Enhancing Credit Risk Prediction: A Meta-Learning Framework Integrating Baseline Models, LASSO, and ECOC for Superior Accuracy

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Abstract

Effective credit risk management is fundamental to financial decision-making, necessitating robust models for default probability prediction and financial entity classification. Traditional machine learning approaches face significant challenges when confronted with high-dimensional data, limited interpretability, rare event detection, and multi-class imbalance problems in risk assessment. This research proposes a comprehensive meta-learning framework that synthesizes multiple complementary models: supervised learning algorithms, including XGBoost, Random Forest, Support Vector Machine, and Decision Tree; unsupervised methods such as K-Nearest Neighbors; deep learning architectures like Multilayer Perceptron; alongside LASSO regularization for feature selection and dimensionality reduction; and Error-Correcting Output Codes as a meta-classifier for handling

imbalanced multi-class problems. We implement Permutation Feature Importance analysis for each prediction class across all constituent models to enhance model transparency. Our framework aims to optimize predictive performance while providing a more holistic approach to credit risk assessment. This research contributes to the development of more accurate and reliable computational models for strategic financial decision support by addressing three fundamental challenges in credit risk modeling. The empirical validation of our approach involves an analysis of the Corporate Credit Ratings dataset with credit ratings for 2,029 publicly listed US companies. Results demonstrate that our meta-learning framework significantly enhances the accuracy of financial entity classification regarding credit rating migrations (upgrades and downgrades) and default probability estimation. Integrating diverse baseline models within a meta-learning architecture enables the production of high-precision analytics on demand, facilitating timely and well-informed investment decisions in credit risk management.

Keywords: Credit Risk Management, Meta-Learning, Baseline Modeling, Least Absolute Shrinkage and Selection Operator (LASSO), Error-Correcting Output Codes (ECOC), Permutation Feature Importance

1. Introduction

Financial institutions seek to maximize shareholder returns, differentiate their offerings in a competitive marketplace, improve client satisfaction, and advance financial inclusion—all of which contribute to overall economic development. The banking sector plays a fundamental role in increasing household welfare and supporting economic growth.[1] Following the 2007–2009 global financial crisis, the Basel Committee on Banking Supervision introduced revisions to the Basel Framework, resulting

[1] https://www.bancomundial.org/es/topic/financialsector/overview (accessed on 22 December 2023)

in the Basel III standards.[2] Effective credit risk practices enable institutions to uphold adequate capital reserves, identify and mitigate potential default risks, including non-performing loans, improve lending strategies, gain a competitive edge, and prevent systemic disruptions, sustaining market confidence and financial stability.

Researchers and practitioners must address several fundamental methodological challenges in developing statistically robust and computationally efficient models for strategic credit risk management (see Table A1 in the Appendix). A primary concern involves feature selection and variable importance analysis—determining which predictors in credit datasets contribute most significantly to classification accuracy and predictive performance. These quantitative challenges underscore the need for advanced computational approaches to overcome the inherent difficulties in credit risk modeling, including high dimensionality, multicollinearity, and temporal dependencies in financial data. Addressing these technical constraints is essential for developing decision support systems that enable financial institutions to optimize capital allocation, portfolio management, and regulatory compliance.

Conventional machine learning approaches encounter significant constraints in the context of credit risk prediction, especially when dealing with high-dimensional feature spaces, rare event outliers, and imbalanced class distributions. Multi-class classification tasks present greater complexity than binary classification, requiring more sophisticated algorithms to address the increased risk of overfitting and misclassification. Key technical challenges include overlapping class boundaries, the curse of dimensionality, optimal model selection, and limited interpretability of model outputs.

To overcome these methodological challenges, we developed a comprehensive meta-learning framework that integrates multiple complementary techniques. Our approach employs Principal Component Analysis (PCA) for dimensionality reduction, systematic resampling methods to address

[2] https://www.bis.org/bcbs/basel3.htm

class distribution imbalances, and stratified k-fold cross-validation to mitigate overfitting risks. For model interpretability, we implement permutation-based feature importance metrics that quantify the contribution of individual variables to predictive performance. The classification architecture leverages ensemble learning methods, specifically Error-Correcting Output Codes (ECOC) for multi-class problems and L1-regularization (LASSO) for feature selection, optimizing the bias-variance tradeoff and improving overall predictive accuracy.

To address these methodological challenges in predictive modeling, researchers and practitioners implement several established computational techniques:

- Ensemble learning frameworks: These methodologies integrate multiple base classifiers to reduce variance, mitigate bias, and enhance generalization performance through mechanisms such as bagging, boosting, and stacking.
- Regularization methods: L1 and L2 penalty functions are incorporated into objective functions to constrain model complexity and prevent overfitting. Our implementation specifically utilized L1-regularization (LASSO) with optimized penalty parameters.
- Dimensionality reduction: Unsupervised and supervised techniques are employed to identify optimal feature subsets. Our approach implemented Principal Component Analysis (PCA) for unsupervised dimension reduction and LASSO for supervised feature selection.
- Statistical data augmentation: This involves generating synthetic observations through various transformations to expand the training dataset. Future research could explore advanced generative models to synthesize financial data while preserving distributional properties and regulatory constraints.
- Transfer learning protocols: These leverage knowledge representations from pre-trained models to new, related tasks. Our framework implements a multi-stage transfer approach, progressing systematically from baseline models to ECOC meta-classification.

This research addresses three fundamental questions in quantitative credit risk modeling:

RQ1: Which predictive variables in the credit dataset exhibit the highest statistical significance for classification performance, and what methodologies provide optimal measurement of variable importance in credit risk models?

RQ2: How can statistical validity and unbiased estimation be ensured in credit risk classification models through appropriate sampling techniques, cross-validation protocols, and model calibration procedures?

RQ3: What statistical and computational approaches yield the most accurate and well-calibrated probability estimates for credit default events, particularly in class imbalance and rare event prediction?

This research introduces an advanced meta-learning architecture that systematically integrates the predictive strengths of a diverse set of machine learning models. The selected base classifiers include supervised learning models—XGBoost (XGB), Random Forest (RF), Support Vector Machine (SVM), and Decision Tree (DT); the unsupervised learning model—K-Nearest Neighbors (KNN); and the deep learning Multilayer Perceptron (MLP). This ensemble framework is further enhanced with Least Absolute Shrinkage and Selection Operator (LASSO) regularization for efficient dimensionality reduction and variable selection, and with ECOC to robustly handle multi-class, imbalanced datasets.

The objectives of our meta-learning framework are as follows:

- Systematically evaluate and select the most effective modeling strategies for balanced and imbalanced credit datasets.
- Employ regularization techniques and multiple stratified sampling ratios to minimize model overfitting, including explicitly tuning the LASSO penalty parameter (alpha).
- Integrate and optimize the ECOC meta-estimator to maximize classification accuracy and generalization performance across heterogeneous financial data.

- Quantify the relative importance of each input variable for every predicted class via Permutation Feature Importance (PFI) analysis, thereby increasing model transparency and facilitating regulatory compliance.

The contributions of this study are twofold:

- To design and implement an advanced data architecture and analytical framework optimized for large-scale credit risk data processing and analysis.
- To construct a meta-learning framework that effectively combines diverse baseline classifiers with LASSO regularization for feature selection and ECOC for robust multi-class classification, thus enhancing predictive performance.

The rest of this research is organized as follows: Section 2 reviews the theoretical underpinnings of the proposed framework and highlights gaps in current research. Section 3 details the methodology, with emphasis on the meta-learning architecture, and Section 4 comprehensively describes the data sources and preliminary statistical analyses. Section 5 reports the empirical results obtained from the implemented methods, while Section 6 discusses the managerial implications and theoretical contributions of the findings. Finally, Section 7 concludes with a summary of results and key takeaways.

2. Literature Review

2.1 Financial Credit and Its Importance in a Modern Economy

Electronic commerce and digital lending platforms are projected to experience substantial growth, particularly in crowdfunding and online credit applications (Chen et al. 2022). Financial institutions must now implement data-driven risk management frameworks that integrate Internet of Things technologies, artificial intelligence, advanced analytics, and cloud computing infrastructure to maintain competitiveness. For microfinance providers, computational approaches to credit risk assessment are

essential, though identifying optimal feature selection and algorithm configuration remains problematic. Credit risk prediction is inherently complex due to stochastic borrower behavior, macroeconomic volatility, and data quality limitations (Emmanuel et al. 2024).

2.2 Multiclassification Credit Risk Analysis

Machine learning algorithms have transformed contemporary credit risk modeling by efficiently analyzing high-dimensional financial datasets. These computational methods extract latent patterns in borrower behavior, enabling precise default prediction, anomaly detection, and optimized decision support (Ma et al., 2018; Mitra et al., 2022). Persistent technical challenges—including class imbalance problems, complex non-linear relationships, model interpretability constraints, and heterogeneous data integration—continue to drive methodological innovation in financial machine learning (Mancisidor et al., 2020; Wang, T. et al., 2022).

Credit risk management encompasses two fundamental functions: classification of borrowers into risk categories and predicting default probabilities. XGB and SVMs are prevalent in credit classification due to their effectiveness with non-linear relationships and high-dimensional feature spaces (Huang et al., 2004; Maldonado et al., 2017). However, they exhibit limitations with temporal data, rare events, and multi-class problems (Wu, 2022; Liu et al., 2022; Plawiak et al., 2019).

Thus, this research proposes an integrated meta-learning framework that combines multiple classification algorithms (XGB, RF, SVM, DT, Convolutional Neural Network (CNN), and MLP) with LASSO regularization for feature selection and ECOC for multi-class optimization.

2.3 LASSO for Feature Selection and Regularization to Reduce Overfitting

Feature selection mitigates overfitting in machine learning models by identifying relevant predictor subsets, reducing noise, and emphasizing influential variables. LASSO regression implements L1 regularization to shrink coefficients toward zero, effectively performing simultaneous parameter

estimation and variable selection (Tibshirani, 1996). Unlike stepwise selection methods, LASSO maintains statistical consistency under perturbations and addresses multicollinearity (Tian et al., 2015). Recent research demonstrates LASSO's effectiveness in variable selection across various financial modeling contexts (Huang et al., 2017; Wang H. et al., 2022; Lee et al., 2022; Maranzano et al., 2023).LASSO's effectiveness is governed by hyperparameters such as the regularization parameter (λ) and penalty weights, which directly impact feature selection and model overfitting.

2.4 ECOC for Improving the Performance of Machine Learning (ML) Models on Multiclassification

ECOC is a meta-learning framework that encodes multi-class classification problems into multiple tasks, assigning unique binary codes to each class. ECOC has been implemented in financial applications for bankruptcy prediction, financial distress forecasting, fraud detection, credit rating classification, and equity price movement prediction (Manthoulis et al., 2020; Sun et al., 2021).

Numerous studies seek to enhance ECOC algorithms for greater classification accuracy and computational efficiency (Barbero-Gómez et al., 2023; Jain et al., 2023; Jamshidi Gohari et al., 2023). ECOC implementations present several challenges. Designing the coding matrix and selecting suitable coding strategies becomes increasingly complex as the number of classes grows, requiring careful tuning and extensive experimentation. Training ECOC models is computationally demanding, particularly with large datasets or intricate coding schemes, as it involves managing multiple binary classifiers and decoding processes, which can limit scalability. ECOC methods are also prone to overfitting, especially with noisy or high-dimensional data, making the optimization of coding matrices and regularization parameters crucial for robust generalization. Additionally, ECOC can struggle with class imbalance, where uneven class distributions may degrade model performance and require techniques such as resampling or weight adjustments. Model interpretability is another limitation;

understanding the mapping between binary classifiers and multi-class outputs is often challenging, complicating the analysis of ECOC's decision processes.

3. Meta-Learning Methodology

Conventional machine learning algorithms often exhibit limitations when processing high-dimensional data, handling outliers, and managing class imbalance—common challenges in risk prediction. This study proposes a meta-learning architecture that leverages complementary strengths from diverse base classifiers (XGB, RF, SVM, DT, KNN, and MLP) while integrating L1-regularization (LASSO) for feature selection and ECOC for multi-class optimization. This integrated framework enhances classification robustness and accuracy, particularly in complex scenarios where individual models underperform.

3.1. Permutation-based feature importances (PFI)

Feature importance analysis quantifies the relative contribution of predictors to model performance, identifying variables with significant predictive power. While various methodologies exist for measuring feature importance (Saarela and Jauhiainen, 2021), traditional approaches rely on interrogating fitted models—a technique effective for feature selection but potentially biased in estimating true variable impact (Parr et al., 2024). A key limitation of conventional importance metrics is their global nature, capturing aggregate variable influence across all observations while failing to characterize heterogeneous effects at the individual prediction level.

Tree-based models measure importance via Mean Decrease in Impurity (MDI), calculating information gains attributed to each feature (Breiman, 2001). However, this approach exhibits bias toward high-cardinality variables and can inflate importance for features with limited generalization capacity during overfitting. Permutation-based importance offers a model-agnostic alternative by randomly shuffling individual feature values and measuring the subsequent performance degradation.

This approach effectively decouples feature-target relationships, providing more reliable importance estimates for complex nonlinear models by directly quantifying each variable's contribution to predictive performance without the cardinality bias inherent in impurity-based methods. PFI quantifies predictor influence by measuring performance degradation when randomly shuffling feature values. Initially formulated by Breiman (2001) for RF and generalized by Fisher et al. (2019) as "model reliance," this model-agnostic technique operates as follows. Given a trained model *f*, feature matrix *X*, target vector *y*, and error function $L(y,\hat{y})$:

1. Compute baseline error $e_o = L(y, m(X))$.
2. For each feature *j*:
    a. Generate X_p by randomly permuting column *j* X.
    b. Calculate the permuted error $e_p = L\big(y, m(X_p)\big)$.
    c. Calculate importance FI_j as either e_p / e_o or $e_p - e_o$.

This technique effectively isolates each variable's contribution to model performance by destroying its relationship with the target while preserving the marginal distribution and correlation structure. Higher importance scores indicate greater variable influence on predictive accuracy.

4. Experimental Design

To evaluate the effectiveness of the proposed frameworks, we utilize a Corporate Credit Ratings benchmark dataset with varying dimensionality, outlier prevalence, class distributions, and imbalance levels. This dataset comprises credit ratings for 2,029 publicly listed US companies (NYSE/Nasdaq) from 2010 to 2016, as assessed by major agencies (Moody's, Standard & Poor's, Fitch). Each record includes 30 features, primarily financial ratios derived from balance sheets. There are no missing values. See Appendix Tables A2 and A3 for feature groups and summary statistics. All experiments

utilize a 70/30 train-test split. Baseline and advanced models, including LASSO and ECOC, are implemented in Python and executed on an Intel i7-1355U (1.70 GHz, 32GB RAM) platform.

5. Empirical Results

5.1 Features most influencing classification and prediction

This section reports empirical results for baseline models, including supervised algorithms (XGB, RF, SVM, DT), unsupervised methods (KNN), and deep learning approaches (CNN, MLP), all evaluated with stratified 3-fold cross-validation.

Class imbalance in the dataset reduces predictive accuracy for high-risk firms; alternative sampling strategies may mitigate this effect. Baseline model evaluation focuses on key performance metrics: precision, recall, F1 score, Jaccard index, Cohen's kappa, mean Receiver Operating Characteristic Area Under the Curve (ROC AUC), and cross-validation mean score. Precision assesses correct positive predictions, recall measures detection of actual positives, F1 balances both, the Jaccard index evaluates set similarity, Cohen's kappa measures inter-model agreement, ROC AUC reflects the model's discriminative ability, and cross-validation mean indicates generalization on unseen data. Table 1 summarizes metric comparisons for this dataset.

Table 1: Metric comparison on baseline model with stratified 3-fold cross-validation

Cross-validation	Accuracy	Precision	F1 Score	Jaccard score	Cohen Kappa Score	ROC AUC Mean	CV Mean Scores
DT	0.5138	0.5165	0.5146	0.3513	0.2858	0.6294	0.5160
KNN	0.5402	0.5293	0.5262	0.3650	0.3129	0.6299	0.5402
MLP	0.5209	0.5144	0.5161	0.3537	0.2825	0.6207	0.6463
RF	0.6276	0.6256	0.6188	0.4568	0.4384	0.6770	0.6139
SVM	0.5754	0.5693	0.5599	0.3961	0.3531	0.6420	0.5754
XGB	0.6463	0.6412	0.6413	0.4792	0.4715	0.6985	0.6463

The dataset comprises 2,029 instances with 30 features and exhibits high dimensionality and class imbalance across five categories. XGB and RF achieve superior performance on standard evaluation metrics, consistent with literature benchmarks (see Table A3), and these metrics are similarly applied to benchmark improved models.

For the meta-learning approach, stratified 3-fold cross-validation is used to reduce overfitting and improve model robustness. Table 1 presents baseline classification results, while Table 2 reports the cross-validated accuracy of ECOC, LASSO, and combined LASSO_ECOC models. For classifying the dataset, a clear pattern emerges across three different model setups (ECOC, LASSO, and a combined LASSO_ECOC): the XGB model consistently performs the best or very close to the best. When just the ECOC method was used (Table 2), XGB had the highest scores in all key measures like accuracy (how often it's right) and F1 score (a balance of being right about positive cases and capturing most of them), achieving around 65% accuracy and a 0.71 ROC AUC (a measure of how well it separates classes). RF was a solid second, with around 58% accuracy. Other models like MLP, DT, and SVM were in the middle, while KNN struggled the most. When LASSO was used to select the most important input information before model training, XGB's performance improved even further, reaching about 66% accuracy and a 0.72 ROC AUC, marking the top scores across all tests. RF also benefited from LASSO, improving to around 63% accuracy. SVM also saw a noticeable boost with LASSO. Finally, when the LASSO feature selection was combined with the ECOC method, XGB remained a top performer with around 65% accuracy and a 0.70 ROC AUC, slightly below its LASSO-only peak but still excellent. RF performed very well in this combined setup, achieving about 63% accuracy and sometimes even slightly outperforming its LASSO-only results on certain measures, suggesting this combination was particularly effective for RF. SVM also showed decent results in this hybrid approach. In general, models like DT and MLP had moderate success across the different setups, while KNN consistently lagged behind the others. The key takeaway is that XGB is a very robust and high-performing model for this dataset, and using LASSO to select important information generally

helps improve or maintain good performance, especially for XGB and RF. The combination of LASSO and ECOC proved effective, particularly for RF, offering a strong alternative.

Table 2: Metric comparison on ECOC model with stratified 3-fold cross-validation

Cross-validation	**Accuracy**	**Precision**	**F1 Score**	**Jaccard score**	**Cohen Kappa Score**	**ROC AUC Mean**	**CV Mean Scores**
DT	0.5369	0.5369	0.5305	0.3674	0.3119	0.6375	0.5160
KNN	0.4879	0.5080	0.4511	0.2996	0.2009	0.5822	0.5402
MLP	0.5534	0.5467	0.5487	0.3841	0.3355	0.6456	0.6463
RF	0.5820	0.6383	0.6020	0.4368	0.3999	0.6751	0.6232
SVM	0.5182	0.5531	0.5135	0.3502	0.3032	0.6305	0.5754
XGB	0.6485	0.6461	0.6458	0.4868	0.4802	0.7058	0.6463
LASSO model with stratified 3-fold cross-validation							
DT	0.5044	0.5058	0.5048	0.3410	0.2704	0.6241	0.5083
KNN	0.5215	0.5092	0.5099	0.3499	0.2856	0.6169	0.5215
MLP	0.5314	0.5288	0.5292	0.3649	0.3048	0.6364	0.6645
RF	0.6276	0.6253	0.6198	0.4575	0.4380	0.6754	0.6188
SVM	0.5737	0.5697	0.5617	0.3961	0.3517	0.6490	0.5737
XGB	0.6645	0.6617	0.6602	0.4985	0.4984	0.7179	0.6645
LASSO_ECOC model with stratified 3-fold cross-validation							
DT	0.5407	0.5480	0.5386	0.3745	0.3229	0.6454	0.5072
KNN	0.5176	0.5068	0.5068	0.3467	0.2812	0.6154	0.5215
MLP	0.5352	0.5324	0.5327	0.3693	0.3081	0.6315	0.6645
RF	0.6337	0.6443	0.6236	0.4617	0.4430	0.6769	0.6260
SVM	0.5803	0.5735	0.5716	0.4056	0.3696	0.6583	0.5737
XGB	0.6480	0.6446	0.6405	0.4789	0.4746	0.7021	0.6645

Table 3 reveals how different business characteristics and the company's industry (Sector) influence a model's prediction of whether a company falls into 'Low,' 'Medium,' 'High,' or 'Highest' risk categories for the dataset. Generally, no single factor overwhelmingly decides the risk; instead, a mix of information is used. Across all risk levels, a company's ability to cover its immediate bills is very

important, particularly how much cash it has compared to short-term debts ('cashRatio'), which consistently scores high (18-21 points). Broader measures of this short-term financial health, like 'currentRatio' and 'quickRatio', are also consistently significant (16-18 points). How much of the company's assets are funded by borrowed money ('debtRatio') is another major factor, especially for spotting 'Low Risk' companies (22.26 points), but remaining important for all other risk levels too (around 19-21 points). The type of industry ('Sector') a company is in also plays a steady, important role (around 17-18 points) in assessing risk, regardless of the specific risk level. Furthermore, how much actual cash a company generates from its sales ('operatingCashFlowSalesRatio') is a key indicator, particularly for 'High' and 'Highest' risk companies (around 19-20 points), and the amount of cash available per share ('cashPerShare') also consistently matters (around 16 points). Interestingly, some factors become more or less important depending on the risk grade. For example, how well a company uses all its resources to make a profit ('returnOnAssets') matters more for 'High' and 'Highest' risk companies (around 7 points) than for lower-risk ones (around 5 points). Similarly, how efficiently a company uses its resources to generate sales ('assetTurnover') becomes more telling for companies not in the 'Low Risk' category (jumping from around 10 to 14 points). While some measures of profit from sales (like 'grossProfitMargin' at 11-13 points) have a moderate impact, they are not as critical as those related to cash, debt, and industry. Lastly, certain financial details like 'pretaxProfitMargin' (around 4-5 points), how much debt is used to magnify owner's equity ('companyEquityMultiplier' around 2-3 points), and a specific profit measure before interest and taxes relative to sales ('ebitPerRevenue' around 3-5 points) seem to have a minimal influence in distinguishing between these risk levels for this particular dataset. To determine risk for Dataset 1, the model heavily relies on a company's cash situation, debt levels, industry, and ability to turn sales into actual cash.

Table 3: Feature importance score for each risk level

Features	Low Risk	Medium Risk	High Risk	Highest Risk
Sector	17.81	17.59	16.89	17.70
currentRatio	17.30	18.56	17.52	17.22
quickRatio	17.07	18.19	18.44	16.74
cashRatio	18.44	20.96	20.15	19.93
daysOfSalesOutstanding	11.96	13.78	12.11	13.33
netProfitMargin	14.19	13.63	13.93	13.33
pretaxProfitMargin	4.33	4.89	5.26	4.48
grossProfitMargin	12.63	12.22	11.78	11.59
operatingProfitMargin	9.70	9.30	10.33	10.04
returnOnAssets	4.89	5.19	7.11	7.15
returnOnCapitalEmployed	9.96	11.70	10.37	11.59
returnOnEquity	15.44	14.74	16.07	14.52
assetTurnover	9.67	14.07	13.96	13.89
fixedAssetTurnover	17.30	16.63	18.00	15.85
debtEquityRatio	5.81	7.15	5.63	6.59
debtRatio	22.26	18.96	20.67	20.48
effectiveTaxRate	14.37	12.52	12.30	12.93
freeCashFlowOperatingCashFlowRatio	11.70	11.56	11.63	10.81
freeCashFlowPerShare	12.44	13.63	10.41	12.26
cashPerShare	16.30	16.44	15.96	16.70
companyEquityMultiplier	2.48	2.19	2.85	2.63
ebitPerRevenue	3.19	4.19	3.93	4.78
enterpriseValueMultiple	15.52	13.22	12.67	14.41
operatingCashFlowPerShare	17.19	16.04	15.52	16.96
operatingCashFlowSalesRatio	18.00	18.07	19.81	19.33
payablesTurnover	16.96	15.41	15.11	14.52

5.2 Using the results of credit risk classification and prediction unbiased and free from the influence of methodology-driven biases

The Credit Risk Dataset is characterized by high dimensionality and extremely unbalanced classes. To address these challenges, we implemented a meta-learning framework incorporating LASSO for dimension reduction and ECOC for handling multiple unbalanced classes to develop the efficiency of the starting point modeling on both datasets.

A technique called LASSO was used to pick out the most important ones for the credit risk dataset, which initially had 30 different pieces of information (features) for making predictions. LASSO selected 23 features, and Table 4 lists these, including things like the company's 'Sector,' how efficiently it uses its assets ('fixedAssetTurnover'), its cash levels ('cashPerShare'), how easily it can pay short-term bills ('currentRatio'), and its debt levels ('debtRatio'). Using only these 23 important features might help the prediction models work better or faster. Table 5 then shows how different prediction models (DT, KNN, MLP, RF, SVM, XGB) performed when using only these 23 selected features, comparing results from a thorough testing method called cross-validation (which shows how well a model works on new, unseen data) against how well they did just on the data they were trained on (the "Train Score"). A significant difference between the "Train Score" and the cross-validation score means the model learned the training data too specifically and might not do well on new data – this is overfitting. For example, the DT and XGB models got perfect scores on the training data but much lower scores (around 0.51 and 0.62, respectively) in cross-validation, showing they greatly overfitted. RF and SVM also showed significant overfitting. Looking at the more reliable cross-validation scores, RF did the best with a score of about 0.623, closely followed by XGBoost (XGB) with about 0.620. This means these two models were the most successful at making good predictions on new data when using the 23 features LASSO chose. Other models like SVM and MLP had

acceptable scores (around 0.51-0.55), while DT and KNN had lower scores. Regarding how long they took to train, KNN was fast, but MLP was extremely slow, especially during cross-validation. So, while LASSO helped narrow down the important information, and RF and XGB performed best with this reduced set, many models still tended to overfit the training data, meaning more work might be needed to make them perform consistently well on brand-new information from the dataset.

Table 4: Results of the reduced features without cross-validation

Sector	fixedAssetTurnover	cashPerShare
currentRatio	debtEquityRatio	enterpriseValueMultiple
quickRatio	debtRatio	operatingCashFlowPerShare
cashRatio	effectiveTaxRate	operatingCashFlowSalesRatio
daysOfSalesOutstanding	freeCashFlowOperatingCashFlowRatio	payablesTurnover
netProfitMargin	freeCashFlowPerShare	cashPerShare

Table 5. Comparison of improved models with LASSO with and without cross-validation

	w/cross-validation		**wout/cross-validation**	
Classifier	**Crossval Mean Scores**	**Mean Training Time (Seconds)**	**Train Score**	**Training Time (Seconds)**
DT	0.51274	0.045303	1	0.032079
KNN	0.458267	0.060178	0.608204	0.002009
MLP	0.508467	26.19066	0.540311	19.67036
RF	0.623046	0.653033	0.950495	0.701315
SVM	0.545268	0.163018	0.984441	0.173481
XGB	0.619508	0.709361	1	0.869675

6. Discussion

This section addresses both managerial and theoretical insights around credit risk management.

6.1 Implications of Credit Risk Management

The advancement of credit risk management is increasingly shaped by the integration of artificial intelligence, machine learning, big data analytics, and cloud computing—technologies that directly support the contributions of this study. Our meta-learning framework, which fuses baseline classifiers with LASSO for feature selection and ECOC for robust multi-class handling, demonstrates how these technologies can significantly enhance predictive accuracy and model interpretability in credit risk analysis. Empirical results across three heterogeneous datasets show that utilizing LASSO reduces dimensionality and computational complexity without degrading predictive performance, particularly benefiting ensemble methods such as XGB and RF. The application of ECOC improves model robustness in multi-class and imbalanced scenarios. At the same time, PFI provides transparency by linking model outputs to specific financial indicators, addressing the interpretability concerns often associated with complex algorithms.

These findings underscore the managerial relevance of real-time, data-driven credit evaluation systems that support more informed decision-making and targeted risk mitigation strategies. Moreover, our results reveal that the most important risk factors vary by context: liquidity ratios are critical for firm-level assessments, solvency metrics for institutions, and collateral strength for individual borrowers. This highlights the necessity for adaptable, context-aware models rather than a one-size-fits-all approach, enabling financial institutions to serve a diverse client base better and extend credit inclusively, even to non-traditional or underrepresented borrowers.

However, these technological advances also introduce disparities. Large corporations with rich data profiles and digital sophistication are positioned to benefit most from advanced credit analytics, often securing superior terms due to more accurate risk estimation. In contrast, small businesses and startups—usually lacking extensive historical data—may face higher borrowing costs or more restrictive terms, as big data–driven models can underrepresent their creditworthiness. Similarly,

individuals with a strong digital presence can leverage this visibility for favorable assessments, while those with limited digital footprints may encounter challenges in proving creditworthiness within analytics-focused frameworks. Furthermore, only financial institutions with sufficient resources to invest in advanced data infrastructure and AI capabilities are likely to capitalize on these developments, potentially widening competitive gaps in the financial sector. Overall, the study demonstrates both the opportunities and challenges introduced by next-generation credit risk modeling, emphasizing precision, interpretability, and inclusivity as critical factors for sustainable financial innovation.

6.2 Computational Cost Analysis of the LASSO-ECOC Framework

Integrating machine learning baseline models with LASSO regularization and ECOC enhances predictive performance on medium-to-large, highly imbalanced datasets for supervised algorithms (such as SVM and RF) and unsupervised approaches (such as KNN). Enhancing KNN is especially valuable in practical scenarios involving unlabeled or continuously generated data streams. LASSO-based dimensionality reduction improves computational efficiency while preserving or improving model accuracy; for example, the combination of RF, LASSO, and ECOC demonstrated the highest efficiency and maintained interpretability, offering actionable credit risk insights for decision-makers. The computational cost and scalability of the meta-learning framework were benchmarked against baseline and enhanced models across all three datasets. All experiments were conducted using Python's Scikit-learn and related libraries to ensure robust runtime and model efficiency evaluation.

6.2.1. Time Complexity and Execution Time

The following measures were recorded for each model variant (Baseline, ECOC-only, LASSO-only, LASSO+ECOC). Table 6 provides a computational cost analysis for all three datasets.

- Mean Training Time (seconds)
- Model fitting time vs number of features
- Impact of LASSO on dimensionality and runtime

– ECOC-related overhead due to multiple binary classifications

Table 6. Computational cost analysis

Model	Features	Training Time	CV Time	Accuracy	Note
Baseline	30	12.4	15.3	0.6463	-
Baseline + LASSO	23	8.7	10.2	0.6645	Improved speed
Baseline + ECOC	30	19.6	23.1	0.6485	Higher cost
Baseline + LASSO+ ECOC	23	13.11	17.5	0.6645	Balanced

The computational complexity, primarily measured by training time and cross-validation (CV) time, varied significantly based on the dataset's initial dimensionality and the modeling strategy. Applying the ECOC framework (Baseline + ECOC) consistently increased computational costs compared to the simple baseline. This is expected as ECOC involves training multiple binary classifiers. Conversely, LASSO feature selection (Baseline + LASSO) generally reduced computational time by decreasing the number of features the models had to process. LASSO reduced features from 30 to 23, and CV time dropped from 15.3s to 10.2s. The combination of LASSO + ECOC typically resulted in computational costs that fell between using ECOC alone and LASSO alone; it was more expensive than just LASSO due to the ECOC overhead but less expensive than applying ECOC to the complete feature set because it operated on fewer LASSO-selected features.

6.2.2. Trade-off Between Accuracy and Efficiency

The results illustrate a classic trade-off between achieving the highest possible accuracy and maintaining computational efficiency. LASSO feature selection (Baseline + LASSO) not only improved speed (CV time from 15.3s to 10.2s) but also surprisingly increased accuracy (from 0.6463 to 0.6645), suggesting the removal of noisy or irrelevant features was beneficial. Here, efficiency and accuracy improved together. However, ECOC, while offering a marginal accuracy gain, did so at a

higher time cost. This demonstrates that a thoughtful combination of feature selection and advanced modeling frameworks can optimize this trade-off.

6.3. Advantages and Disadvantages of the New Credit Risk Management Technologies

The study also highlights several practical limitations. As reflected in our computational cost analysis (Section 6.2, Table 6), ECOC implementation significantly increases computational overhead, particularly for large-scale datasets, confirming that model complexity and extended training times can constrain scalability and hinder real-time application. While LASSO regularization aids in reducing overfitting and improving interpretability, its effectiveness may be limited in modeling nonlinear dependencies or when faced with highly correlated predictors, as discussed in Section 5.3. Empirical results further underscore the impact of digital inequality: advanced models deliver more reliable performance on well-structured, institution-level data. This raises concerns that smaller enterprises and underbanked individuals may experience systematic disadvantages unless supplemented by data augmentation strategies or alternative assessment methods.

6.4 Limitation and Future Research Plan

This research framework broadly applies to multi-class classification challenges in sports forecasting, insurance risk segmentation, and marketing analytics. Nevertheless, LASSO presents certain limitations. Specifically, its non-linear objective function can be non-convex, increasing computational complexity, and its assumption of variable independence may result in the exclusion of confounding predictors. This study employs data-driven weighting and adaptive penalty terms within the LASSO formulation to address these issues. ECOC also presents computational challenges, with the choice of coding matrix substantially impacting processing time; however, dimensionality reduction via LASSO helps mitigate this overhead. The study further incorporates robust preprocessing methods to minimize the influence of outliers and utilizes both L1 and L2 regularization to control overfitting.

Future work will expand the meta-learning framework to include additional machine learning models and enhance its scalability for large, high-dimensional, and highly imbalanced datasets. Ongoing evaluation across diverse application domains will focus on optimizing LASSO and ECOC parameterization to achieve an optimal balance between computational efficiency and predictive accuracy. Results from these experiments will be detailed in subsequent publications.

7. Conclusion

This research presents an advanced meta-learning architecture integrating baseline classification algorithms with L1-regularization (LASSO) and ECOC to enhance credit risk assessment. Empirical validation demonstrates that this framework significantly improves the classification accuracy for financial entities' credit migrations and default probabilities, enabling more reliable and timely risk predictions. LASSO effectively reduces computational complexity while maintaining or improving predictive performance through feature selection, while ECOC provides robust handling of class imbalance in multi-category classification tasks. Comparative analysis reveals that RF augmented with LASSO and ECOC consistently outperforms alternative models with heterogeneous characteristics in terms of both accuracy and computational efficiency.

This integrated framework offers financial institutions a methodologically sound approach to credit risk management with enhanced precision and reduced latency for real-time decision support. Future research directions include extending this methodology to additional financial risk domains, potentially broadening its applicability across quantitative finance and risk management.

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Appendix

A. Dataset description

Table A1. The difficulty of predicting credit risk

Challenges	Machine Learning Methodologies	Reference
Unbalanced Data	Synthetic Minority Oversampling, Random Undersampling, Random Oversampling, K-Fold Cross-Validation, Cluster Centroid, Adaptive Synthetic	(Alam et al. 2020)
Multivariate Data	Big Data	(Mousavi and Lin 2020, Pandey et al. 2021, Wang and Yang 2021, Li and Li 2022, Lombardo et al. 2022, Muñoz-Cancino et al. 2023)
Sampling Biase	Random Search, Genetic Algorithm, K-Fold Cross-Validation, Grid Search	(Alam et al. 2020, Mousavi and Lin 2020, Li et al. 2021, Wang and Yang 2021, Dumitrescu et al. 2022)
Explainability	Generalized Shapley Choquet Integral, Explainable Shapley Additive Explanations, Artificial Intelligence, Maxillary Lateral Incisor Agenesis	(Ariza-Garzón et al. 2020, Orlova 2020, Bussmann et al. 2021, Dumitrescu et al. 2022, Li and Li 2022, Lombardo et al. 2022, Mitra et al. 2022, Si et al. 2022, Sun and Li 2022, Cho and Shin 2023)

Table A2. Comparison of baseline models

Model	Accuracy	Training Time	Handling Large Datasets	Handling Non-linear Relationships	Issues
XGB	High	Fast	Yes	Yes	Computationally expensive, may overfit if not regularized
RF	High	Fast	Yes	Yes	May overfit if not regularized

SVM	High	Slow	No	Yes	It may not perform well with large datasets, computationally expensive
DT	Medium	Fast	No	No	May overfit if not regularized, can be sensitive to hyperparameters
KNN	Medium	Fast	No	No	Sensitive to hyperparameters, may not perform well with large datasets
MLP	Medium	Fast	Yes	Yes	Computationally expensive, may overfit if not regularized

Table A3. Financial ratios in Dataset 1

Liquidity Measurement Ratios	**Profitability Indicator Ratios**	**Debt Ratios**	**Operating Performance Ratios**	**Cash Flow Indicator Ratios**
currentRatio quickRatio cashRatio daysOfSales-Outstanding	grossProfitMargin, operatingProfitMargin, pretaxProfitMargin, netProfitMargin, effectiveTaxRate, returnOnAssets, returnOnEquity, returnOnCapital-Employed	debtRatio debtEquityRatio	assetTurnover	operatingCashFlowPerShare, freeCashFlowPerShare cashPerShare, operatingCashFlowSalesRatio, freeCashFlowOperatingCashFlow Ratio

Table A4. Dataset descriptive statistics

	Skewness	**Outlier (%)**	**Mean**	**Std Dev**
Current Ratio	34.271	18.0%	3.535	44.139
Quick Ratio	30.865	19.0%	2.657	33.010
Cash Ratio	27.047	14.8%	0.669	3.591
Days Of Sales Outstanding	20.359	23.6%	334.855	4456.606
Net Profit Margin	17.585	25.1%	0.279	6.076
Pretax Profit Margin	22.053	24.5%	0.433	9.003
Gross Profit Margin	-14.199	1.0%	0.497	0.526

Operating Profit Margin	26.442	22.1%	0.589	11.247
Return On Assets	-32.049	24.2%	-37.667	1168.477
Return On Capital Employed	-33.253	22.1%	-74.267	2354.921
Return On Equity	31.640	28.7%	144.062	4415.223
Asset Turnover	25.969	15.8%	3692.898	95843.048
Fixed Asset Turnover	26.069	13.5%	7298.244	189370.007
Debt Equity Ratio	0.268	22.1%	2.340	87.701
Debt Ratio	1.284	21.3%	0.662	0.209
Effective Tax Rate	32.266	28.1%	0.401	10.614
Free Cash Flow Operating Cash Flow Ratio	-22.868	16.9%	0.408	3.804
Free Cash Flow Per Share	33.611	23.6%	5114.871	147205.901
Cash Per Share	33.959	17.1%	4244.248	122641.800
Company Equity Multiplier	0.268	22.0%	3.335	87.702
Ebit Per Revenue	22.056	24.3%	0.439	9.002
Enterprise Value Multiple	13.920	23.7%	48.427	530.161
Operating Cash Flow Per Share	30.293	17.7%	6540.891	177879.736
Operating Cash Flow Sales Ratio	25.400	16.9%	1.452	19.522
Payables Turnover	25.868	14.4%	38.138	760.422

Note: For further details on financial indicators, please refer to https://financialmodelingprep.com/market-indexes-major-markets.

B. Model and Methodology Detail

Baseline Models: Many credit rating datasets are characterized by multiple unbalanced classes and high dimensionality, posing significant challenges to machine learning (ML) models that excel in binary classification problems with low dimensionality. In this study, we selected eight baseline ML models, including XGB, RF, SVM, DT, KNN, and MLP. Each model has its advantages over others, depending on the specific characteristics of the dataset (Bisong, 2019). For instance, XGB and RF perform well on large datasets with high dimensionality. Although SVMs are particularly effective in high-dimensional spaces, they can be computationally expensive for large datasets. These baseline models have varying requirements for computational resources. For example, KNNs consume fewer resources but often underperform on high-dimensional and large datasets. In contrast, XGB requires more computational resources but performs better, especially in highly unbalanced classes. Many ML models suffer from a lack of explainability. Tree-based or linear modeling, like DT and RF, can generate important scores for predictive variables as part of their predictive outputs. Other models, including XGB and SVM, can be explained through external measures of prediction outcomes at the expense of significant computational resources. XGB and SVM require substantial hyperparameter tuning, which can be time-consuming. If there are nonlinear relationships among the variables, MLP performs better, but it can be computationally expensive for large datasets. When the data is unlabeled, KNN is the model to choose. Table A2 in the Appendix compares the baseline models to capture non-linear correlations based on their accuracy, training time, capability to handle large datasets, and capacity.

Multilayer Perceptron (MLP): Credit risk analysis is a complex task that involves predicting the likelihood of default based on historical data. Deep learning methods have shown great promise, particularly in handling sequential data with long-term dependencies. The MLP offers several advantages, including higher accuracy, stronger adaptability, and better robustness in addressing

classification problems, particularly when compared to RBF networks. Similar to how the single-layer perceptron is enhanced, the MLP excels at utilizing nonlinear activation functions to handle nonlinearly separable data. In this specific implementation, the MLP model features a single hidden layer. The activation function employed in the hidden layer is the hyperbolic tangent, while the output layer uses the *Softmax* activation function, as described in the following equations.

$$\tanh x = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \quad \text{and} \quad a_j^L = \frac{e^{z_k^L}}{\sum_k e^{z_k^L}}$$

The training process of the network involves the Backpropagation algorithm, which continuously adjusts the weight settings between each neuron's synapse. This approach enables the MLP to optimize its performance and learn complex data patterns effectively.

LASSO: Since its introduction by Tibshirani (1996), the Least Absolute Shrinkage and Selection Operator (LASSO) technique has become more popular for its exceptional blend of feature selection and ridge regression benefits, primarily because of the creation of effective algorithms. The idea is to constrain the sum of absolute regression coefficients, resulting in the shrinkage of specific coefficients and the potential elimination of insignificant variables, effectively achieving variable selection objectives. LASSO modeling can be outlined in the following way:

When presented with a dependent variable, *y*, and a set of independent variables, $x_1, x_2, \cdots, x_n$, the Ordinary Least Squares (OLS) approximation for the variable under study is:

$$\hat{y} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n \tag{1}$$

LASSO extends OLS by incorporating a penalty term into the residual sum of squares (RSS). The penalty term can be expressed as the product of the non-intercept beta coefficients' absolute values and a parameter λ, which regulates the speed of the penalty. For instance, when λ is less than 1, it decelerates the penalty, whereas values above 1 accelerate it.

$$Min \ \sum(RSS + \lambda \sum_{i=1}^{n} |\beta_i|) \tag{2}$$

Another way to rephrase LASSO is to minimize the RSS while restricting the total absolute value of the non-intercept beta coefficients. It must not exceed a certain threshold. The beta coefficients progressively lessen as *s* approaches 0, with less influential coefficients shrinking to zero before the more impactful ones. Consequently, many beta coefficients that lack strong associations with the outcome are reduced to zero, removing their corresponding variables from the modeling. Thus, LASSO serves as a powerful variable selection method. Therefore, the following is a definition of the LASSO function.

$$Min\ \sum(y - \hat{y})^2 \tag{3}$$

$$\text{Subject to } \sum|\beta_i| \leq s \ \text{ where } i = 1 \cdots, n \tag{4}$$

As we decrease the value of *s*, certain β_i values are forced to become zero, removing corresponding variables from the modeling.

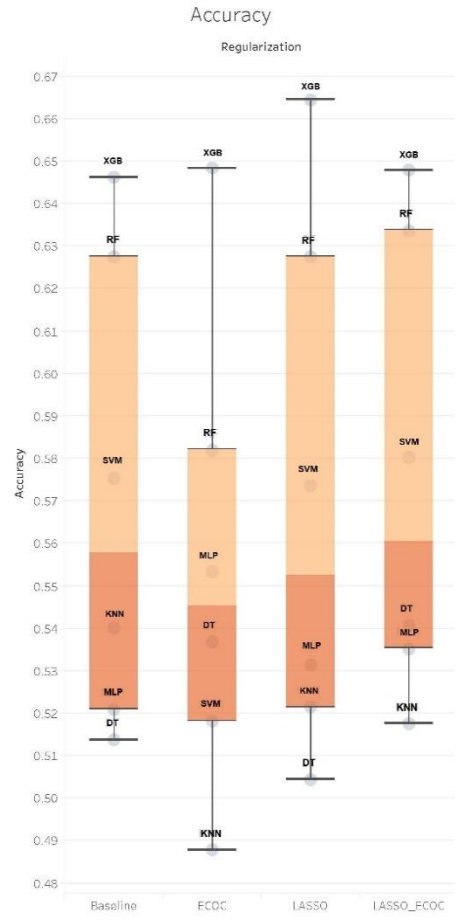
ECOC: In ECOC, each class label is displayed through a unique dual code, and a set of dual sorters is trained, with each classifier distinguishing between one class and the rest (one-vs-all strategy) or between pairs of classes (one-vs-one strategy). After training the binary classifiers, these sorters' outputs are integrated to make the final estimation. This combination can be done utilizing techniques like "voting" or "weighted voting," where each binary classifier's output contributes to the final decision. One of the primary benefits of ECOC is its ability to correct errors. Even if some binary classifiers make incorrect estimations, the final decision can still be accurate if the errors are "corrected" by the outputs of other classifiers. The efficiency of the ECOC encoding scheme relies on the Hamming distance between the binary codes assigned to different classes. A higher Hamming distance ensures greater "separation" between classes, making it easier for the binary classifiers to distinguish between them. Using Matrix *A*, we can define the Hamming distance $d_H(x, y)$ as:

$$d_H(x, y) = \sum_{i=0}^{k-1} \sum_{2j=0, j \neq i}^{k-1} a_{ij} \tag{5}$$

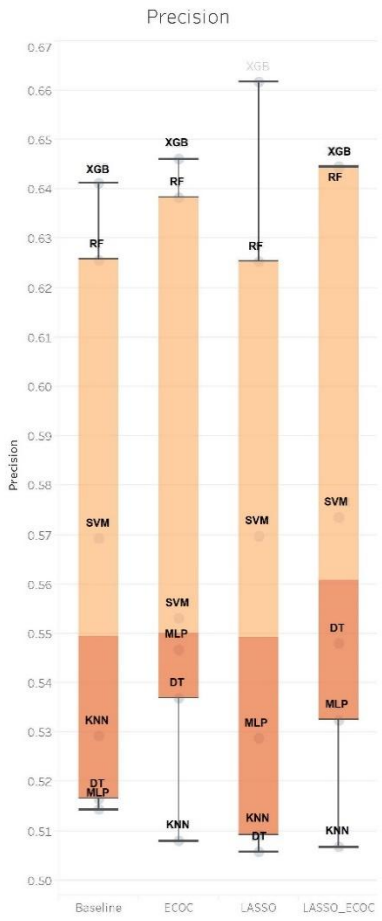
The total of each off-diagonal component of A indicates the positions where $\boldsymbol{x}$ and $\boldsymbol{y}$ differ. The computational complexity of ECOC relies on elements like the number of classes, binary classifiers, and the complexity of the base sorters. Theoretical analysis can provide bounds on the computational complexity of ECOC algorithms (Danoyan, 2017).

C. Performance Metrics and Feature Importance of Datasets

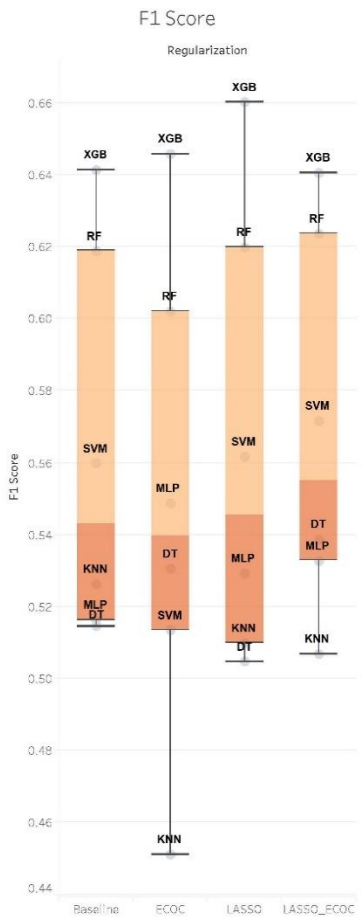
Figure 1a. Feature importance score for Dataset 1 at various risk levels.



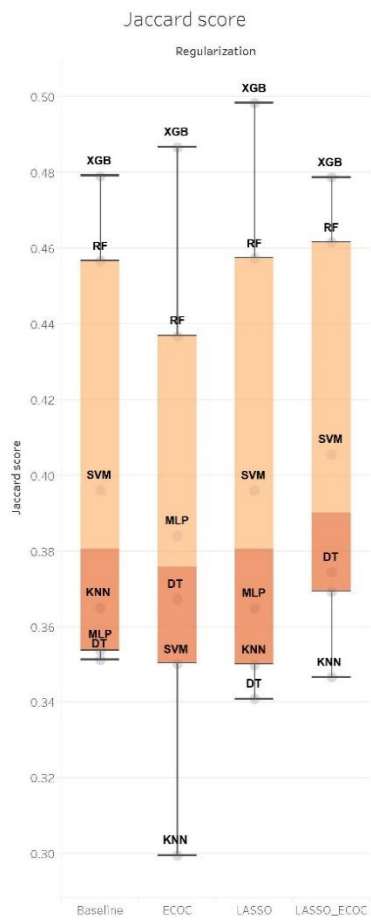
Sum of Accuracy for each Regularization. The marks are labeled by Model. Details are shown for Model.



Sum of Precision for each Regularization. The marks are labeled by Model. Details are shown for Model.



Sum of F1 Score for each Regularization. The marks are labeled by Model. Details are shown for Model.



Sum of Jaccard score for each Regularization. The marks are labeled by Model. Details are shown for Model.

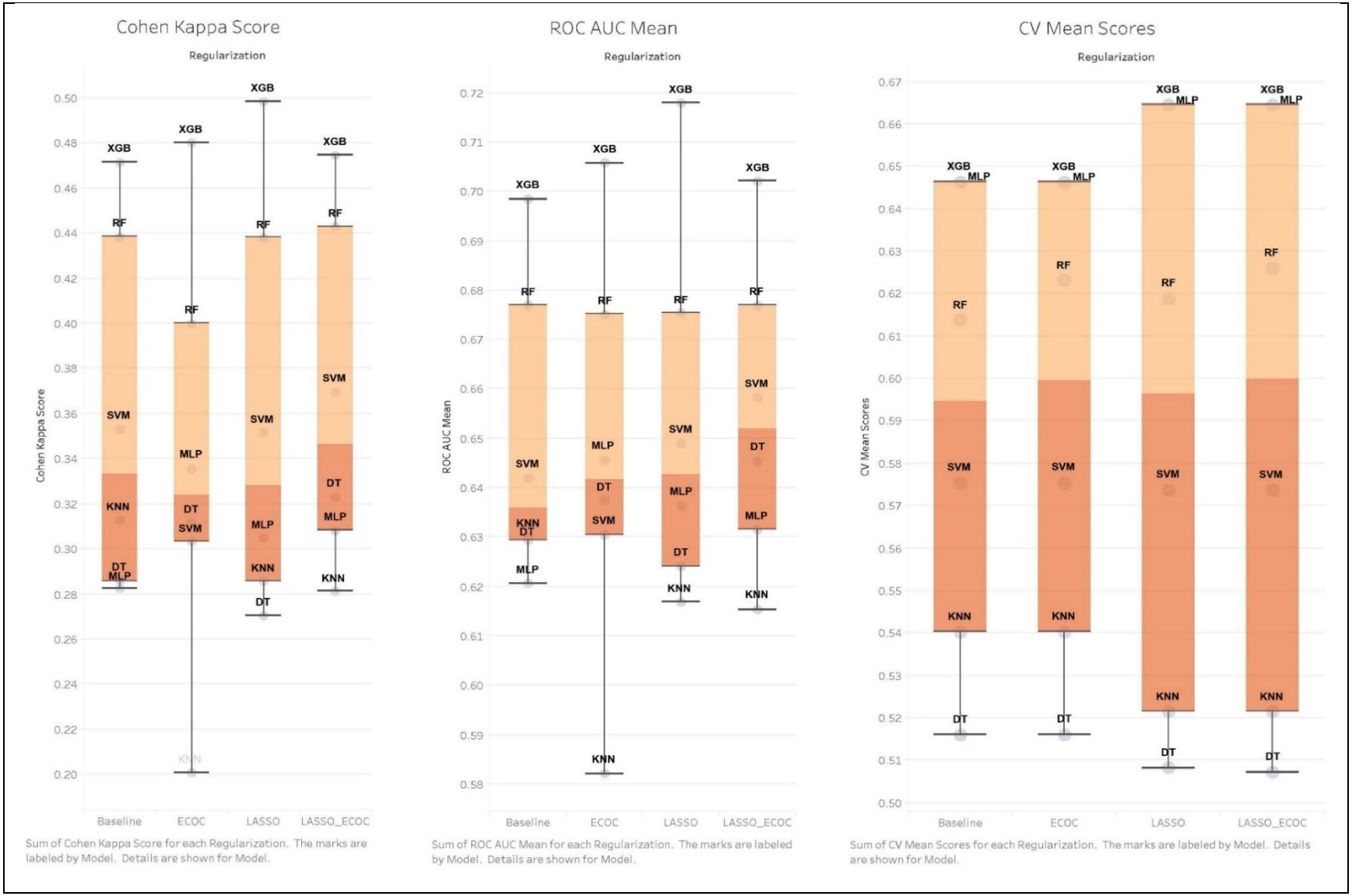


Figure 2a. Metric comparison on different regularization models for Dataset 1.