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August 24, 2025

1 F&B Process Data Exploration

2 Honeywell Hackathon - Anomaly Detection System

3

4 This script explores the food & beverage manufacturing process data to understand patterns, distributions, and relationships between parameters.

5 Import required libraries

[26]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
from plotly.subplots import make_subplots
import warnings
warnings.filterwarnings('ignore')
```

[27]:
```
# Configure visualization settings
plt.style.use('seaborn-v0_8-darkgrid')
sns.set_palette('husl')
%matplotlib inline
```

[28]:
```
#Import custom modules
import sys
sys.path.append('..')
from src.data_processor import DataProcessor
from src.config import PROCESS_PARAMS, DATA_CONFIG
```

6 1. Load and Inspect Data

[29]:
```
# Initialize data processor
processor = DataProcessor()

# Load data
file_path = '../data/raw/FnB_Process_Data_Batch_Wise.xlsx'
process_data, quality_data = processor.load_data(file_path)

print(f"Process data shape: {process_data.shape}")
print(f"Quality data batches: {len(quality_data)}")
print("\nFirst 5 rows of process data:")
print(process_data.head())
```

```
2025-08-23 19:58:01.007 | INFO     |
src.data_processor:__init__:34 - DataProcessor

initialized
2025-08-23 19:58:01.022 | INFO     |
src.data_processor:load_data:50 - Loading data

from ../data/raw/FnB_Process_Data_Batch_Wise.xlsx
2025-08-23 19:58:01.873 | INFO     |
src.data_processor:load_data:74 - Loaded 1500

rows of process data
2025-08-23 19:58:01.878 | INFO     |
src.data_processor:load_data:75 - Loaded quality

data for 25 batches

Process data shape: (1500, 12)
Quality data batches: 25

First 5 rows of process data:
   Batch_ID  Time  Flour (kg)  Sugar (kg)  Yeast (kg)  Water Temp (C)  \
0         1     0    9.665776    4.873814    1.905794       24.835601
1         1     1    9.697343    4.829029    2.128480       24.738654
2         1     2   10.283522    5.027350    1.881150       24.920889
3         1     3   10.218504    5.190817    2.121848       25.810604
4         1     4    9.891061    5.170880    2.034122       25.650082

   Salt (kg)  Mixer Speed (RPM)  Mixing Temp (C)  Fermentation Temp (C)  \
0   0.989292         150.837154        34.839420              36.682875
1   1.073903         151.711438        34.561631              37.037835
2   1.035247         155.260479        35.177363              36.791121
3   0.982195         156.019976        35.091781              37.000395
4   1.003725         158.813999        36.721006              37.119620

   Oven Temp (C)  Oven Humidity (%)
```

```
0     181.140068          44.162910
1     179.046961          45.034372
2     181.054036          45.700564
3     181.532873          43.654986
4     180.049328          45.722447
```

[30]:
```
# Data information
print("Data Types:")
print(process_data.dtypes)
print("\nData Info:")
process_data.info()
```

```
Data Types:
Batch_ID                    int64
Time                        int64
Flour (kg)                float64
Sugar (kg)                float64
Yeast (kg)                float64
Water Temp (C)            float64
Salt (kg)                 float64
Mixer Speed (RPM)         float64
Mixing Temp (C)           float64
Fermentation Temp (C)     float64
Oven Temp (C)             float64
Oven Humidity (%)         float64
dtype: object

Data Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1500 entries, 0 to 1499
Data columns (total 12 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   Batch_ID               1500 non-null   int64
 1   Time                   1500 non-null   int64
 2   Flour (kg)             1500 non-null   float64
 3   Sugar (kg)             1500 non-null   float64
 4   Yeast (kg)             1500 non-null   float64
 5   Water Temp (C)         1500 non-null   float64
 6   Salt (kg)              1500 non-null   float64
 7   Mixer Speed (RPM)      1500 non-null   float64
 8   Mixing Temp (C)        1500 non-null   float64
 9   Fermentation Temp (C)  1500 non-null   float64
 10  Oven Temp (C)          1500 non-null   float64
 11  Oven Humidity (%)      1500 non-null   float64
dtypes: float64(10), int64(2)
memory usage: 140.8 KB
```

7 2. Data Cleaning and Preprocessing

[31]:
```
# Clean the data
clean_data = processor.clean_data(process_data)

print(f"Clean data shape: {clean_data.shape}")
print(f"Unique batches: {clean_data['Batch_ID'].nunique()}")
print(f"Time points per batch: {clean_data.groupby('Batch_ID').size().mean():.
  ↪0f}")
```

```
2025-08-23 19:58:02.041 | INFO     |
src.data_processor:clean_data:93 - Starting data

cleaning process
2025-08-23 19:58:02.062 | INFO     |
src.data_processor:clean_data:104 - Missing

values before cleaning: 0
2025-08-23 19:58:02.141 | INFO     |
src.data_processor:clean_data:117 - Missing

values after cleaning: 0
2025-08-23 19:58:02.152 | INFO     |
src.data_processor:clean_data:122 - Data cleaned:

1500 rows remaining

Clean data shape: (1500, 12)
Unique batches: 25
Time points per batch: 60
```

[32]:
```
# Check for missing values
missing_values = clean_data.isnull().sum()
if missing_values.sum() > 0:
    print("Missing values:")
    print(missing_values[missing_values > 0])
else:
    print("No missing values found after cleaning!")
```

```
No missing values found after cleaning!
```

8 3. Statistical Analysis

[33]:
```
# Basic statistics
process_params = list(PROCESS_PARAMS.keys())
statistics = clean_data[process_params].describe()

# Add ideal values for comparison
```

```
ideal_values = pd.Series({param: config['ideal'] for param, config in␣
 ↪PROCESS_PARAMS.items()})
statistics.loc['ideal'] = ideal_values

print("Statistical Summary with Ideal Values:")
print(statistics.round(2))

# Calculate coefficient of variation for each parameter
cv_analysis = pd.DataFrame({
    'Parameter': process_params,
    'Mean': clean_data[process_params].mean(),
    'Std Dev': clean_data[process_params].std(),
    'CV (%)': (clean_data[process_params].std() / clean_data[process_params].
 ↪mean() * 100)
})

cv_analysis = cv_analysis.sort_values('CV (%)', ascending=False)
print("Coefficient of Variation Analysis:")
print(cv_analysis)
```

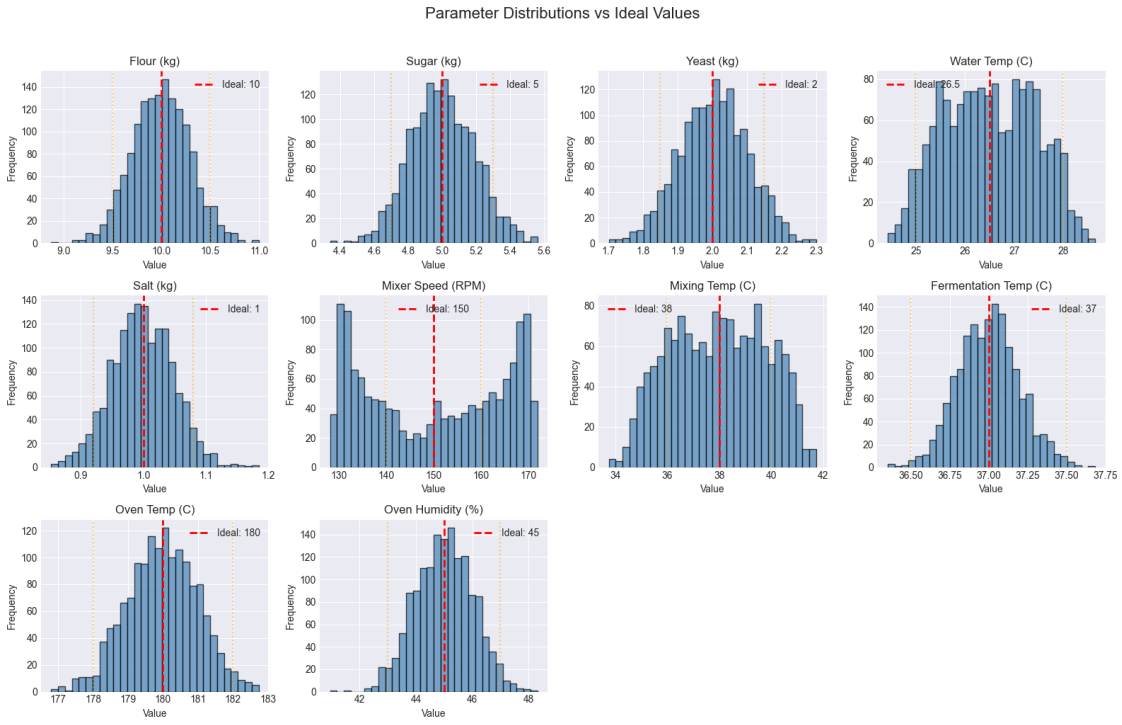
```
Statistical Summary with Ideal Values:
       Flour (kg)  Sugar (kg)  Yeast (kg)  Water Temp (C)  Salt (kg)  \
count     1500.00     1500.00     1500.00         1500.00    1500.00
mean        10.00        5.00        2.00           26.49       1.00
std          0.30        0.19        0.10            0.92       0.05
min          8.87        4.34        1.70           24.43       0.85
25%          9.80        4.87        1.94           25.75       0.96
50%         10.00        4.99        2.00           26.49       1.00
75%         10.20        5.13        2.07           27.24       1.03
max         11.00        5.56        2.30           28.64       1.18
ideal       10.00        5.00        2.00           26.50       1.00

       Mixer Speed (RPM)  Mixing Temp (C)  Fermentation Temp (C)  \
count            1500.00          1500.00                1500.00
mean              150.18            37.94                  37.00
std                14.51             1.82                   0.20
min               128.12            33.75                  36.35
25%               135.29            36.44                  36.87
50%               151.31            37.99                  37.00
75%               164.73            39.43                  37.13
max               171.88            41.74                  37.68
ideal             150.00            38.00                  37.00

       Oven Temp (C)  Oven Humidity (%)
count        1500.00            1500.00
mean          179.97              45.00
std             1.01               1.01
```

```
min           176.80              40.95
25%           179.30              44.28
50%           179.99              45.01
75%           180.68              45.71
max           182.74              48.32
ideal         180.00              45.00
Coefficient of Variation Analysis:
                                 Parameter        Mean    Std Dev    CV (%)
Mixer Speed (RPM)          Mixer Speed (RPM)  150.183858  14.514063  9.664196
Salt (kg)                          Salt (kg)    0.998364   0.049699  4.978055
Yeast (kg)                        Yeast (kg)    2.003528   0.098577  4.920177
Mixing Temp (C)              Mixing Temp (C)   37.941785   1.819611  4.795798
Sugar (kg)                        Sugar (kg)    4.999799   0.190234  3.804828
Water Temp (C)               Water Temp (C)   26.494856   0.918932  3.468340
Flour (kg)                        Flour (kg)    9.997708   0.297034  2.971025
Oven Humidity (%)          Oven Humidity (%)   45.000126   1.013946  2.253208
Oven Temp (C)                Oven Temp (C)  179.973951   1.008847  0.560552
Fermentation Temp (C)  Fermentation Temp (C)   36.999412   0.197363  0.533422
```

9 4. Distribution Analysis

[34]:
```
# Create distribution plots for all parameters
fig, axes = plt.subplots(3, 4, figsize=(16, 10))
axes = axes.ravel()

for idx, param in enumerate(process_params):
    ax = axes[idx]

    # Plot distribution
    ax.hist(clean_data[param], bins=30, alpha=0.7, color='steelblue',␣
 ↪edgecolor='black')

    # Add ideal value line
    ideal = PROCESS_PARAMS[param]['ideal']
    ax.axvline(ideal, color='red', linestyle='--', linewidth=2, label=f'Ideal:␣
 ↪{ideal}')

    # Add tolerance bands
    tolerance = PROCESS_PARAMS[param]['tolerance']
    ax.axvline(ideal - tolerance, color='orange', linestyle=':', alpha=0.5)
    ax.axvline(ideal + tolerance, color='orange', linestyle=':', alpha=0.5)

    ax.set_title(param)
    ax.set_xlabel('Value')
    ax.set_ylabel('Frequency')
    ax.legend()
```

```
# Hide extra subplots
for idx in range(len(process_params), len(axes)):
    axes[idx].set_visible(False)

plt.suptitle('Parameter Distributions vs Ideal Values', fontsize=16, y=1.02)
plt.tight_layout()
plt.show()
```



10 5. Outlier Detection

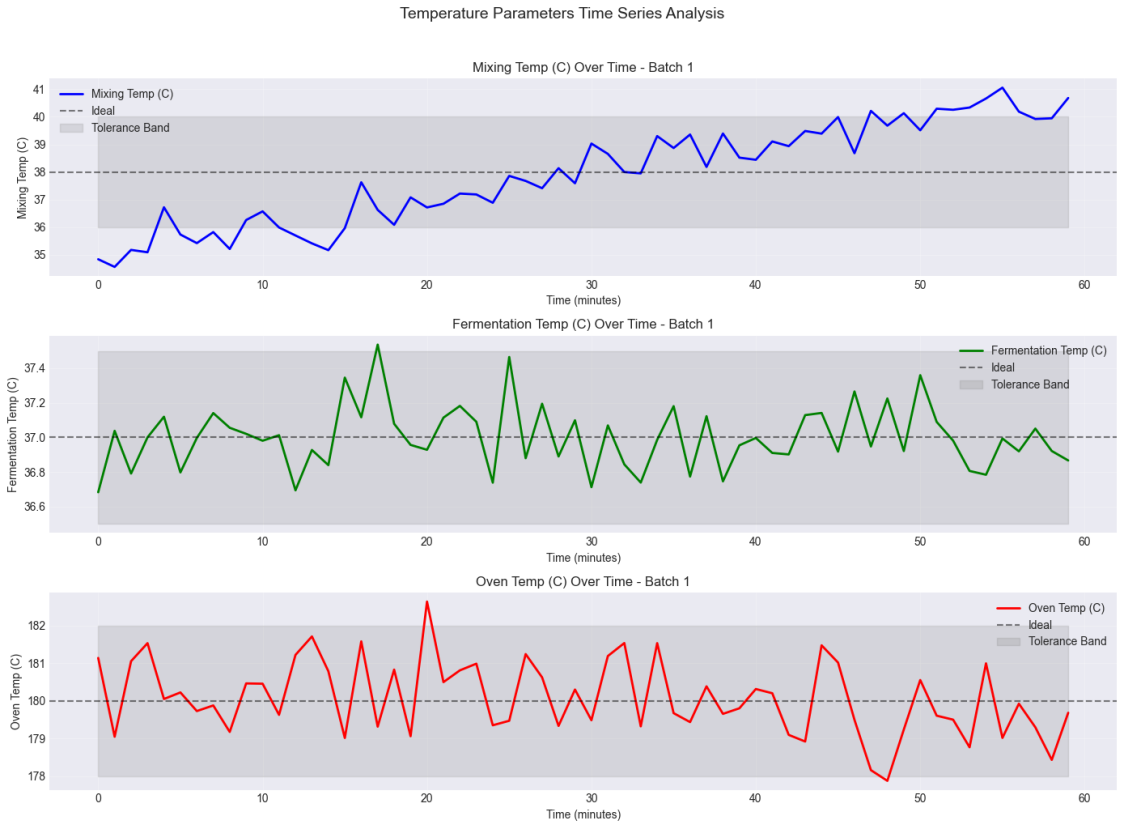
[1]:
```
#Detect outliers using IQR method
outlier_flags = processor.detect_outliers(clean_data, method='iqr')

# Count outliers per parameter
outlier_summary = pd.DataFrame({
    'Parameter': [col.replace('_outlier', '') for col in outlier_flags.columns],
    'Outlier Count': outlier_flags.sum().values,
    'Outlier %': (outlier_flags.sum() / len(clean_data) * 100).values
})

outlier_summary = outlier_summary.sort_values('Outlier %', ascending=False)
print("Outlier Summary:")
```

```
print(outlier_summary)

# Visualize outliers with boxplots
fig = make_subplots(
    rows=2, cols=5,
    subplot_titles=process_params,
    vertical_spacing=0.15
)

for idx, param in enumerate(process_params):
    row = idx // 5 + 1
    col = idx % 5 + 1

    fig.add_trace(
        go.Box(
            y=clean_data[param],
            name=param,
            boxmean='sd',
            marker_color='lightblue'
        ),
        row=row, col=col
    )

fig.update_layout(
    title='Outlier Detection - Box Plots',
    showlegend=False,
    height=600
)

# fig.show()
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[1], line 2
      1 #Detect outliers using IQR method
----> 2 outlier_flags = processor.detect_outliers(clean_data, method='iqr')
      4 # Count outliers per parameter
      5 outlier_summary = pd.DataFrame({
      6     'Parameter': [col.replace('_outlier', '') for col in outlier_flags.
 ↪columns],
      7     'Outlier Count': outlier_flags.sum().values,
      8     'Outlier %': (outlier_flags.sum() / len(clean_data) * 100).values
      9 })

NameError: name 'processor' is not defined
```

11 6. Time Series Analysis

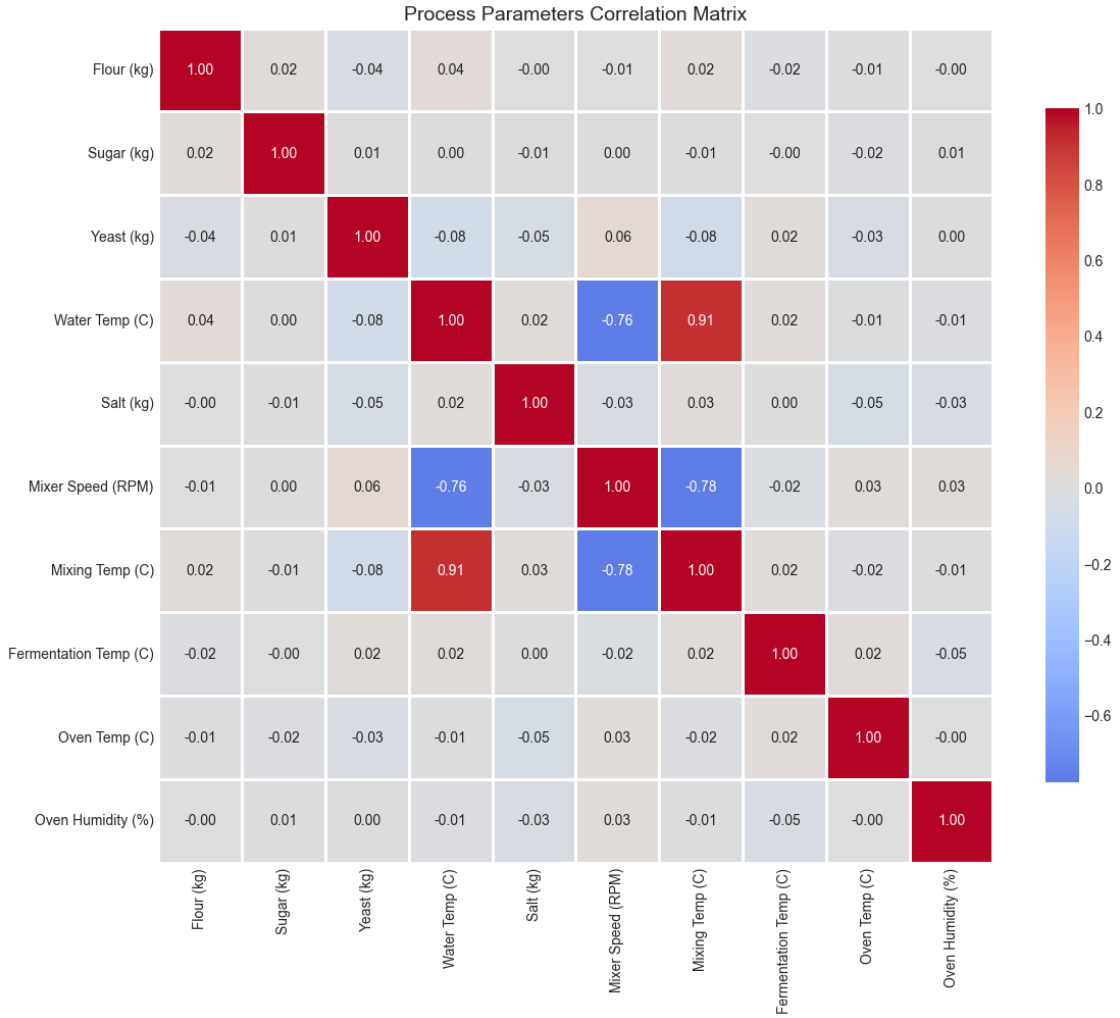
[ ]:
```
# Analyze time series for a sample batch
sample_batch = clean_data[clean_data['Batch_ID'] == 1]

fig, axes = plt.subplots(3, 1, figsize=(14, 10))

# Temperature parameters
temp_params = ['Mixing Temp (C)', 'Fermentation Temp (C)', 'Oven Temp (C)']
colors = ['blue', 'green', 'red']

for idx, (param, color) in enumerate(zip(temp_params, colors)):
    ax = axes[idx]

    # Plot time series
    ax.plot(sample_batch['Time'], sample_batch[param],
            color=color, linewidth=2, label=param)

    # Add ideal value and tolerance bands
    ideal = PROCESS_PARAMS[param]['ideal']
    tolerance = PROCESS_PARAMS[param]['tolerance']

    ax.axhline(ideal, color='black', linestyle='--', alpha=0.5, label='Ideal')
    ax.fill_between(sample_batch['Time'],
                    ideal - tolerance, ideal + tolerance,
                    alpha=0.2, color='gray', label='Tolerance Band')

    ax.set_xlabel('Time (minutes)')
    ax.set_ylabel(f'{param}')
    ax.set_title(f'{param} Over Time - Batch 1')
    ax.legend()
    ax.grid(True, alpha=0.3)

plt.suptitle('Temperature Parameters Time Series Analysis', fontsize=14, y=1.02)
plt.tight_layout()
plt.show()
```



12 7. Correlation Analysis

[ ]:
```
# Calculate correlation matrix
correlation_matrix = clean_data[process_params].corr()

# Create heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix,
            annot=True,
            fmt='.2f',
            cmap='coolwarm',
            center=0,
            square=True,
            linewidths=1,
            cbar_kws={"shrink": 0.8})

plt.title('Process Parameters Correlation Matrix', fontsize=14)
plt.tight_layout()
plt.show()
```

```python
# Find strong correlations
strong_correlations = []
for i in range(len(correlation_matrix.columns)):
    for j in range(i+1, len(correlation_matrix.columns)):
        if abs(correlation_matrix.iloc[i, j]) > 0.5:
            strong_correlations.append({
                'Parameter 1': correlation_matrix.columns[i],
                'Parameter 2': correlation_matrix.columns[j],
                'Correlation': correlation_matrix.iloc[i, j]
            })

if strong_correlations:
    print("\nStrong Correlations (|r| > 0.5):")
    print(pd.DataFrame(strong_correlations).sort_values('Correlation',
                                                        key=abs,
                                                        ascending=False))
```



```
Strong Correlations (|r| > 0.5):
         Parameter 1        Parameter 2  Correlation
1     Water Temp (C)    Mixing Temp (C)     0.905314
2  Mixer Speed (RPM)    Mixing Temp (C)    -0.777703
0     Water Temp (C)  Mixer Speed (RPM)    -0.764395
```

13 8. Batch-wise Analysis

[ ]:
```
# Analyze batch-wise statistics
batch_stats = clean_data.groupby('Batch_ID')[process_params].agg(['mean',␣
 ↪'std'])

# Calculate quality metrics for each batch (using simulated data)
batch_quality = pd.DataFrame(quality_data).T
batch_quality.index.name = 'Batch_ID'

print("Batch-wise Statistics (First 5 batches):")
print(batch_stats.head())

# Identify best and worst performing batches
if 'Quality Score' in batch_quality.columns:
    best_batches = batch_quality.nlargest(5, 'Quality Score')
    worst_batches = batch_quality.nsmallest(5, 'Quality Score')

    print("Top 5 Best Quality Batches:")
    print(best_batches)
    print("\nBottom 5 Worst Quality Batches:")
    print(worst_batches)
```

```
Batch-wise Statistics (First 5 batches):
         Flour (kg)           Sugar (kg)           Yeast (kg)            \
               mean       std       mean       std       mean       std
Batch_ID
1          9.970360  0.258529   4.971863  0.189242   2.011490  0.092035
2         10.033188  0.267176   4.961258  0.182626   1.987529  0.084448
3          9.930110  0.332547   4.976926  0.214315   1.998987  0.109859
4          9.981613  0.315475   5.029651  0.195760   1.982227  0.104986
5          9.984823  0.255384   5.037456  0.195456   2.001497  0.103189

         Water Temp (C)           Salt (kg)           Mixer Speed (RPM)  \
                   mean       std      mean       std              mean
Batch_ID
1             26.470261  0.921196  1.019163  0.048211        150.430115
2             26.508925  0.887126  0.987527  0.054065        150.339110
```

```
3             26.494229  0.982542  0.993391  0.048404        150.090660
4             26.430344  0.899255  0.992305  0.045233        150.036026
5             26.452686  0.924717  1.005295  0.043533        150.074780

                  Mixing Temp (C)           Fermentation Temp (C)            \
                              std            mean       std                   mean       std
Batch_ID
1                        14.827211       37.912165  1.816133             36.999521  0.183596
2                        14.654231       37.932237  1.908481             36.952305  0.202761
3                        14.784371       38.033178  1.846919             36.965357  0.206379
4                        14.612895       37.950697  1.860176             37.003443  0.173567
5                        14.722505       38.023202  1.860228             36.985828  0.192274

         Oven Temp (C)           Oven Humidity (%)
                  mean       std              mean       std
Batch_ID
1           180.078945  0.992683         44.907159  0.959573
2           179.936729  0.971747         44.885906  1.065398
3           179.808255  1.148513         44.876172  0.935411
4           179.990305  1.122307         45.161714  0.936430
5           180.119595  1.043727         44.924124  1.151459
Top 5 Best Quality Batches:
          Final Weight  Quality Score
Batch_ID
23           48.252434      96.710203
12           50.188461      96.265063
2            49.998787      95.056180
11           50.547584      94.680085
13           50.982520      93.798259

Bottom 5 Worst Quality Batches:
          Final Weight  Quality Score
Batch_ID
17           50.220470      80.106050
18           55.039415      80.116832
1            51.146188      81.845380
20           51.380606      83.567500
15           51.784021      83.627760
```

14 9. Deviation Analysis

[ ]:
```
# !pip install nbformat
```

```
Requirement already satisfied: nbformat in d:\nosql\honeywell\gcvenv\lib\site-
packages (5.10.4)
Requirement already satisfied: jsonschema>=2.6 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from nbformat) (4.19.0)
```

```
Requirement already satisfied: fastjsonschema>=2.15 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from nbformat) (2.21.2)
Requirement already satisfied: jupyter-core!=5.0.*,>=4.12 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from nbformat) (5.8.1)
Requirement already satisfied: traitlets>=5.1 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from nbformat) (5.14.3)
Requirement already satisfied: attrs>=22.2.0 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jsonschema>=2.6->nbformat)
(25.3.0)
Requirement already satisfied: jsonschema-specifications>=2023.03.6 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jsonschema>=2.6->nbformat)
(2025.4.1)
Requirement already satisfied: rpds-py>=0.7.1 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jsonschema>=2.6->nbformat)
(0.27.0)
Requirement already satisfied: referencing>=0.28.4 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jsonschema>=2.6->nbformat)
(0.36.2)
Requirement already satisfied: pywin32>=300 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jupyter-
core!=5.0.*,>=4.12->nbformat) (311)
Requirement already satisfied: platformdirs>=2.5 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from jupyter-
core!=5.0.*,>=4.12->nbformat) (4.3.8)
Requirement already satisfied: typing-extensions>=4.4.0 in
d:\nosql\honeywell\gcvenv\lib\site-packages (from
referencing>=0.28.4->jsonschema>=2.6->nbformat) (4.14.1)

WARNING: You are using pip version 22.0.4; however, version 25.2 is available.
You should consider upgrading via the
'D:\NoSQL\Honeywell\gcvenv\Scripts\python.exe -m pip install --upgrade pip'
command.
```

15 10. Key Findings and Insights

[ ]:
```python
# Generate comprehensive data quality report
quality_report = processor.generate_data_quality_report(clean_data)

print("="*60)
print("DATA EXPLORATION SUMMARY")
print("="*60)

print(f"\n1. Dataset Overview:")
print(f"   - Total records: {quality_report['total_rows']:,}")
print(f"   - Total features: {quality_report['total_columns']}")
print(f"   - Number of batches: {clean_data['Batch_ID'].nunique()}")
```

```
print(f"   - Time points per batch: {clean_data.groupby('Batch_ID').size().
 ↪mean():.0f}")

print(f"\n2. Data Quality:")
print(f"   - Missing values: {len(quality_report['missing_values'])} columns")
print(f"   - Outliers detected: {len(quality_report['outliers'])} parameters")

print(f"\n3. Key Observations:")
print(f"   - Most variable parameter: {cv_analysis.iloc[0]['Parameter']} (CV:␣
 ↪{cv_analysis.iloc[0]['CV (%)']:.1f}%)")
print(f"   - Most stable parameter: {cv_analysis.iloc[-1]['Parameter']} (CV:␣
 ↪{cv_analysis.iloc[-1]['CV (%)']:.1f}%)")
print(f"   - Parameters with high outliers:␣
 ↪{outlier_summary[outlier_summary['Outlier %'] > 5]['Parameter'].tolist()}")

print(f"\n4. Process Insights:")
for param, config in PROCESS_PARAMS.items():
    if param in clean_data.columns:
        mean_val = clean_data[param].mean()
        ideal_val = config['ideal']
        deviation = ((mean_val - ideal_val) / ideal_val) * 100
        if abs(deviation) > 5:
            print(f"   - {param}: Average {deviation:+.1f}% from ideal")

print(f"\n5. Recommendations for Model Training:")
print(f"   - Focus on high-variance parameters for anomaly detection")
print(f"   - Consider time-series features for temperature parameters")
print(f"   - Include interaction features between correlated parameters")
print(f"   - Apply outlier treatment for robust model training")

print("="*60)
```

```
2025-08-23 19:26:42.710 | INFO     |
src.data_processor:generate_data_quality_report:324 -
Generating data quality report
2025-08-23 19:26:42.714 | INFO     |
src.data_processor:detect_outliers:138 -
Detecting outliers using iqr method
2025-08-23 19:26:42.738 | INFO     |
src.data_processor:detect_outliers:161 - Total

outliers detected: 66
2025-08-23 19:26:42.769 | INFO     |
src.data_processor:generate_data_quality_report:367 -
Data quality report generated

============================================================
DATA EXPLORATION SUMMARY
```

```
============================================================

1. Dataset Overview:
   - Total records: 1,500
   - Total features: 12
   - Number of batches: 25
   - Time points per batch: 60

2. Data Quality:
   - Missing values: 0 columns
   - Outliers detected: 7 parameters

3. Key Observations:
   - Most variable parameter: Mixer Speed (RPM) (CV: 9.7%)
   - Most stable parameter: Fermentation Temp (C) (CV: 0.5%)
   - Parameters with high outliers: []

4. Process Insights:

5. Recommendations for Model Training:
   - Focus on high-variance parameters for anomaly detection
   - Consider time-series features for temperature parameters
   - Include interaction features between correlated parameters
   - Apply outlier treatment for robust model training
============================================================
```