Polish Sector Classification

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12/8
Github

Predicting Corporate Sector Classification from Financial Ratios

Predicting Company Sector Using Machine Learning

Goal: Predict what sector a company belongs to using ML

Importance: Sector classification drives investment decisions, portfolio construction, risk modeling, and peer benchmarking.

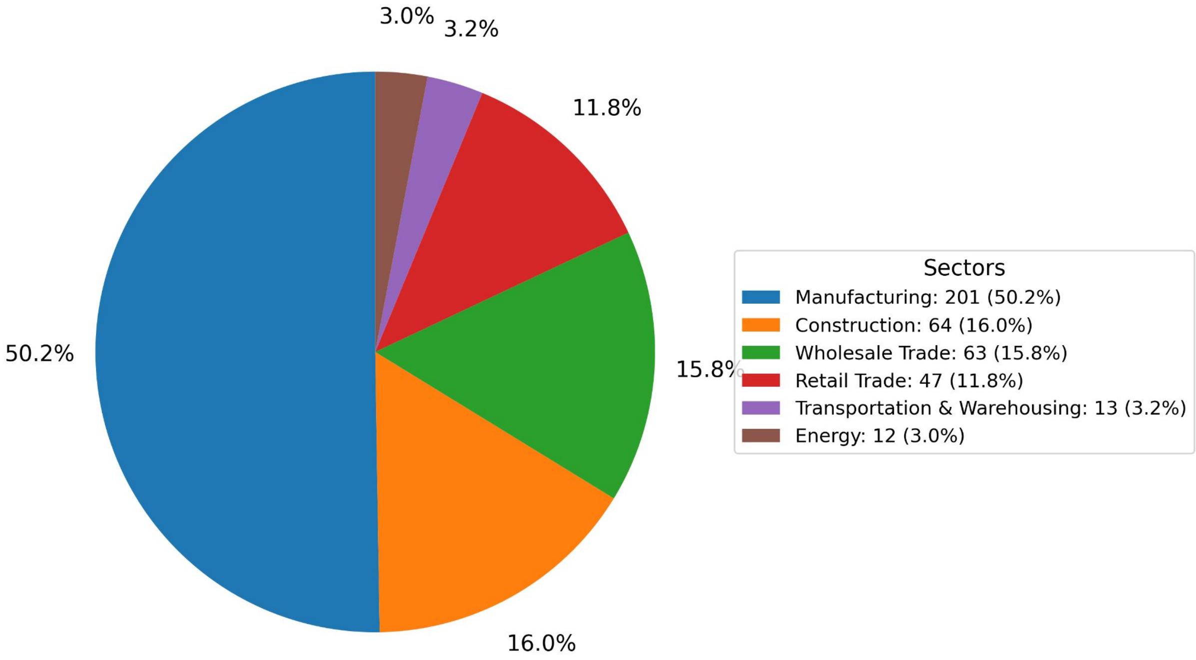
Multi-Class Classification: Transportation & Warehousing, Wholesale Trade, Manufacturing, Retail Trade, Energy, and Construction

Data Source: UC Irvine

Collected: Contains 400 real companies from Poland. Includes 85 attributes - dominantly numeric features representing profitability, leverage, liquidity, and efficiency ratios.

Difficulties: Missing Data

Target Distribution

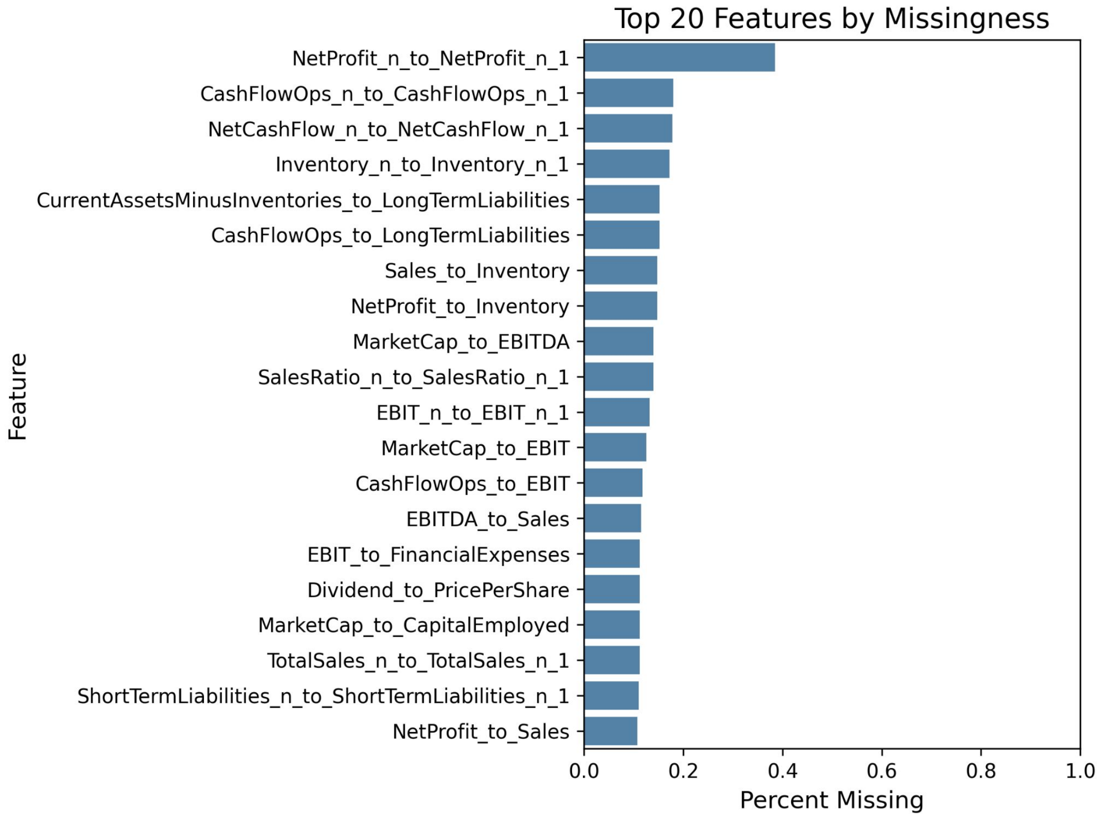


Target variable is imbalanced

Important for fair training and evaluation

CV=StratifiedKFold

Top 20 Missing Features By Percentage



The most missing features are:

Dynamic ratios (comparing year n vs year n - 1)

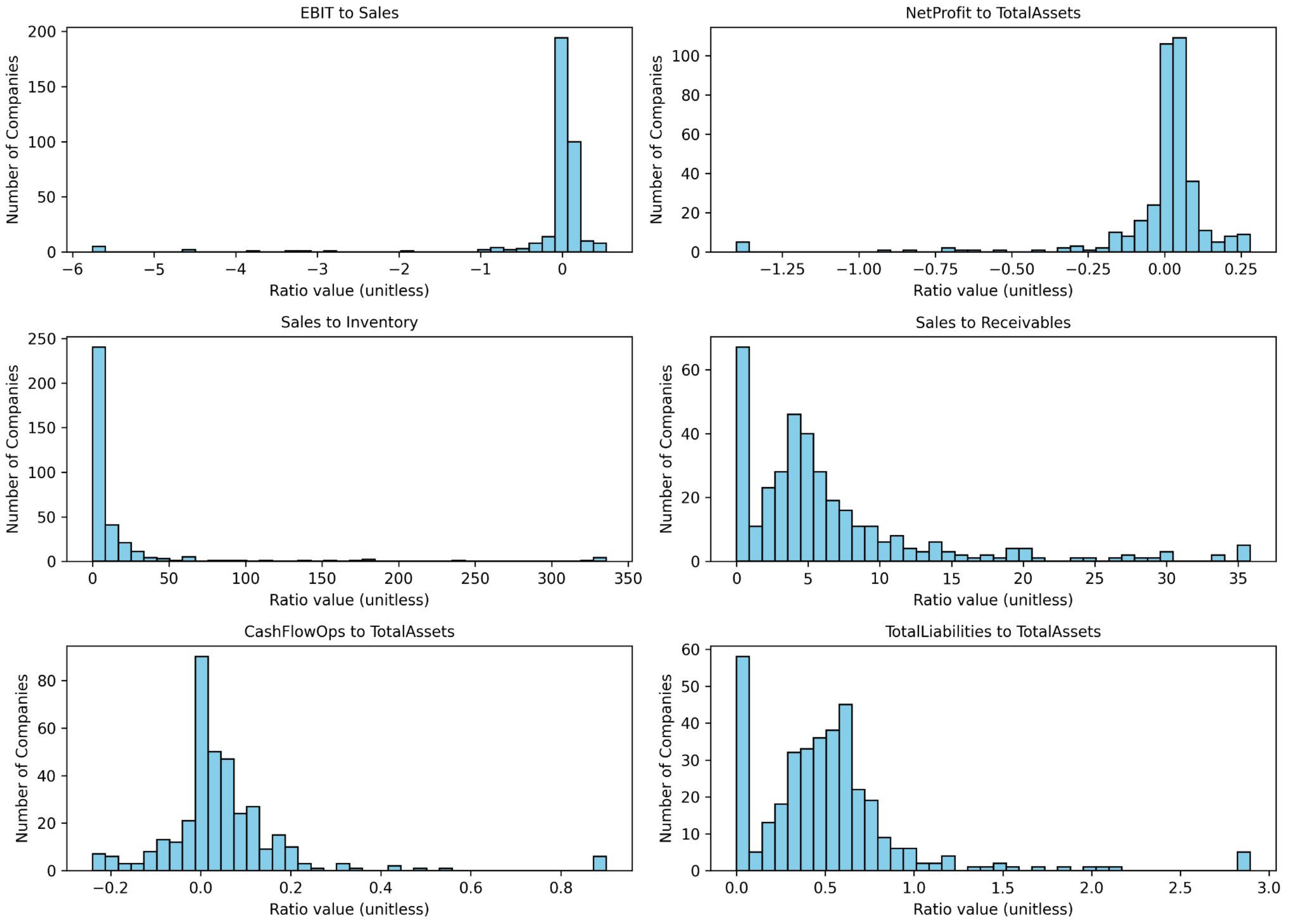
1. Profitability ratios
2. Cash flow / liquidity ratios
3. Efficiency (inventory) ratios
4. Valuation ratios
5. Leverage ratios (small representation)

Correlation Heatmap

The heatmap shows large clusters of highly correlated profitability, leverage, and cash-flow ratios - indicating redundancy - and a few inverse relationships, mainly between leverage and profitability, which could provide meaningful predictive signal.

Multicollinearity → Regularization or PCA

Distribution of Selected Financial Ratios (Clipped at 1st and 99th Percentiles)



Profitability

Efficiency

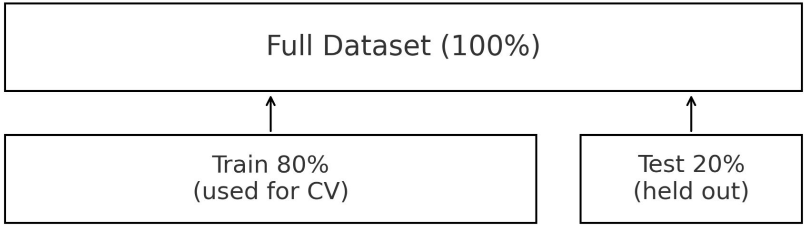
Leverage

Splitting and Preprocessing

StratifiedKFold: We use an 80/20 split to hold out a clean test set, and perform stratified K-Fold only on the training portion. Cross-validation rotates validation folds within the training data, but the test set remains untouched and unbiased. Stratification ensures class balance in every fold, which is critical for imbalanced multiclass data.

Preprocessing:

1. StandardScaler
2. IterativeImputer
    a. Randomforest



Algos and Scoring

Scoring = Macro-F1 → the unweighted average of class-wise F1 scores, giving equal importance to performance on each class regardless of frequency

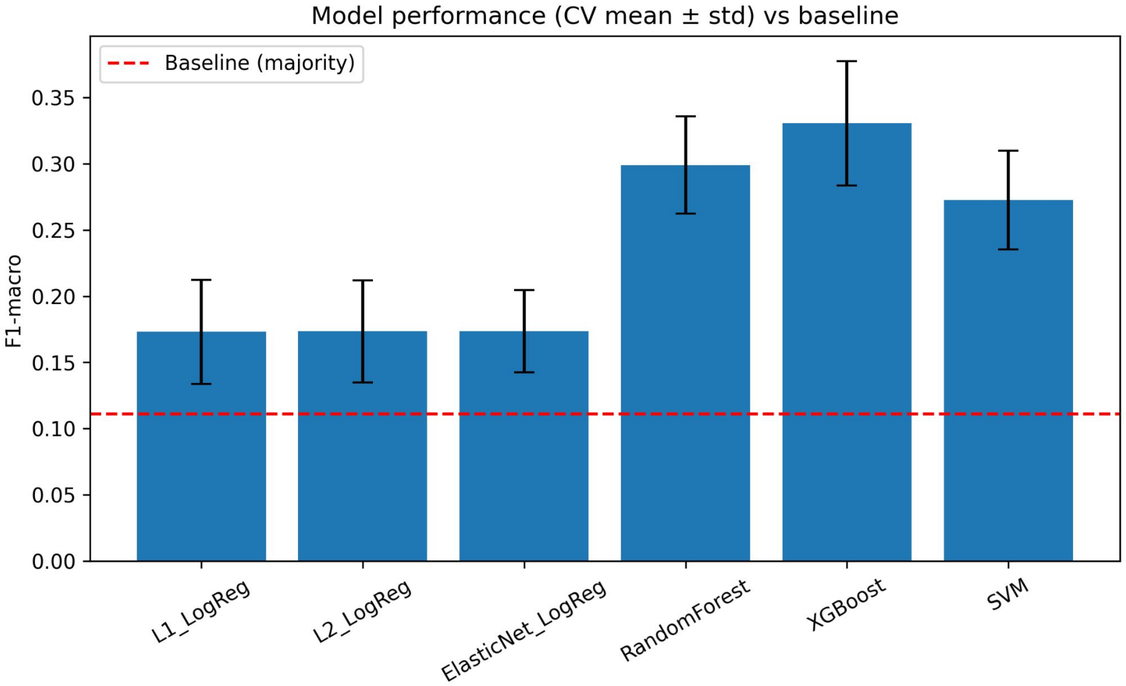
Pros for imbalanced date:

- Balances precision and recall
- Macro averages across classes equally, so minority classes matter
- Robust to imbalance

Algorithm	Parameters Tuned	Search Space
Logistic Regression (L1)	C, penalty, class_weight	C ∈ logspace[-2,2] (5); penalty=l1; class_weight=balanced
Logistic Regression (L2)	C, penalty, class_weight	C ∈ logspace[-2,2] (5); penalty=l2; class_weight=balanced
Elastic Net Logistic Regression	C, l1_ratio, penalty, class_weight	C ∈ logspace[-2,2]; l1_ratio ∈ linspace[0,1] (10); penalty=elasticnet; class_weight=balanced
Random Forest	n_estimators, max_depth, min_samples_leaf, max_features, class_weight	n_estimators=[550,600,650]; max_depth=[None,1]; min_samples_leaf=[3,5,6]; max_features=[sqrt,log2]; class_weight=balanced_subsample
XGBoost	n_estimators, max_depth, learning_rate, subsample, colsample_bytree	n_estimators=[525,550]; max_depth=[4,5]; learning_rate=[0.03,0.04]; subsample=[0.6,0.65]; colsample_bytree=[0.8,0.85]
SVM (RBF)	C, gamma, class_weight	C ∈ logspace[-2,2] (5); gamma ∈ logspace[-3,0] (4); class_weight=balanced

Cross Validation

Model	CV mean F1-macro	CV std F1-macro
L1_LogReg	0.173	0.039
L2_LogReg	0.173	0.039
ElasticNet_LogReg	0.174	0.031
RandomForest	0.299	0.037
XGBoost	0.331	0.047
SVM	0.273	0.037

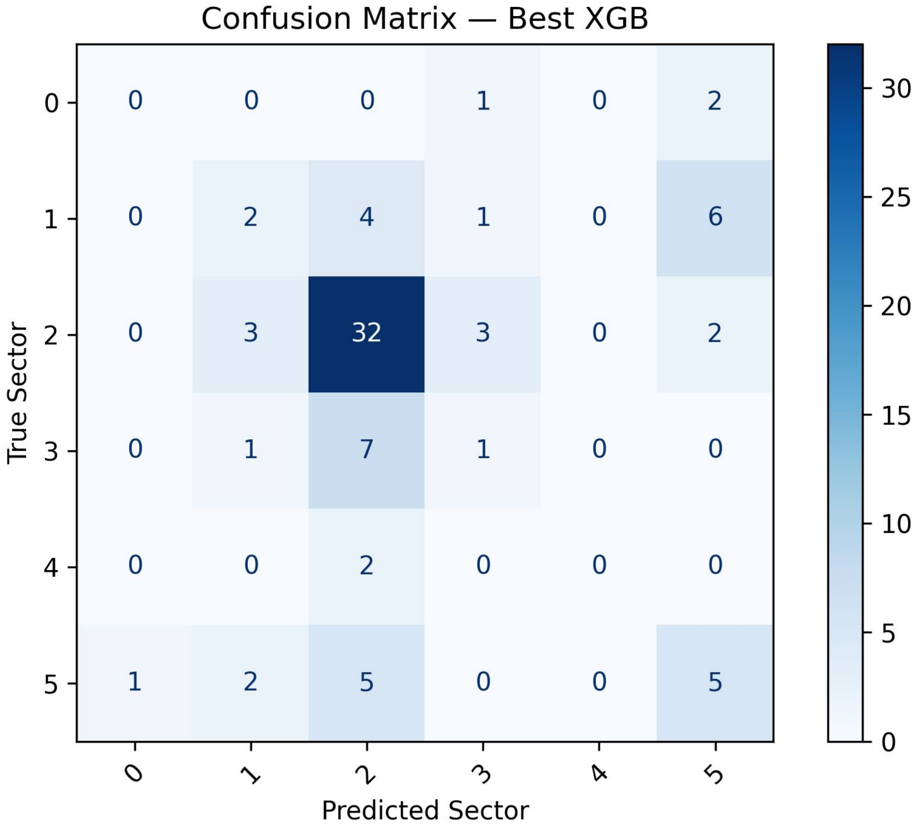


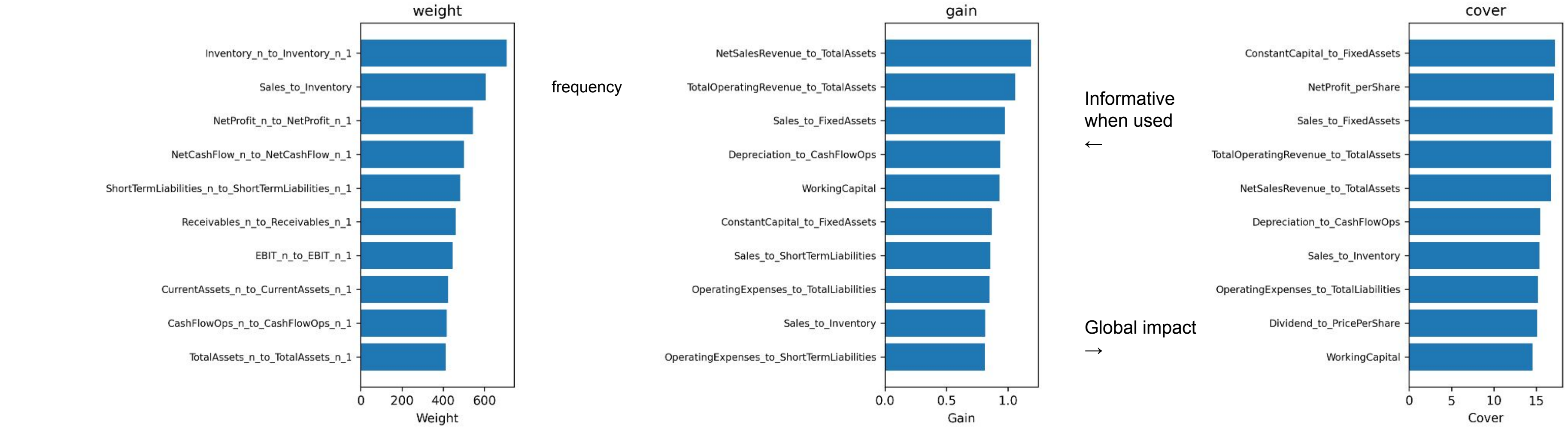
Model Performance - XGBoost

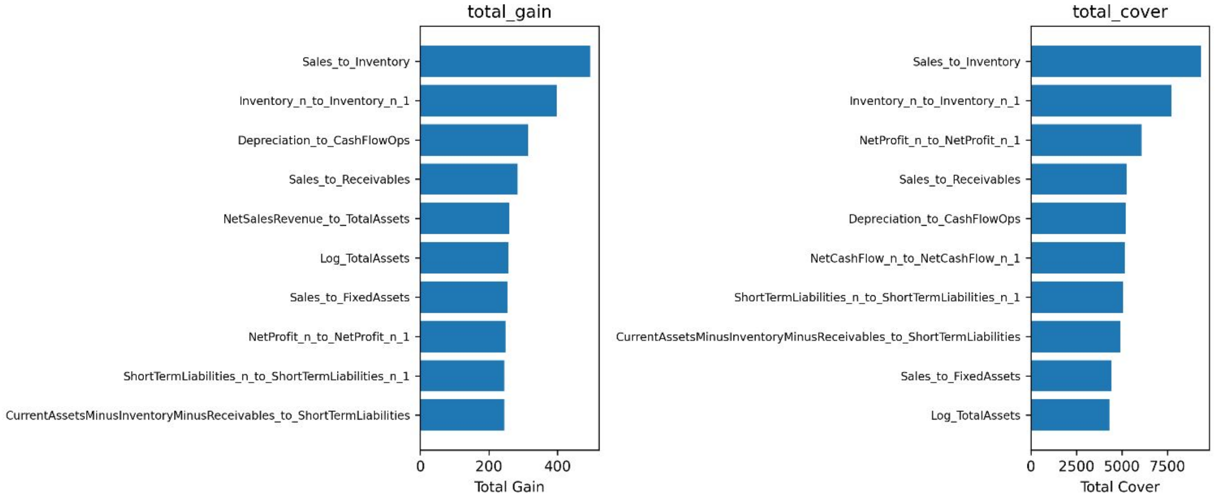
- The model performs well on the majority class (Manufacturing)
- Minority sectors show low F1-scores due to limited representation and class imbalance.
- Errors are economically structured, not random, suggesting the need for class-balancing rather than a different model.
- Overall result (macro-F1 = 0.23) reflects good performance on dominant classes but weak coverage of rare ones.

Classification Report:

	precision	recall	f1-score	support
0	0.000	0.000	0.000	3
1	0.250	0.154	0.190	13
2	0.640	0.800	0.711	40
3	0.167	0.111	0.133	9
4	0.000	0.000	0.000	2
5	0.333	0.385	0.357	13
accuracy			0.500	80
macro avg	0.232	0.242	0.232	80
weighted avg	0.434	0.500	0.460	80



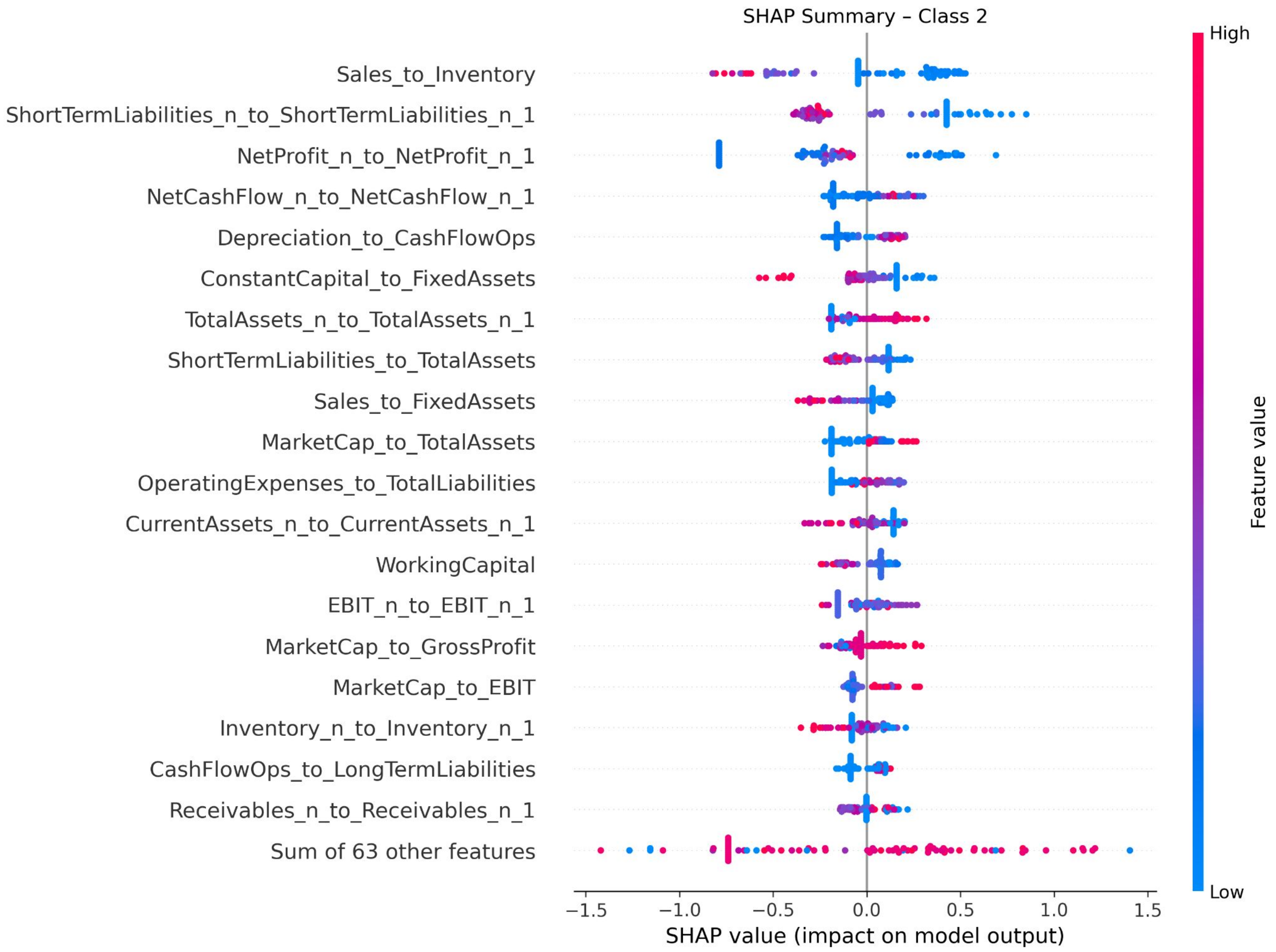




XGBoost
Global Interpretability

Operational efficiency and asset utilization are the most globally informative indicators of sector identity.

SHAP



SHAP Summary – Class 2
Sales_to_Inventory
ShortTermLiabilities_n_to_ShortTermLiabilities_n_1
NetProfit_n_to_NetProfit_n_1
NetCashFlow_n_to_NetCashFlow_n_1
Depreciation_to_CashFlowOps
ConstantCapital_to_FixedAssets
TotalAssets_n_to_TotalAssets_n_1
ShortTermLiabilities_to_TotalAssets
Sales_to_FixedAssets
MarketCap_to_TotalAssets
OperatingExpenses_to_TotalLiabilities
CurrentAssets_n_to_CurrentAssets_n_1
WorkingCapital
EBIT_n_to_EBIT_n_1
MarketCap_to_GrossProfit
MarketCap_to_EBIT
Inventory_n_to_Inventory_n_1
CashFlowOps_to_LongTermLiabilities
Receivables_n_to_Receivables_n_1
Sum of 63 other features
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
SHAP value (impact on model output)
High
Low
Feature value

Outlook

Improvements would focus on addressing class imbalance and feature redundancy, while using more advanced optimization and interpretability techniques to stabilize predictions and better understand feature interactions.

- Address class imbalance (Synthetic Minority Over-sampling Technique)
- Expand hyperparameter tuning
- Feature engineering using financial domain insight
- Reduce redundancy via dimensionality reduction (PCA)

Thank you!

Q&A?