AIT 511 — MACHINE LEARNING PROJECT

TOPIC: OBESITY RISK PREDICTION (KAGGLE)

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Upload Dataset

```
#Obesity Risk Prediction
from google.colab import files
uploaded = files.upload()
```

Choose Files 3 files
sample_submission.csv(text/csv) - 276818 bytes, last modified: 9/28/2025 - 100% done
test.csv(text/csv) - 606882 bytes, last modified: 9/28/2025 - 100% done
train.csv(text/csv) - 2036684 bytes, last modified: 9/28/2025 - 100% done

```
Saving sample_submission.csv to sample_submission.csv
Saving test.csv to test.csv
Saving train.csv to train.csv
```

Load Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from xgboost import XGBClassifier
import warnings
warnings.filterwarnings('ignore')
```

Load Data

```
train = pd.read_csv("train.csv")# Reading training and test data
test = pd.read_csv("test.csv")
test_ids = test["id"]# Keeping test IDs for final submission
# Removing ID column from train and test
train = train.drop(columns=['id'])
test = test.drop(columns=['id'])
```

DATA shape and Basic Overview of data

```
print("Train shape:", train.shape)
print("Test shape:", test.shape)
print("\nColumns:", train.columns.tolist())
print("\nMissing values:\n", train.isnull().sum())
```

```
Train shape: (15533, 18)
Test shape: (5225, 17)

Columns: ['id', 'Gender', 'Age', 'Height', 'Weight', 'family_history_with_overweight', 'FAVC', 'FCVC', 'NCP', 'CAEC', 'SMOKE', 'CH

Missing values:
 id                               0
Gender                            0
Age                               0
Height                            0
Weight                            0
family_history_with_overweight    0
FAVC                              0
FCVC                              0
NCP                               0
CAEC                              0
SMOKE                             0
CH2O                              0
SCC                               0
FAF                               0
TUE                               0
CALC                              0
MTRANS                            0
WeightCategory                    0
dtype: int64
```

```
train.head()
```

	id	Gender	Age	Height	Weight	family_history_with_overweight	FAVC	FCVC	NCP	CAEC	SMOKE	CH2O	SCC	
0	0	Male	24.443011	1.699998	81.669950	yes	yes	2.000000	2.983297	Sometimes	no	2.763573	no	0.0
1	1	Female	18.000000	1.560000	57.000000	yes	yes	2.000000	3.000000	Frequently	no	2.000000	no	1.0
2	2	Female	18.000000	1.711460	50.165754	yes	yes	1.880534	1.411685	Sometimes	no	1.910378	no	0.8
3	3	Female	20.952737	1.710730	131.274851	yes	yes	3.000000	3.000000	Sometimes	no	1.674061	no	1.4
4	4	Male	31.641081	1.914186	93.798055	yes	yes	2.679664	1.971472	Sometimes	no	1.979848	no	1.9

Next steps: Generate code with train   New interactive sheet

Exploratory Data Analysis(EDA)

Data Preprocessing

```
# Converting Yes/No columns to 1/0
yes_no_cols = ['family_history_with_overweight', 'FAVC', 'SMOKE', 'SCC']
for col in yes_no_cols:
    train[col] = train[col].map({'yes': 1, 'no': 0})
    test[col] = test[col].map({'yes': 1, 'no': 0})
```

```
# Frequency-type categorical mapping
mapping = {'no': 0, 'Sometimes': 1, 'Frequently': 2, 'Always': 3}
for col in ['CAEC', 'CALC']:
    train[col] = train[col].map(mapping)
    test[col] = test[col].map(mapping)
```

```
# Encode transport column (MTRANS)
le_mtrans = LabelEncoder()
combined_transport = pd.concat([train['MTRANS'], test['MTRANS']], axis=0)
le_mtrans.fit(combined_transport)
train['MTRANS'] = le_mtrans.transform(train['MTRANS'])
test['MTRANS'] = le_mtrans.transform(test['MTRANS'])
```

```
# Encode target
le_weight = LabelEncoder()
train['WeightCategory'] = le_weight.fit_transform(train['WeightCategory'])
print("\ncomplete!")
```

```
complete!
```

Train–Validation Split

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt

```

```
# Separating input and target
X = train.drop(columns=['WeightCategory'])
y = train['WeightCategory']

# Spliting into train and validation sets
X_train, X_val, y_train, y_val = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
print(f"Train size: {X_train.shape}, Validation size: {X_val.shape}")

```

```
Train size: (12426, 17), Validation size: (3107, 17)
```

```
# Encode categorical columns
for col in X_train.select_dtypes(include='object').columns:
    le = LabelEncoder()
    X_train[col] = le.fit_transform(X_train[col])
    X_val[col] = le.transform(X_val[col])
```

XGBoost Parameters

```
#  Defining refined XGBoost parameters

refined_params = {
    'objective': 'multi:softmax',   # multi-class classification
    'num_class': len(np.unique(y)), # number of output categories
```

```python
    'eval_metric': 'mlogloss',      # loss function to evaluate
    'use_label_encoder': False,     # avoid old warnings
    'tree_method': 'hist',          # fast histogram-based algorithm
    'grow_policy': 'lossguide',     # builds deeper trees efficiently
    'random_state': 42,             # for reproducibility

    # Fine-tuned hyperparameters
    'learning_rate': 0.021,         # how fast model learns (lower = slower, more stable)
    'max_depth': 6,                 # max depth of each tree
    'min_child_weight': 2,          # minimum data in a leaf
    'subsample': 0.71,              # fraction of training data per tree
    'colsample_bytree': 0.74,       # fraction of features per tree
    'gamma': 0.8,                   # controls overfitting
    'reg_lambda': 2.4,              # L2 regularization
    'reg_alpha': 0.22,              # L1 regularization
    'max_bin': 290                  # how fine-grained histogram splits are
}
```

```python
from xgboost import XGBClassifier
from sklearn.metrics import accuracy_score
best_acc = 0.0  # Manual early stopping
best_n = None
best_model = None
accuracy_scores = []
```

```python
refined_params.pop('n_estimators', None)

n_estimator_values = [900, 1000, 1100, 1200, 1220, 1230, 1250, 1270, 1300, 1400]
# Loop through different n_estimators values
for n in n_estimator_values:
    temp_model = XGBClassifier(**refined_params, n_estimators=n)
    temp_model.fit(X_train, y_train)

    preds = temp_model.predict(X_val)
    acc = accuracy_score(y_val, preds)
    accuracy_scores.append(acc)

    print(f"n_estimators={n} → Validation Accuracy: {acc*100:.3f}%")

     # Keep track of best performing model
    if acc > best_acc:
        best_acc = acc
        best_n = n
        best_model = temp_model

print(f"\n=== Best Model Summary ===")
print(f"Best Validation Accuracy: {best_acc*100:.3f}%")
print(f"Best n_estimators: {best_n}")

```

```
n_estimators=900 → Validation Accuracy: 90.441%
n_estimators=1000 → Validation Accuracy: 90.409%
n_estimators=1100 → Validation Accuracy: 90.505%
n_estimators=1200 → Validation Accuracy: 90.473%
n_estimators=1220 → Validation Accuracy: 90.441%
n_estimators=1230 → Validation Accuracy: 90.473%
n_estimators=1250 → Validation Accuracy: 90.505%
n_estimators=1270 → Validation Accuracy: 90.441%
n_estimators=1300 → Validation Accuracy: 90.409%
n_estimators=1400 → Validation Accuracy: 90.473%

=== Best Model Summary ===
Best Validation Accuracy: 90.505%
Best n_estimators: 1100
```

Retrain Final Model on Full Data

```python
from sklearn.preprocessing import LabelEncoder
from xgboost import XGBClassifier

# Make a copy of X to avoid modifying original dataframe
X_full = X.copy()
y_full = y.copy()

# Encode categorical columns
for col in X_full.select_dtypes(include='object').columns:
    le = LabelEncoder()
    X_full[col] = le.fit_transform(X_full[col])

# Add best n_estimators to parameters
refined_params['n_estimators'] = best_n

# Train final model on full dataset
final_model = XGBClassifier(**refined_params)
final_model.fit(X_full, y_full)
```

```
▾                                XGBClassifier
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=0.74, device=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric='mlogloss',
              feature_types=None, feature_weights=None, gamma=0.8,
              grow_policy='lossguide', importance_type=None,
              interaction_constraints=None, learning_rate=0.021, max_bin=290,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=6, max_leaves=None,
              min_child_weight=2, missing=nan, monotone_constraints=None,
              multi_strategy=None, n_estimators=1100, n_jobs=None, num_class=7, ...)
```

Predictions on Test Set

```python
# Make a copy of the test set
X_test = test.copy()

# Encode categorical columns in test set
for col in X_test.select_dtypes(include='object').columns:
    le = LabelEncoder()
    # Fit-transform on training data, transform on test
    # Here, we assume you have stored the mapping from training
    # If not, simplest is to fit on test too (may cause mismatch)
    X_test[col] = le.fit_transform(X_test[col])

# Predict on test data
test_preds = final_model.predict(X_test)

# Decode labels back to original
pred_labels = le_weight.inverse_transform(test_preds)

# Prepare submission
submission = pd.DataFrame({
    "id": test_ids,
    "WeightCategory": pred_labels
})

submission.to_csv("submission_final.csv", index=False)
print("Submission saved successfully")

```

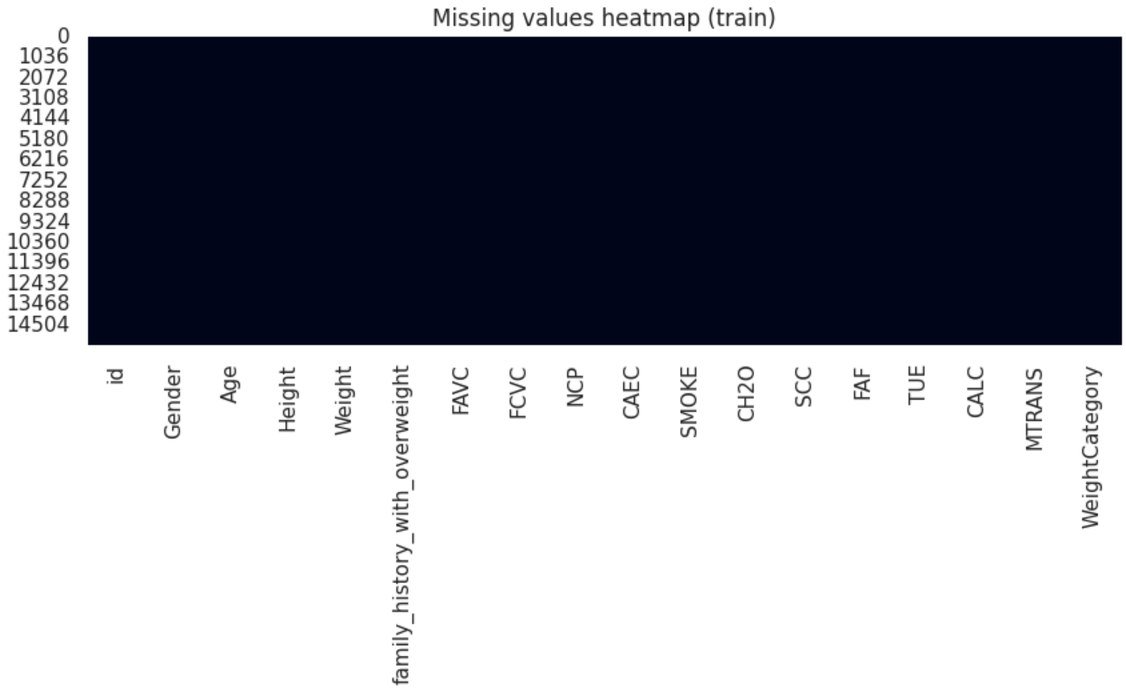
```
Submission saved successfully
```

```python
from google.colab import files
files.download("submission_final.csv")
```

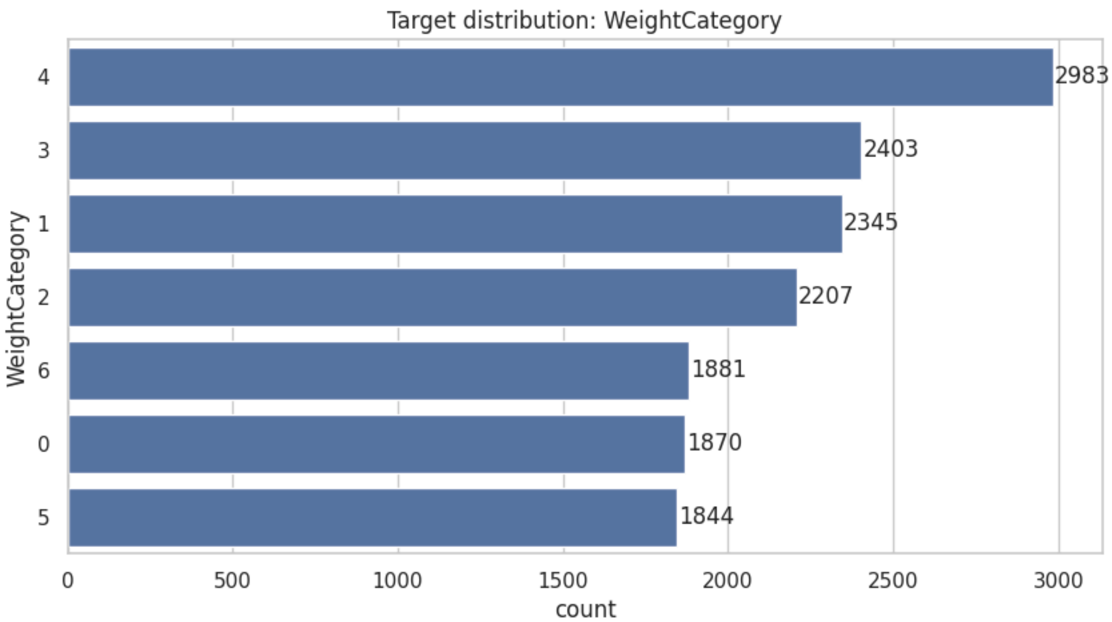
```python
sns.set(style='whitegrid')

print("\n========= BASIC INFO =========")
print("Train shape:", train.shape)
print("Test shape:", test.shape)
display(train.info())
```

```
========= BASIC INFO =========
Train shape: (15533, 18)
Test shape: (5225, 17)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15533 entries, 0 to 15532
Data columns (total 18 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   id                              15533 non-null  int64
 1   Gender                          15533 non-null  object
 2   Age                             15533 non-null  float64
 3   Height                          15533 non-null  float64
 4   Weight                          15533 non-null  float64
 5   family_history_with_overweight  15533 non-null  int64
 6   FAVC                            15533 non-null  int64
 7   FCVC                            15533 non-null  float64
 8   NCP                             15533 non-null  float64
 9   CAEC                            15533 non-null  int64
 10  SMOKE                           15533 non-null  int64
 11  CH2O                            15533 non-null  float64
 12  SCC                             15533 non-null  int64
 13  FAF                             15533 non-null  float64
 14  TUE                             15533 non-null  float64
 15  CALC                            15533 non-null  int64
 16  MTRANS                          15533 non-null  int64
 17  WeightCategory                  15533 non-null  int64
dtypes: float64(8), int64(9), object(1)
memory usage: 2.1+ MB
None
```

```python
# Missing values
plt.figure(figsize=(10,3))
sns.heatmap(train.isnull(), cbar=False)
plt.title("Missing values heatmap (train)")
plt.show()
```




```python
# Target distribution
target_col = 'WeightCategory'
plt.figure(figsize=(10,5))
order = train[target_col].value_counts().index
ax = sns.countplot(y=target_col, data=train, order=order)
plt.title("Target distribution: WeightCategory")
for p in ax.patches:
    ax.text(p.get_width()+5, p.get_y()+p.get_height()/2,
            int(p.get_width()), va='center')
plt.show()

```

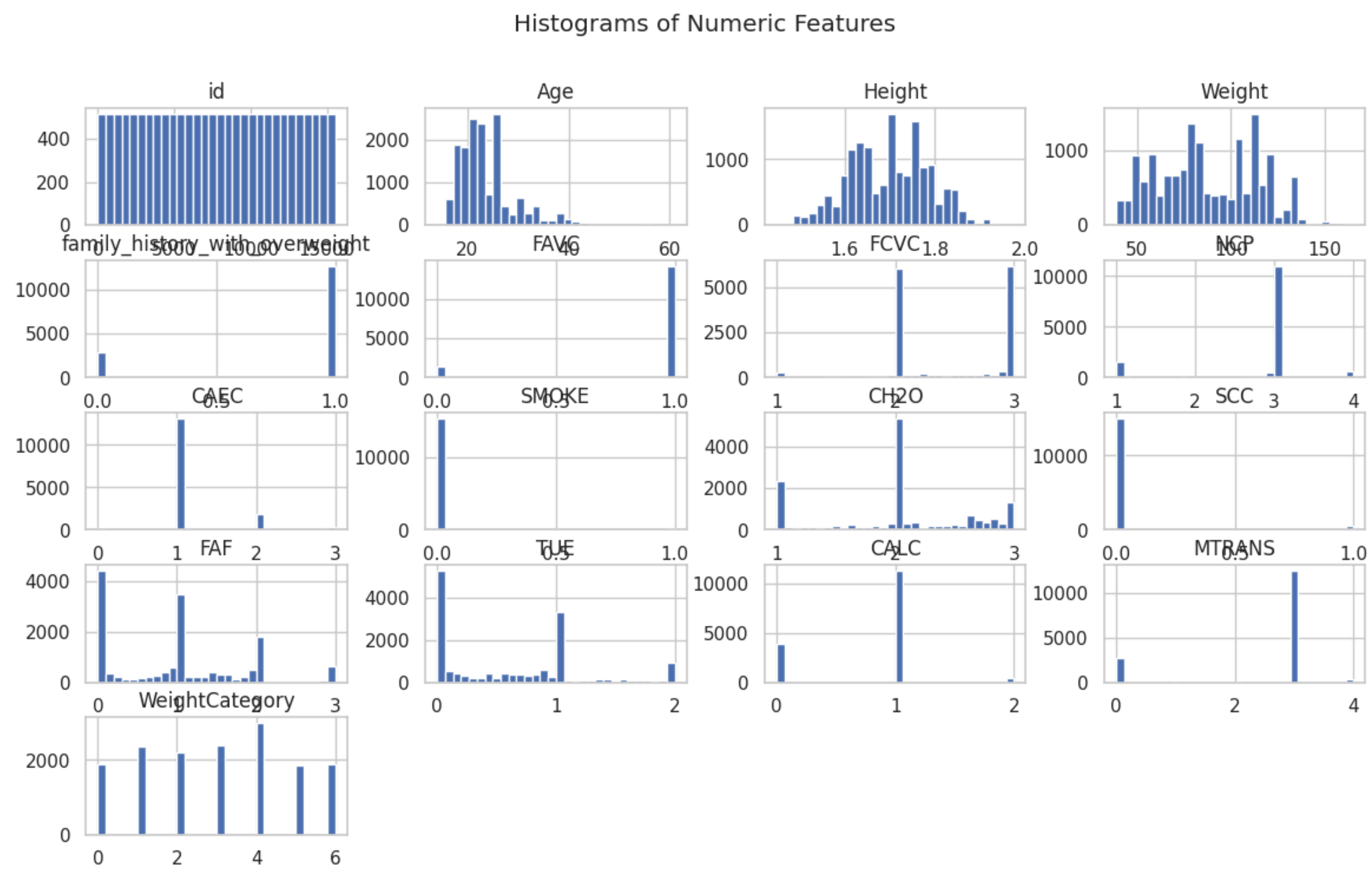



```python

print("\nTarget Class Percentages:")
print((train[target_col].value_counts(normalize=True)*100).round(2))

# Numeric summary
numeric_cols = train.select_dtypes(include=[np.number]).columns.tolist()
display(train[numeric_cols].describe().T)
```

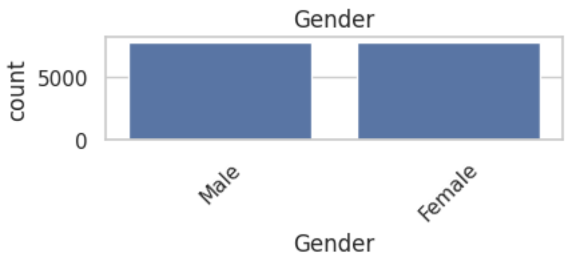
```
Target Class Percentages:
WeightCategory
4    19.20
3    15.47
1    15.10
2    14.21
6    12.11
0    12.04
5    11.87
Name: proportion, dtype: float64
```

	count	mean	std	min	25%	50%	75%	max
id	15533.0	7766.000000	4484.135201	0.00	3883.000000	7766.000000	11649.000000	15532.000000
Age	15533.0	23.816308	5.663167	14.00	20.000000	22.771612	26.000000	61.000000
Height	15533.0	1.699918	0.087670	1.45	1.630927	1.700000	1.762921	1.975663
Weight	15533.0	87.785225	26.369144	39.00	66.000000	84.000000	111.600553	165.057269
family_history_with_overweight	15533.0	0.817357	0.386386	0.00	1.000000	1.000000	1.000000	1.000000
FAVC	15533.0	0.913153	0.281620	0.00	1.000000	1.000000	1.000000	1.000000
FCVC	15533.0	2.442917	0.530895	1.00	2.000000	2.342220	3.000000	3.000000
NCP	15533.0	2.760425	0.706463	1.00	3.000000	3.000000	3.000000	4.000000
CAEC	15533.0	1.151098	0.446058	0.00	1.000000	1.000000	1.000000	3.000000
SMOKE	15533.0	0.011395	0.106141	0.00	0.000000	0.000000	0.000000	1.000000
CH2O	15533.0	2.027626	0.607733	1.00	1.796257	2.000000	2.531456	3.000000
SCC	15533.0	0.033091	0.178880	0.00	0.000000	0.000000	0.000000	1.000000
FAF	15533.0	0.976968	0.836841	0.00	0.007050	1.000000	1.582675	3.000000
TUE	15533.0	0.613813	0.602223	0.00	0.000000	0.566353	1.000000	2.000000
CALC	15533.0	0.778922	0.473942	0.00	1.000000	1.000000	1.000000	2.000000
MTRANS	15533.0	2.501384	1.152353	0.00	3.000000	3.000000	3.000000	4.000000
WeightCategory	15533.0	2.987575	1.893756	0.00	1.000000	3.000000	4.000000	6.000000

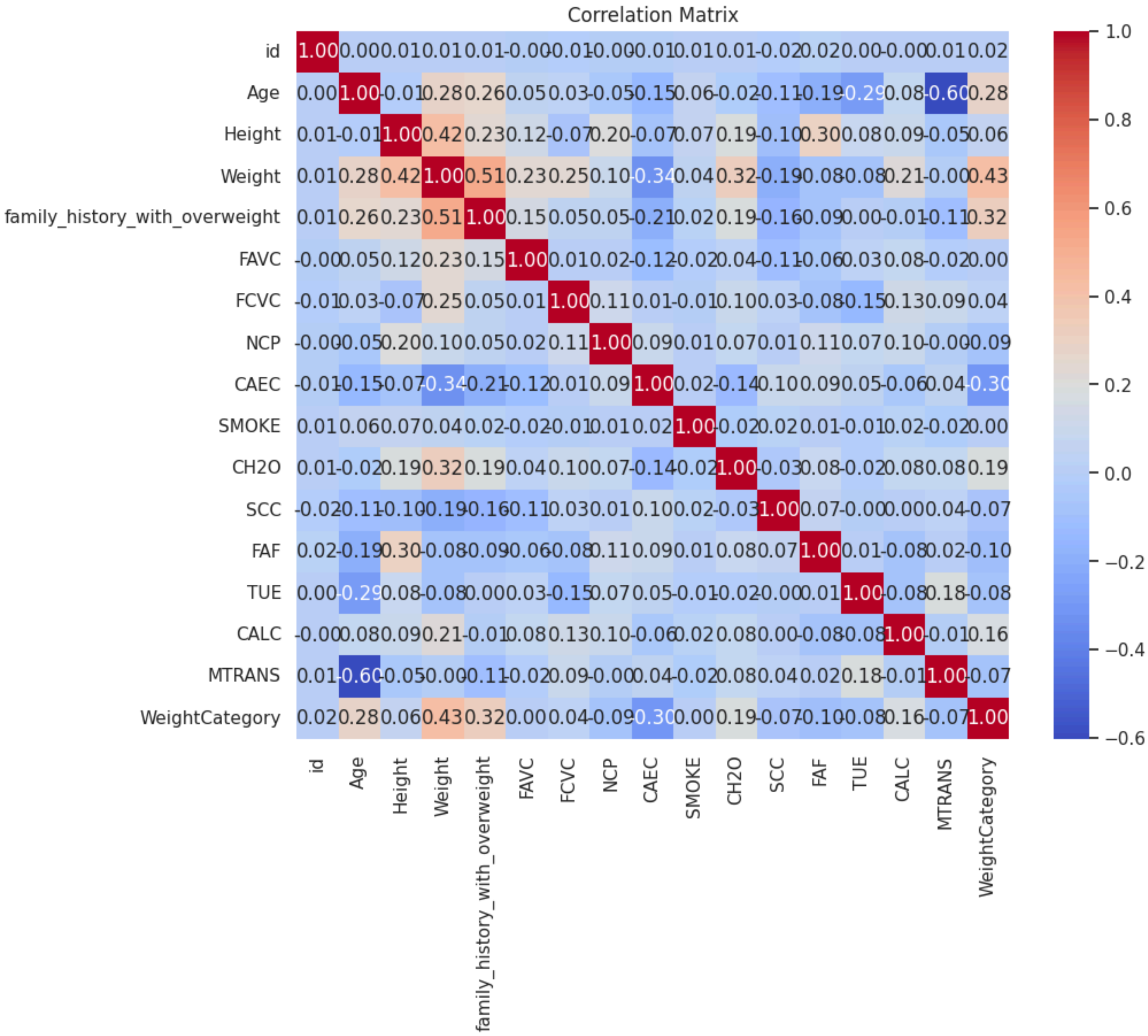
```
1 # Histograms
2 train[numeric_cols].hist(bins=30, figsize=(14,8))
3 plt.suptitle("Histograms of Numeric Features")
4 plt.show()
```



```python
# Categorical feature distributions
cat_cols = train.select_dtypes(include=['object']).columns.tolist()
if cat_cols:
    plt.figure(figsize=(15,4*len(cat_cols)//3))
    for i, c in enumerate(cat_cols, 1):
        plt.subplot((len(cat_cols)+2)//3, 3, i)
        sns.countplot(x=c, data=train, order=train[c].value_counts().index)
        plt.title(c)
        plt.xticks(rotation=45)
    plt.tight_layout()
    plt.show()
```

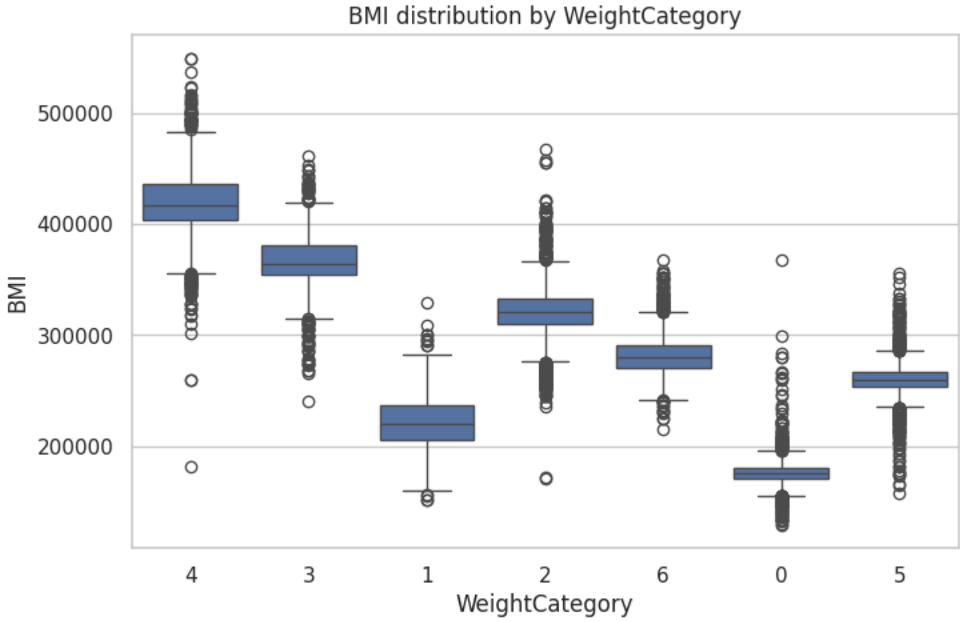



```python
# Correlation matrix
plt.figure(figsize=(10,8))
sns.heatmap(train[numeric_cols].corr(), annot=True, fmt=".2f", cmap="coolwarm")
plt.title("Correlation Matrix")
plt.show()

```




```python
# BMI analysis if Height/Weight present
if set(['Height', 'Weight']).issubset(train.columns):
    train['Height_m'] = train['Height'] / 100.0
    train['BMI'] = train['Weight'] / (train['Height_m']**2)
    plt.figure(figsize=(8,5))
    sns.boxplot(x=target_col, y='BMI', data=train, order=order)
    plt.title("BMI distribution by WeightCategory")
```

```
plt.show()
display(train.groupby(target_col)['BMI'].describe().T)
```



WeightCategory	0	1	2	3	4	5	6
count	1870.000000	2345.000000	2207.000000	2403.000000	2983.000000	1844.000000	1881.000000
mean	176208.069429	220227.886205	321409.896045	365718.139940	418170.010105	260918.382493	282031.880946
std	14360.967040	21992.403195	25631.576473	21144.410780	26903.022934	18002.078553	17973.725467
min	128685.407075	150947.953146	170992.784105	240484.601993	181786.703601	157618.802836	215138.585105
25%	170373.404091	205693.296602	310204.081633	354453.927155	404162.831736	253906.250000	270992.510068
50%	175324.670676	220385.674931	320799.694079	363906.286912	417700.837480	259819.784973	280557.057869
75%	180620.379165	237118.446310	333205.177496	380716.248163	436348.210102	266727.632983	290914.331827
max	367781.150966	328824.141519	468051.876636	462224.831931	549979.913613	355555.555556	367414.556033

Model Evaluation (Validation Performance)

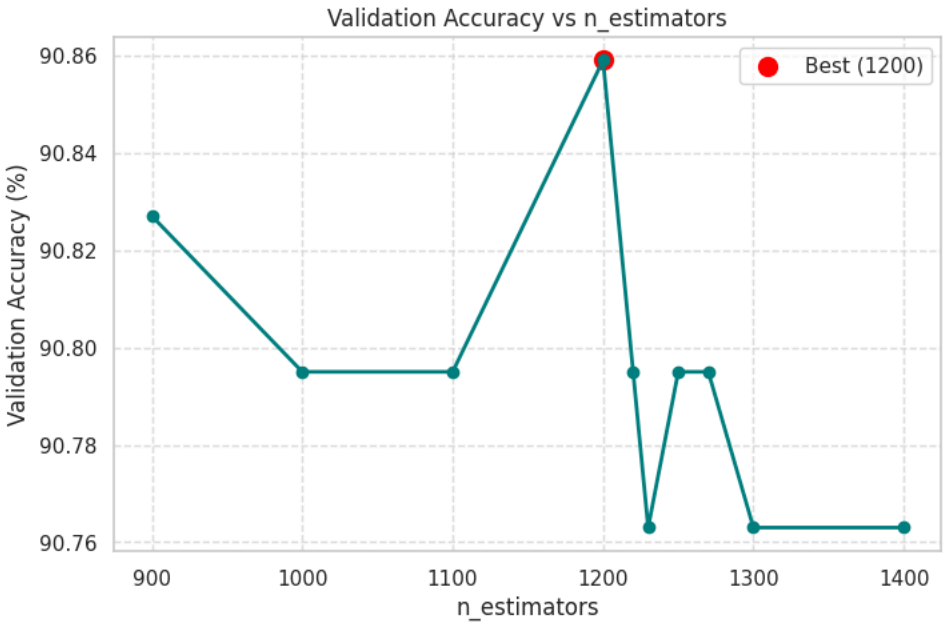
```
y_pred = best_model.predict(X_val)
cm = confusion_matrix(y_val, y_pred)
acc = accuracy_score(y_val, y_pred)

print(f"\nBest Validation Accuracy: {acc*100:.3f}%")
print("\nClassification Report:\n")
print(classification_report(y_val, y_pred))

plt.figure(figsize=(6,5))
sns.heatmap(cm, annot=True, fmt='d', cmap='coolwarm', cbar=False)
plt.title("Confusion Matrix for Best Model")
plt.xlabel("Predicted")
plt.ylabel("True")
plt.show()
```

```
Best Validation Accuracy: 90.505%

Classification Report:

              precision    recall  f1-score   support

           0       0.91      0.94      0.93       374
           1       0.89      0.89      0.89       469
           2       0.89      0.88      0.88       441
           3       0.96      0.97      0.97       481
           4       0.99      1.00      0.99       597
           5       0.81      0.75      0.78       369
           6       0.81      0.84      0.82       376

    accuracy                           0.91      3107
   macro avg       0.90      0.90      0.90      3107
weighted avg       0.90      0.91      0.90      3107
```

Accuracy vs n_estimators Plot

Confusion Matrix for Best Model

```python
accuracy_list = [90.827, 90.795, 90.795, 90.859, 90.795, 90.763, 90.795, 90.795, 90.763, 90.763]

plt.figure(figsize=(8,5))
plt.plot(n_estimator_values, accuracy_list, marker='o', color='teal', linewidth=2)
plt.title("Validation Accuracy vs n_estimators")
plt.xlabel("n_estimators")
plt.ylabel("Validation Accuracy (%)")
plt.grid(True, linestyle='--', alpha=0.6)

best_idx = accuracy_list.index(max(accuracy_list))
plt.scatter(n_estimator_values[best_idx], accuracy_list[best_idx],
            color='red', s=100, label=f"Best ({n_estimator_values[best_idx]})")
plt.legend()
plt.show()

```




```
Start coding or generate with AI.
```