activity?
TUE	How much time do you use technological devices?
CALC	How often do you drink alcohol?
MTRANS	Which transportation do you usually use?
NObeyesdad	Obesity level

Identify Missing Data

First, we want to check if the dataset contains any missing values.

In [3]:
```
# Print data type of each column
df.dtypes
```

Out[3]:
```
Gender                            object
Age                              float64
Height                           float64
Weight                           float64
family_history_with_overweight    object
FAVC                              object
FCVC                             float64
NCP                              float64
CAEC                              object
SMOKE                             object
CH2O                             float64
SCC                               object
FAF                              float64
TUE                              float64
CALC                              object
MTRANS                            object
NObeyesdad                        object
dtype: object
```

We can see that some columns have `object` data type, which can potentially include missing values.

In [4]:
```
# Print unique values of column with 'object' data type
for col in df.select_dtypes(include='object').columns:
    print(col, ": ", df[col].unique())
```

```
Gender :  ['Female' 'Male']
family_history_with_overweight :  ['yes' 'no']
FAVC :  ['no' 'yes']
CAEC :  ['Sometimes' 'Frequently' 'Always' 'no']
SMOKE :  ['no' 'yes']
SCC :  ['no' 'yes']
CALC :  ['no' 'Sometimes' 'Frequently' 'Always']
MTRANS :  ['Public_Transportation' 'Walking' 'Automobile' 'Motorbike' 'Bike']
NObeyesdad :  ['Normal_Weight' 'Overweight_Level_I' 'Overweight_Level_II'
 'Obesity_Type_I' 'Insufficient_Weight' 'Obesity_Type_II'
 'Obesity_Type_III']
```

Since there are no values indicating missing data such as `NaN`, we can proceed to the next step.

Format the Data for Decision Trees

First, we split our dataset into the following:

- `X` : data of **feature variables**, which we will use to predict classifications.
- `y` : data of **target variable**, which is obesity level stored in the `NObeyesdad` column.

In [5]:
```
# Split data into X and y (use copy to preserve the original data)
X = df.drop('NObeyesdad', axis=1).copy()
y = df['NObeyesdad'].copy()
```

Now, we observe that our feature variables can be divided into two categories:

- **Physical attributes**: `Gender` , `Age` , `Height` , `Weight`
- **Daily habits**: `family_history_with_overweight` , `FAVC` , `FCVC` , `NCP` , `CAEC` , `SMOKE` , `CH2O` , `SCC` , `FAF` , `TUE` , `CALC` , `MTRANS`

Since physical attributes are likely too directly linked to obesity, we decide to omit these variables.

Instead, we aim to estimate obesity based solely on daily habits.

In [6]:
```
# Drop physical features
X = X.drop(columns=['Gender', 'Age', 'Height', 'Weight'])
```

Next, we can categorize the remaining feature variables as follows:

- **Quantitative**: `FCVC` , `NCP` , `CH2O` , `FAF` , `TUE`
- **Categorical**:
  - **Ordinal**: `family_history_with_overweight` , `FAVC` , `SMOKE` , `SCC` , `CAEC` , `CALC`
  - **Nominal**: `MTRANS`

To prepare the data for building a decision tree, we map **ordinal** variables to numerical values and apply *one-hot encoding* to **nominal** variables.

In [7]:
```
# Silence the warning for replace()
pd.set_option('future.no_silent_downcasting', True)

# Replace (yes, no) with (1, 0)
X = X.replace({'yes': 1, 'no': 0})

# Replace (no, Sometimes, Frequently, Always) with (0, 1, 2, 3)
X = X.replace({'Sometimes': 1, 'Frequently': 2, 'Always': 3})

# Apply one-hot encoding to 'MTRANS'
X = pd.get_dummies(X, columns=['MTRANS'])

X.head()
```

Out[7]:

	family_history_with_overweight	FAVC	FCVC	NCP	CAEC	SMOKE	CH2O	SCC	FAF	TUE	CALC	MTRANS_Automobile	MTRANS_Bike	MTRA
0	1	0	2.0	3.0	1	0	2.0	0	0.0	1.0	0	False	False	
1	1	0	3.0	3.0	1	1	3.0	1	3.0	0.0	1	False	False	
2	1	0	2.0	3.0	1	0	2.0	0	2.0	1.0	2	False	False	
3	0	0	3.0	3.0	1	0	2.0	0	2.0	0.0	2	False	False	
4	0	0	2.0	1.0	1	0	2.0	0	0.0	0.0	1	False	False	

For `y` , we simplify the problem to a **binary classification**. We define the categories as:

- `0` (Not Obese): *Insufficient_Weight*, *Normal_Weight*, *Overweight_Level_I*, *Overweight_Level_II*
- `1` (Obese): *Obesity_Type_I*, *Obesity_Type_II*, *Obesity_Type_III*

In [8]:
```
# Classify y as binary
y.loc[y.str.startswith('Obesity')] = 1
y.loc[y != 1] = 0
y = y.astype(int)

y.unique()
```

Out[8]:
```
array([0, 1])
```

Build a Preliminary Classification Tree

To begin with, we split our data into **training** dataset and **testing** dataset.

Then, we use the training set to build the decision tree.

To evaluate performance, we use **balanced accuracy**, which takes into account the accuracy on each class equally.

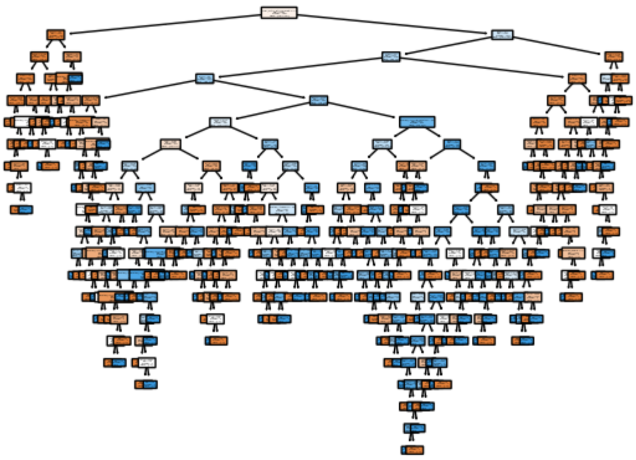
In [9]:
```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y)

# Create a decision tree and fit it to the training data
clf_dt = DecisionTreeClassifier(random_state=42)
clf_dt.fit(X_train, y_train)

# Plot the tree
plot_tree(clf_dt,
          filled=True,
          rounded=True,
          class_names=["Not Obese", "Obese"],
          feature_names=X.columns)

# Compute balanced accuracy for training and testing dataset
print("Balanced Accuracy on Training Dataset:", balanced_accuracy_score(y_train, clf_dt.predict(X_train)))
print("Balanced Accuracy on Testing Dataset:", balanced_accuracy_score(y_test, clf_dt.predict(X_test)))
```

```
Balanced Accuracy on Training Dataset: 1.0
Balanced Accuracy on Testing Dataset: 0.8428070175438597
```



Observations:

- We have constructed a **classification tree** with high accuracy on both the training and testing datasets.
- However, since the accuracy on training dataset is significantly higher (≈100%), this indicates that our model is **overfitting**.
- Additionally, the tree appears to be too large and complex.

To address this, we now aim to simplify the tree while maintaining its accuracy.

Apply Cost Complexity Pruning

As the next step, we apply **Cost Complexity Pruning** to reduce the tree size.

The pruning parameter `α` controls the penalty for adding more leaves to the tree.

A higher `α` results in a smaller tree, but can potentially lead to underfitting.

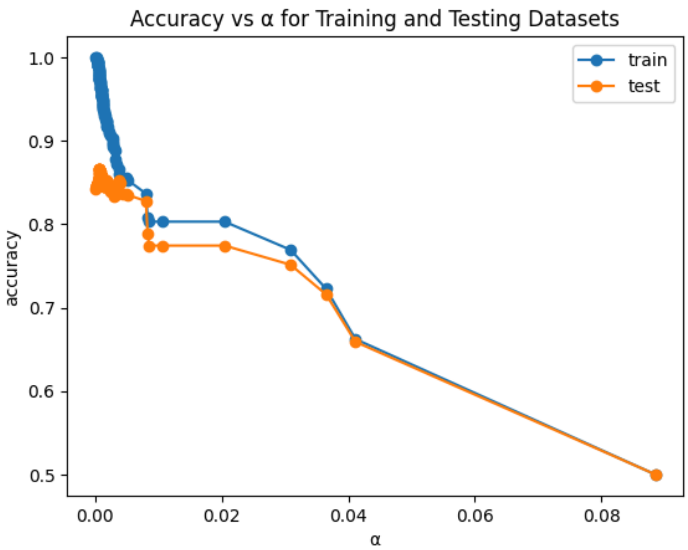
Our goal is to find the optimal value of `α`.

In [10]:
```
# Extract different values for α
path = clf_dt.cost_complexity_pruning_path(X_train, y_train)
ccp_alphas = path.ccp_alphas

# Create one decision tree per value for α
clf_dts = []
for ccp_alpha in ccp_alphas:
    clf_dt = DecisionTreeClassifier(random_state=42, ccp_alpha=ccp_alpha)
    clf_dt.fit(X_train, y_train)
    clf_dts.append(clf_dt)
```

In [11]:
```
# Compute accuracy for training and testing dataset
train_scores = []
test_scores = []
for clf_dt in clf_dts:
    train_scores.append(balanced_accuracy_score(y_train, clf_dt.predict(X_train)))
    test_scores.append(balanced_accuracy_score(y_test, clf_dt.predict(X_test)))

# Plot accuracy vs alpha
plt.plot(ccp_alphas, train_scores, marker='o', label="train")
plt.plot(ccp_alphas, test_scores, marker='o', label="test")
plt.xlabel("α")
plt.ylabel("accuracy")
plt.title("Accuracy vs α for Training and Testing Datasets")
plt.legend()
plt.show()
```



Observations:

- The maximum accuracy occurs at a very small value of `α`.
- After this point, both training and testing accuracy decrease and gradually converge.
- An *elbow point* is observed at `α ≈ 0.02`, where the accuracy remains stable for a while, then starts to decline more sharply.

We decide to pick `α ≈ 0.02` to be our potential optimal `α` even though it results in a slight accuracy loss compared to the previous model.

This is a **trade-off** of accepting a small loss in accuracy in exchange for a simpler, more interpretable tree and reduced overfitting.

Perform Cross Validation

One concern now is that our optimal `α` can be subjective to the specific split of training and testing dataset.

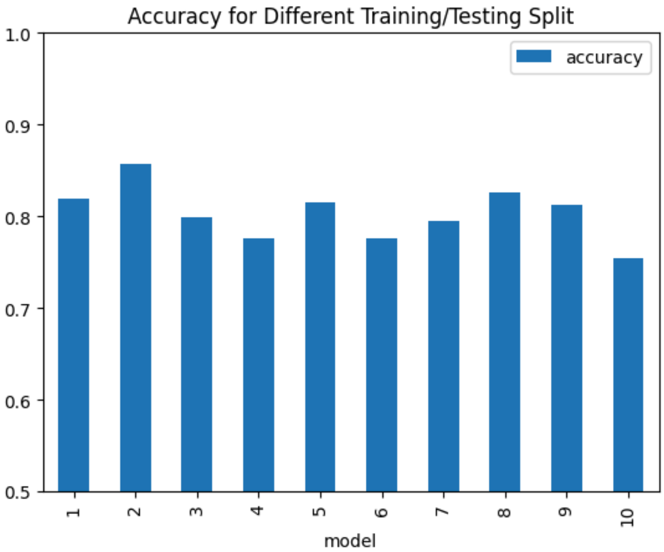
To investigate this, we use **10-fold Cross Validation** to demonstrate how different splits can result in varying accuracy for `α = 0.02`.

In [16]:
```
# Create the tree with alpha = 0.02
clf_dt = DecisionTreeClassifier(random_state=42, ccp_alpha=0.02)

# Perform 10-fold cross validation
scores = cross_val_score(clf_dt, X_train, y_train, cv=10, scoring='balanced_accuracy')

# Plot accuracy vs model
df = pd.DataFrame(data={'model': range(1,11), 'accuracy': scores})
df.plot.bar(x='model', y='accuracy', ylim=(0.5,1), title="Accuracy for Different Training/Testing Split")
```

Out[16]:
```
<Axes: title={'center': 'Accuracy for Different Training/Testing Split'}, xlabel='model'>
```

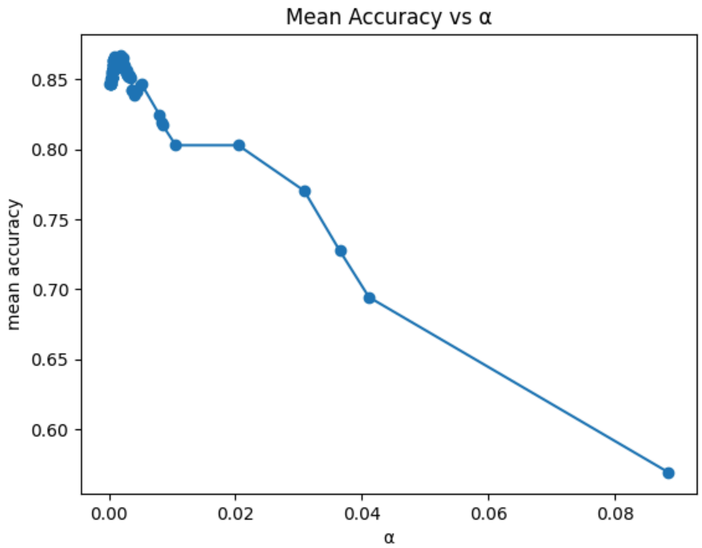


We can verify that accuracy varies depending on the training/testing split.

To account for this variability, we calculate the **mean accuracy** across the 10 models (from 10-fold Cross Validation) for each value of `α`.

In [13]:
```
# Perform cross validation for each α
mean_accuracy = []
for ccp_alpha in ccp_alphas:
    clf_dt = DecisionTreeClassifier(random_state=42, ccp_alpha=ccp_alpha)
    scores = cross_val_score(clf_dt, X_train, y_train, cv=10, scoring='balanced_accuracy')
    # Compute mean accuracy
    mean_accuracy.append(np.mean(scores))

# Plot mean accuracy vs alpha
plt.plot(ccp_alphas,mean_accuracy,marker='o')
plt.xlabel("α")
plt.ylabel("mean accuracy")
plt.title("Mean Accuracy vs α")
plt.show()
```



Here, we observe a similar pattern in the mean accuracy.

Therefore, we conclude that the elbow point at `α ≈ 0.02` is a reliable choice for our optimal `α`.

In [14]:
```
# Extract the optimal α
ccp_alpha_opt = ccp_alphas[(ccp_alphas > 0.02)][0]

print("Optimal α:", ccp_alpha_opt)
```

```
Optimal α: 0.02044896579510605
```

Build and Interpret the Final Classification Tree

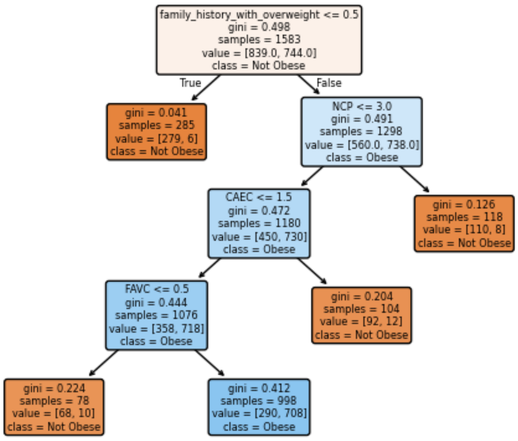
With our optimal `α` identified, we now build the final classification tree.

In [15]:
```
# Build tree with optimal α
clf_dt_pruned = DecisionTreeClassifier(random_state=42, ccp_alpha=ccp_alpha_opt)
clf_dt_pruned = clf_dt_pruned.fit(X_train, y_train)

# Plot the tree
plot_tree(clf_dt_pruned,
          filled=True,
          rounded=True,
          class_names=["Not Obese", "Obese"],
          feature_names=X.columns)

# Compute the balanced accuracy
print("Balanced Accuracy on Training Dataset:", balanced_accuracy_score(y_train, clf_dt_pruned.predict(X_train)))
print("Balanced Accuracy on Testing Dataset:", balanced_accuracy_score(y_test, clf_dt_pruned.predict(X_test)))
```

```
Balanced Accuracy on Training Dataset: 0.8029816601945481
Balanced Accuracy on Testing Dataset: 0.774298245614035
```



Interpretation:

We can interpret the decision path for predicting obesity in this tree as follows:

1. Has a family member suffered or suffers from overweight? (*family_history_with_overweight <= 0.5*)

   Yes -> Go to Step `2`

   No -> `Not Obese`

2. How many main meals do you have daily? (*NCP <= 3.0*)

   More than 3.0 -> `Not Obese`

   Otherwise -> Go to Step `3`

3. Do you eat any food between meals? (*CAEC <= 1.5*)

   (No, Sometimes) -> Go to Step `4`

   (Frequently, Always) -> `Not Obese`

4. Do you eat high caloric food frequently? (*FAVC <= 0.5*)

   Yes -> `Obese`

   No -> `Not Obese`

Observations:

- We were able to build a much more concise and interpretable tree with relatively high accuracy on both the training and testing datasets.
- The tree uses only four variables:
  - `family_history_with_overweight` (Has a family member suffered or suffers from overweight?)
  - `NCP` (How many main meals do you have daily?)
  - `CAEC` (Do you eat any food between meals?)
  - `FAVC` (Do you eat high caloric food frequently?)
- This highlights that **genetics** and **diet** are key factors in predicting obesity.
- Steps 2 and 3 yield somewhat unexpected results, suggesting that more frequent meals may contribute to a healthy weight.

Source

- StatQuest with Josh Starmer. (2020, June 6). *Classification Trees in Python from Start to Finish* [Video]. YouTube. https://youtu.be/q90UDEgYqeI