

AI-Supported Evaluation of Insulating Transformer Data

Characterizing the Moderate-Class Diagnostic Bottleneck in ML-Based Transformer Defect Diagnosis

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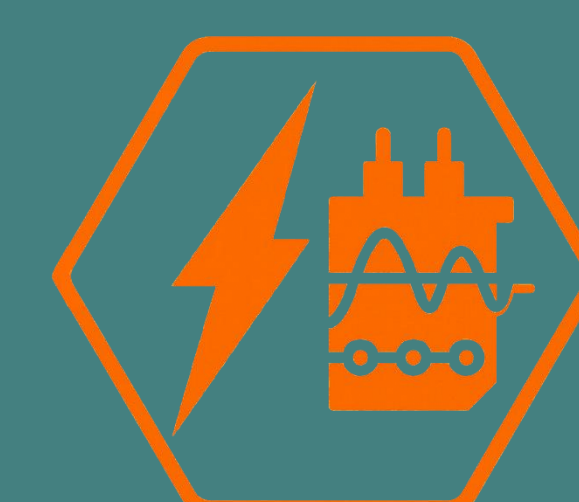
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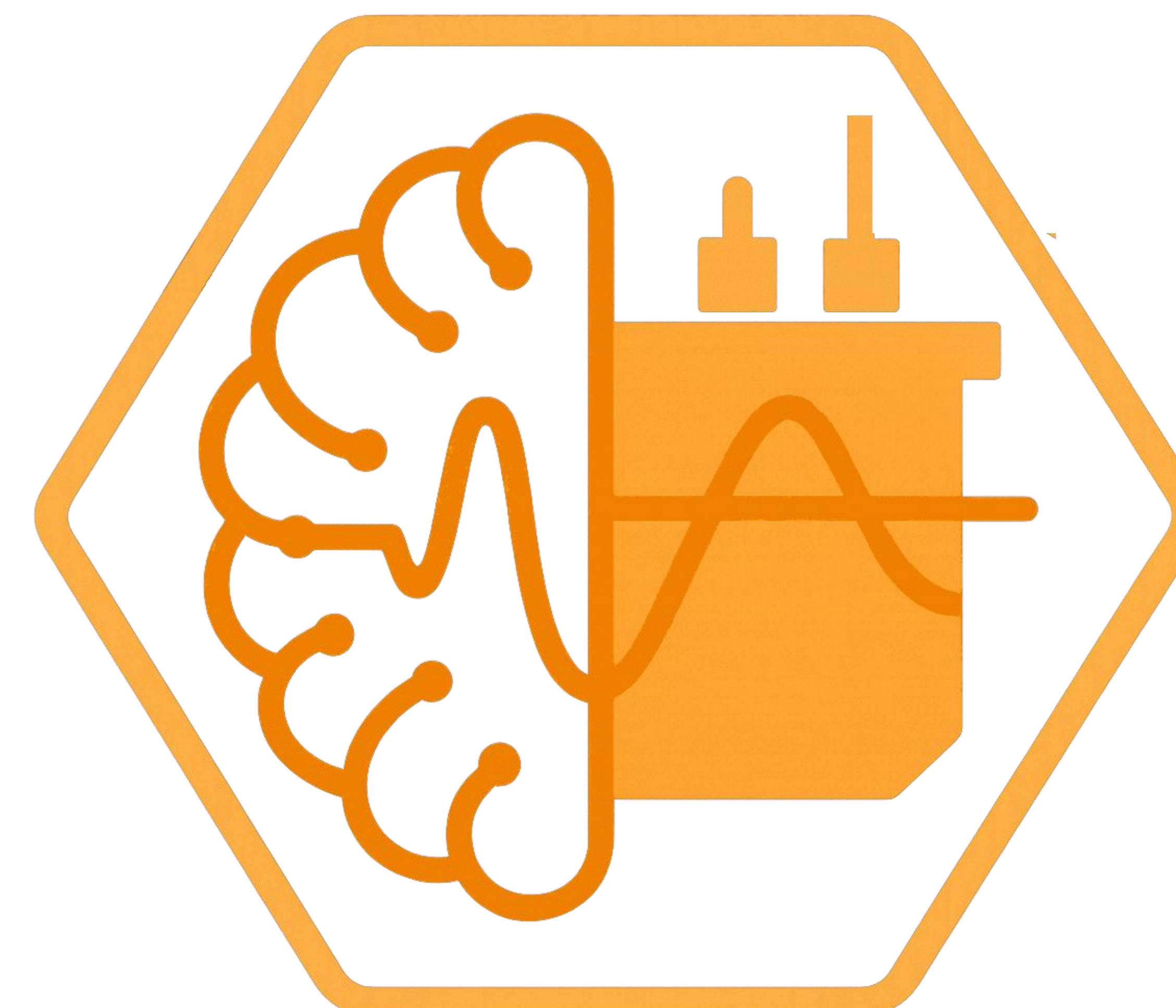
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- Introduction
- Methodology & Approach
- Experimental Results
- Discussion
- Future Outlook



Brief Overview:

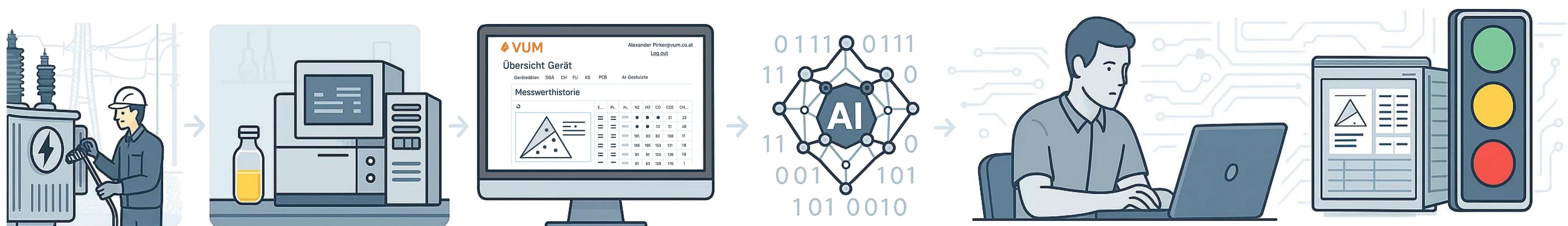
- Transformers are powerful systems that are used to regulate voltage.
- Their failures will cause problems in the economy.
- Traditional approaches are good but not effective when large fleets are involved.
- Applying AI-supported evaluation will help experts to make informed decisions.

Objectives:

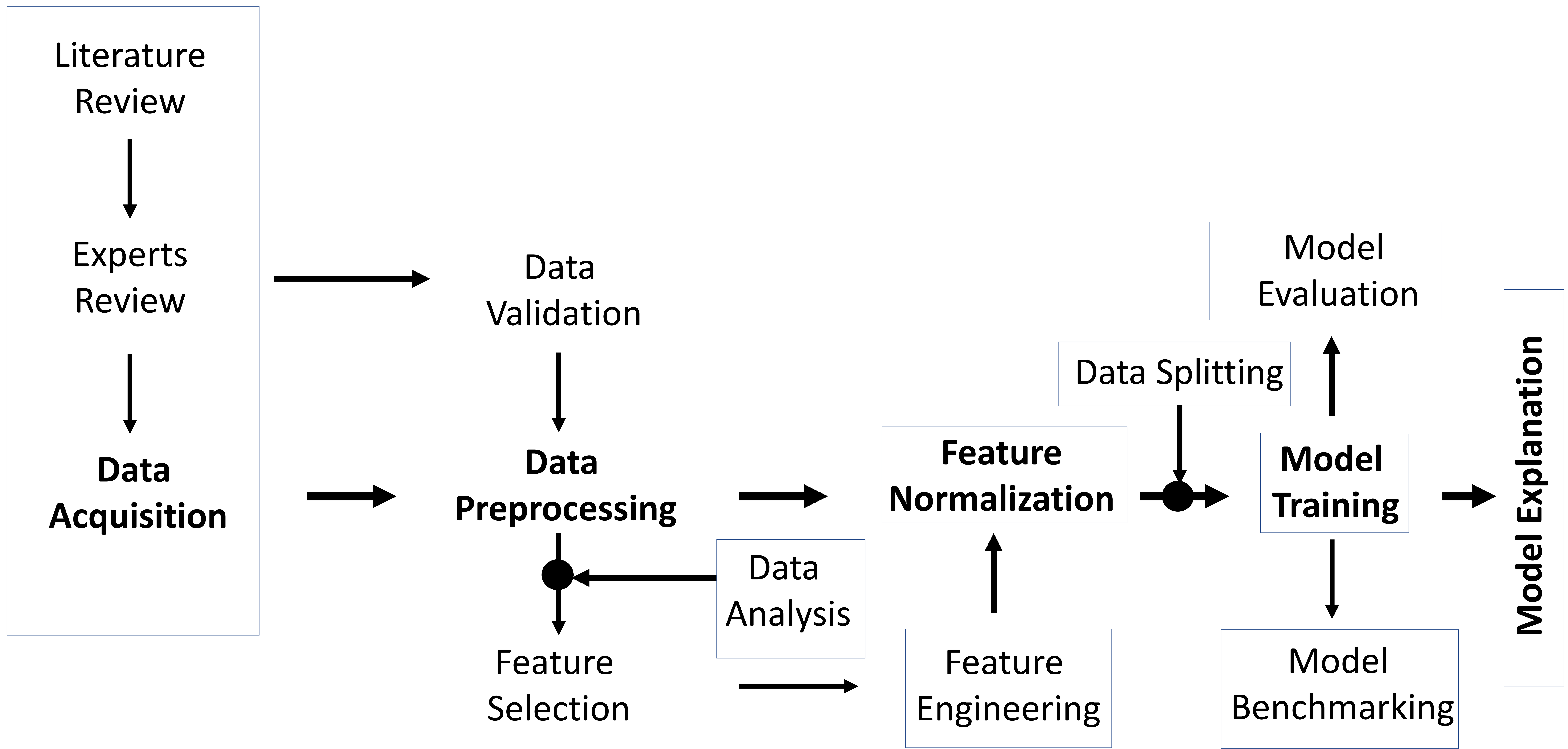
- Identify critical parameters in insulating oil data that influence transformer health.
- Develop a machine learning model for accurate fault classification for predictive maintenance.
- Evaluate the efficiency and predictive capabilities of the AI model compared to existing standard diagnostic methods.

Research Questions:

- How can AI support the condition assessment of transformers?
- What features can be used and evaluation method?
- What are the prediction bottlenecks & mitigation strategies?



Research Design





- 110,635 datasets
 - 63 parameter
 - 1960s - 2024
 - Large data variation (faults, generation, distribution, transmission, industry etc.)
- Good quality dataset
 - 19,251 instr. transformer
 - 3,387 power transformer
 - 30 parameter
 - Large data variation



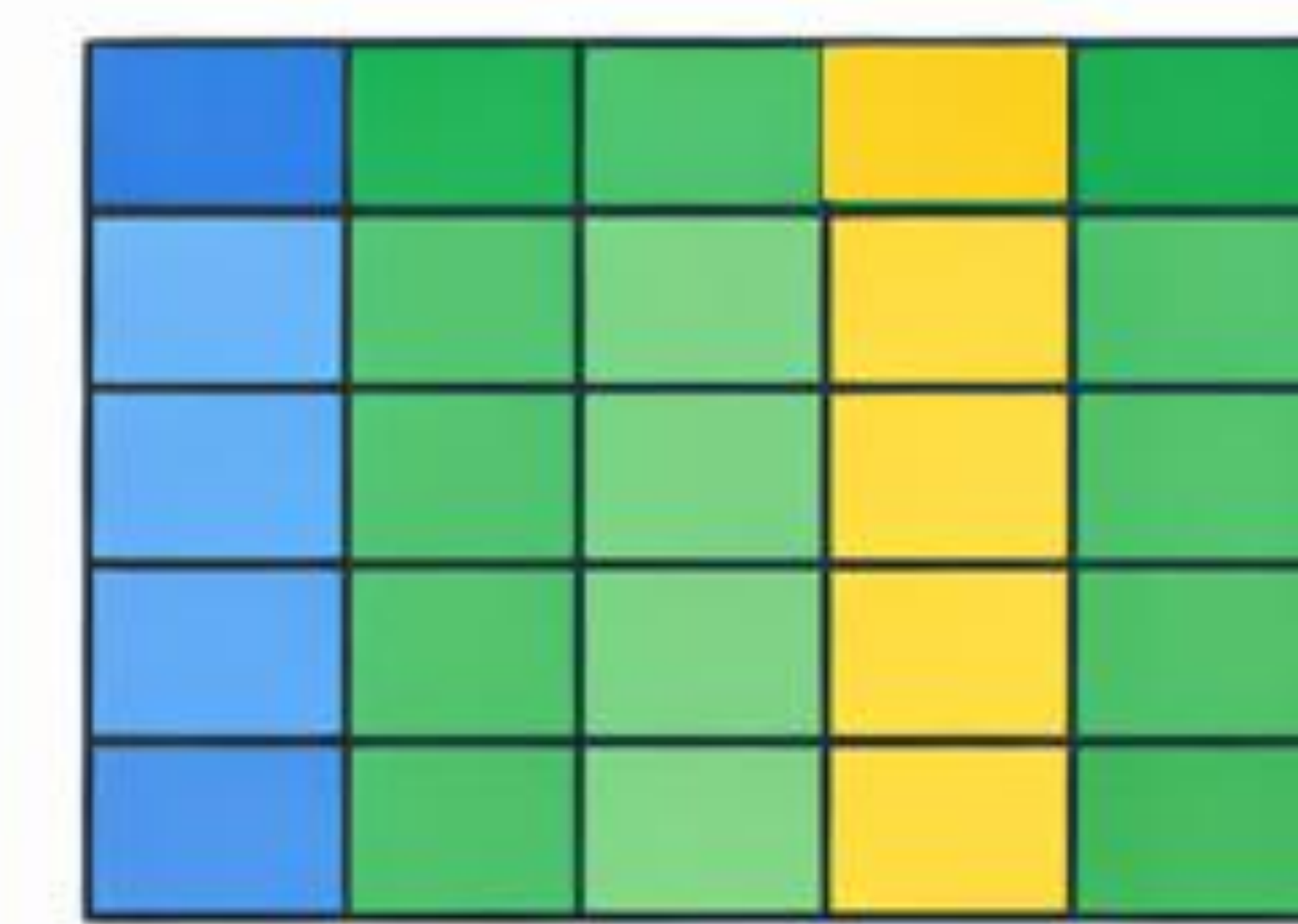
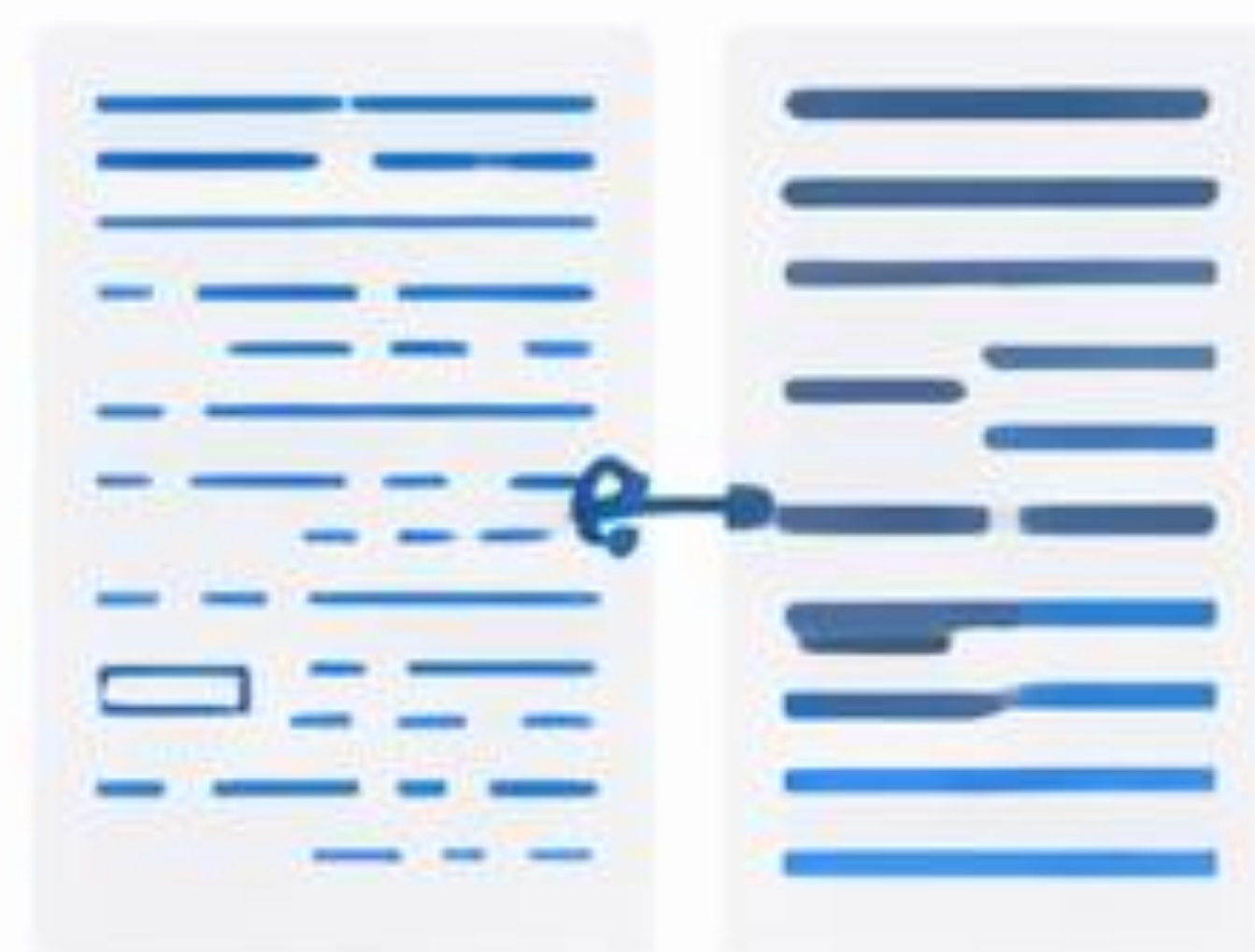
UNSTRUCTURED

INCOMPATIBLE

INCORRECT

INCOMPLETE

PERFECT QUALITY



RAW DATA

DATA
CLEANING

DATA
TRANSFORMATION

DATA
PREPARATION

READY
DATA

Missing Data Imputation

- Ambient temperature: daily-to-monthly averaging per transformer (35% missingness).
- Oil temperature: multivariate iterative imputation.

Feature Engineering

- **Gas Gradients**

$$GR = \frac{G_2 - G_1}{T_2 - T_1}$$

- Gas ratios: R_1 (CH₄/H₂), R_2 (C₂H₂/C₂H₄), R_3 (C₂H₂/CH₄), R_5 (C₂H₆/C₂H₂), and CO₂/CO.

Feature Set	Components	Purpose
M1	Sample Age + seven gas concentrations	Baseline
M2	M1 + five ratios	Capture fault relations
M3	M2 + gas generation rates	Include temporal dynamics
M4	M3 + oil and ambient temperatures	Full operational context

. Feature sets M1–M4

Summary Plots

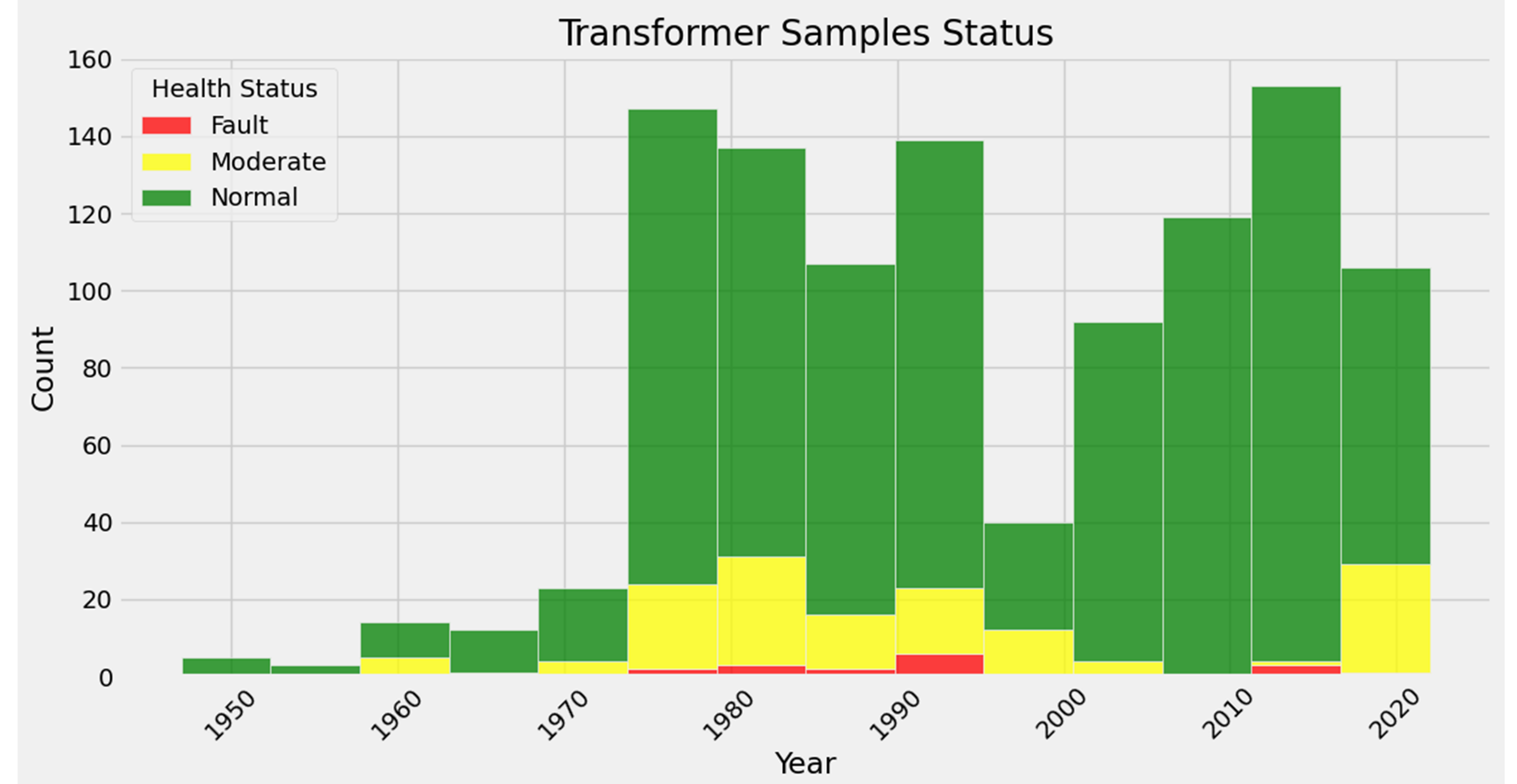
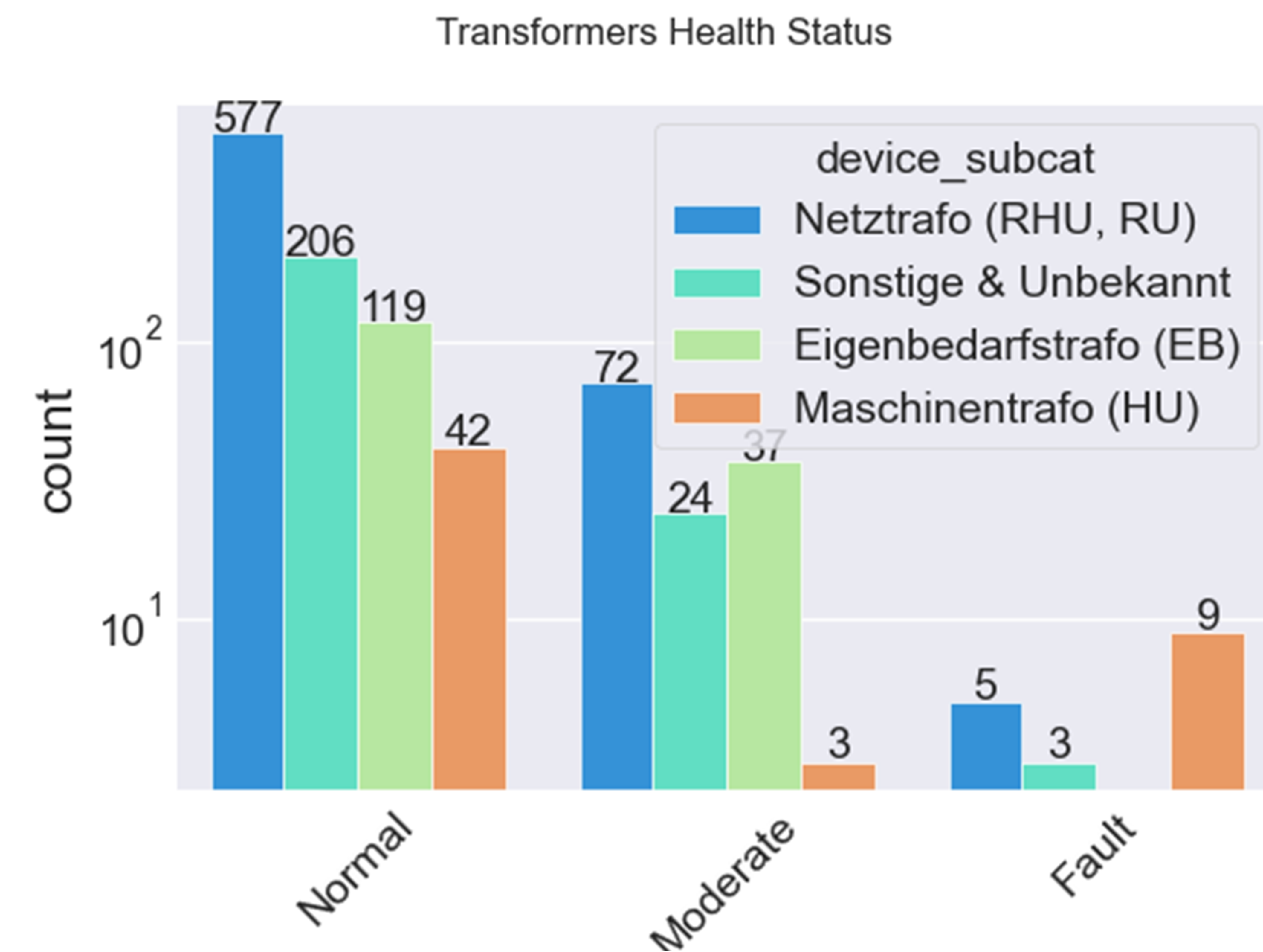
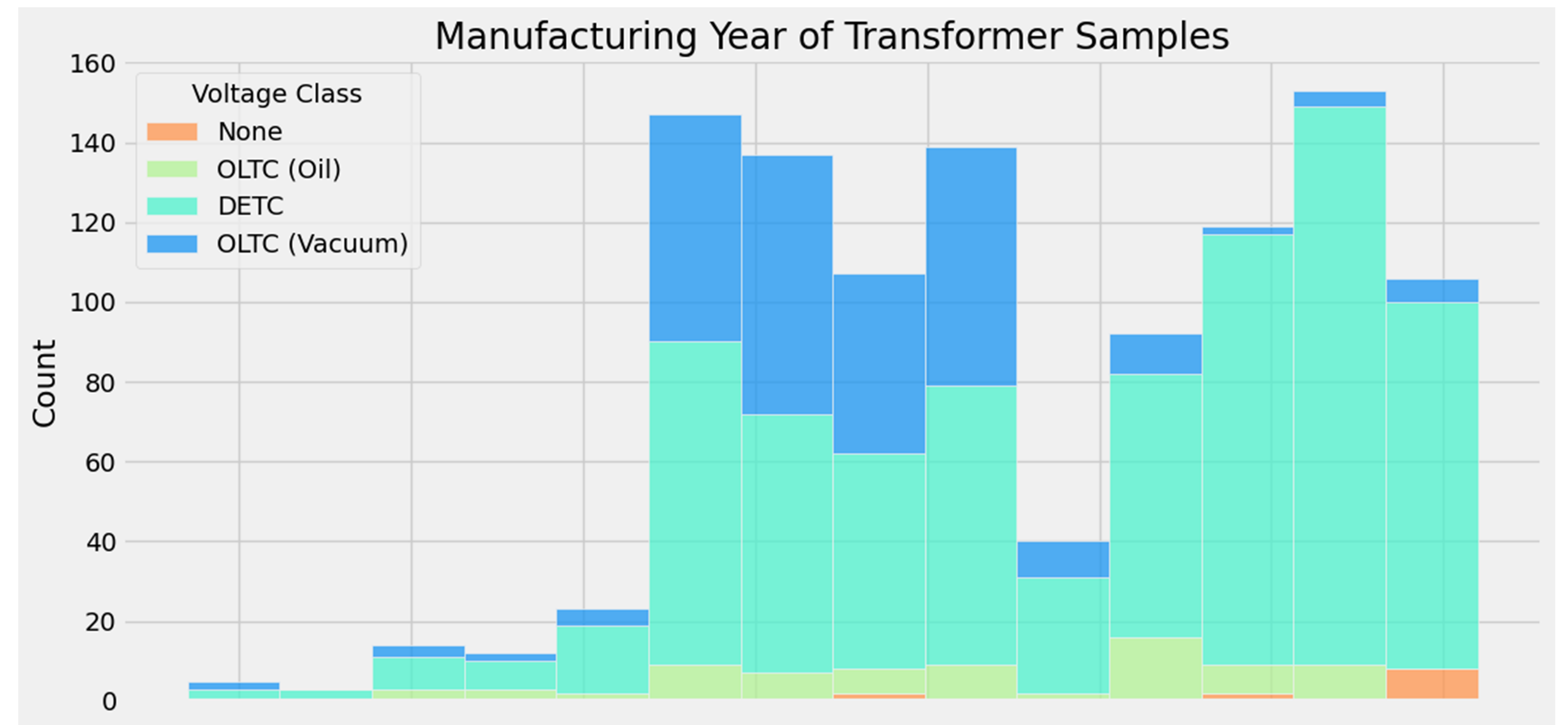
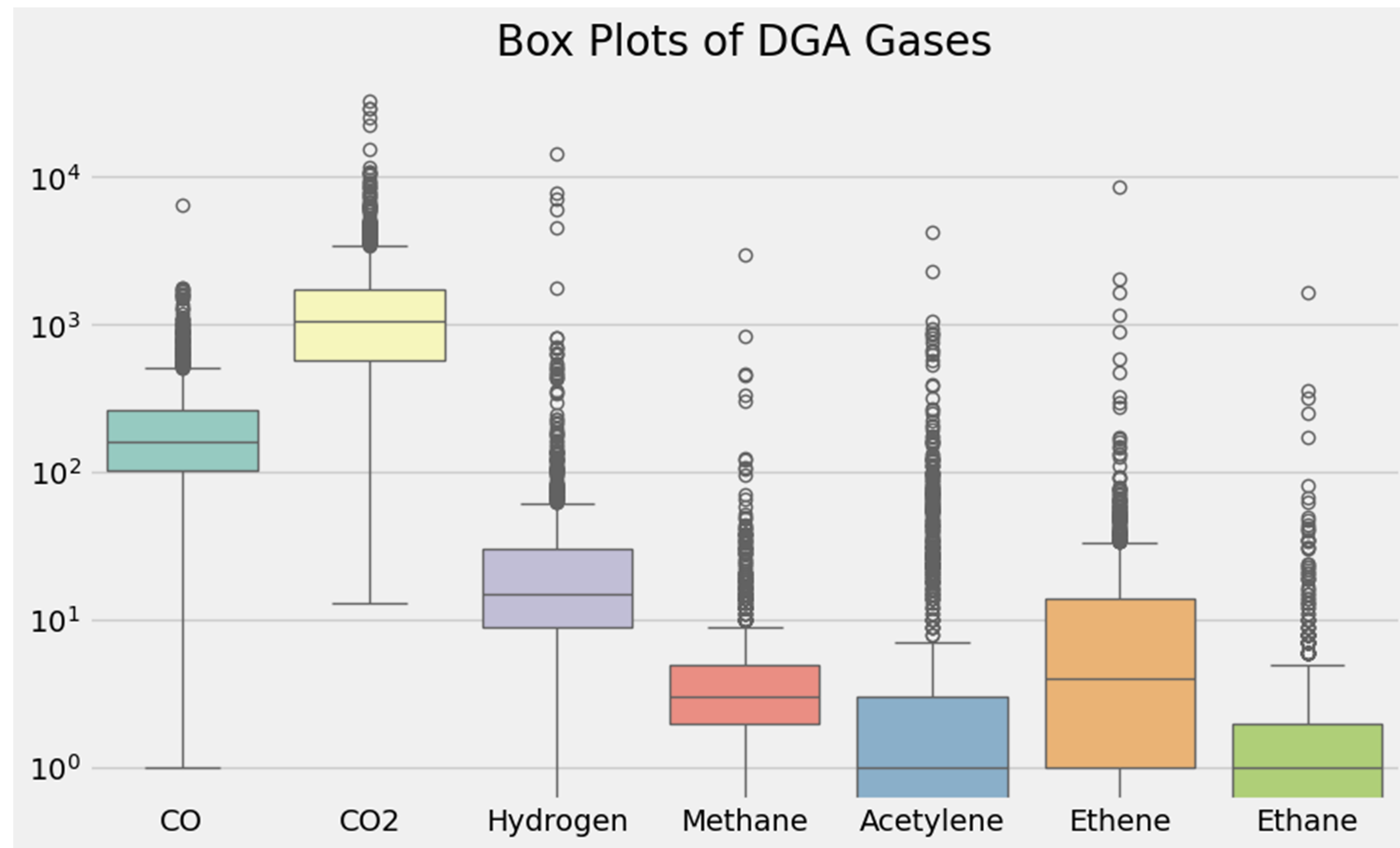


Figure 1: Summary of EDA Plots

Class Distribution	Train set	Val Set	Test Set
Normal	565	190	189
Moderate	82	27	27
Fault	10	3	4

SMOTE Method
 $x_{new} = x_i + \lambda(x_{nn} - x_i)$
 Stratified KFold = 5

MODEL 1:

FEATURES: M1 = Age + Gases only

Model	Train Acc	Val Acc	Val F1 Score
ETC	0.9923	0.9045	0.8330
RFC	0.9917	0.9045	0.7862
XGB	0.9912	0.9000	0.7188

MODEL 2:

FEATURES: M2 = M1 + Gas Ratios

Model	Train Acc	Val Acc	Val F1 Score
ABC	0.9935	0.8864	0.6526
ETC	0.9935	0.9091	0.8493
XGB	0.9923	0.9091	0.7345

MODEL 3:

FEATURES: M3 = M2 + Gas Gradients

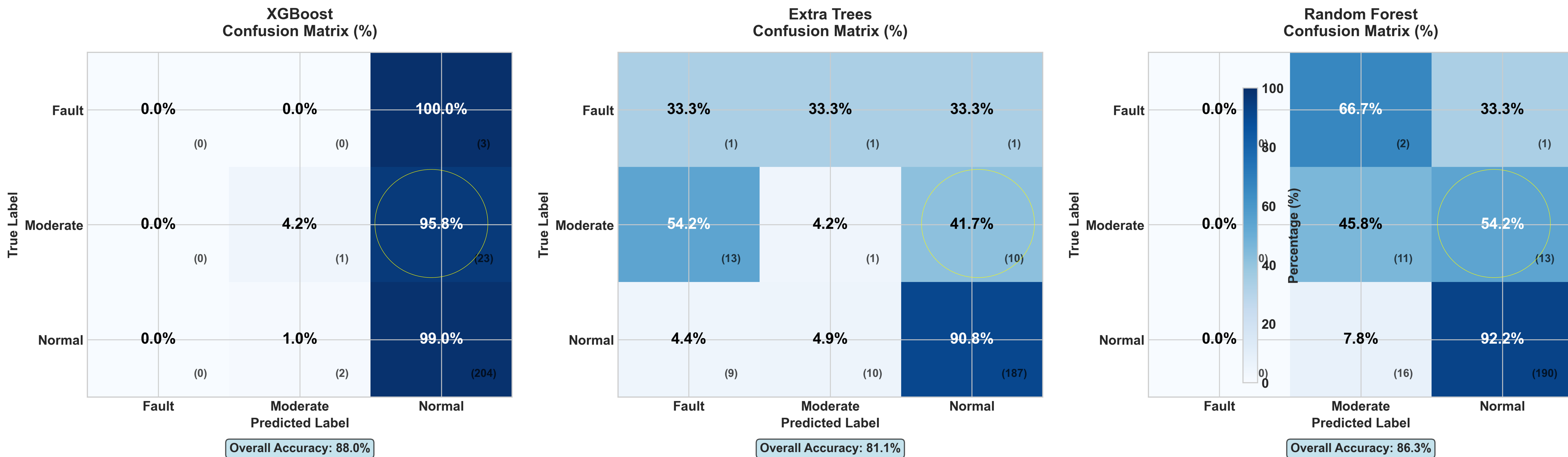
Model	Train Acc	Val Acc	Val F1 Score
ABC	0.9953	0.8909	0.7125
XGB	0.9947	0.9136	0.7962
ETC	0.9941	0.9045	0.7796

MODEL 4:

FEATURES: M4 = M3 + Operational parameters

Model	Train Acc	Val Acc	Val F1 Score
XGB	0.9947	0.9091	0.7846
ABC	0.9935	0.9045	0.7639
ETC	0.9935	0.9136	0.7962

Moderate condition exhibits an intrinsic classification bottleneck



Different models, same failure mode—Moderate is indistinguishable from Normal.

- **XGBoost:** ~96% of Moderate → Normal
- **Extra Trees:** ~42% of Moderate → Normal
- **Random Forest:** ~54% of Moderate → Normal

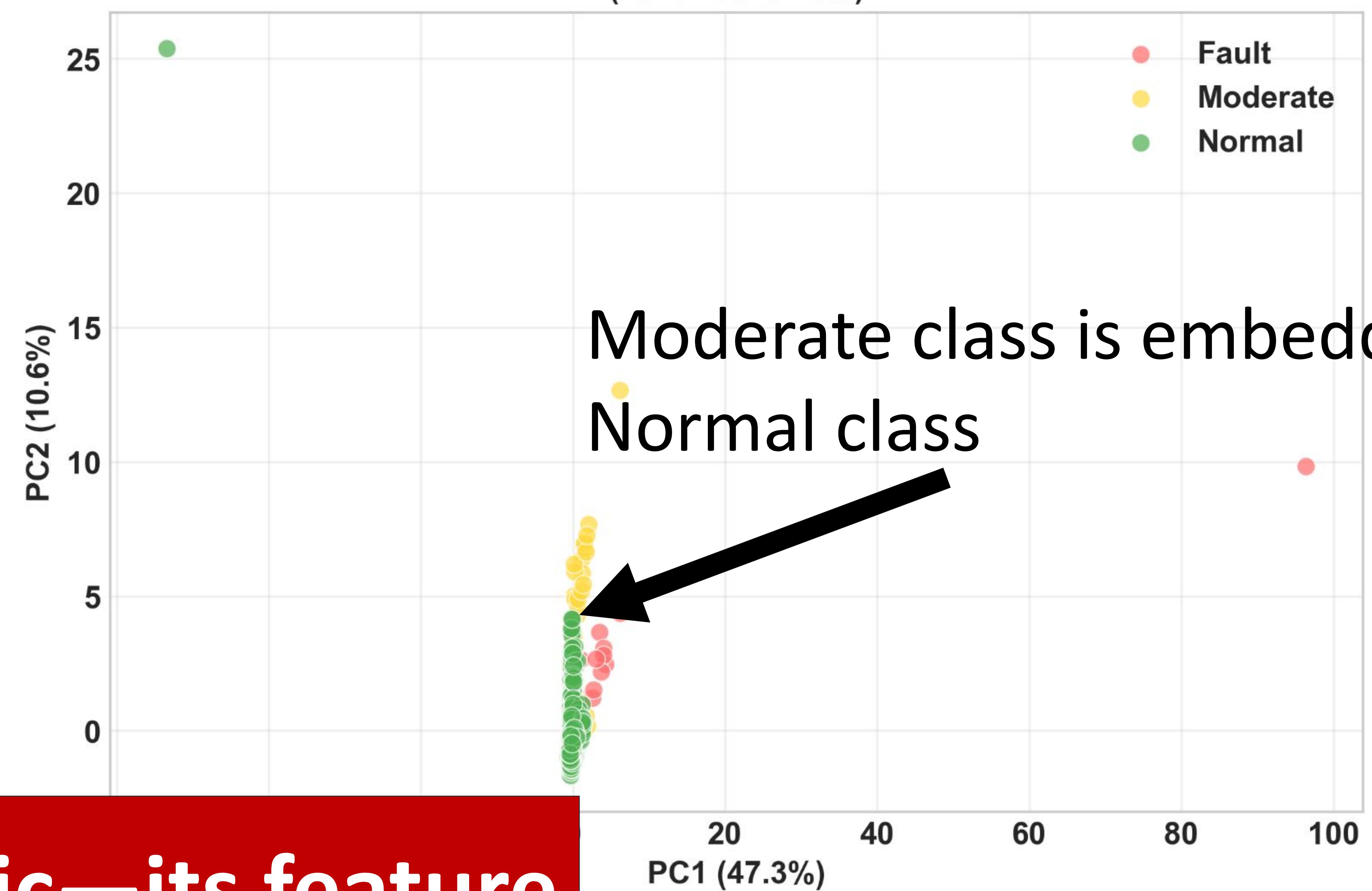
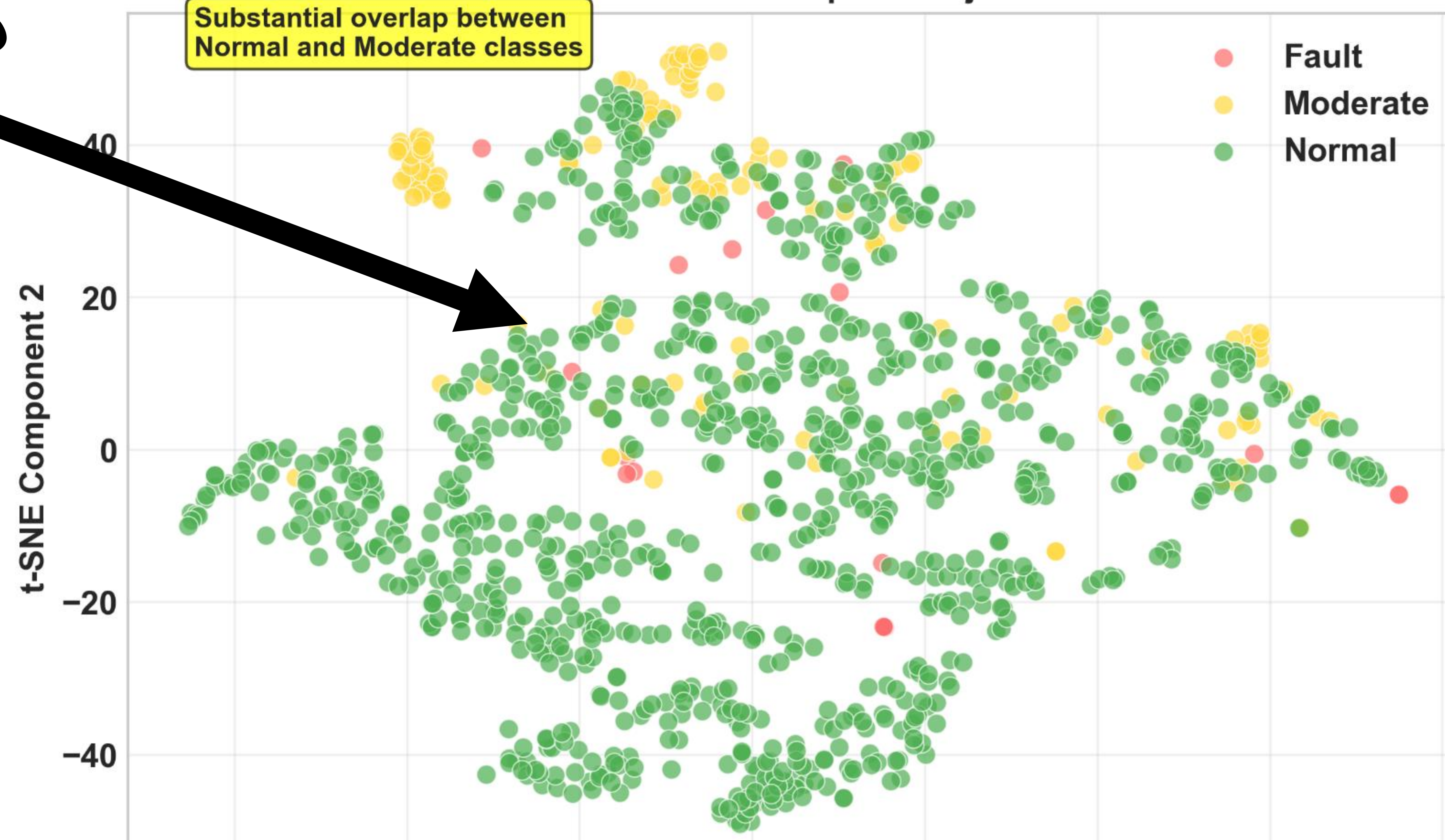
Across all models, the Moderate state is systematically confused with Normal, revealing a data-level ambiguity rather than a model-specific limitation.

Feature Space Analysis: Visualizing the Moderate-Class Bottleneck

Feature Set: M4

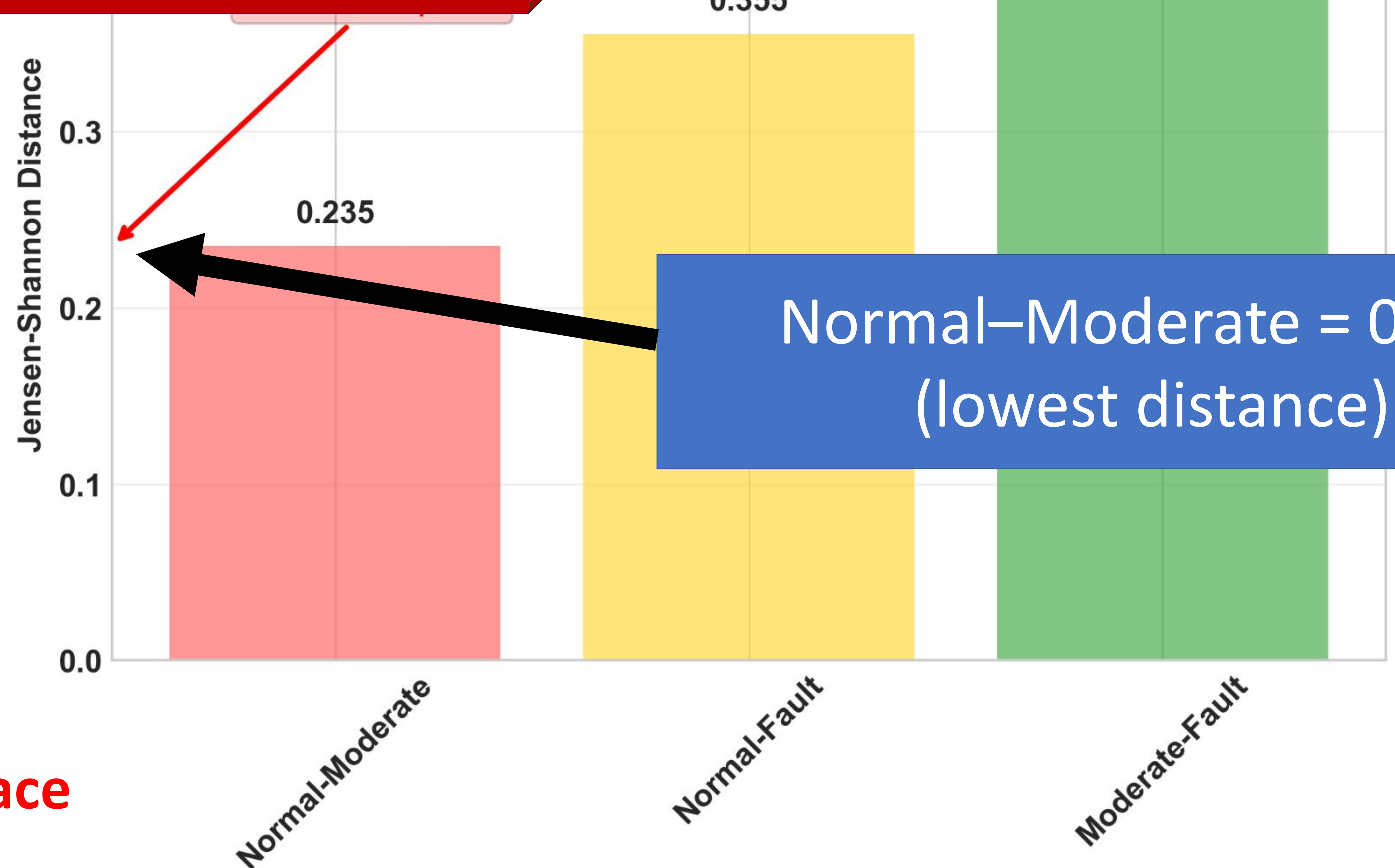
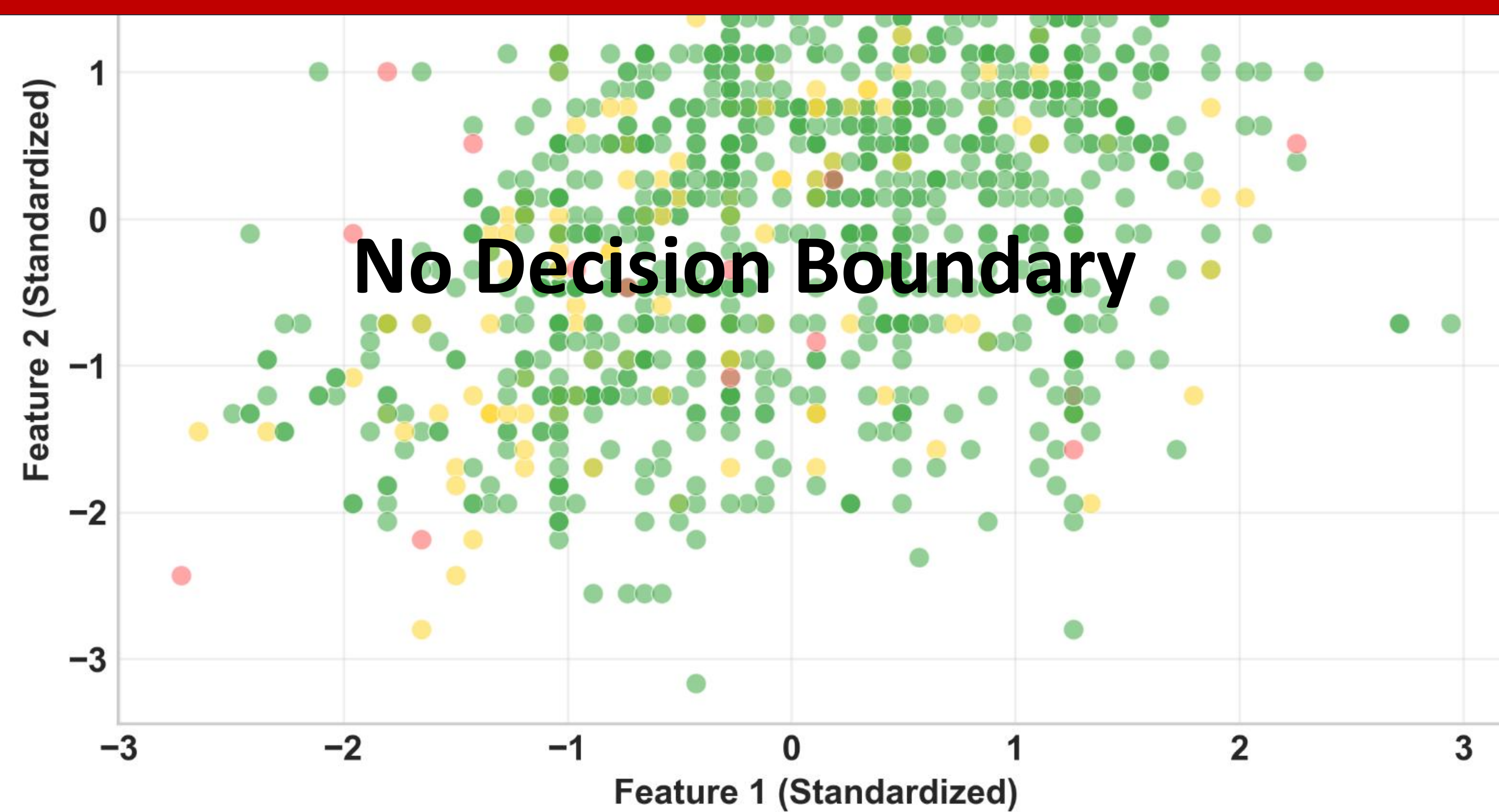
PCA: First Two Principal Components
(Variance: 57.9%)

t-SNE: 2D Feature Space Projection

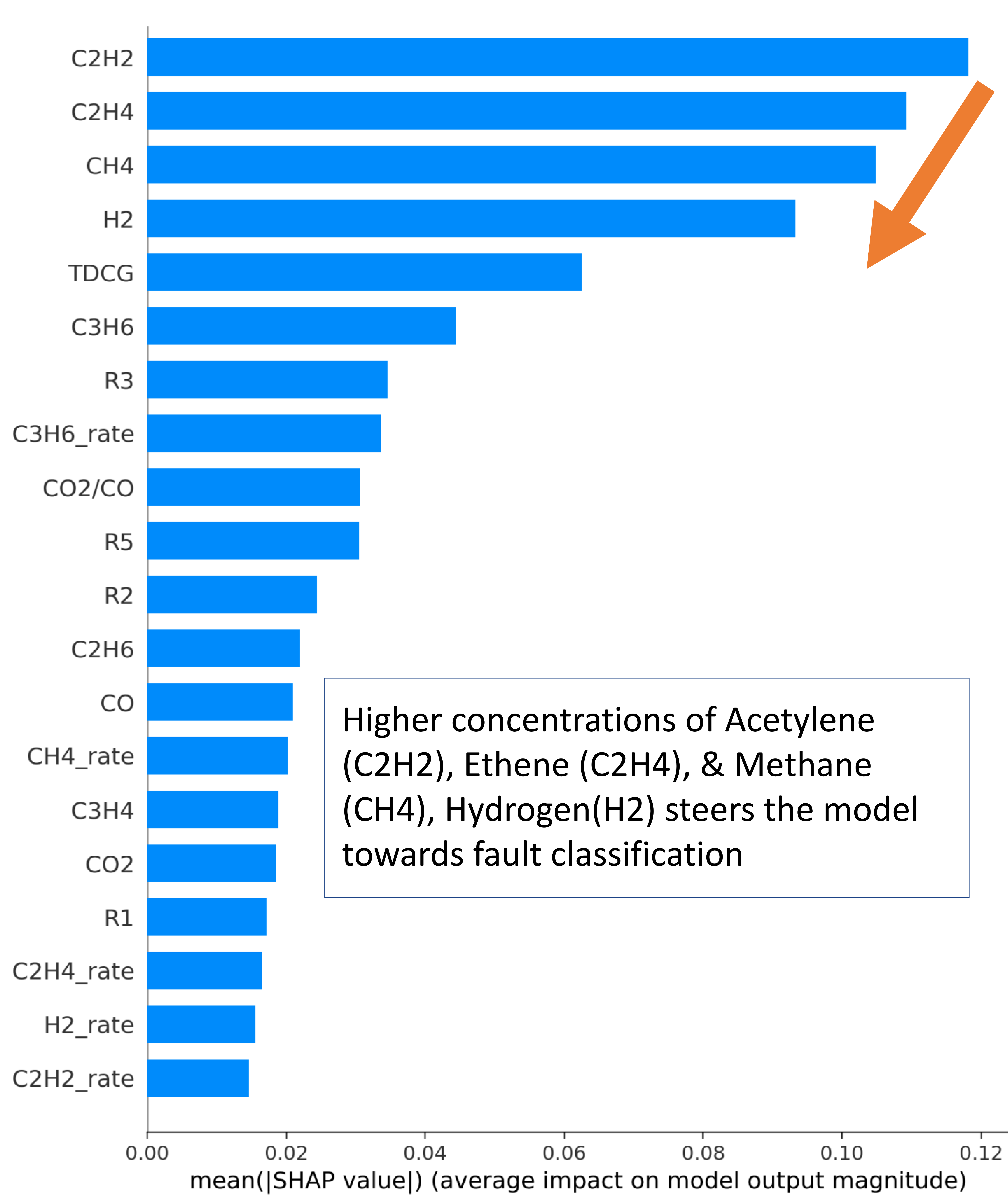


The Moderate class bottleneck is intrinsic—its feature distribution overlaps most strongly with Normal.

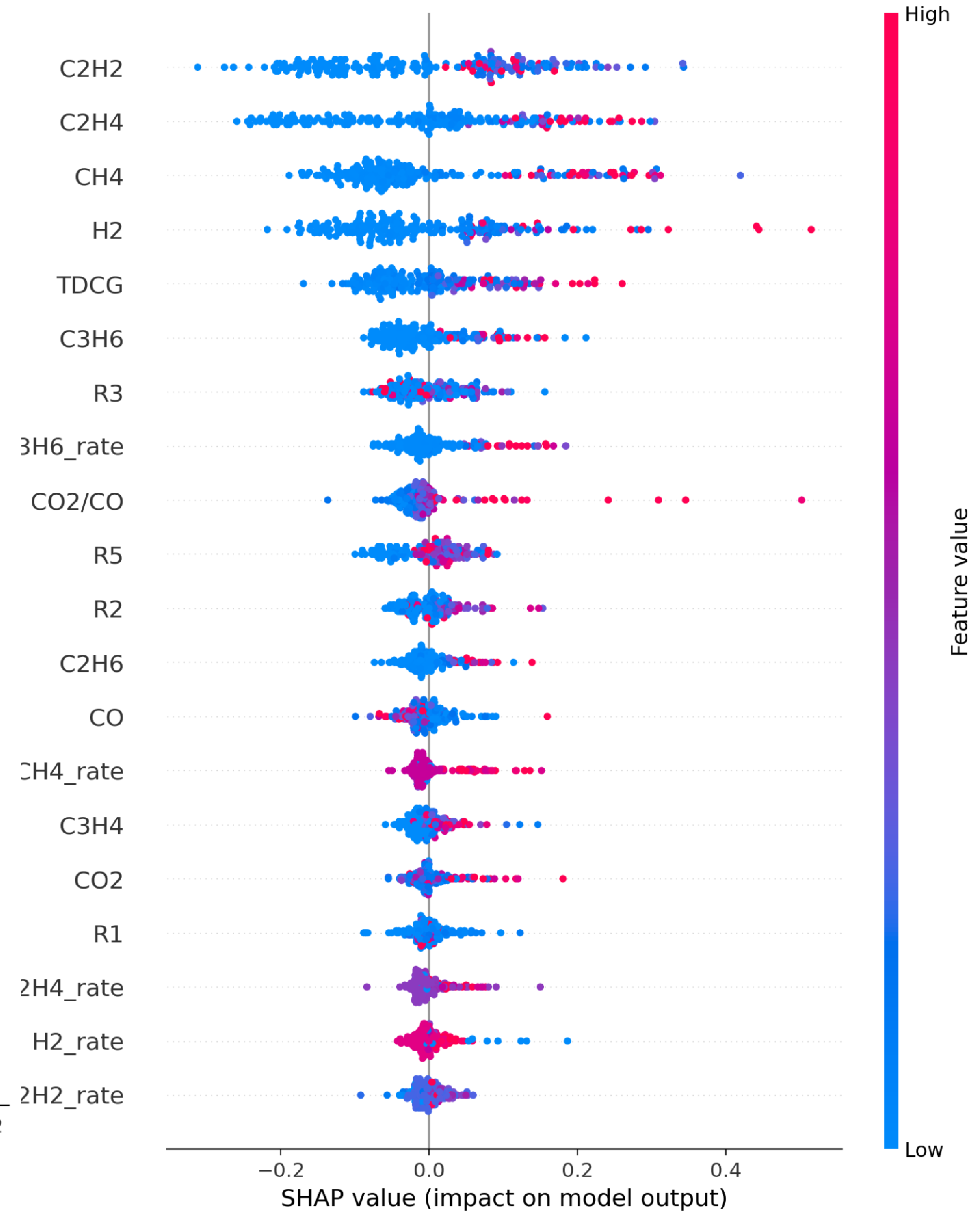
Similarity (Jensen-Shannon Divergence)
Lower = More Similar



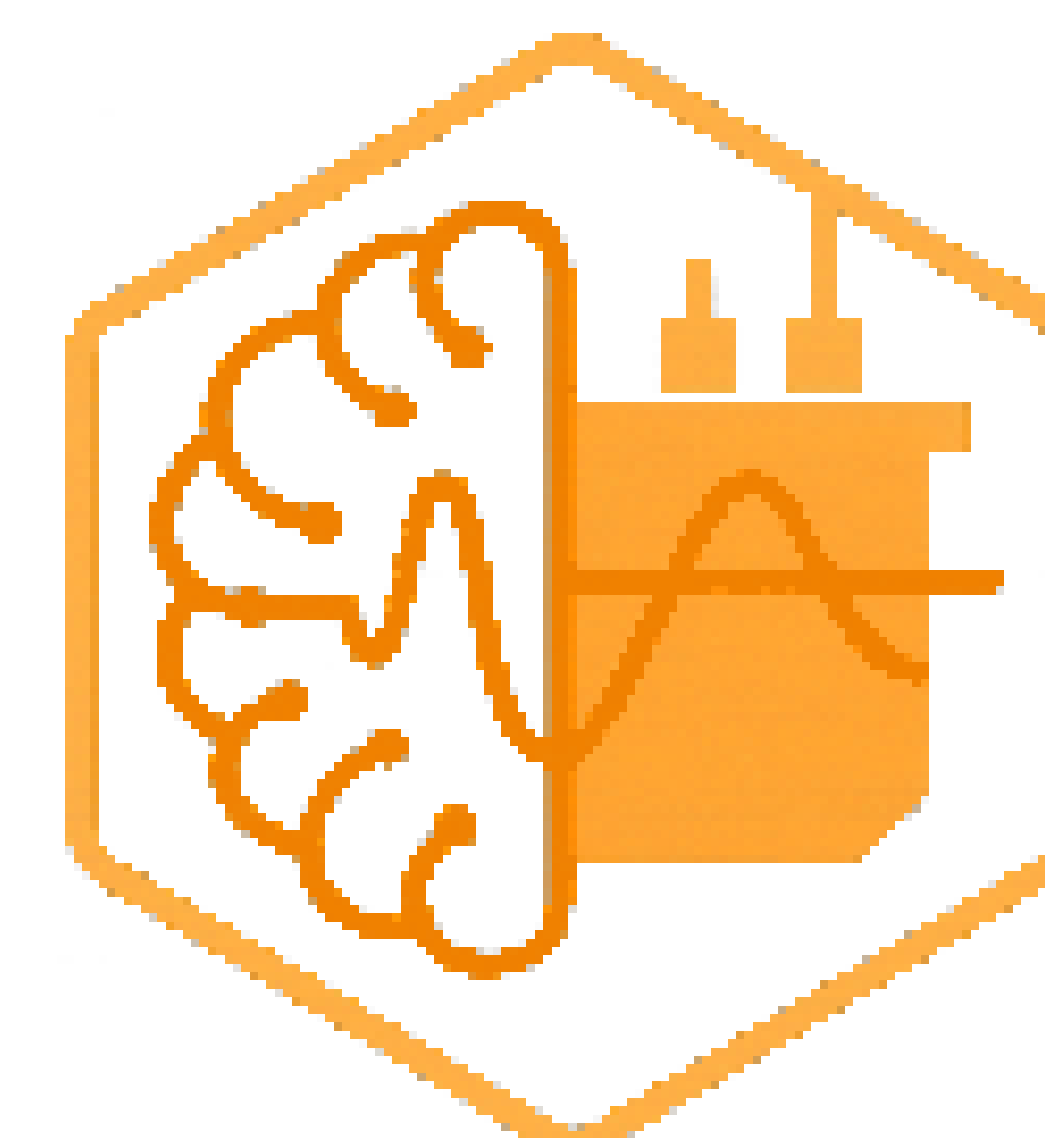
Moderate and Normal states are indistinguishable in feature space



Higher concentrations of Acetylene (C2H2), Ethene (C2H4), & Methane (CH4), Hydrogen(H2) steers the model towards fault classification



DGA-Dashboard AI-Based Methods



AI Predictions

	Model	Prediction
0	AdaBoost	Fault
1	BalancedRandomForest	Fault
2	DecisionTree	Fault
3	ExtraTreeClassifier	Fault
4	LogisticRegression	Fault
5	NeuralNetwork	Normal
6	RandomForest	Fault

Model Probability Scores

	Model	Normal	Moderate	Fault
0	AdaBoost	0.315000	0.320000	0.366000
1	BalancedRandomForest	0.080000	0.150000	0.770000
3	DecisionTree	0.000000	0.000000	1.000000
5	ExtraTreeClassifier	0.000000	0.000000	1.000000
7	LogisticRegression	0.000000	0.000000	1.000000
8	NeuralNetwork	1.000000	0.000000	0.000000
9	RandomForest	0.300000	0.210000	0.490000

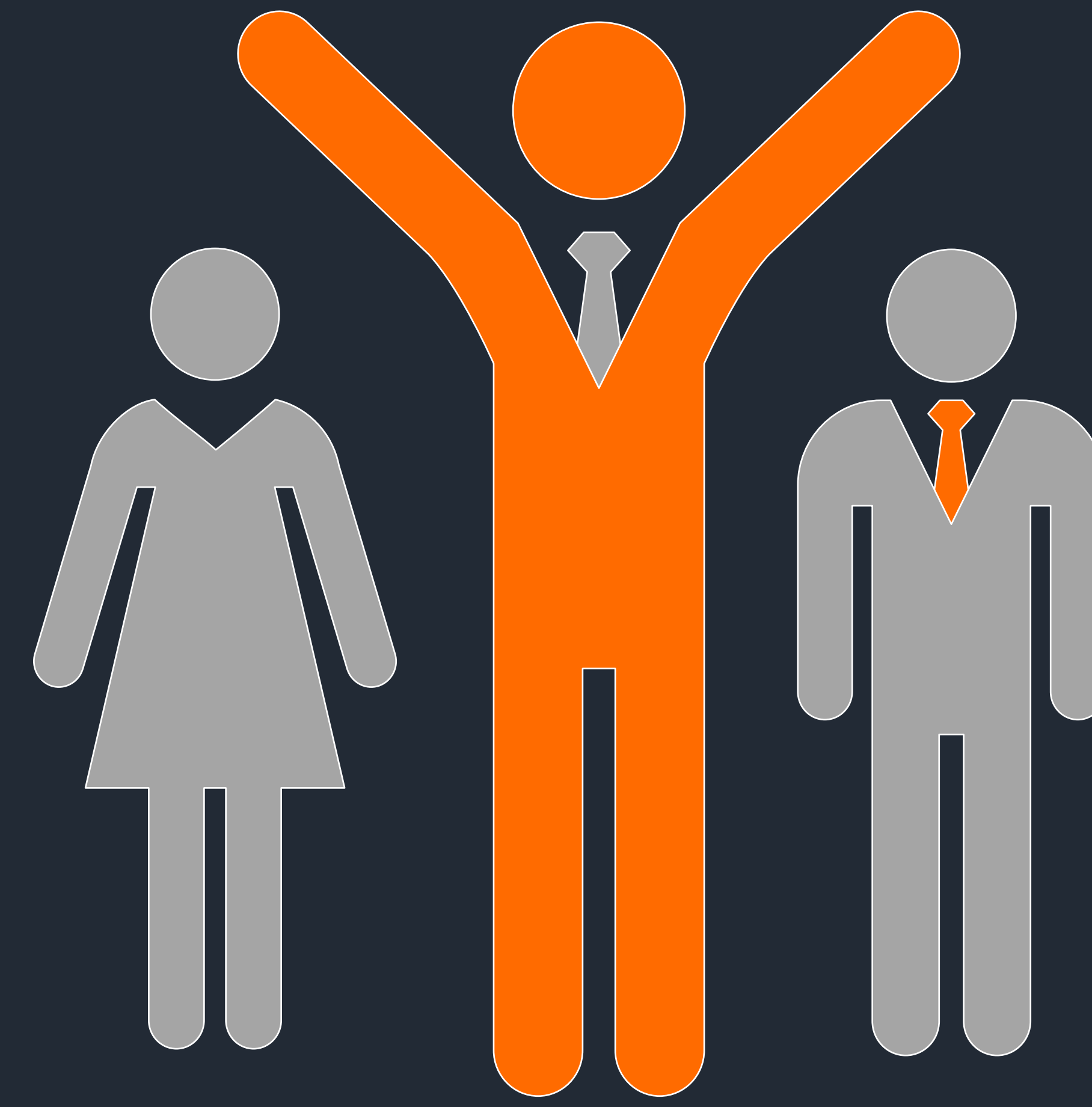
Classical Methods

	CO	CO2	H2	CH4	C2H2	C2H4	C2H6	TDCG
Messwerte	583.0	1554.0	870.0	975.0	13.0	176.0	816.0	3433.0
IEC 60599	Typical	Typical	Atypical	Atypical	Typical	Typical	Atypical	n/a
IEEE C57.104	C3	C1	C3	C3	C3	C3	C4	C3
CIGRÉ TB761	Acceptable	New	Bad	Acceptable	Bad	Acceptable	Extreme	n/a

Key Findings & Implications

- ML reliably detects severe faults but consistently misclassifies early/moderate cases as Normal.
- Moderate and Normal states overlap in static DGA feature space, especially at low gas levels.
- This limitation can delay intervention, allowing early degradation to progress toward failure.
- Use model uncertainty as a review flag, for example, high prediction entropy for moderate cases signals where expert validation is crucial.
- Combine ML alerts with expert review and temporal/multimodal data to improve early detection.

Thank You



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