AI-Powered Defect Detection & Recommendation System: A Case Study

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The Business Problem & Our Goal

The High Cost of Late Detection

- **Problem: Currently, defects are found late in the process.**
- **Impact: This leads to costly rework, wasted materials, and potential quality issues.**
- **To build an AI system that detects early warning signs of defects and recommends corrective actions to operators in real-time.**

Data-Driven Approach

From Raw Data to Actionable Intelligence

- **A 4-step flow diagram:**

1) EDA: Understand the hidden patterns in our factory data.

2) Predict & Classify (ML Model): Build a model to predict defects before they happen.

3) Explain & Recommend: Understand why a defect is happening to recommend a fix.

4) Potential risks associated with solutions.

Feature Explanations

batch_id, machine_id, operator_id: First, we have the basic tracking information for each batch: its unique batch_id, the machine_id it was produced on, and the operator_id who did the run. This allows us to trace every product and group our data by machine or operator to find patterns.

timestamp_start / timestamp_end: The timestamps tell us exactly when each batch was produced, which is crucial for analyzing trends over time and for calculating the total production duration for each batch.

temperature_C: This is the average operating temperature inside the machine, measured in Celsius. It's a critical physical parameter that directly affects the material's properties as it's being formed.

pressure_bar: This measures the pressure, or the force, used to shape the product. As we'll see, this is a key factor for structural integrity.

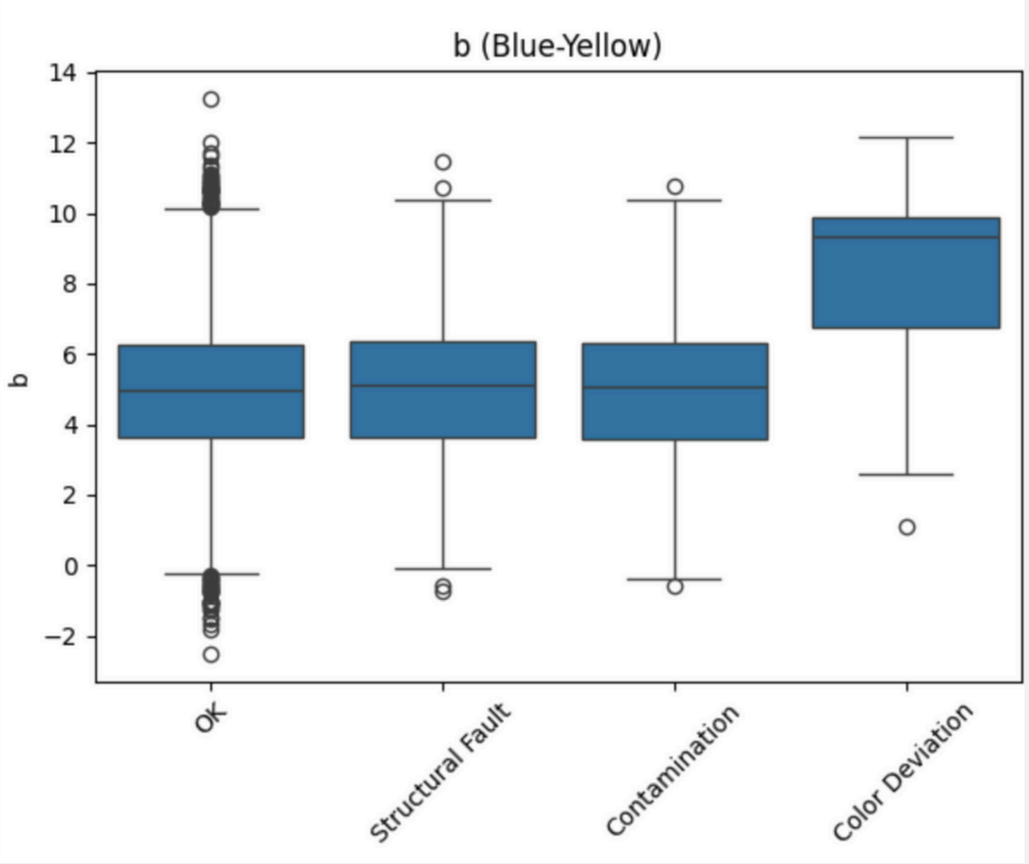
machine_speed_rpm: This is the machine's operating speed in revolutions per minute. It controls how fast the product is made and can influence its final finish and consistency.

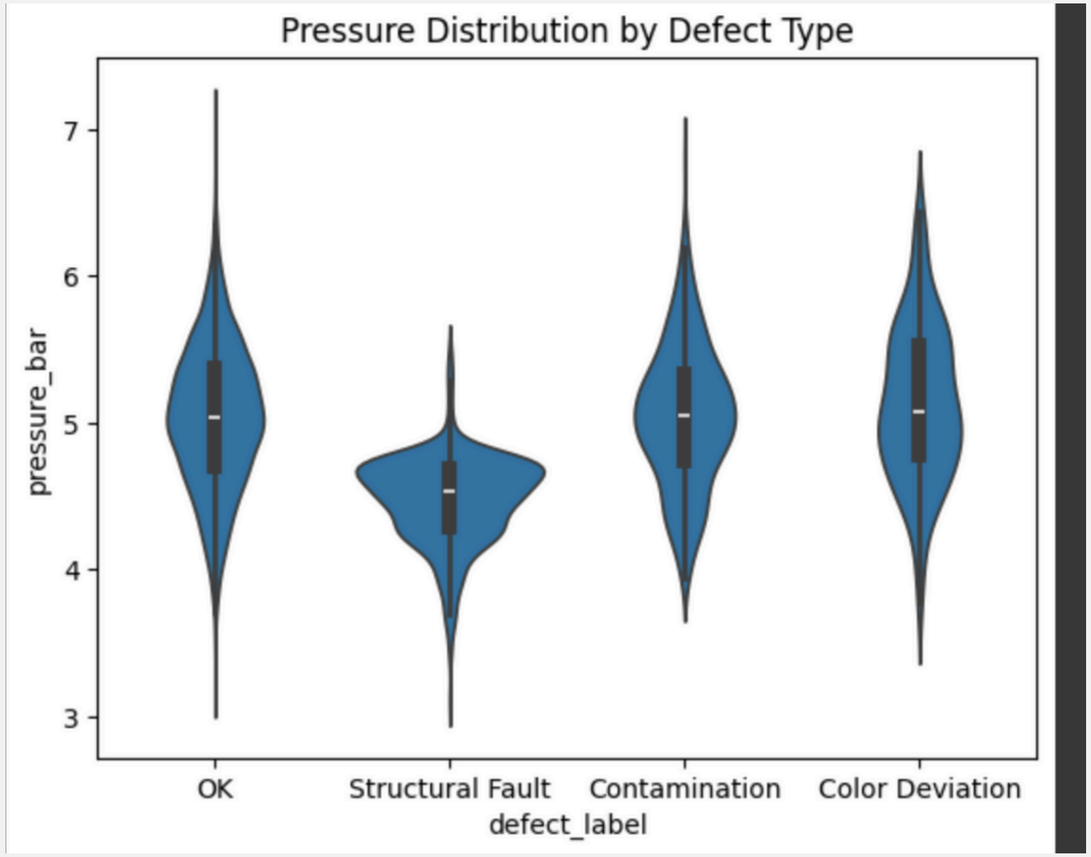
L, a, b (The Lab color space): After production, we get precise lab measurements. The most important for color are the L, a, and b values. This is a standard way to measure color: 'L' is for Lightness, 'a' is the green-to-red scale, and 'b' is the blue-to-yellow scale. This gives us an objective way to identify color defects.

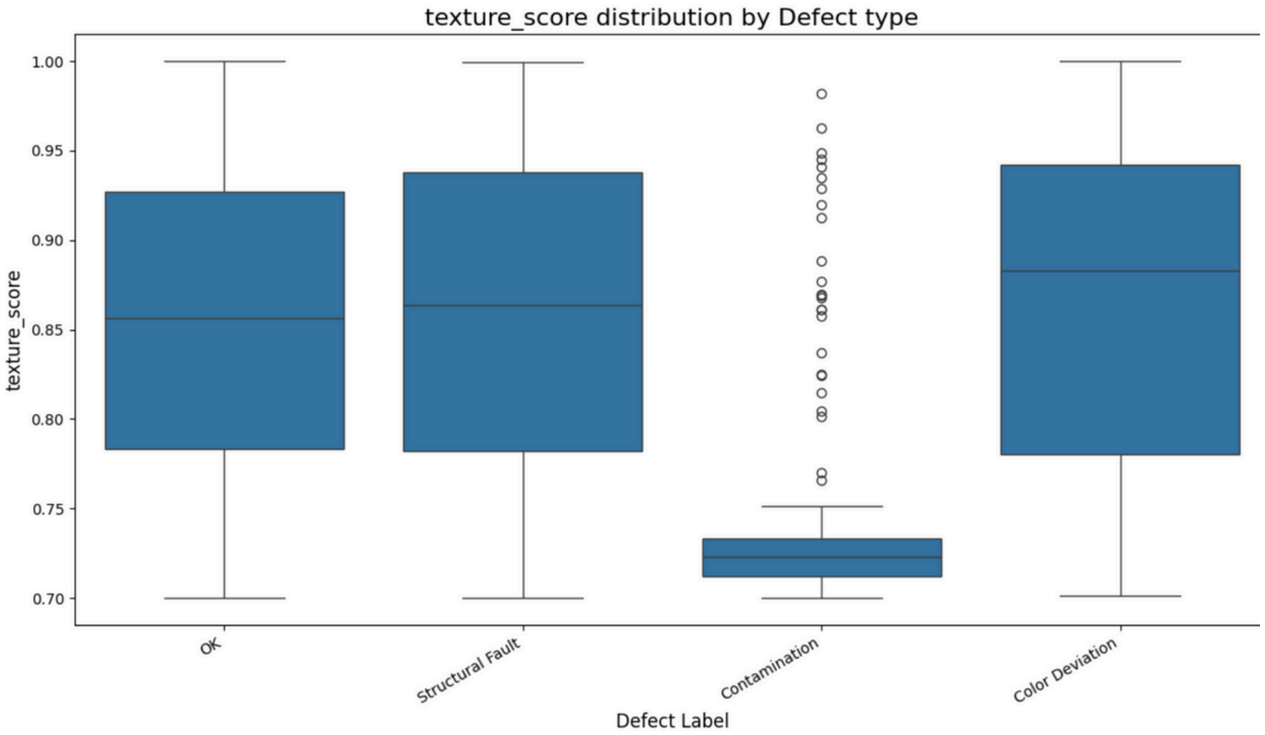
moisture_percent: This measures the final moisture percentage in the product. For many materials, having the correct moisture level is essential to prevent defects and ensure stability

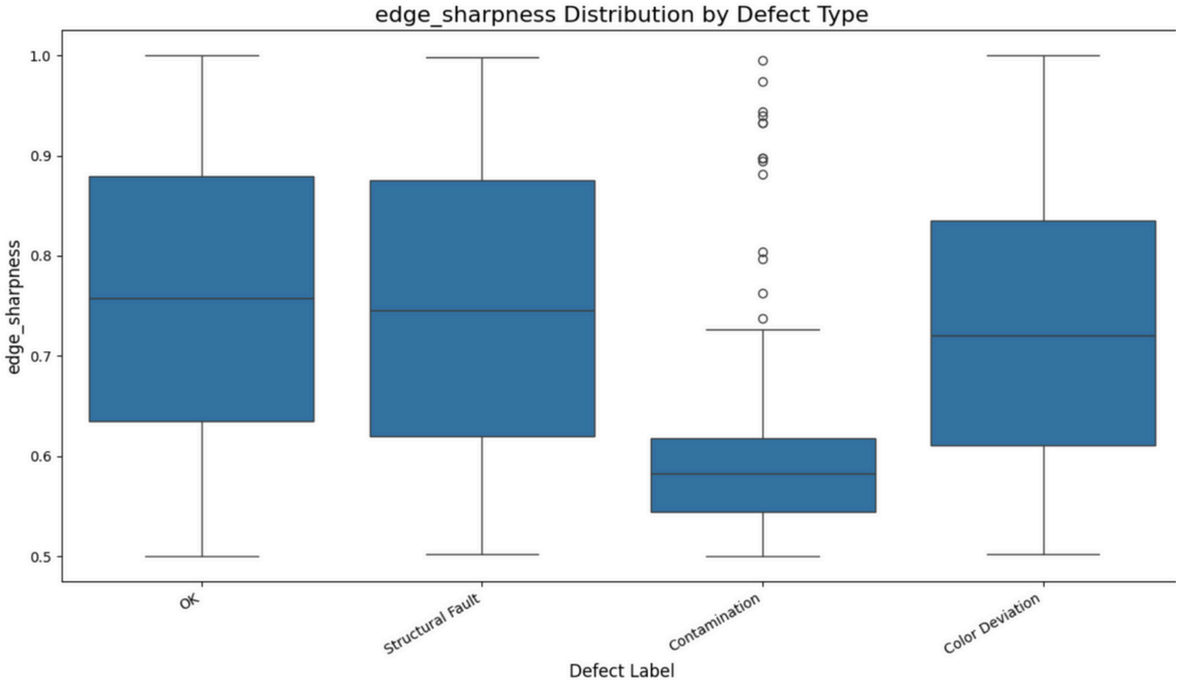
EDA

Found Direct Links Between Measurements and Defects

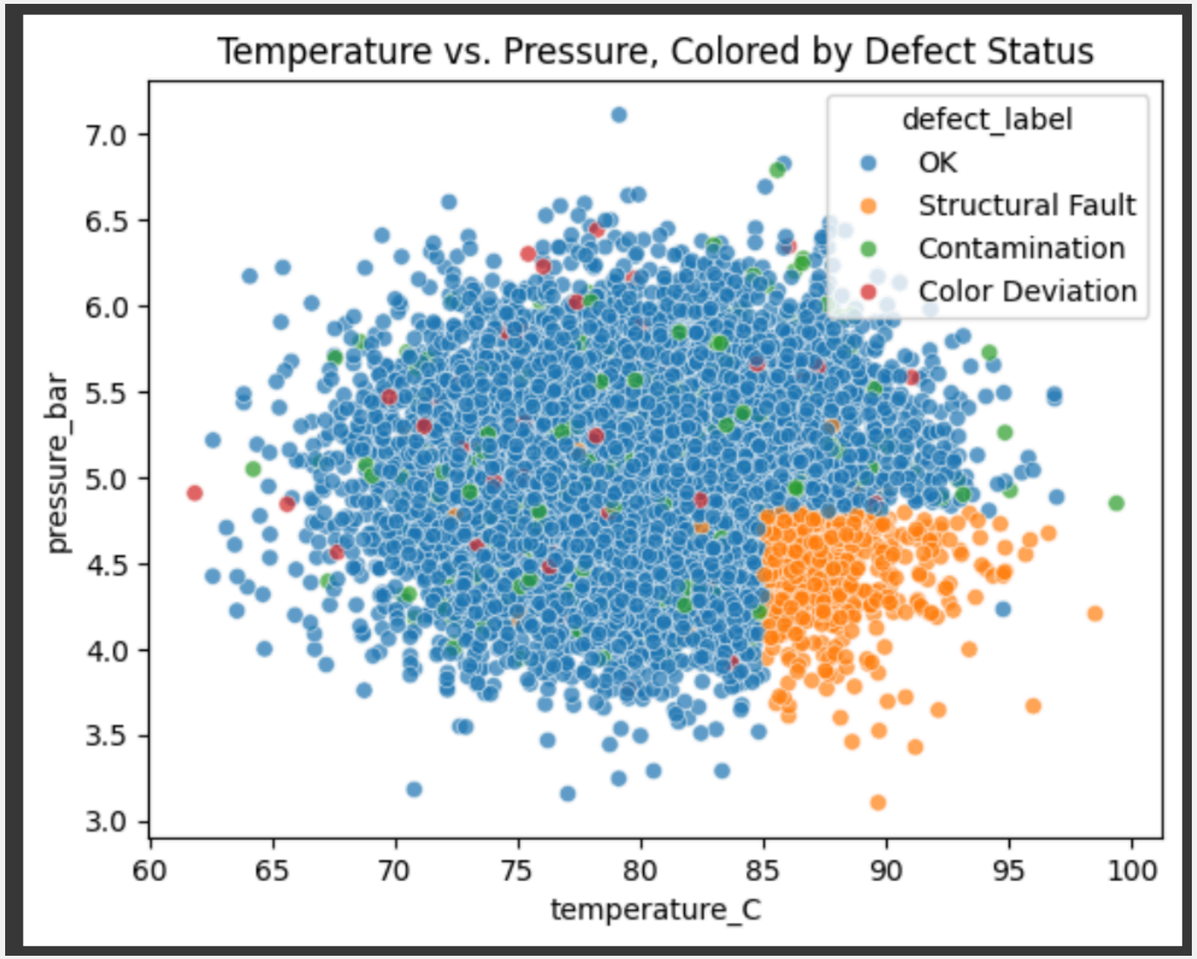


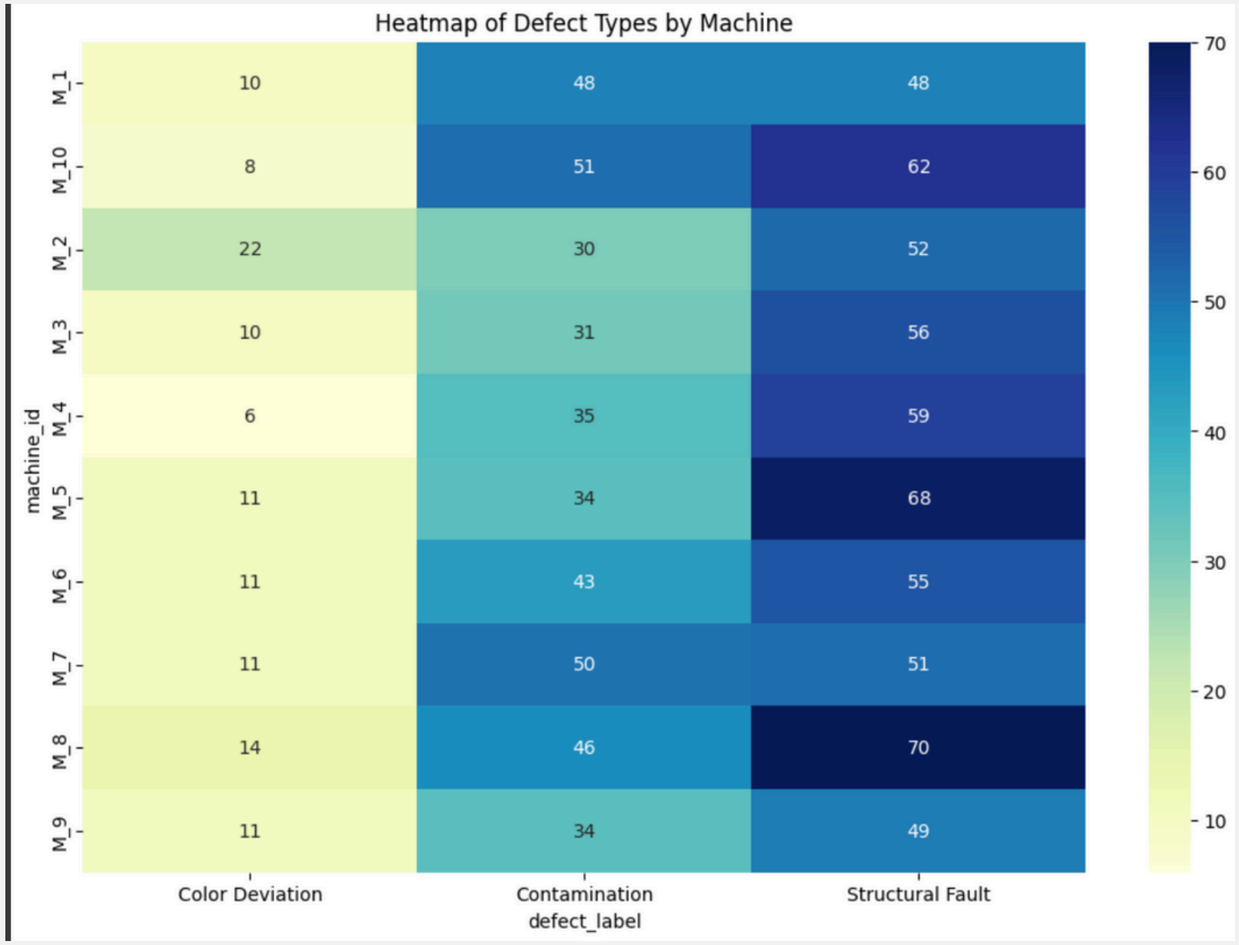


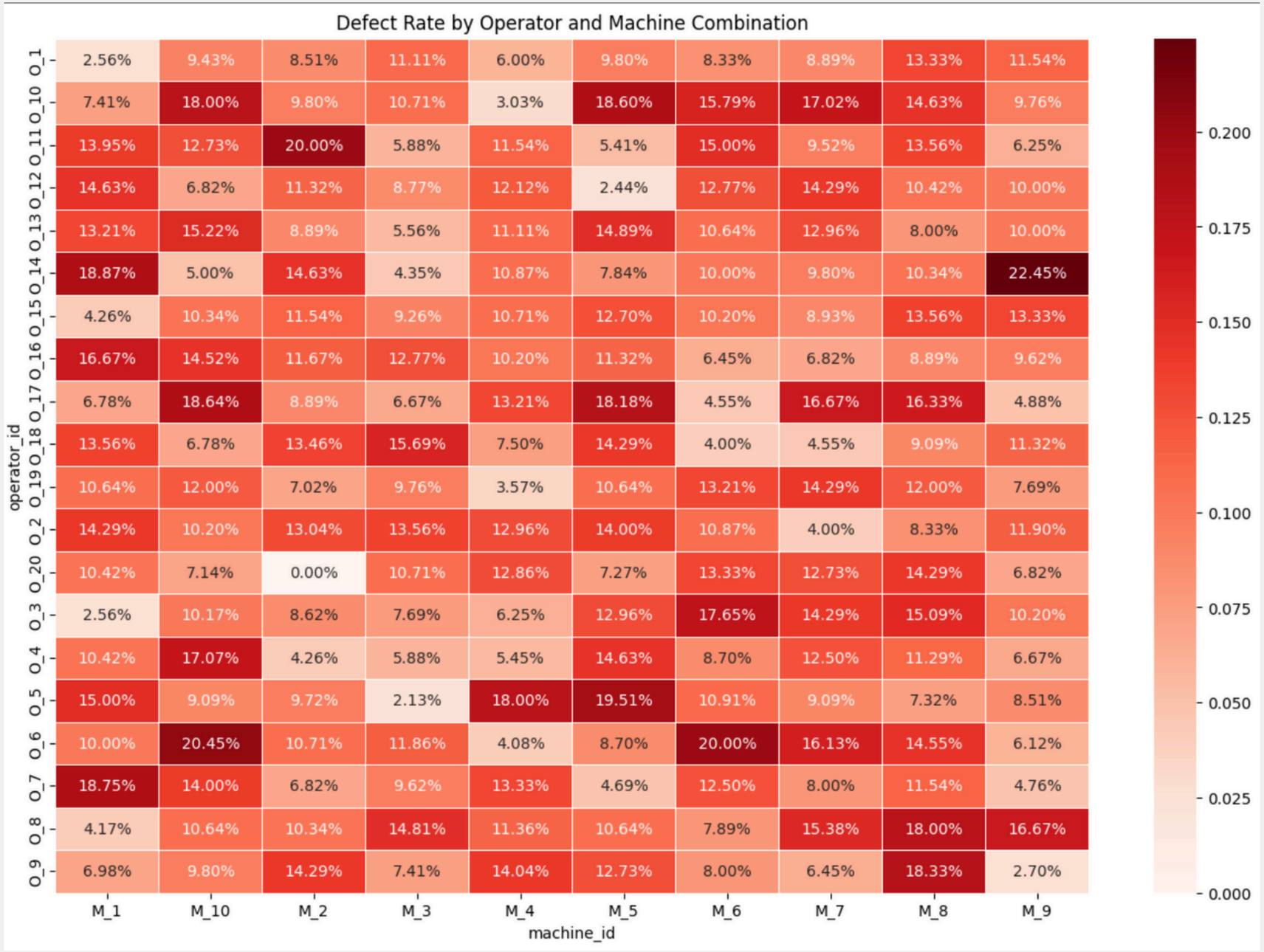

texture_score distribution by Defect type
texture_score
1.00
0.95
0.90
0.85
0.80
0.75
0.70
OK
Structural Fault
Contamination
Color Deviation
Defect Label


edge_sharpness Distribution by Defect Type
edge_sharpness
1.0
0.9
0.8
0.7
0.6
0.5
OK
Structural Fault
Contamination
Color Deviation
Defect Label

Temperature and Pressure tell us a lot about Structural Faults !!






Defect Rate by Operator and Machine Combination
operator_id
machine_id
O_1 2.56% 9.43% 8.51% 11.11% 6.00% 9.80% 8.33% 8.89% 13.33% 11.54%
O_10 7.41% 18.00% 9.80% 10.71% 3.03% 18.60% 15.79% 17.02% 14.63% 9.76%
O_11 13.95% 12.73% 20.00% 5.88% 11.54% 5.41% 15.00% 9.52% 13.56% 6.25%
O_12 14.63% 6.82% 11.32% 8.77% 12.12% 2.44% 12.77% 14.29% 10.42% 10.00%
O_13 13.21% 15.22% 8.89% 5.56% 11.11% 14.89% 10.64% 12.96% 8.00% 10.00%
O_14 18.87% 5.00% 14.63% 4.35% 10.87% 7.84% 10.00% 9.80% 10.34% 22.45%
O_15 4.26% 10.34% 11.54% 9.26% 10.71% 12.70% 10.20% 8.93% 13.56% 13.33%
O_16 16.67% 14.52% 11.67% 12.77% 10.20% 11.32% 6.45% 6.82% 8.89% 9.62%
O_17 6.78% 18.64% 8.89% 6.67% 13.21% 18.18% 4.55% 16.67% 16.33% 4.88%
O_18 13.56% 6.78% 13.46% 15.69% 7.50% 14.29% 4.00% 4.55% 9.09% 11.32%
O_19 10.64% 12.00% 7.02% 9.76% 3.57% 10.64% 13.21% 14.29% 12.00% 7.69%
O_2 14.29% 10.20% 13.04% 13.56% 12.96% 14.00% 10.87% 4.00% 8.33% 11.90%
O_20 10.42% 7.14% 0.00% 10.71% 12.86% 7.27% 13.33% 12.73% 14.29% 6.82%
O_3 2.56% 10.17% 8.62% 7.69% 6.25% 12.96% 17.65% 14.29% 15.09% 10.20%
O_4 10.42% 17.07% 4.26% 5.88% 5.45% 14.63% 8.70% 12.50% 11.29% 6.67%
O_5 15.00% 9.09% 9.72% 2.13% 18.00% 19.51% 10.91% 9.09% 7.32% 8.51%
O_6 10.00% 20.45% 10.71% 11.86% 4.08% 8.70% 20.00% 16.13% 14.55% 6.12%
O_7 18.75% 14.00% 6.82% 9.62% 13.33% 4.69% 12.50% 8.00% 11.54% 4.76%
O_8 4.17% 10.64% 10.34% 14.81% 11.36% 10.64% 7.89% 15.38% 18.00% 16.67%
O_9 6.98% 9.80% 14.29% 7.41% 14.04% 12.73% 8.00% 6.45% 18.33% 2.70%
M_1 M_10 M_2 M_3 M_4 M_5 M_6 M_7 M_8 M_9
0.200 0.175 0.150 0.125 0.100 0.075 0.050 0.025 0.000

ML problem framing

Doing time-based splitting to mimic real world scenario as much as possible

Training data from 2024-01-01 05:00:00 to 2028-07-17 19:00:00
Testing data from 2028-07-18 05:00:00 to 2029-09-14 03:00:00

Baseline model

```
--- Logistic Regression ---
Macro F1-Score: 0.4486

                  precision    recall  f1-score   support

 Color Deviation       0.04      0.72      0.07        18
   Contamination       0.27      0.92      0.42        86
              OK       0.99      0.61      0.76      1774
Structural Fault       0.39      0.87      0.54       122

        accuracy                           0.64      2000
       macro avg       0.42      0.78      0.45      2000
    weighted avg       0.91      0.64      0.72      2000
```

Random Forest

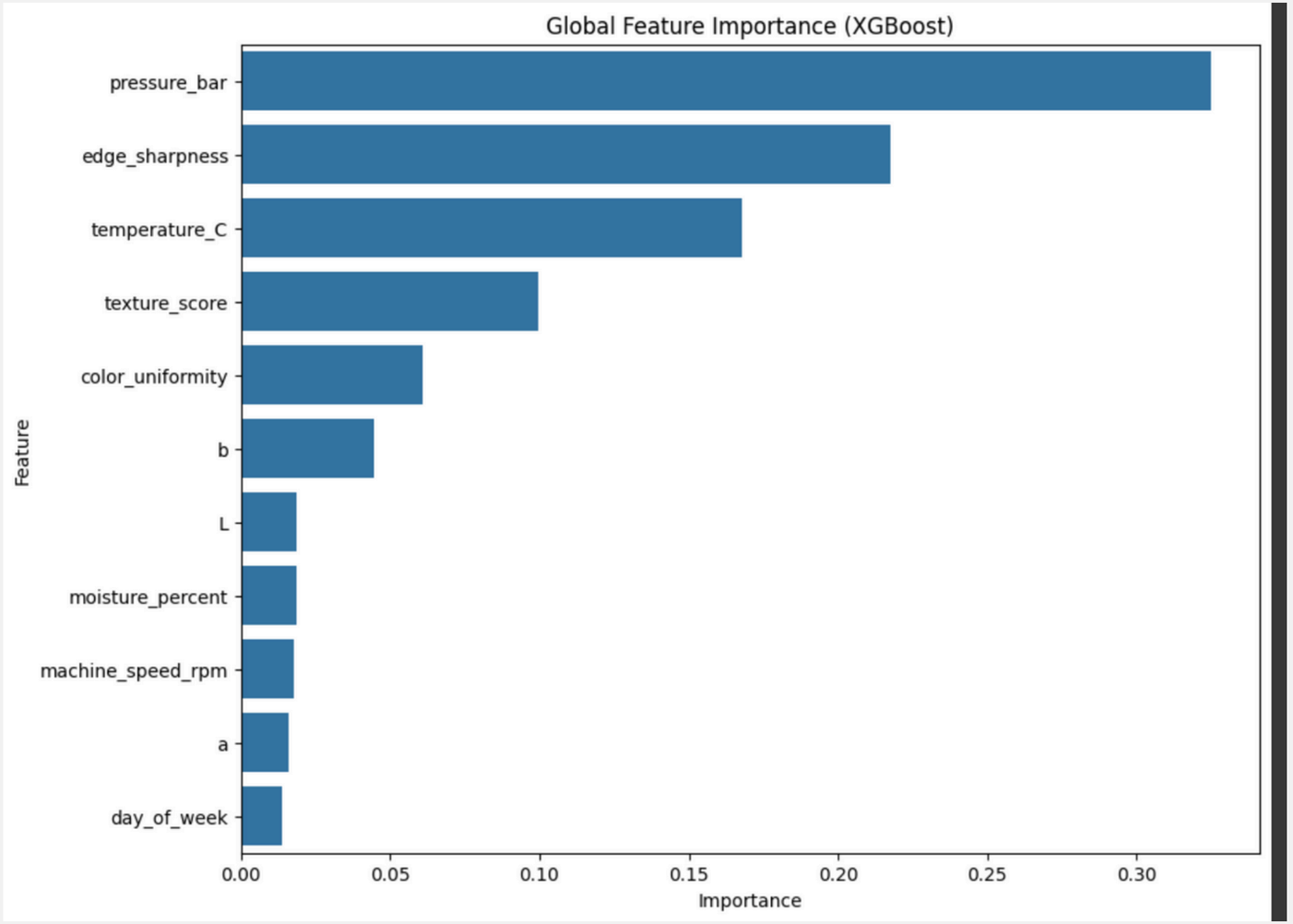
```
Macro F1-Score: 0.9152

                  precision    recall  f1-score   support

 Color Deviation       1.00      0.61      0.76        18
   Contamination       0.96      0.95      0.96        86
              OK       0.99      1.00      0.99      1774
Structural Fault       0.99      0.91      0.95       122

        accuracy                           0.99      2000
       macro avg       0.99      0.87      0.92      2000
    weighted avg       0.99      0.99      0.99      2000
```

Xgboost

Macro F1-Score: 0.9278

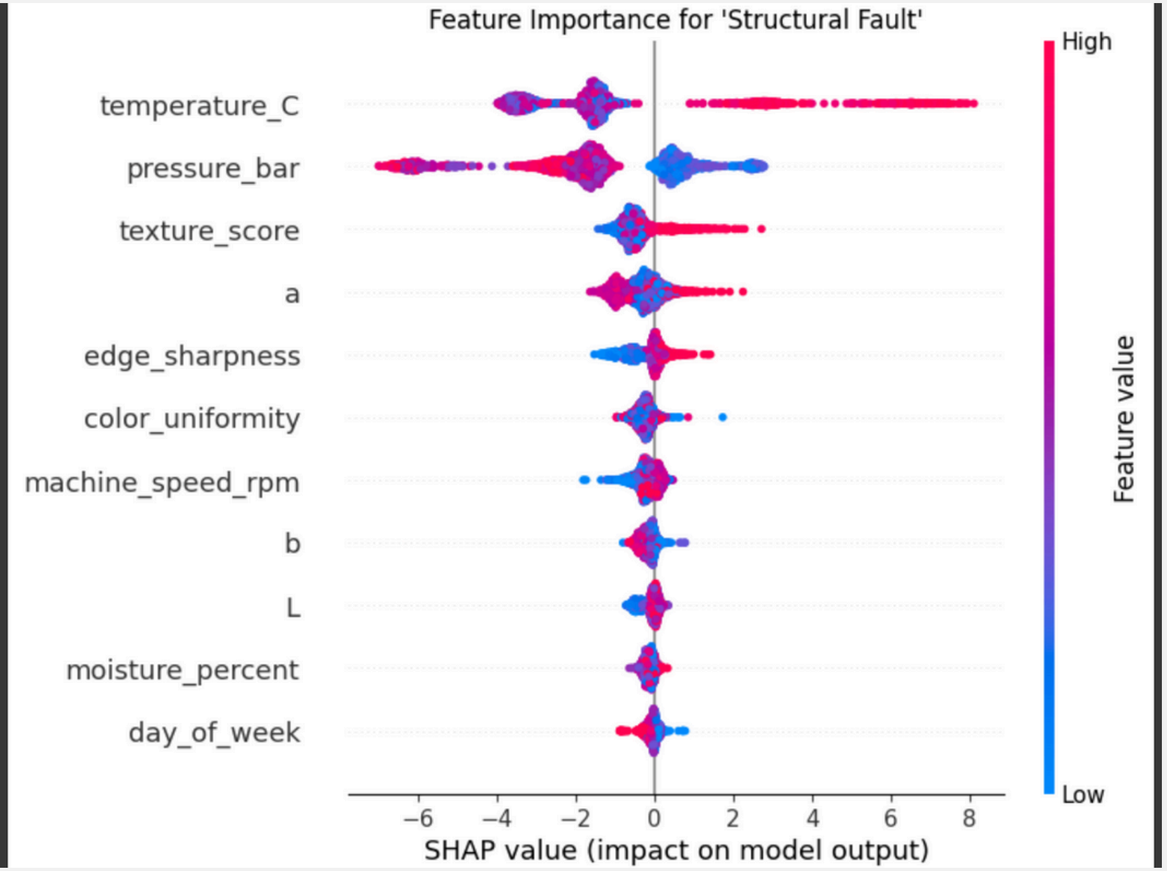
Classification Report:

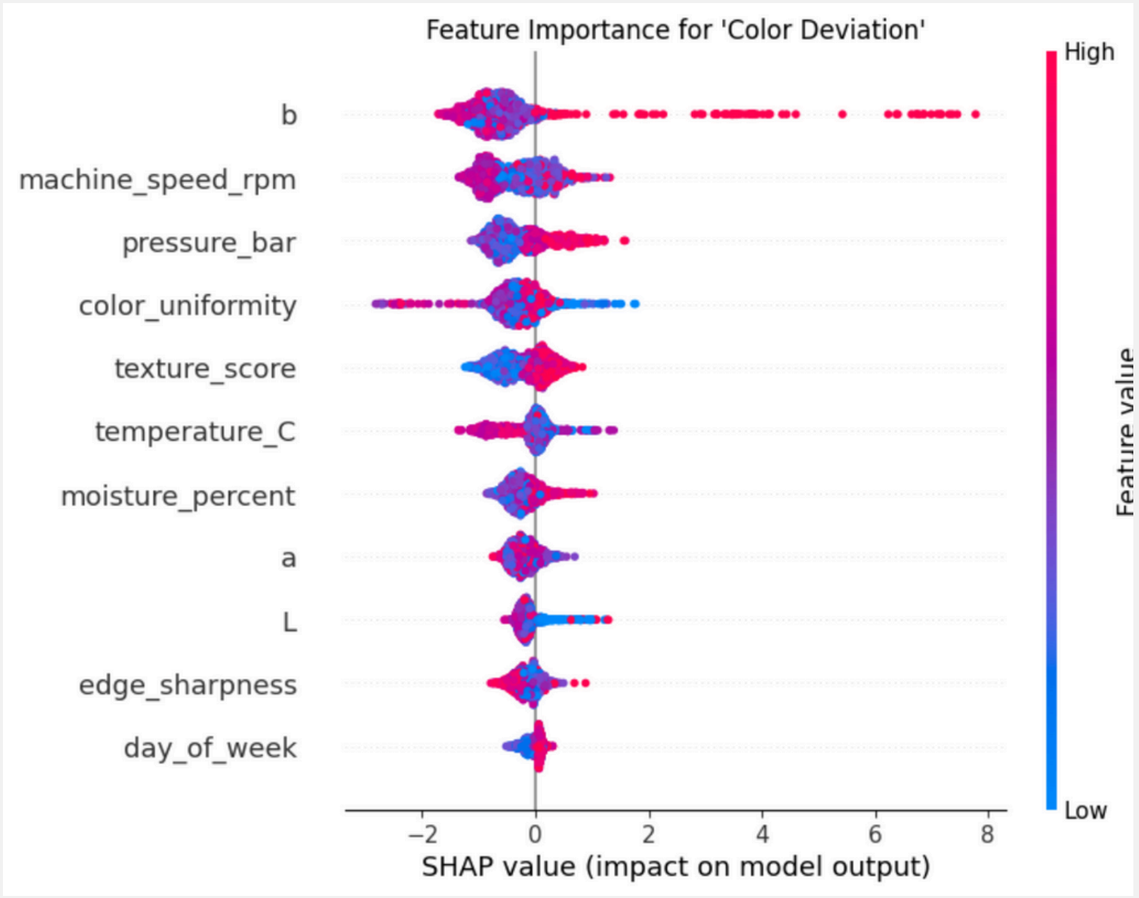
	precision	recall	f1-score	support
Color Deviation	1.00	0.65	0.79	23
Contamination	0.97	0.93	0.95	80
OK	0.99	1.00	1.00	1783
Structural Fault	1.00	0.96	0.98	114
accuracy			0.99	2000
macro avg	0.99	0.88	0.93	2000
weighted avg	0.99	0.99	0.99	2000

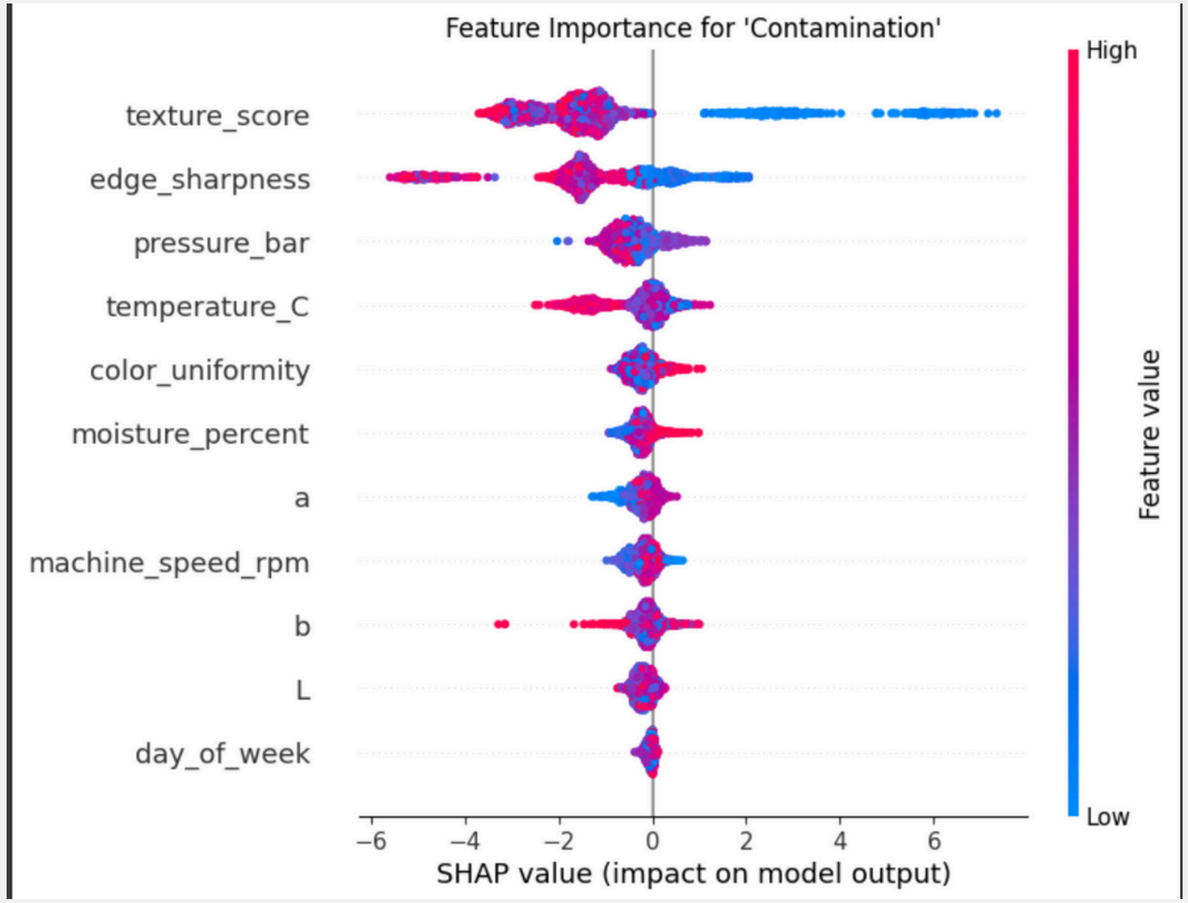


Explainability and actionable insights for business decision making

SHAP values







Structural Fault

Temperature is the #1 driver.

Pressure is the #2 driver

Color Deviation

The 'b' Color Value is the #1 driver.

Contamination

Texture Score is the #1 driver.

Edge Sharpness is #2.

Potential risks associated with solutions

Implement stricter control limits and alerts for temperature and pressure based on the model's findings.

Problem:

1) If new limits are too tight, the system may trigger the alarm for minor problems. This could cause operators to miss the alarms including critical ones.

2)Might lead new problems, for example lowering temperature to avoid structural fault might cause other defects.

Calibrate the color sensors to ensure the b* value readings are accurate.

Thank You!