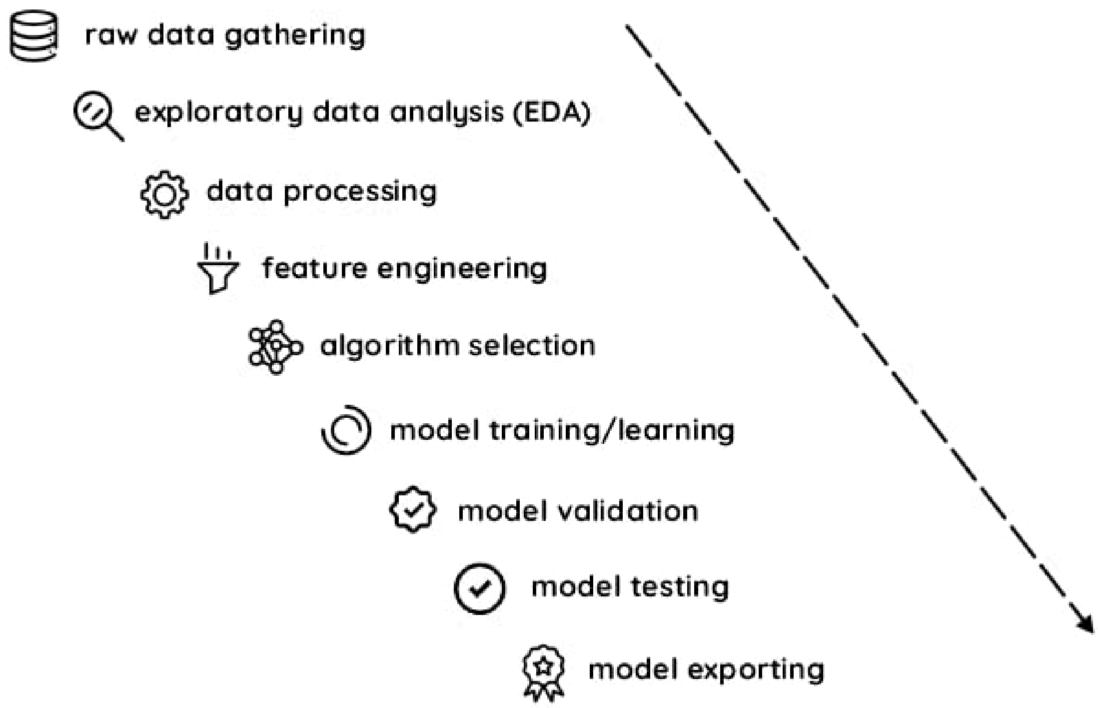
Goal: Create machine learning model that will predict quality of the wheat

Roadmap:



Loading libraries:

In [ ]:
```
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import LinearSVC
from sklearn.metrics import classification_report, accuracy_score
import joblib
from sklearn.preprocessing import LabelEncoder
```

1. Raw data gathering

In [2]:
```
#dataset from: https://www.kaggle.com/datasets/muratkokludataset/durum-wh
path = "/home/darko/Desktop/durum_wheat/durum_wheat_ml/Durum_Wheat_Datase

try:
    df = pd.read_excel(path, sheet_name=0)
    print(df.head())
except Exception as e:
    print(f"An unexpected error occurred: {e}")
```

```
     Target  AREA   MAJORAXIS  MINORAXIS  ECCENTRICITY     EQDIASQ  \
0  Vitreous   168  109.576157  39.396721      0.973060  213.904236
1  Vitreous   162  105.584457  43.366894      0.964173  206.264801
2  Vitreous   145   97.360207  35.532028      0.903072  184.619720
3  Vitreous   178  104.080582  49.040062      1.272657  226.636627
4  Vitreous   187  103.716667  40.885876     -1.469139  238.095779

    PERIMETER  SOLIDITY  ROUNDNESS  SHAPEFACTOR  ...  Gabor_Y9(XYZ)  \
0  202.794052  0.087454   0.017815     0.051334  ...       1.187631
1  194.794052  0.081901   0.018502     0.053650  ...       2.437782
2  177.722961  0.096026   0.019477     0.057689  ...       0.527286
3  202.509750  0.080507   0.020921     0.054543  ...       2.277434
4  198.811234  0.097650   0.022134     0.059452  ...       2.337524

   Gabor_Z1(XYZ)  Gabor_Z2(XYZ)  Gabor_Z3(XYZ)  Gabor_Z4(XYZ)  Gabor_Z5(XY
Z)  \
0       0.003489       0.013901       0.031153       0.003591       0.0143
29
1       0.003794       0.015126       0.033886       0.004166       0.0169
21
2       0.003069       0.012269       0.027538       0.003092       0.0124
59
3       0.003743       0.014940       0.033508       0.003966       0.0155
13
4       0.003599       0.014423       0.032525       0.003922       0.0150
26

   Gabor_Z6(XYZ)  Gabor_Z7(XYZ)  Gabor_Z8(XYZ)  Gabor_Z9(XYZ)
0       0.032405       0.235286       0.651593       0.775182
1       0.038586       0.368535       1.074773       1.577847
2       0.028380       0.111476       0.191517       0.350966
3       0.034776       0.180135       0.887808       1.446794
4       0.034003       0.199192       0.928664       1.786701

[5 rows x 237 columns]
```

2. EDA

In [3]:
```
print("Dataset shape (rows, columns):", df.shape)
print('*' * 40)

print("\nDataset info:")
df.info()
print('*' * 40)


df.describe()

print('*' * 40)
```

```
print("Missing values per column:")
print(df.isna().sum())

print('*' * 40)
print("Number of duplicate rows:", df.duplicated().sum())

print('*' * 40)
sample = df.sample(random_state=42, n=5)
print("Random sample of 5 rows:\n", sample)
```

```
Dataset shape (rows, columns): (9000, 237)
****************************************

Dataset info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9000 entries, 0 to 8999
Columns: 237 entries, Target to Gabor_Z9(XYZ)
dtypes: float64(235), int64(1), object(1)
memory usage: 16.3+ MB
****************************************
****************************************
Missing values per column:
Target           0
AREA             0
MAJORAXIS        0
MINORAXIS        0
ECCENTRICITY     0
                ..
Gabor_Z5(XYZ)    0
Gabor_Z6(XYZ)    0
Gabor_Z7(XYZ)    0
Gabor_Z8(XYZ)    0
Gabor_Z9(XYZ)    0
Length: 237, dtype: int64
****************************************
Number of duplicate rows: 0
****************************************
Random sample of 5 rows:
        Target  AREA   MAJORAXIS  MINORAXIS  ECCENTRICITY     EQDIASQ  \
7940   Foreign   113   72.095627  31.201622      0.606692  143.876068
1162  Vitreous   154  101.589783  38.577065      0.906564  196.078888
582   Vitreous   201  108.948685  40.072151     -0.972156  255.921143
4081   Starchy   164   93.014153  43.781296      0.127331  208.811279
8412   Foreign   136   86.967949  28.108158     -1.063594  173.160568

       PERIMETER  SOLIDITY  ROUNDNESS  SHAPEFACTOR  ...  Gabor_Y9(XYZ)  \
7940  134.610229  0.113682   0.027680     0.078367  ...       1.923140
1162  187.137177  0.090909   0.018999     0.055260  ...       1.086189
582   206.936188  0.101721   0.021561     0.058984  ...       1.710551
4081  180.710724  0.092655   0.024135     0.063108  ...       0.852951
8412  163.338165  0.126394   0.022894     0.064058  ...       3.202615

      Gabor_Z1(XYZ)  Gabor_Z2(XYZ)  Gabor_Z3(XYZ)  Gabor_Z4(XYZ)  \
7940       0.010843       0.043354       0.097381       0.011022
1162       0.003581       0.014349       0.032340       0.003637
582        0.004272       0.017132       0.038665       0.004399
4081       0.004487       0.017879       0.040034       0.004561
8412       0.019331       0.077476       0.174817       0.019529

      Gabor_Z5(XYZ)  Gabor_Z6(XYZ)  Gabor_Z7(XYZ)  Gabor_Z8(XYZ)  \
7940       0.044028       0.099094       0.488496       1.024959
1162       0.014513       0.032752       0.228496       0.429636
582        0.017277       0.038844       0.207177       1.108145
4081       0.018653       0.043123       0.224375       0.412812
8412       0.077734       0.175071       0.692397       3.212104

      Gabor_Z9(XYZ)
7940       1.716980
1162       0.692616
582        1.099306
```

```
4081       0.481957
8412       3.325619

[5 rows x 237 columns]
```

Columns explained:

Target: main variable indicating wheat quality

- 'Vitreous' : high-quality, hard durum wheat

- 'Starchy' : softer wheat

- 'Foreign' : non-durum or defective grains

Morphological features (shape and size):

- AREA : surface area of the grain

- MAJORAXIS : length of the major axis

- MINORAXIS : length of the minor axis

- ECCENTRICITY: measure of how elongated the grain is (0 = circle, 1 = line)

- PERIMETER : perimeter of the grain

- ROUNDNESS : roundness measure

- SOLIDITY : compactness of the grain shape

- SHAPEFACTOR : general shape descriptor

- EQDIASQ : equivalent diameter squared (derived from AREA)

Textural features (from Gabor filters on images):

- Gabor_X1(XYZ) ... Gabor_X9(XYZ) : horizontal/vertical orientation texture descriptors

- Gabor_Y1(XYZ) ... Gabor_Y9(XYZ) : diagonal texture descriptors

- Gabor_Z1(XYZ) ... Gabor_Z9(XYZ) : high-frequency/energy texture descriptors

Notes:

- All numerical features can be used for ML models

- Target is categorical; use LabelEncoder or one-hot encoding

- Gabor features help capture subtle differences in surface texture, important for distinguishing wheat quality

Category count

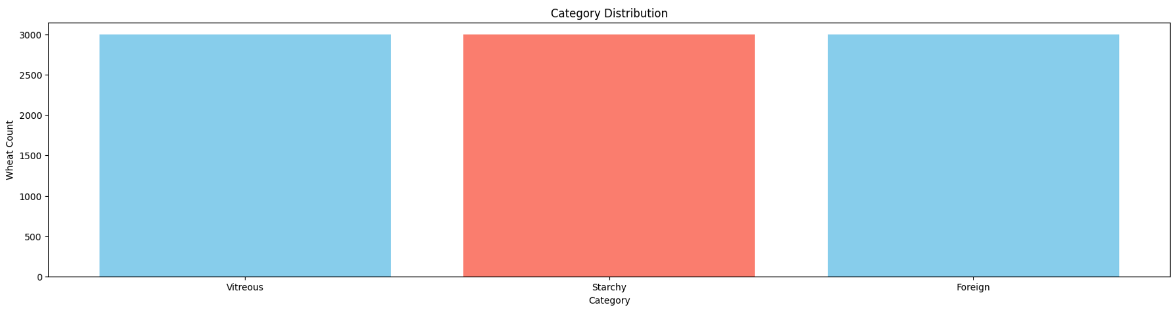
In [4]:
```
category_counts = df['Target'].value_counts()

print("Category distribution (counts):")
print(category_counts)
```

```
Category distribution (counts):
Target
Vitreous    3000
Starchy     3000
Foreign     3000
Name: count, dtype: int64
```

Category visualisation

In [5]:
```
plt.figure(figsize=(22, 5))
plt.bar(category_counts.index, category_counts.values, color=['skyblue',
plt.title("Category Distribution")
plt.xlabel("Category")
plt.ylabel("Wheat Count")
plt.show()
```



3. Data processing (cleaning)

In [6]:
```
def standardize_data(df):
    df.columns = df.columns.str.lower().str.replace(' ', '_').str.replace
    return df

def prepare_data(df):
    return standardize_data(df)
```

Data after cleaning:

In [7]:
```
df = prepare_data(df)

print(df.dtypes)
```

```
target           object
area              int64
majoraxis       float64
minoraxis       float64
eccentricity    float64
                 ...
gabor_z5xyz     float64
gabor_z6xyz     float64
gabor_z7xyz     float64
gabor_z8xyz     float64
gabor_z9xyz     float64
Length: 237, dtype: object
```

4. Feature engineering

Deciding which columns are relevant for our future model...

In [8]:
```
le = LabelEncoder()
df['target_encoded'] = le.fit_transform(df['target'])

correlations = df.corr(numeric_only=True)['target_encoded'].sort_values(a
print(correlations)
```

```
target_encoded    1.000000
gabor_a*3         0.774117
gabor_a*2         0.773761
gabor_a*1         0.773103
mean_a*           0.772723
                    ...
gabor_b6         -0.727447
mean_b           -0.729039
gabor_b1         -0.729089
gabor_b2         -0.729253
gabor_b3         -0.729451
Name: target_encoded, Length: 237, dtype: float64
```

Separating important columns (with correlation more than 0.3)

In [9]:
```
important_features = correlations[correlations.abs() > 0.3].index.tolist(

print("Important features based on correlation threshold:\n", important_f

important_features_without_column_target = [f for f in important_features

print('Number of columns in important_features_without_column_target:', l
```

```
Important features based on correlation threshold:
 ['target_encoded', 'gabor_a*3', 'gabor_a*2', 'gabor_a*1', 'mean_a*', 'gab
or_a*6', 'gabor_a*4', 'gabor_a*5', 'db4_a*', 'gabor_cr3', 'gabor_cr2', 'ga
bor_cr1', 'mean_cr', 'gabor_cr6', 'gabor_cr5', 'gabor_cr4', 'db4_cr', 'ske
w_v', 'skew_r', 'skew_l', 'skew_g', 'skew_y', 'skew_yxyz', 'mean_s', 'gabo
r_s1', 'gabor_s2', 'gabor_s3', 'gabor_s5', 'gabor_s6', 'gabor_s4', 'skew_x
xyz', 'db4_s', 'entropy_s', 'entropy_v', 'entropy_b', 'skew_zxyz', 'skew_
b', 'skew_b*', 'entropy_g', 'kurtosis_yxyz', 'kurtosis_xxyz', 'stddev_s',
'entropyl', 'entropy_y', 'minoraxis', 'db4_b*', 'mean_b*', 'gabor_b*1', 'g
abor_b*6', 'gabor_b*5', 'gabor_b*2', 'gabor_b*3', 'gabor_b*4', 'majoraxi
s', 'kurtosis_zxyz', 'perimeter', 'entropy_r', 'eqdiasq', 'area', 'gabor_x
8xyz', 'gabor_cb3', 'gabor_cb2', 'gabor_cb1', 'roundness', 'mean_cb', 'ent
ropy_yxyz', 'db4_cb', 'stddev_cb', 'gabor_y8xyz', 'gabor_x7xyz', 'gabor_cb
5', 'gabor_cb4', 'gabor_cb6', 'gabor_cr7', 'gabor_y7xyz', 'gabor_b*7', 'en
tropy_b*', 'gabor_cb7', 'stddev_b*', 'gabor_cr8', 'shapefactor', 'gabor_x9
xyz', 'gabor_y9xyz', 'gabor_b*8', 'gabor_cb8', 'compactness', 'entropy_xxy
z', 'skew_a*', 'stddev_zxyz', 'stddev_a*', 'gabor_a*9', 'gabor_z8xyz', 'ga
bor_cr9', 'gabor_a*8', 'gabor_b*9', 'gabor_z7xyz', 'solidity', 'kurtosis_
s', 'gabor_cb9', 'gabor_a*7', 'gabor_z9xyz', 'entropy_cr', 'entropy_a*',
'entropy_h', 'db4_r', 'gabor_r4', 'gabor_r2', 'gabor_r1', 'gabor_r3', 'mea
n_r', 'gabor_r5', 'gabor_r6', 'skew_cb', 'gabor_h7', 'gabor_h8', 'stddev_
h', 'gabor_h9', 'entropy_zxyz', 'db4_xxyz', 'gabor_x4xyz', 'gabor_x5xyz',
'gabor_x2xyz', 'gabor_x3xyz', 'gabor_x1xyz', 'mean_xxyz', 'gabor_x6xyz',
'db4_yxyz', 'gabor_y4xyz', 'gabor_y3xyz', 'gabor_y2xyz', 'gabor_y5xyz', 'g
abor_y1xyz', 'mean_yxyz', 'gabor_y6xyz', 'db4_h', 'db4_zxyz', 'mean_h', 'g
abor_h1', 'gabor_h3', 'gabor_h2', 'gabor_z4xyz', 'gabor_z5xyz', 'gabor_z6x
yz', 'db4_y', 'gabor_h6', 'mean_zxyz', 'gabor_z1xyz', 'gabor_z2xyz', 'gabo
r_z3xyz', 'gabor_h5', 'gabor_y4', 'gabor_h4', 'gabor_y2', 'gabor_y1', 'gab
or_y3', 'mean_y', 'gabor_y5', 'gabor_y6', 'db4_l', 'db4_v', 'gabor_l4', 'g
abor_l2', 'gabor_l1', 'gabor_l3', 'mean_l', 'gabor_l5', 'gabor_l6', 'gabor
_v4', 'gabor_v2', 'gabor_v1', 'gabor_v3', 'mean_v', 'gabor_v5', 'gabor_v
6', 'db4_g', 'gabor_g4', 'gabor_g2', 'gabor_g3', 'gabor_g1', 'mean_g', 'ga
bor_g5', 'gabor_g6', 'db4_b', 'gabor_b4', 'gabor_b5', 'gabor_b6', 'mean_
b', 'gabor_b1', 'gabor_b2', 'gabor_b3']
Number of columns in important_features_without_column_target: 189
```

5: Algorithm selection:

In [10]:

```
X = df[important_features_without_column_target]
y = df["target_encoded"]

X_train, X_test, y_train, y_test = train_test_split(
    X, y, test_size=0.2, random_state=42, stratify=y
)
```

Model selection

In [11]:

```
numeric_features = X_train.columns.tolist()
preprocessor = ColumnTransformer([
    ('scaler', StandardScaler(), numeric_features)
])

models = {
    "Logistic Regression": LogisticRegression(max_iter=1000),
    "Naive Bayes": GaussianNB(),
    "Decision Tree": DecisionTreeClassifier(),
    "Random Forest": RandomForestClassifier(),
```

```python
    "Support Vector Machine": LinearSVC(max_iter=10000)
}

for name, model in models.items():
    print(f"\nModel: {name}")

    pipeline = Pipeline([
        ('preprocessing', preprocessor),
        ('classifier', model)
    ])

    pipeline.fit(X_train, y_train)
    y_pred = pipeline.predict(X_test)

    print("Accuracy:", round(accuracy_score(y_test, y_pred), 2))
    print(classification_report(y_test, y_pred))
```

```
Model: Logistic Regression
```

```
Accuracy: 0.96
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       600
           1       0.95      0.94      0.95       600
           2       0.94      0.96      0.95       600

    accuracy                           0.96      1800
   macro avg       0.96      0.96      0.96      1800
weighted avg       0.96      0.96      0.96      1800


Model: Naive Bayes
Accuracy: 0.87
              precision    recall  f1-score   support

           0       0.97      0.93      0.95       600
           1       0.88      0.73      0.80       600
           2       0.79      0.95      0.86       600

    accuracy                           0.87      1800
   macro avg       0.88      0.87      0.87      1800
weighted avg       0.88      0.87      0.87      1800


Model: Decision Tree
Accuracy: 0.98
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       600
           1       0.98      0.95      0.97       600
           2       0.96      0.98      0.97       600

    accuracy                           0.98      1800
   macro avg       0.98      0.98      0.98      1800
weighted avg       0.98      0.98      0.98      1800


Model: Random Forest
Accuracy: 0.98
              precision    recall  f1-score   support

           0       0.99      1.00      1.00       600
           1       0.99      0.96      0.98       600
           2       0.97      0.99      0.98       600

    accuracy                           0.98      1800
   macro avg       0.99      0.98      0.98      1800
weighted avg       0.99      0.98      0.98      1800


Model: Support Vector Machine
Accuracy: 0.97
              precision    recall  f1-score   support

           0       0.99      0.99      0.99       600
           1       0.96      0.95      0.96       600
           2       0.95      0.96      0.96       600

    accuracy                           0.97      1800
```

```
   macro avg       0.97      0.97      0.97      1800
weighted avg       0.97      0.97      0.97      1800
```

Winner is Random Forest (Accuracy 0.99)

6. Model training

In [12]:
```
pipeline = Pipeline([
    ("preprocessing", preprocessor),
    ("Random Forest", RandomForestClassifier())
])



pipeline.fit(X, y)

joblib.dump(pipeline, "../model/wheat_sorting.pkl")

print(" Model trained and saved as 'model/wheat_sorting.pkl'")
```

```
Model trained and saved as 'model/wheat_sorting.pkl'
```

7. Model testing:

In [15]:
```
n_samples = 5

test_df = pd.DataFrame(
    np.random.rand(n_samples, X_train.shape[1]) * 100,
    columns=X_train.columns
)

predictions = pipeline.predict(test_df)

predicted_labels = le.inverse_transform(predictions)

# Prikaz rezultata
print("Test samples:\n", test_df.head())
print("\nPredicted wheat quality:\n", predicted_labels)
```

```
Test samples:
    gabor_a*3  gabor_a*2  gabor_a*1    mean_a*  gabor_a*6  gabor_a*4  \
0  18.807395  79.103037   7.982325  54.600536  62.992982  53.693457   
1  72.333991  13.344556   8.692794  56.281361  38.393546   8.534602   
2   0.262963  95.831198  54.737749  94.508253  54.024845  93.677031   
3  28.463300  77.571470  19.528751  84.624257  44.567241  20.248151   
4  91.269872   2.820933  98.469592  69.223971  29.314132  30.136178   

   gabor_a*5     db4_a*  gabor_cr3  gabor_cr2  ...   gabor_g5   gabor_g6  
\
0  31.483925  24.057640  80.509177  10.648369  ...  97.097530   3.390181   
1  98.828300   1.118506  38.563131  23.163078  ...  52.155998  44.393741   
2  79.057352  28.311180  16.185022  66.309305  ...  44.849881  43.302500   
3   9.795285  58.482125   0.770230  87.915045  ...  51.267018  28.327253   
4  85.879433  77.698837  12.998159  62.197095  ...  31.437740  65.929588   

      db4_b   gabor_b4   gabor_b5   gabor_b6     mean_b   gabor_b1  \
0  61.673019  98.608413  18.029573   5.050664  55.514526  23.453444   
1  78.754682   3.845860  89.640629   5.399869  41.502671  54.467619   
2  52.968647  34.621883  40.945439  52.481519  97.711657  17.140010   
3  11.567126  79.055754  39.880538  43.120465  48.414567  24.243372   
4  38.505289  85.102734  64.549089  62.136134  77.314197  47.544149   

    gabor_b2   gabor_b3  
0  77.998856  76.209147  
1  60.539825  48.420923  
2  85.121329  68.814534  
3  72.113943  34.189959  
4  78.355905   0.736214  

[5 rows x 189 columns]

Predicted wheat quality:
 ['Foreign' 'Starchy' 'Foreign' 'Foreign' 'Foreign']
```

8. Model exporting: