Exploratory Analysis for Identifying Key Drivers of Anode Cracking Using Explainable Machine Learning

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Executive Summary

Problem	Anode cracking reduces production efficiency and increases scrap, rework, and operational risk in aluminum smelting. The process involves many interacting parameters, making it difficult to identify the dominant causes of cracking using conventional analysis.
Approach	Explainable machine learning (CatBoost + SHAP) is used as an exploratory tool to screen key drivers from complex production data. The model is not treated as a final predictor, but as a guide to focus exploratory data analysis and process interpretation.
Key Findings	Cracking is highly concentrated in the middle layer, with a crack rate more than twice that of the upper and lower layers. Binder level and building location, especially A2, also show strong association with crack risk. EDA confirms that cracking is driven by higher-risk conditions, not by higher production volume.
Implication	The results identify strong drivers but not yet final root causes. The middle layer is the most critical zone and should be the first priority for deeper investigation
Recommendation	Shift from broad trial and error adjustments to hypothesis-driven investigation. Focus first on thermal behavior, material sensitivity, and handling practices in the middle layer, and validate root causes through controlled trials and process audits.

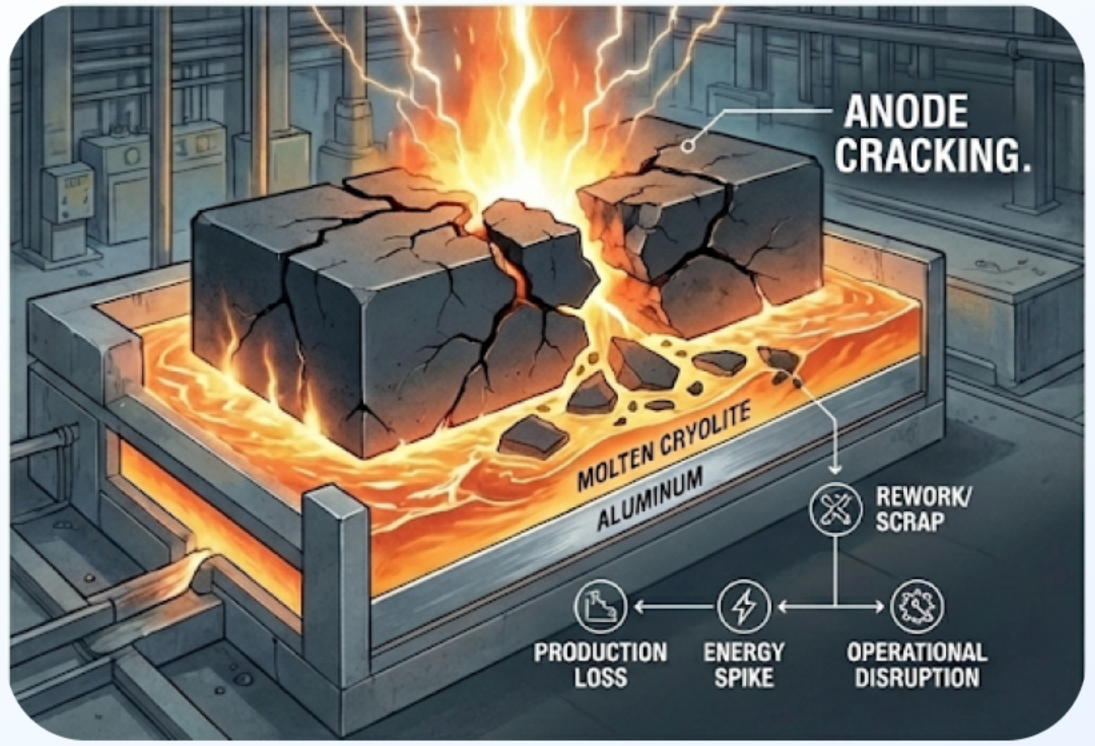
Background

In the aluminum smelting industry, the anode is a critical component that determines the stability and efficiency of the electrolysis process. Anode quality strongly affects energy consumption, pot lifetime, and production continuity.

During anode forming and baking processes, defects such as anode cracking frequently occur. Cracked anodes may become broken anodes.

The Impacts of Anode Cracking

- Anodes must be reworked or discarded as scrap
- Production time increases due to anode replacement
- Energy consumption and operating costs rise
- The risk of operational disturbances in the potline becomes higher



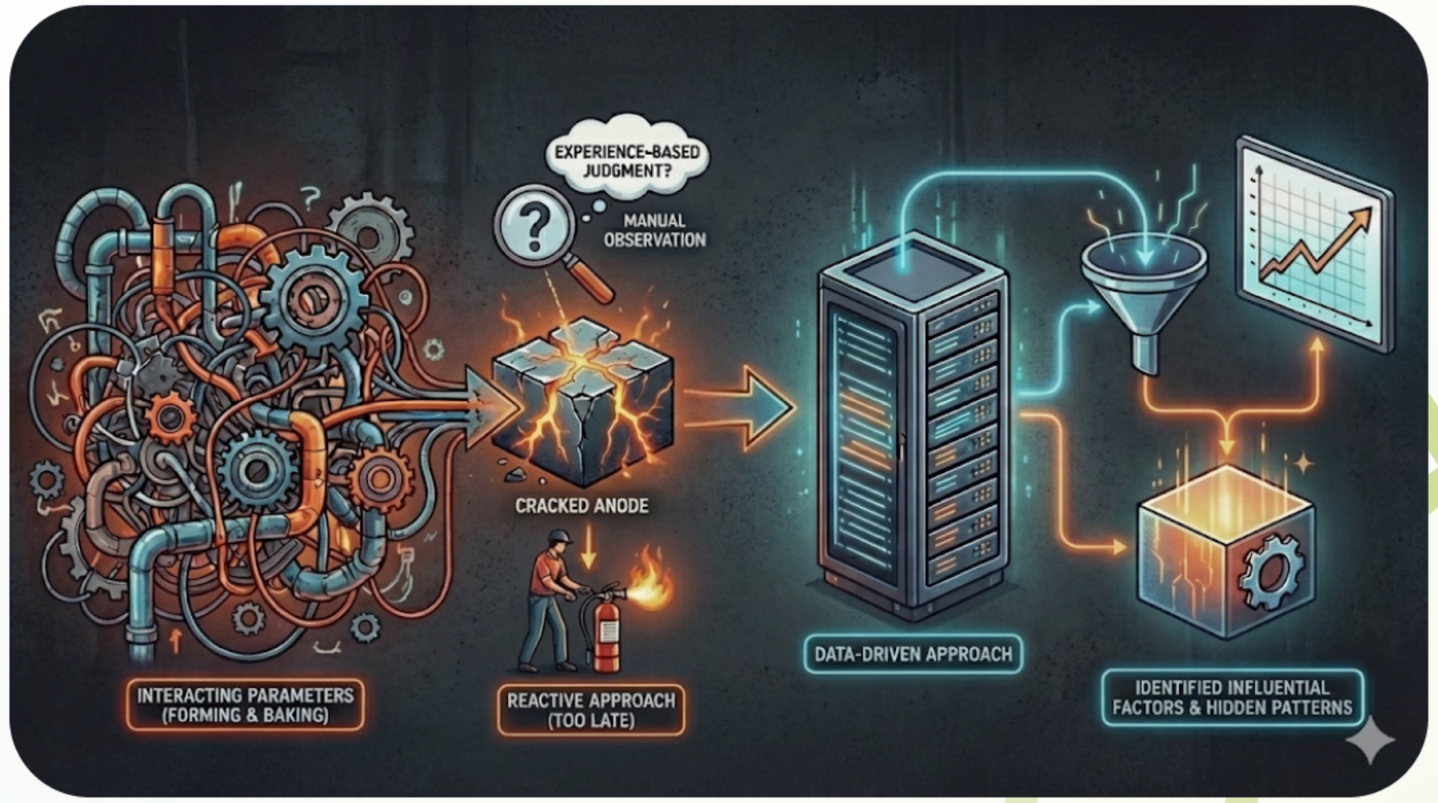
Although large volumes of process data are available, The complexity of process parameters makes the relationship between production conditions and cracking difficult to quantify

Problem Statement

The anode forming and baking processes involve many operational parameters, ranging from raw material preparation, mixing, molding, and shaping to baking in the furnace. These parameters interact with each other and can jointly contribute to anode cracking.

Currently, identifying the causes of cracking faces several major challenges:

- It is difficult to determine the dominant factors due to the large number of interacting process variables
- Analysis still relies heavily on experience-based judgment and manual observation
- The approach is mostly reactive, addressing problems only after cracks occur
- There is no consistent quantitative method to filter the most influential factors



As a result, crack reduction efforts are often unfocused and require long trial periods to find effective solutions. A data-driven approach is needed to uncover hidden patterns in production data and to guide investigation toward the factors that truly matter.

Objective

This study aims to use production data and machine learning as an exploratory tool to understand patterns related to anode cracking.

Identify process factors that are most strongly associated with anode cracking

Use machine learning as a screening tool to filter key drivers from many process variables

Guide Exploratory Data Analysis (EDA) toward the most relevant factors

Generate initial hypotheses about process mechanisms that may lead to cracking

This study does not aim to build a final operational prediction system, but rather to use machine learning as an exploratory aid to understand patterns and direct further process investigation in a systematic, data-driven way.

Methodology

Data Collection

Production data were collected from mixing, forming, baking, and inspection processes.

Data Cleaning and Preprocessing

Missing values, inconsistent formats, and data type issues were handled and standardized.

Feature Engineering

Process-relevant features were created to represent material properties, geometry, and baking conditions.

Machine Learning for Exploration

Machine learning models were trained as exploratory tools to learn relationships between process parameters and cracking.

Explainability (SHAP)

SHAP was used to identify the most influential factors affecting crack variation.

Focused EDA

In-depth EDA was conducted on the top drivers identified by the model.

Process Interpretation

Results were interpreted using process knowledge to generate hypotheses about potential crack mechanisms.

Recomendation

Insights were translated into actionable strategies to optimize key process parameters and mitigate cracking risks.

Model Performance

Performance of several models evaluated using a time-based split to avoid data leakage. The main metrics used are ROC-AUC and PR-AUC.

Model	Accuracy	Precision	Recall	F1- Score	ROC-AUC	PR-AUC
Catboost	0.69	0.55	0.62	0.58	**0.73**	**0.59**
LightGBM	0.69	0.56	0.56	0.56	0.71	0.55
Random Forest	0.67	0.54	0.54	0.54	0.67	0.51
XGBoost	0.69	0.57	0.47	0.51	0.69	0.54

ROC-AUC of 0.73 means that the model is able to correctly rank a cracked anode higher than a non-cracked anode in about 73% of random pair comparisons.

This indicates a good but not perfect ability to separate cracked and non-cracked cases under realistic production conditions.

PR-AUC of 0.59 is significantly higher than the baseline PR-AUC (which is equal to the crack rate in the data, around 0.33).

This shows that the model meaningfully improves the identification of high-risk crack cases compared to random guessing.

After multiple rounds of feature engineering, time-based validation, and model tuning, performance stabilized around ROC-AUC ≈ 0.73.

The remaining limitation is not mainly due to model choice, but more likely due to:

- Inherent noise in inspection labels,
- Changing process conditions over time, and
- Limited information in the available process variables.

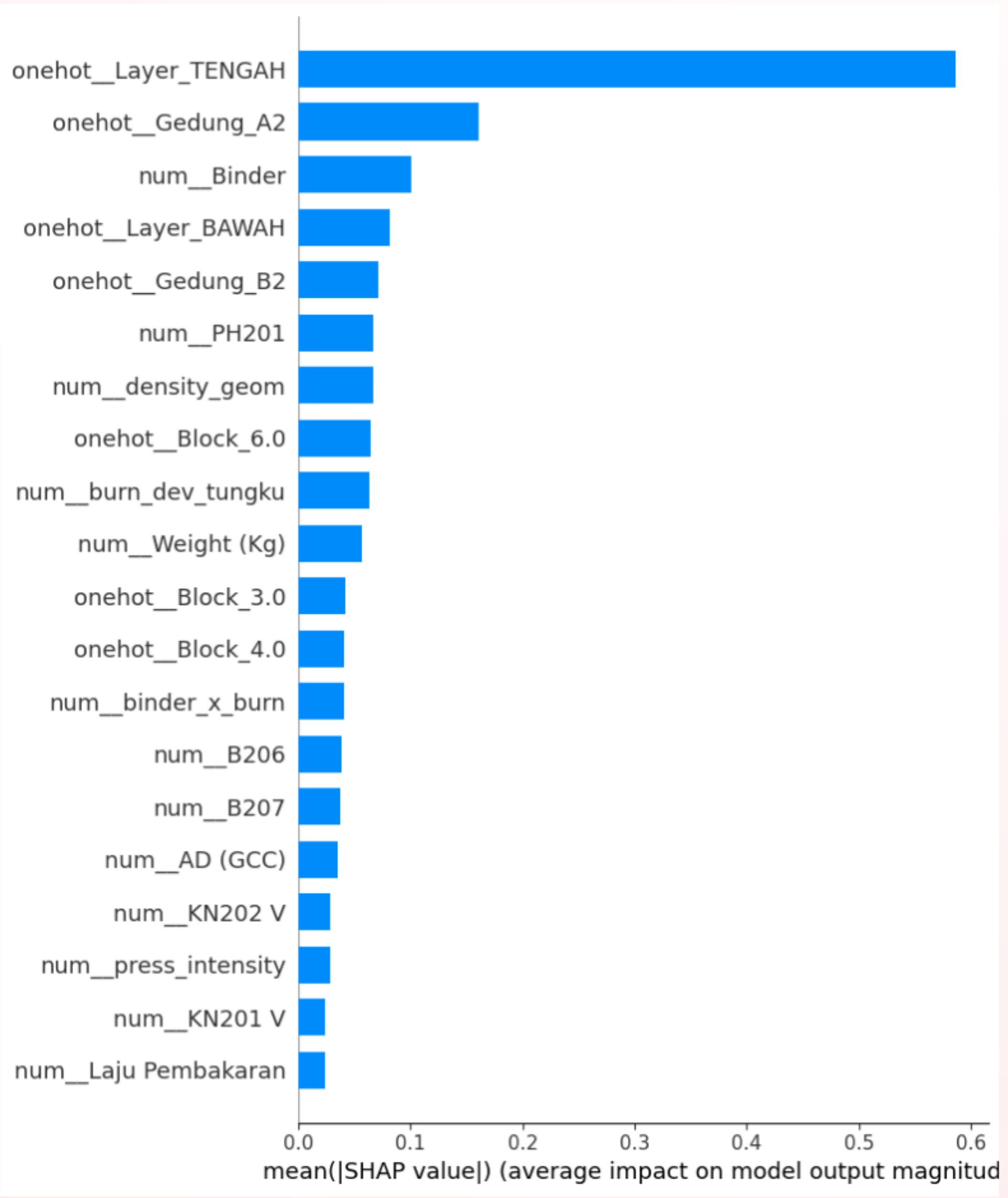
CatBoost was selected as the main exploratory model

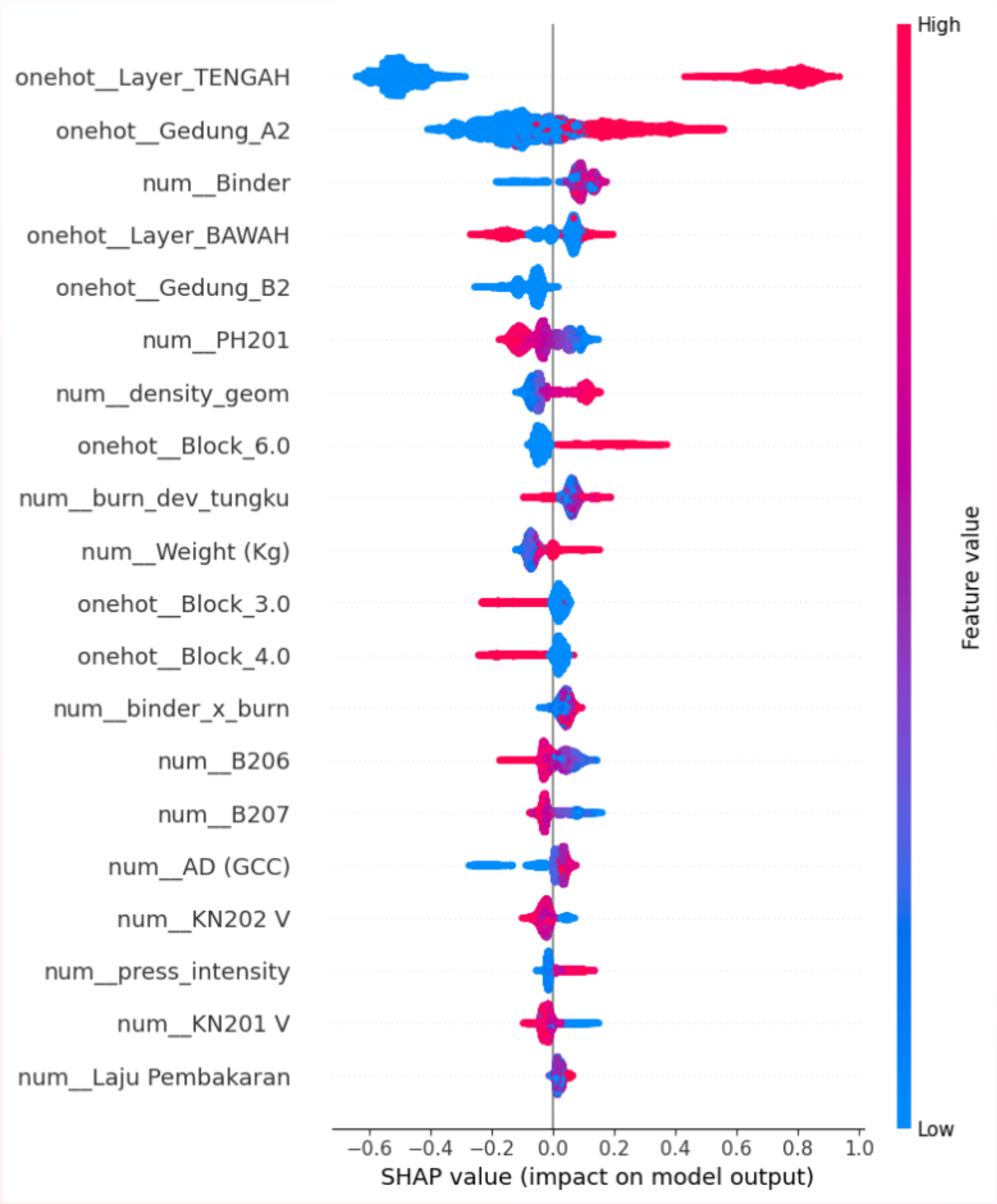
- Catboost consistently produced the highest or most stable ROC-AUC and PR-AUC,
- Catboost provides reliable SHAP explanations, which are critical for exploratory and root cause analysis.

Key Takeaway

A ROC-AUC of 0.73 shows that the model can reasonably rank crack risk under real production conditions, and CatBoost is chosen because it gives the most stable performance and the clearest explanations for identifying key drivers.

SHAP for Model Explainability





To understand how the model makes decisions, SHAP (SHapley Additive exPlanations) is used as an explainability method.

SHAP assigns a contribution value to each feature for every prediction, showing:

- Which features push the model toward “crack”
- Which features push the model toward “no crack”
- How strong each feature’s influence is

Using mean(|SHAP value|), features are ranked by their average impact on the model output.

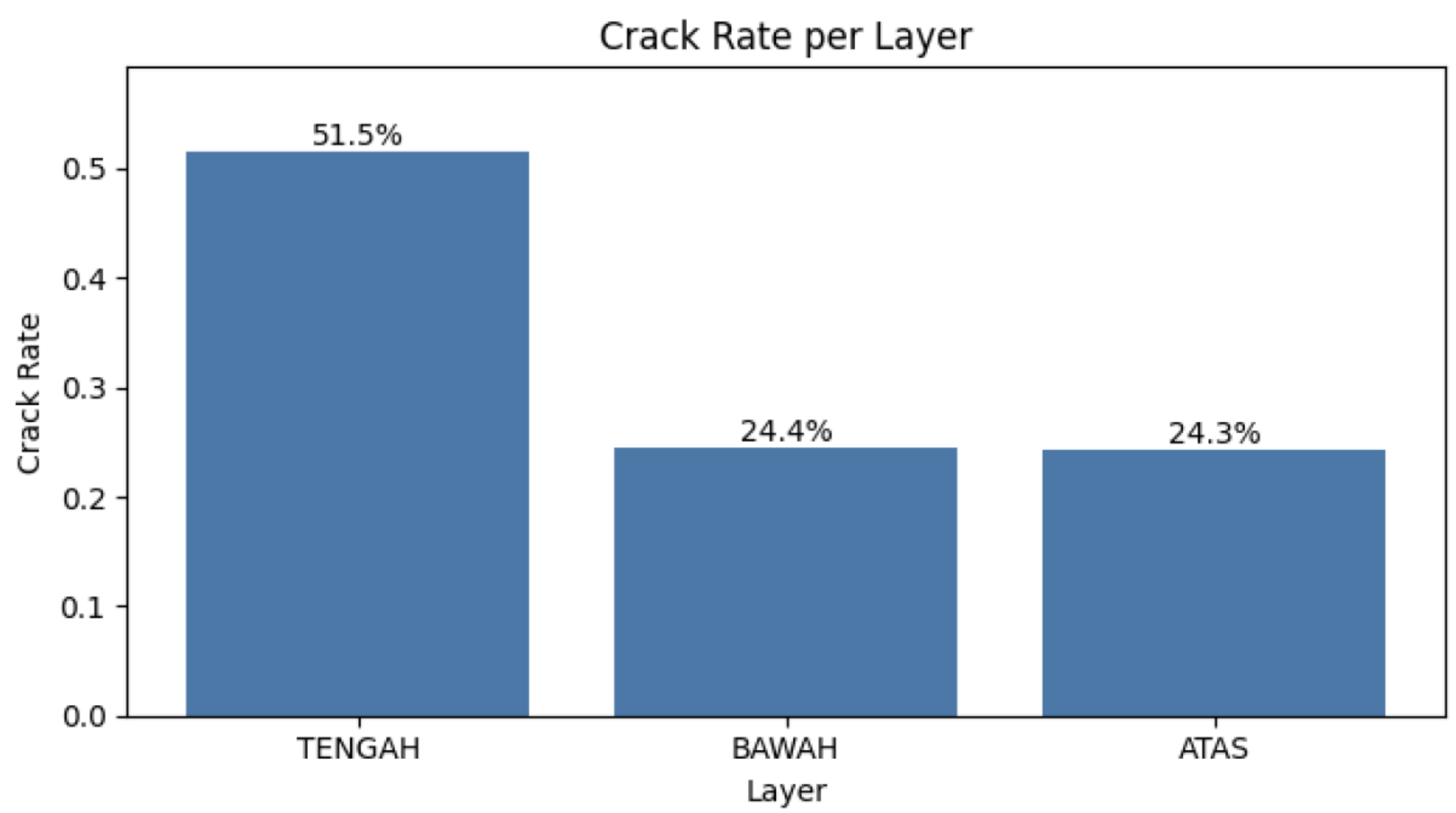
Top 3 Key Driver for Anode Cracking

Layer_TENGAH

Gedung_A2

Binder

Layer Tengah as the Main Driver of Anode Cracking



Layer	Crack Rate	Num of Anode
Tengah	51%	27456
Bawah	24%	27261
Atas	24%	27548

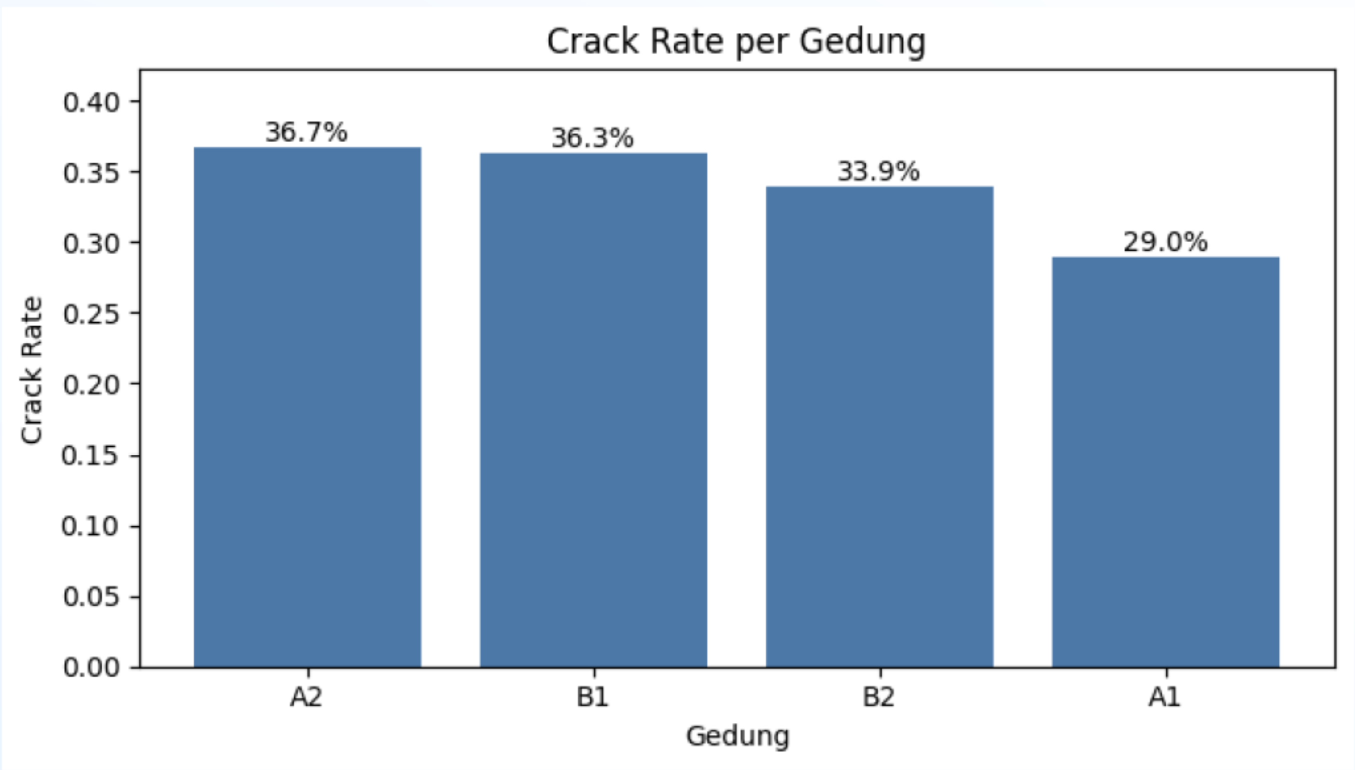
Main Points

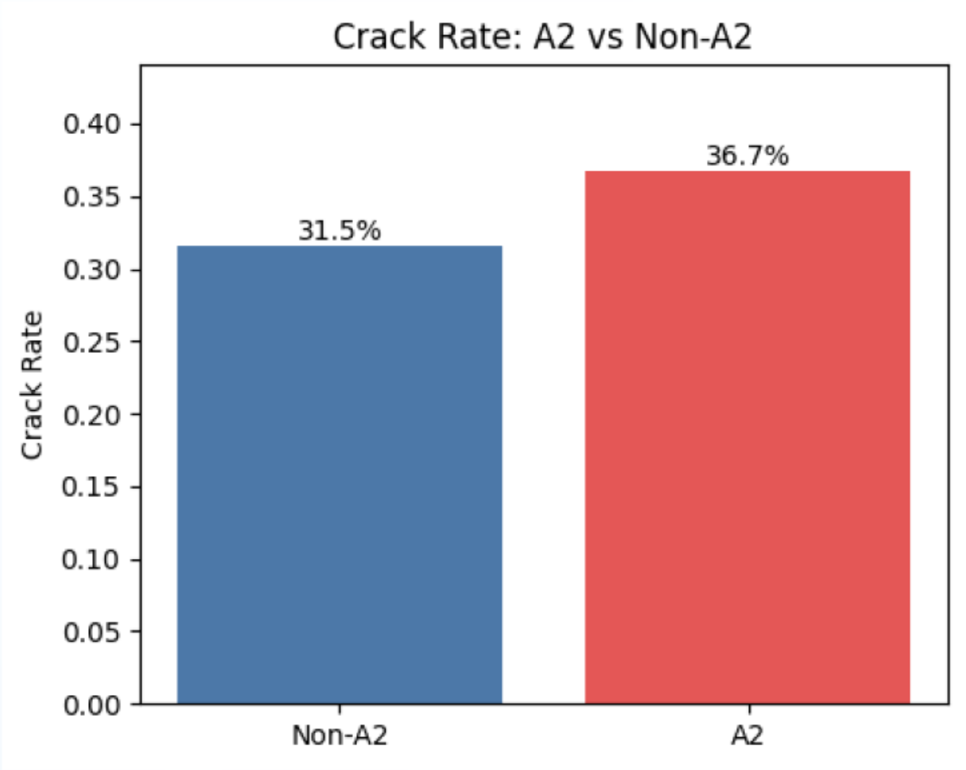
- Anode distribution across layers is relatively balanced
- Middle layer crack rate ≈ 51%
- Upper and lower layers crack rate ≈ 24%
- Difference is not caused by volume, but by risk per anode
- Result confirms ML and SHAP findings

Key Takeaway

Cracking is highly concentrated in the middle layer, making it the most critical zone for understanding and reducing anode crack.

Higher Crack Risk in Gedung A2





Key Takeaway

Gedung A2 consistently has the highest crack rate. When compared directly, anodes produced in A2 have a noticeably higher crack probability than those from non-A2 buildings.

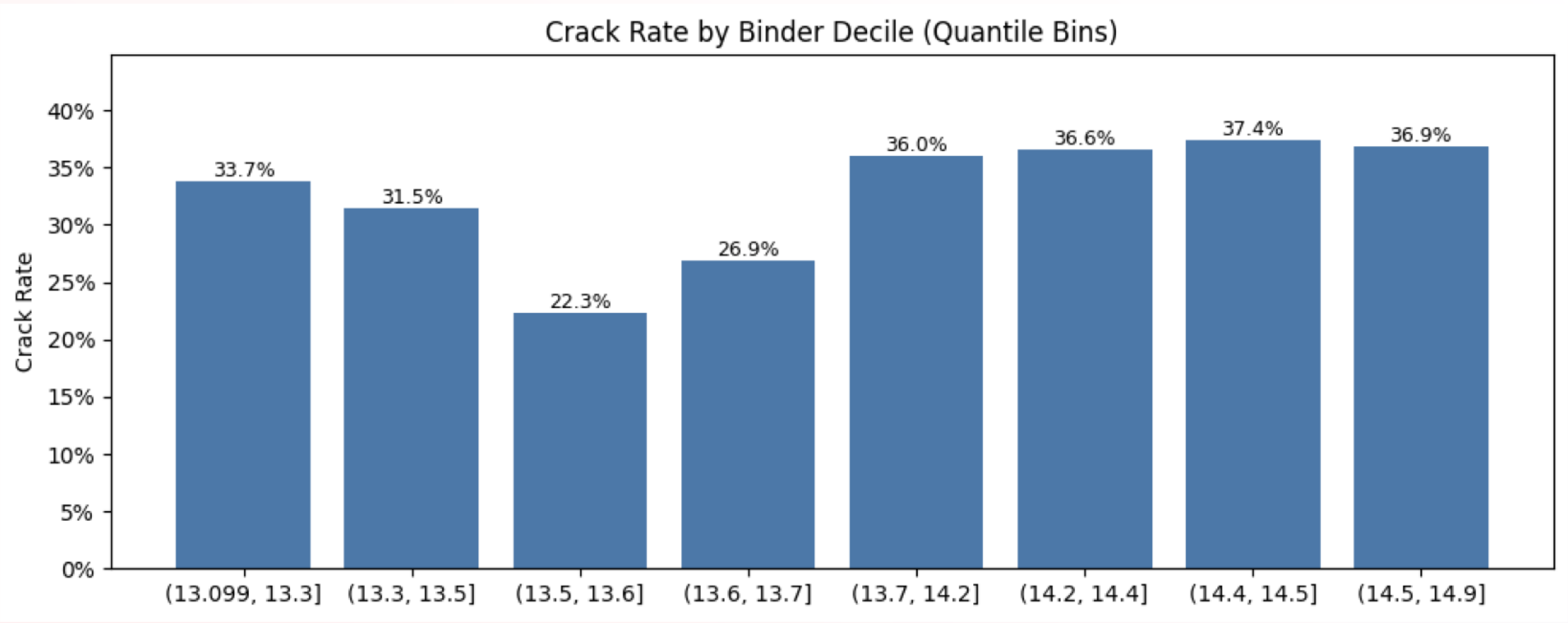
Gedung A2 should therefore be prioritized for deeper technical investigation.

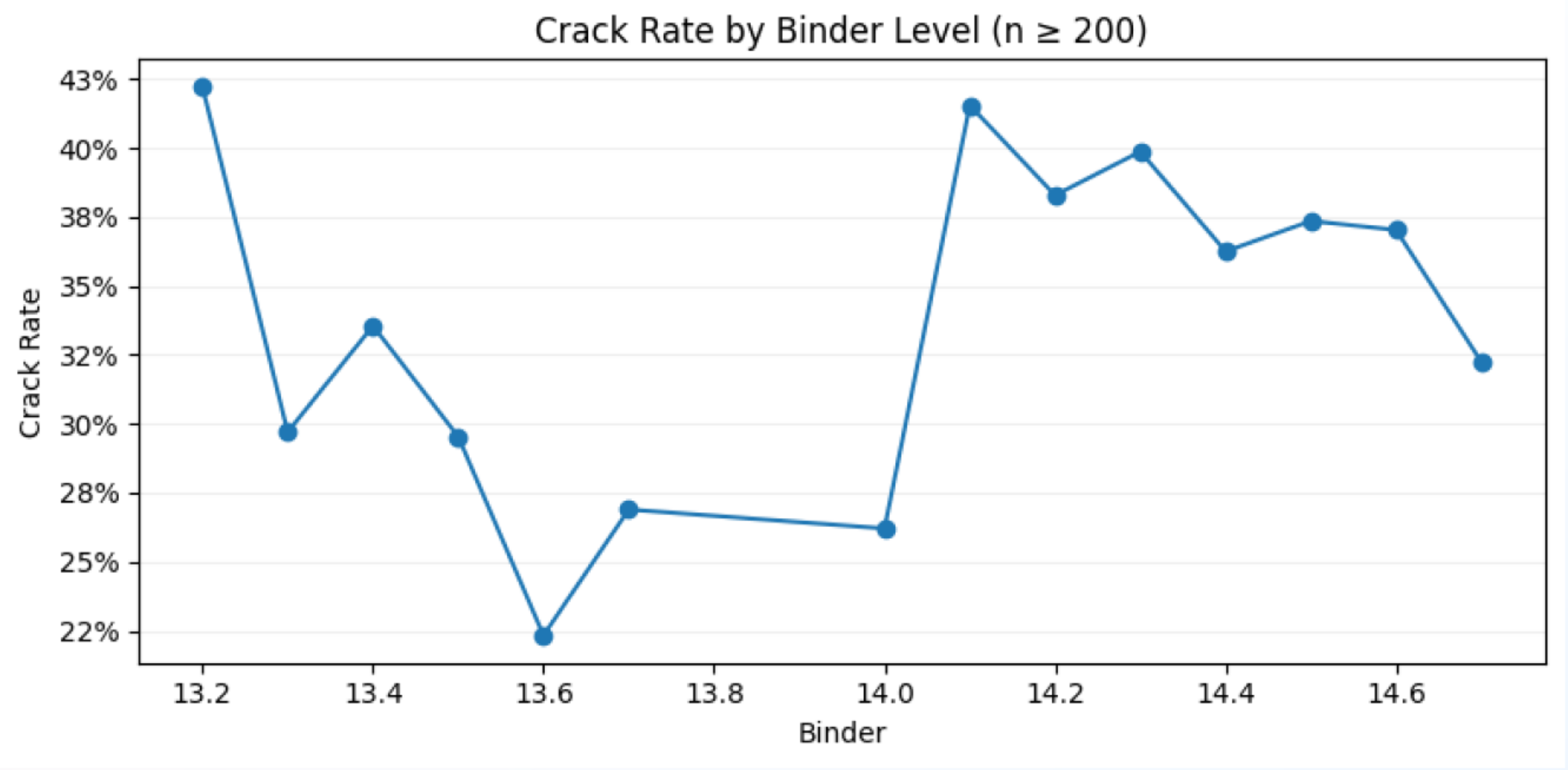
Gedung	Crack Rate	Num of Anode
A2	36,7%	29846
B1	36,3%	11089
B2	33,9%	11003
A1	29,0%	30327

Main Points

- A2 has higher crack rate than overall non-A2 (31.5%)
- Difference is not only random, but consistent across large sample size
- A2 also appears in top drivers from SHAP

Binder Effect on Anode Crack





Main Points

- Crack rate minimum pada binder sekitar 13.5–13.6
- Binder di bawah atau di atas rentang 13.5–13.6 meningkatkan risiko crack
- Binder di atas 13.7 menunjukkan kenaikan crack yang konsisten

Key Takeaway

Anode crack is minimized at moderate binder levels (~13.5–13.6), while both low and high binder significantly increase crack risk.

Recommendation

What We Have Learned

Explainable ML and EDA consistently show Layer Tengah as the strongest driver of anode crack.

Other important contributors: Binder, Gedung (especially A2)

Current analysis is exploratory: it identifies patterns, not final root cause.

Proposed Hypotheses to Test

H1: Thermal Non-Uniformity

Middle layer experiences higher thermal gradient or uneven heating.

H2: Material Sensitivity

Certain binder/density ranges are more crack-prone when placed in middle layer.

H3: Process Handling Effect

Loading/unloading or stacking pattern creates mechanical stress at middle layer.

H4: Furnace/Zoning Effect

Certain furnaces or buildings (e.g., A2) amplify middle-layer risk.

Main Recommendation

Focus improvement efforts on the middle layer as the highest-risk zone, since both ML and EDA consistently show that cracking is concentrated there. Rather than changing many parameters at once, use a hypothesis-driven approach: First investigate thermal behavior in the middle layer (temperature uniformity, heating and cooling rate), then test material sensitivity, especially binder under similar baking conditions, and audit stacking and handling practices that may add mechanical stress. These investigations should be done through small, controlled trials with clear before and after comparison. Only factors that consistently reduce crack in these trials should be treated as true root causes and converted into standard process controls.

Summary

This study uses explainable machine learning and exploratory data analysis to understand patterns behind anode cracking. The results consistently show that cracking is strongly concentrated in the middle layer, while binder level and building location, especially A2, also play important roles. Machine learning is used not as a final prediction tool, but as a screening method to identify key drivers, which are then validated through focused EDA. These findings indicate that cracking is driven by higher-risk process conditions rather than by production volume. The main outcome of this work is not a final root cause, but a clear direction for investigation: the middle layer should be treated as the highest-priority zone for deeper, hypothesis-driven process studies to identify and confirm the true mechanisms behind anode cracking.

Thank You