Assignment 5: Build and Evaluate Classification Models

Student: Abigail Albury-Bloom Focus: Multi-class obesity risk classification

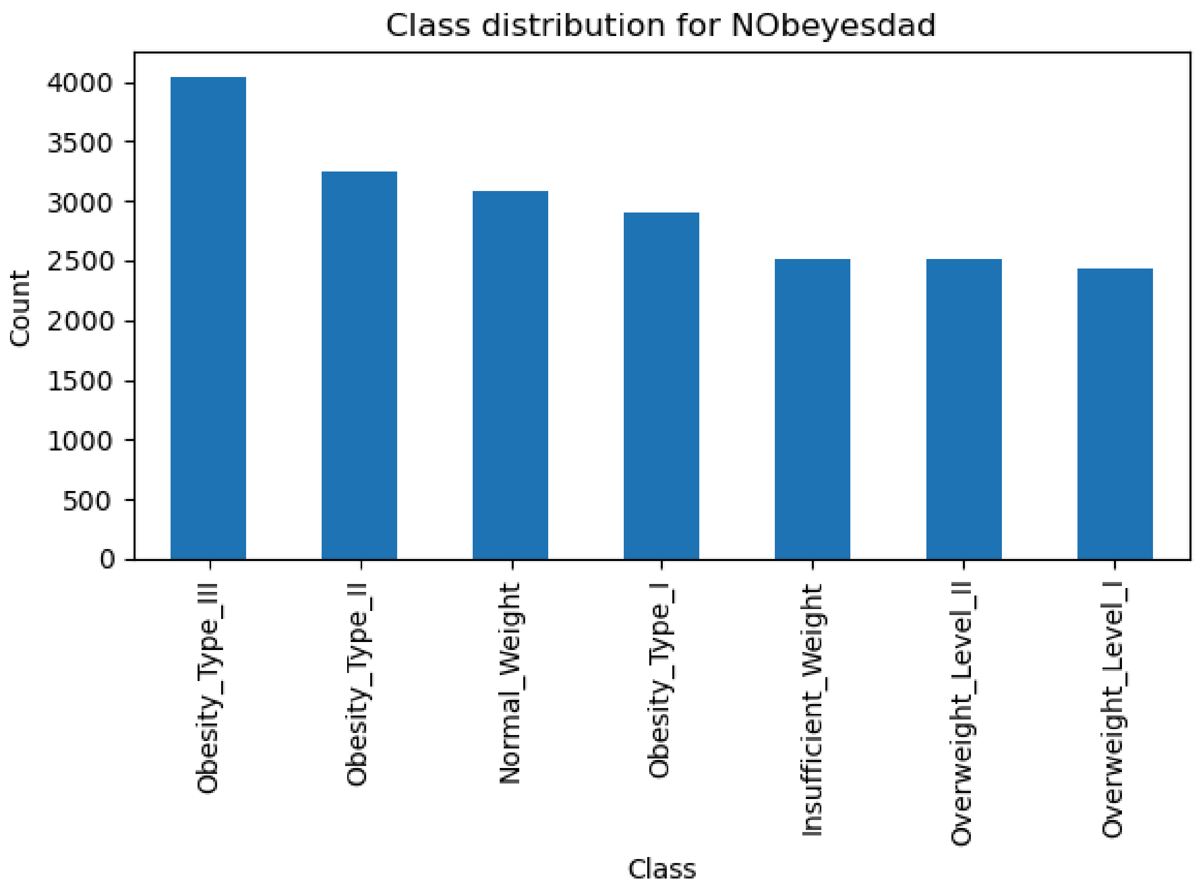
1. Data loading and basic structure

In [1]:
```python
import pandas as pd, numpy as np
from pathlib import Path

# Expect train.csv and test.csv in the same folder as this notebook
train = pd.read_csv(Path('train.csv'))
test = pd.read_csv(Path('test.csv'))
target = 'NObeyesdad'
X = train.drop(columns=[target, 'id'])
y = train[target]

print('Train shape:', train.shape)
print('Test shape:', test.shape)
print('Target classes:', y.unique())
```

```
Train shape: (20758, 18)
Test shape: (13840, 17)
Target classes: ['Overweight_Level_II' 'Normal_Weight' 'Insufficient_Weight'
 'Obesity_Type_III' 'Obesity_Type_II' 'Overweight_Level_I'
 'Obesity_Type_I']
```

2. Class distribution and feature summary

In [2]:
```python
import matplotlib.pyplot as plt

plt.figure()
y.value_counts().plot(kind='bar')
plt.title('Class distribution for NObeyesdad')
plt.xlabel('Class')
plt.ylabel('Count')
plt.tight_layout()
plt.show()

print('Numeric feature summary:')
display(X.select_dtypes(include=[np.number]).describe().T)
```



```
Numeric feature summary:
```

	count	mean	std	min	25%	50%	75%	
Age	20758.0	23.841804	5.688072	14.00	20.000000	22.815416	26.000000	61.0
Height	20758.0	1.700245	0.087312	1.45	1.631856	1.700000	1.762887	1.9
Weight	20758.0	87.887768	26.379443	39.00	66.000000	84.064875	111.600553	165.0
FCVC	20758.0	2.445908	0.533218	1.00	2.000000	2.393837	3.000000	3.0
NCP	20758.0	2.761332	0.705375	1.00	3.000000	3.000000	3.000000	4.0
CH2O	20758.0	2.029418	0.608467	1.00	1.792022	2.000000	2.549617	3.0
FAF	20758.0	0.981747	0.838302	0.00	0.008013	1.000000	1.587406	3.0
TUE	20758.0	0.616756	0.602113	0.00	0.000000	0.573887	1.000000	2.0

3. Feature types and preprocessing pipeline

In [3]:
```python
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler

numeric_cols = X.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = X.select_dtypes(exclude=[np.number]).columns.tolist()
print('Numeric columns:', numeric_cols)
print('Categorical columns:', categorical_cols)
```

```
preprocess = ColumnTransformer([
    ('num', StandardScaler(), numeric_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore', sparse_output=False), cat
])
```

```
Numeric columns: ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF',
'TUE']
Categorical columns: ['Gender', 'family_history_with_overweight', 'FAVC', 'C
AEC', 'SMOKE', 'SCC', 'CALC', 'MTRANS']
```

4. Cross-validated performance for four classifiers

In [4]:

```
from sklearn.pipeline import Pipeline
from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

base_models = {
    'Logistic_L2': LogisticRegression(penalty='l2', max_iter=1000),
    'LDA': LinearDiscriminantAnalysis(),
    'GaussianNB': GaussianNB(),
    'SVM_RBF': SVC(kernel='rbf', C=1, gamma='scale', decision_function_shape
}

cv_results = []
for name, clf in base_models.items():
    pipe = Pipeline([('pre', preprocess), ('clf', clf)])
    scores = cross_val_score(pipe, X, y, cv=cv, scoring='accuracy')
    cv_results.append({'Model': name, 'Mean_Accuracy': scores.mean(), 'Std_A
    print(f"{name}: {scores.mean():.4f} mean ± {scores.std():.4f} sd")
```

```
Logistic_L2: 0.8620 mean ± 0.0046 sd
LDA: 0.8207 mean ± 0.0032 sd
GaussianNB: 0.5874 mean ± 0.0053 sd
SVM_RBF: 0.8788 mean ± 0.0058 sd
```

5. Cross-validated accuracy comparison table

In [5]:

```
cv_df = pd.DataFrame(cv_results).sort_values(by='Mean_Accuracy', ascending=F
display(cv_df)
```

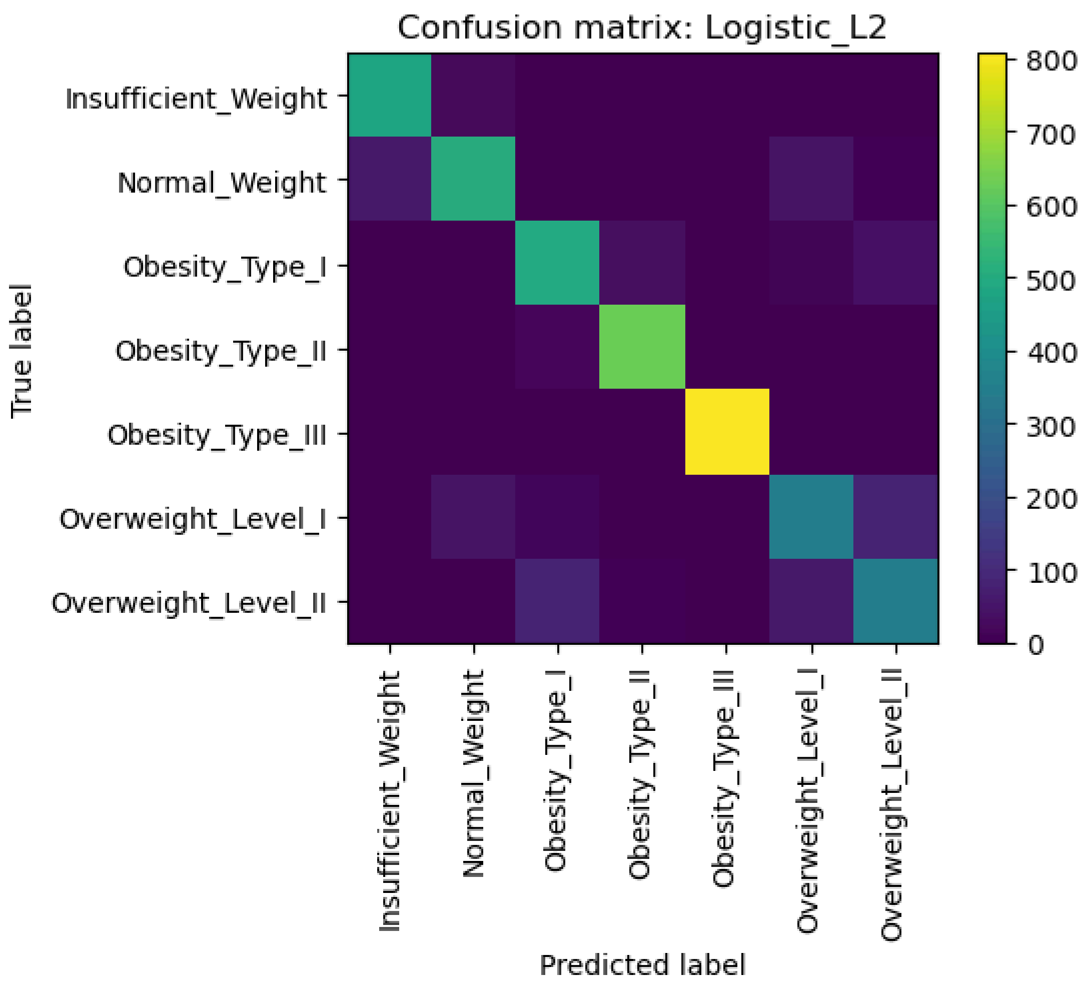
	Model	Mean_Accuracy	Std_Accuracy
0	SVM_RBF	0.878841	0.005776
1	Logistic_L2	0.862029	0.004608
2	LDA	0.820744	0.003238
3	GaussianNB	0.587388	0.005335

6. Holdout validation and confusion matrices

In [6]:
```python
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

validation_results = []
label_order = sorted(y.unique())

for name, clf in base_models.items():
    pipe = Pipeline([('pre', preprocess), ('clf', clf)])
    pipe.fit(X_train, y_train)
    preds = pipe.predict(X_val)
    acc = accuracy_score(y_val, preds)
    validation_results.append({'Model': name, 'Holdout_Accuracy': acc})
    print(f"\n{name} holdout accuracy: {acc:.4f}")
    cm = confusion_matrix(y_val, preds, labels=label_order)
    cm_df = pd.DataFrame(cm, index=label_order, columns=label_order)
    display(cm_df)

    # Confusion matrix heatmap for visuals
    plt.figure(figsize=(6, 5))
    plt.imshow(cm, interpolation='nearest')
    plt.title(f'Confusion matrix: {name}')
    plt.colorbar()
    tick_marks = range(len(label_order))
    plt.xticks(tick_marks, label_order, rotation=90)
    plt.yticks(tick_marks, label_order)
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
    plt.show()
```

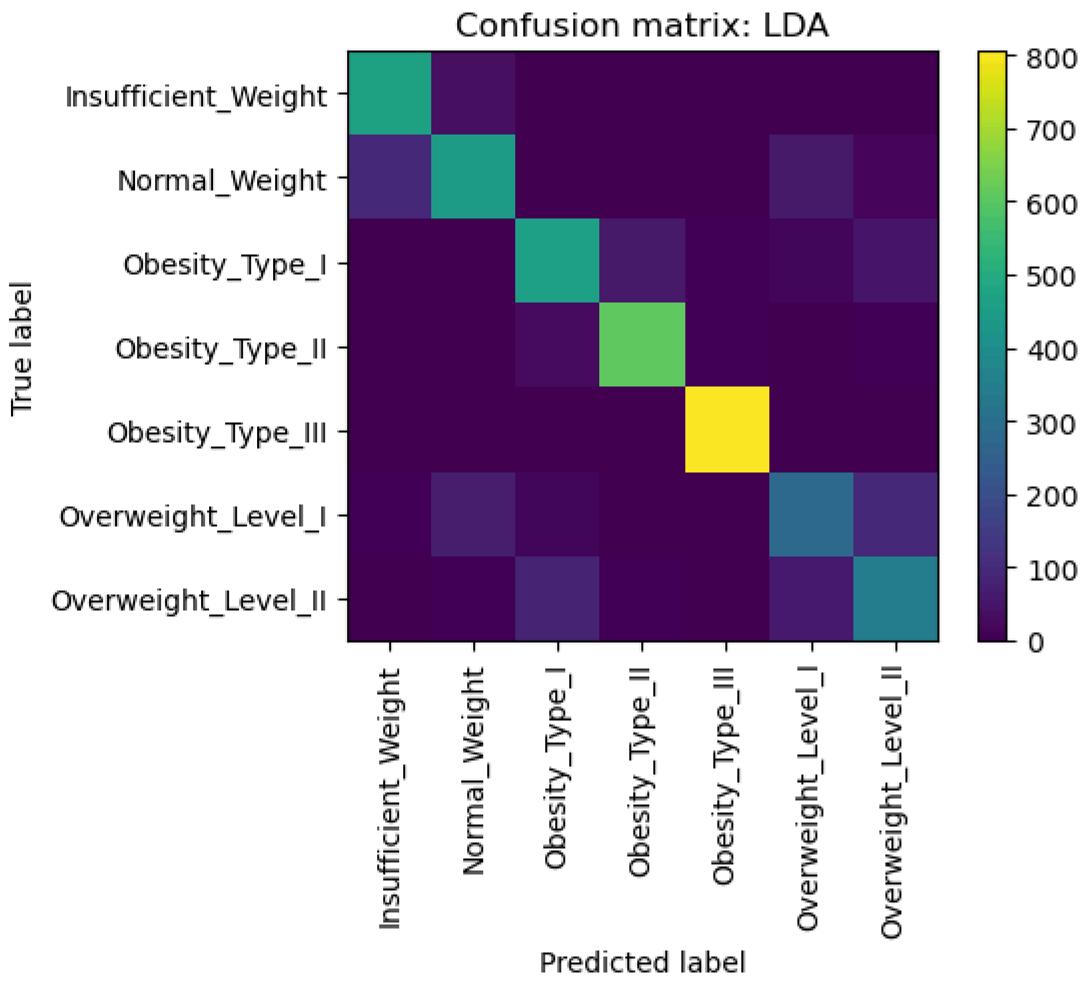
```
Logistic_L2 holdout accuracy: 0.8683
```

	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_
Insufficient_Weight	479	25	0	
Normal_Weight	58	505	2	
Obesity_Type_I	1	0	492	3
Obesity_Type_II	0	0	22	62
Obesity_Type_III	0	0	0	
Overweight_Level_I	1	46	15	
Overweight_Level_II	0	3	79	



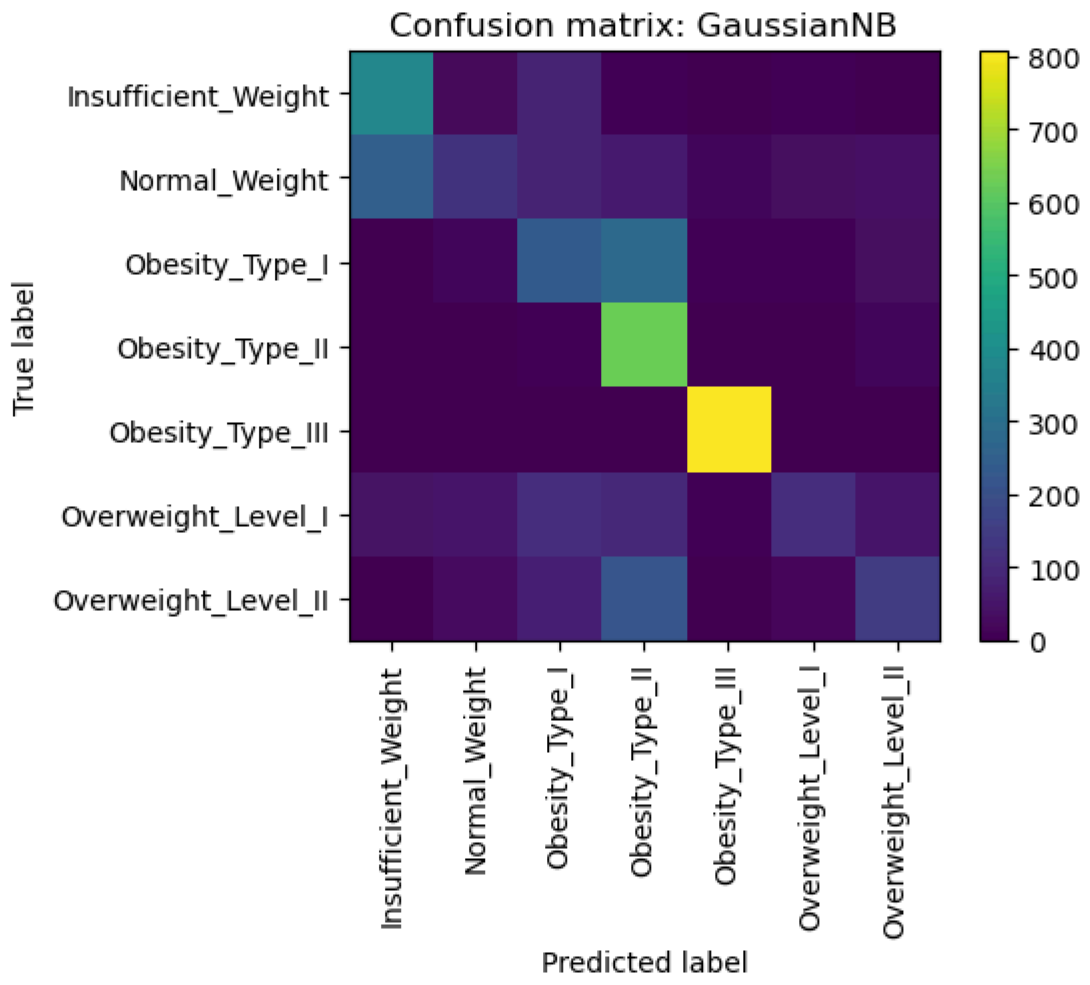
```
LDA holdout accuracy: 0.8230
```

	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_
Insufficient_Weight	470	33	0	
Normal_Weight	101	442	1	
Obesity_Type_I	1	1	456	5
Obesity_Type_II	0	0	29	6
Obesity_Type_III	0	0	1	
Overweight_Level_I	6	74	16	
Overweight_Level_II	0	9	82	



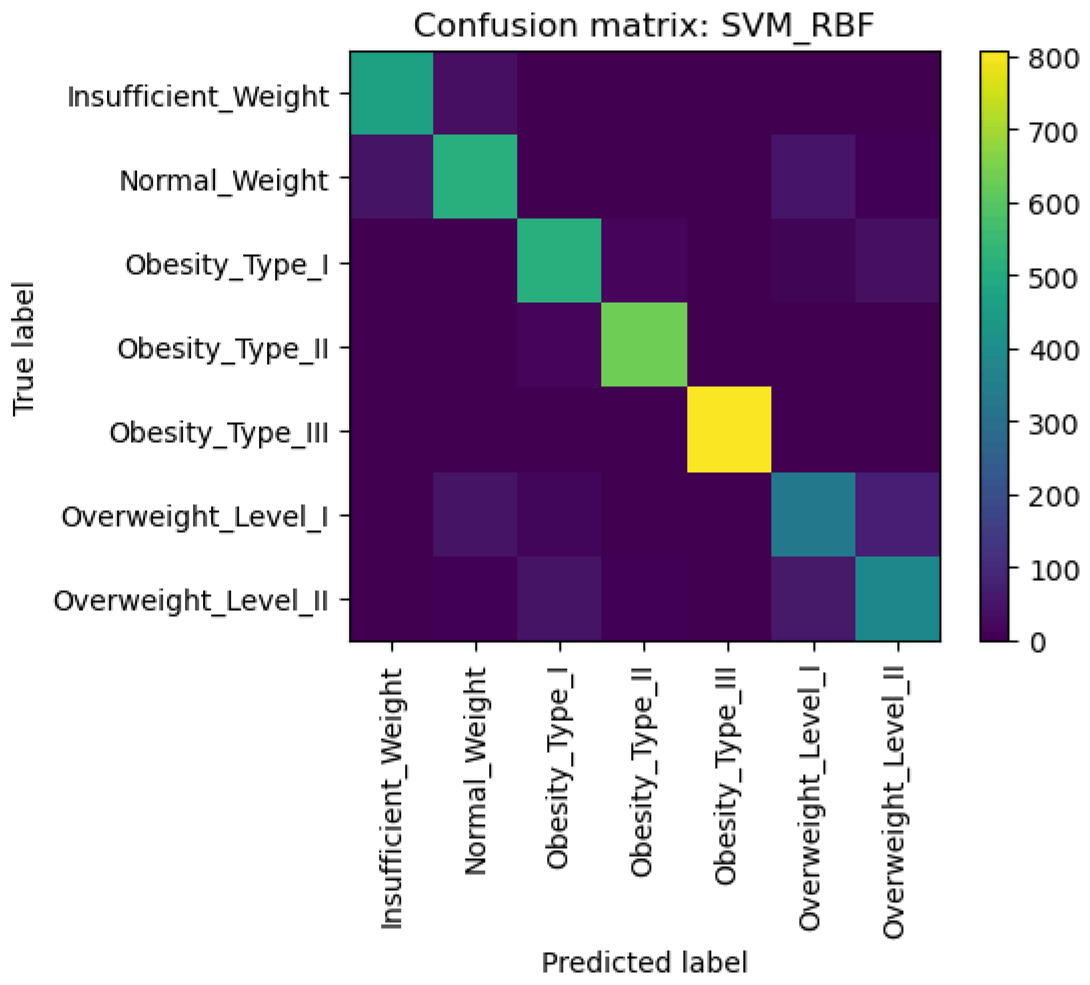
```
GaussianNB holdout accuracy: 0.5860
```

	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_
Insufficient_Weight	377	25	89	
Normal_Weight	257	123	82	6
Obesity_Type_I	1	17	239	27
Obesity_Type_II	0	2	5	62
Obesity_Type_III	0	1	0	
Overweight_Level_I	42	53	113	10
Overweight_Level_II	2	29	77	22



```
SVM_RBF holdout accuracy: 0.8810
```

	Insufficient_Weight	Normal_Weight	Obesity_Type_I	Obesity_Type_
Insufficient_Weight	472	32	0	
Normal_Weight	47	510	1	
Obesity_Type_I	1	0	513	2
Obesity_Type_II	0	0	19	63
Obesity_Type_III	0	0	2	
Overweight_Level_I	2	47	18	
Overweight_Level_II	0	6	47	



7. Holdout accuracy comparison table

In [7]:
```
holdout_df = pd.DataFrame(validation_results).sort_values(by='Holdout_Accura
display(holdout_df)
```

	Model	Holdout_Accuracy
0	SVM_RBF	0.881021
1	Logistic_L2	0.868256
2	LDA	0.822977
3	GaussianNB	0.585983

8. Train final models on full data and generate prediction files

In [8]:
```
final_predictions = {}
X_test_features = test.drop(columns=['id'])

for name, clf in base_models.items():
    pipe = Pipeline([('pre', preprocess), ('clf', clf)])
    pipe.fit(X, y)
    preds = pipe.predict(X_test_features)
    final_predictions[name] = preds
    out_df = pd.DataFrame({'id': test['id'], target: preds})
    out_name = f'submission_{name}.csv'
    out_df.to_csv(out_name, index=False)
    print(f'Saved {out_name}')
```

```
Saved submission_Logistic_L2.csv
Saved submission_LDA.csv
Saved submission_GaussianNB.csv
Saved submission_SVM_RBF.csv
```

1. Data loading and initial structure

In [9]:
```
import pandas as pd
import numpy as np
from pathlib import Path

# Expect train.csv, test.csv, and sample_submission.csv to be in the same fo
base_path = Path('.')
train_path = base_path / 'train.csv'
test_path = base_path / 'test.csv'
sample_path = base_path / 'sample_submission.csv'

train = pd.read_csv(train_path)
test = pd.read_csv(test_path)
sample = pd.read_csv(sample_path)

target = 'NObeyesdad'
X = train.drop(columns=[target, 'id'])
y = train[target]

X.head()
```

Out[9]:

	Gender	Age	Height	Weight	family_history_with_overweight	FAVC	
0	Male	24.443011	1.699998	81.669950	yes	yes	2.
1	Female	18.000000	1.560000	57.000000	yes	yes	2.
2	Female	18.000000	1.711460	50.165754	yes	yes	1.
3	Female	20.952737	1.710730	131.274851	yes	yes	3.
4	Male	31.641081	1.914186	93.798055	yes	yes	2.

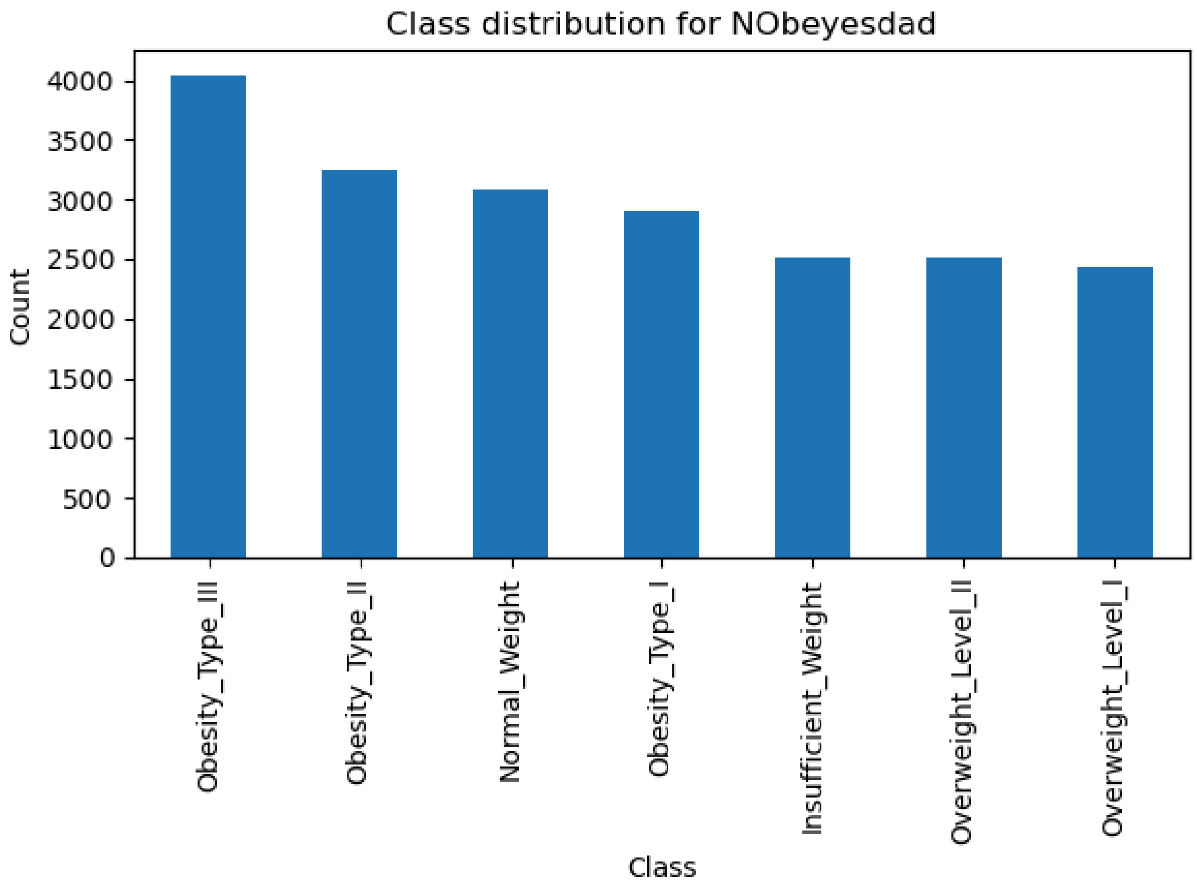
2. Feature types and preprocessing pipeline

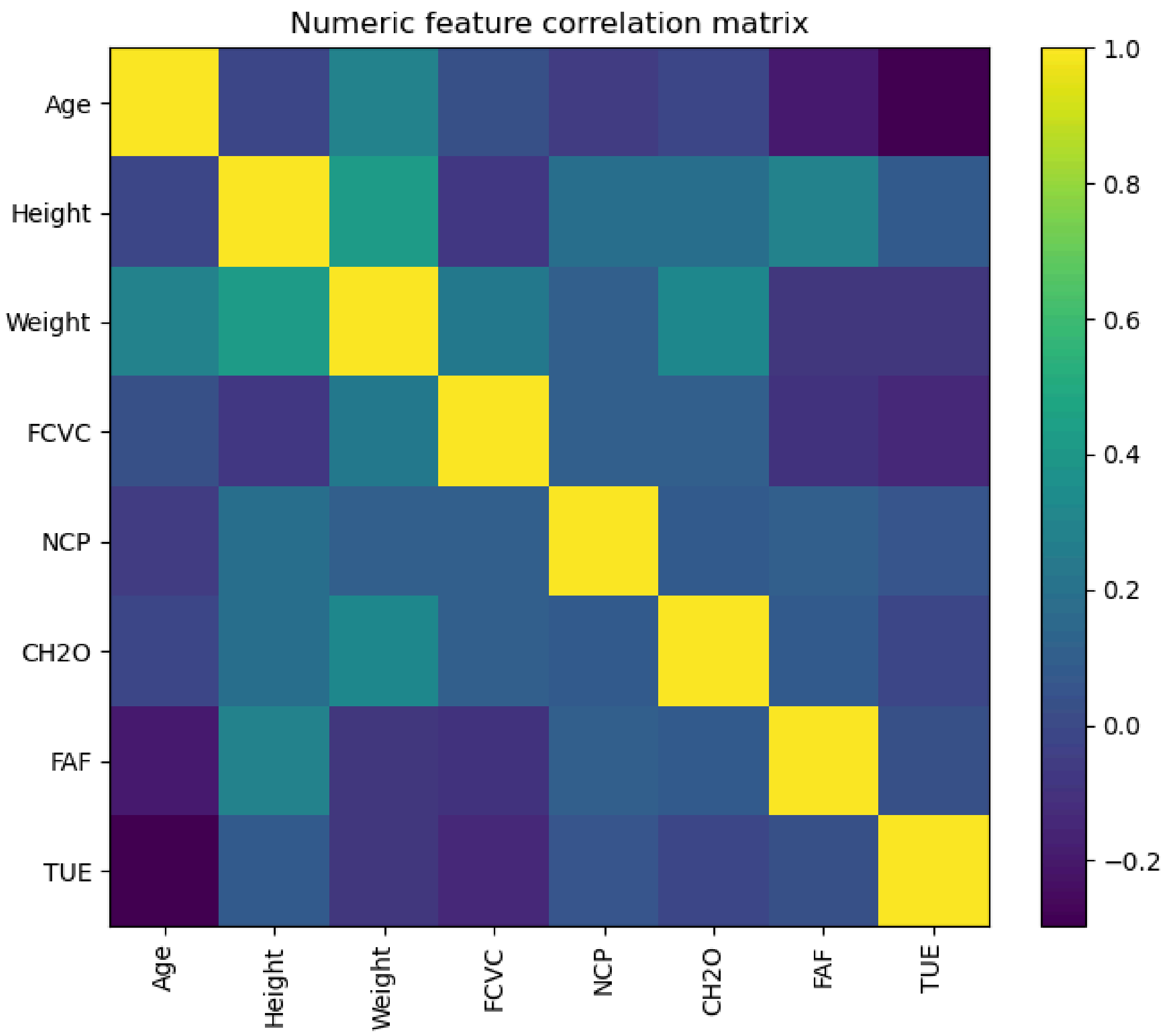
In [10]:
```
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import OneHotEncoder, StandardScaler
from sklearn.pipeline import Pipeline

numeric_cols = X.select_dtypes(include=[np.number]).columns.tolist()
categorical_cols = X.select_dtypes(exclude=[np.number]).columns.tolist()
print('Numeric columns:', numeric_cols)
print('Categorical columns:', categorical_cols)

preprocess = ColumnTransformer([
    ('num', StandardScaler(), numeric_cols),
    ('cat', OneHotEncoder(handle_unknown='ignore', sparse_output=False), cat
])
```

```
Numeric columns: ['Age', 'Height', 'Weight', 'FCVC', 'NCP', 'CH2O', 'FAF',
'TUE']
Categorical columns: ['Gender', 'family_history_with_overweight', 'FAVC', 'C
AEC', 'SMOKE', 'SCC', 'CALC', 'MTRANS']
```

3. Class distribution and numeric correlations

In [11]:
```
import matplotlib.pyplot as plt

# Class distribution
plt.figure()
train[target].value_counts().plot(kind='bar')
plt.title('Class distribution for NObeyesdad')
plt.xlabel('Class')
plt.ylabel('Count')
plt.tight_layout()
plt.show()

# Correlation heatmap for numeric features
corr = train[numeric_cols].corr()
plt.figure(figsize=(8, 6))
im = plt.imshow(corr, interpolation='nearest')
plt.title('Numeric feature correlation matrix')
plt.colorbar(im, fraction=0.046, pad=0.04)
plt.xticks(range(len(numeric_cols)), numeric_cols, rotation=90)
plt.yticks(range(len(numeric_cols)), numeric_cols)
plt.tight_layout()
plt.show()
```





4. Cross-validated model performance (four classifiers)

```
In [12]: from sklearn.model_selection import StratifiedKFold, cross_val_score
from sklearn.metrics import accuracy_score, confusion_matrix
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression

cv = StratifiedKFold(n_splits=5, shuffle=True, random_state=42)

def train_and_eval(name, model):
    pipe = Pipeline([('pre', preprocess), ('clf', model)])
    scores = cross_val_score(pipe, X, y, cv=cv, scoring='accuracy')
    print(f"{name}: {scores.mean():.4f} mean ± {scores.std():.4f} sd")
    pipe.fit(X, y)
    return pipe

# 1. Multinomial logistic regression with L2 regularization
logit_model = train_and_eval('Multinomial logistic regression (L2)', Logisti
```

```python
# 2. Linear Discriminant Analysis
lda_model = train_and_eval('Linear Discriminant Analysis', LinearDiscriminar

# 3. Gaussian Naive Bayes
nb_model = train_and_eval('Gaussian Naive Bayes', GaussianNB())

# 4. Support Vector Machine with RBF kernel
svm_model = train_and_eval('RBF-kernel Support Vector Machine', SVC(kernel='
```

```
Multinomial logistic regression (L2): 0.8620 mean ± 0.0046 sd
Linear Discriminant Analysis: 0.8207 mean ± 0.0032 sd
Gaussian Naive Bayes: 0.5874 mean ± 0.0053 sd
RBF-kernel Support Vector Machine: 0.8788 mean ± 0.0058 sd
```

5. Validation split and confusion matrices

In [13]:

```python
from sklearn.model_selection import train_test_split

X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.2, stratify=y, random_state=42
)

models_for_validation = [
    ('Multinomial logistic regression (L2)', LogisticRegression(penalty='l2'
    ('Linear Discriminant Analysis', LinearDiscriminantAnalysis()),
    ('Gaussian Naive Bayes', GaussianNB()),
    ('RBF-kernel Support Vector Machine', SVC(kernel='rbf', C=1, gamma='scal
]

for name, clf in models_for_validation:
    pipe = Pipeline([('pre', preprocess), ('clf', clf)])
    pipe.fit(X_train, y_train)
    preds = pipe.predict(X_val)
    acc = accuracy_score(y_val, preds)
    print(f"\n{name} validation accuracy: {acc:.4f}")
    cm = confusion_matrix(y_val, preds, labels=sorted(y.unique()))
    cm_df = pd.DataFrame(cm, index=sorted(y.unique()), columns=sorted(y.unic
    print(cm_df)
```

```
Multinomial logistic regression (L2) validation accuracy: 0.8683
                     Insufficient_Weight  Normal_Weight  Obesity_Type_I  \
Insufficient_Weight                  479             25               0
Normal_Weight                         58            505               2
Obesity_Type_I                         1              0             492
Obesity_Type_II                        0              0              22
Obesity_Type_III                       0              0               0
Overweight_Level_I                     1             46              15
Overweight_Level_II                    0              3              79

                     Obesity_Type_II  Obesity_Type_III  Overweight_Level_I
\
Insufficient_Weight                0                 0                   1
Normal_Weight                      0                 0                  43
Obesity_Type_I                    37                 3                  11
Obesity_Type_II                  625                 0                   0
Obesity_Type_III                   1               807                   1
Overweight_Level_I                 0                 0                 342
Overweight_Level_II                8                 0                  59

                     Overweight_Level_II
Insufficient_Weight                    0
Normal_Weight                          9
Obesity_Type_I                        38
Obesity_Type_II                        3
Obesity_Type_III                       0
Overweight_Level_I                    81
Overweight_Level_II                  355

Linear Discriminant Analysis validation accuracy: 0.8230
                     Insufficient_Weight  Normal_Weight  Obesity_Type_I  \
Insufficient_Weight                  470             33               0
Normal_Weight                        101            442               1
Obesity_Type_I                         1              1             456
Obesity_Type_II                        0              0              29
Obesity_Type_III                       0              0               1
Overweight_Level_I                     6             74              16
Overweight_Level_II                    0              9              82

                     Obesity_Type_II  Obesity_Type_III  Overweight_Level_I
\
Insufficient_Weight                0                 0                   1
Normal_Weight                      0                 0                  54
Obesity_Type_I                    54                 7                  13
Obesity_Type_II                  612                 5                   0
Obesity_Type_III                   2               805                   1
Overweight_Level_I                 0                 0                 289
Overweight_Level_II                4                 0                  66

                     Overweight_Level_II
Insufficient_Weight                    1
Normal_Weight                         19
Obesity_Type_I                        50
Obesity_Type_II                        4
Obesity_Type_III                       0
Overweight_Level_I                   100
```

```
Overweight_Level_II                 343

Gaussian Naive Bayes validation accuracy: 0.5860
                    Insufficient_Weight  Normal_Weight  Obesity_Type_I  \
Insufficient_Weight                 377             25              89   
Normal_Weight                       257            123              82   
Obesity_Type_I                        1             17             239   
Obesity_Type_II                       0              2               5   
Obesity_Type_III                      0              1               0   
Overweight_Level_I                   42             53             113   
Overweight_Level_II                   2             29              77   

                    Obesity_Type_II  Obesity_Type_III  Overweight_Level_I  
\
Insufficient_Weight                4                 2                   5   
Normal_Weight                     61                17                  37   
Obesity_Type_I                   275                 5                   9   
Obesity_Type_II                  624                 0                   3   
Obesity_Type_III                   1               806                   1   
Overweight_Level_I               103                 9                 114   
Overweight_Level_II              223                 1                  22   

                    Overweight_Level_II  
Insufficient_Weight                   3  
Normal_Weight                        40  
Obesity_Type_I                       36  
Obesity_Type_II                      16  
Obesity_Type_III                      0  
Overweight_Level_I                   51  
Overweight_Level_II                 150  

RBF-kernel Support Vector Machine validation accuracy: 0.8810
                    Insufficient_Weight  Normal_Weight  Obesity_Type_I  \
Insufficient_Weight                 472             32               0   
Normal_Weight                        47            510               1   
Obesity_Type_I                        1              0             513   
Obesity_Type_II                       0              0              19   
Obesity_Type_III                      0              0               2   
Overweight_Level_I                    2             47              18   
Overweight_Level_II                   0              6              47   

                    Obesity_Type_II  Obesity_Type_III  Overweight_Level_I  
\
Insufficient_Weight                0                 0                   1   
Normal_Weight                      0                 0                  51   
Obesity_Type_I                    21                 3                  12   
Obesity_Type_II                  630                 0                   0   
Obesity_Type_III                   1               806                   0   
Overweight_Level_I                 1                 0                 340   
Overweight_Level_II                6                 0                  58   

                    Overweight_Level_II  
Insufficient_Weight                   0  
Normal_Weight                         8  
Obesity_Type_I                       32  
Obesity_Type_II                       1  
```

```
Obesity_Type_III                0
Overweight_Level_I             77
Overweight_Level_II           387
```

6. Generate prediction files for all four models

In [14]:
```
# Fit each model on the full training data and generate prediction files
logit_pipe = Pipeline([('pre', preprocess), ('clf', LogisticRegression(penal
lda_pipe = Pipeline([('pre', preprocess), ('clf', LinearDiscriminantAnalysis
nb_pipe = Pipeline([('pre', preprocess), ('clf', GaussianNB())])
svm_pipe = Pipeline([('pre', preprocess), ('clf', SVC(kernel='rbf', C=1, gam

logit_pipe.fit(X, y)
lda_pipe.fit(X, y)
nb_pipe.fit(X, y)
svm_pipe.fit(X, y)

logit_preds = logit_pipe.predict(test.drop(columns=['id']))
lda_preds = lda_pipe.predict(test.drop(columns=['id']))
nb_preds = nb_pipe.predict(test.drop(columns=['id']))
svm_preds = svm_pipe.predict(test.drop(columns=['id']))

pd.DataFrame({'id': test['id'], target: logit_preds}).to_csv('submission_log
pd.DataFrame({'id': test['id'], target: lda_preds}).to_csv('submission_lda.c
pd.DataFrame({'id': test['id'], target: nb_preds}).to_csv('submission_gaussi
pd.DataFrame({'id': test['id'], target: svm_preds}).to_csv('submission_svm_r

print('Prediction files generated:')
print(' - submission_logistic_l2.csv')
print(' - submission_lda.csv')
print(' - submission_gaussian_nb.csv')
print(' - submission_svm_rbf.csv')
```

```
Prediction files generated:
 - submission_logistic_l2.csv
 - submission_lda.csv
 - submission_gaussian_nb.csv
 - submission_svm_rbf.csv
```