Machine Learning Classification of Stock Performance

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DATA 3461 | Final Project

Motivation

The Challenge

- Stock prediction is notoriously difficult
- Even expert investors struggle to consistently beat the market
- Traditional approaches rely on complex models with many data sources

Our Question: Can we predict stock performance using **only fundamental accounting data and specific features**?

Why It Matters

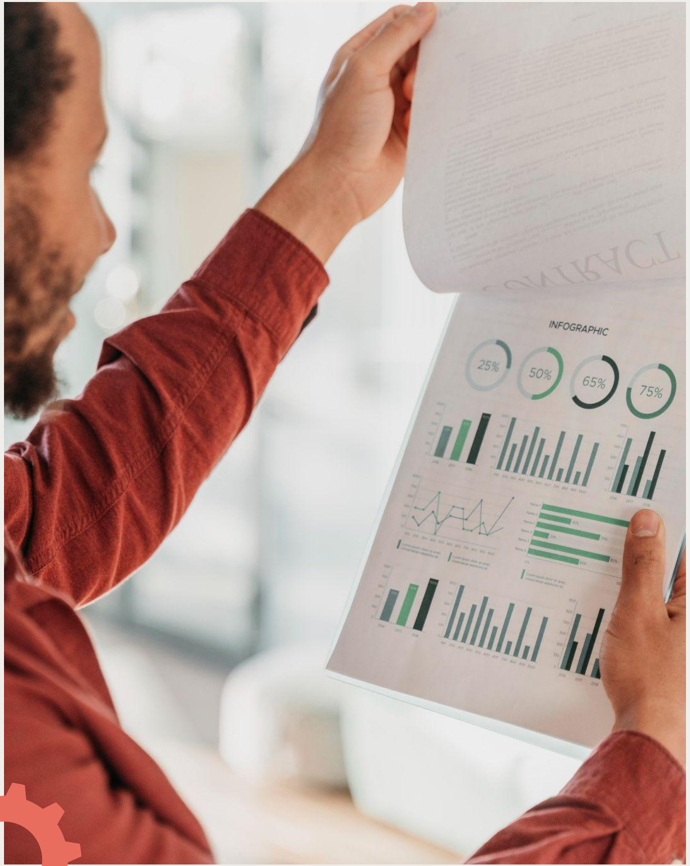
- Fundamental analysis is the foundation of value investing
- Understanding which financial metrics drive returns informs investment strategy
- Machine learning can uncover nonlinear patterns humans miss

Research Questions

1. Can machine learning models accurately predict whether a US stock will increase in value in 2019 based on financial indicators from 2018?

2. Which financial indicators are the most influential in determining whether a stock's price will rise the following year?

3. Which algorithm (Logistic Regression, Random Forest, Gradient Boosting) performs best for forecasting stock price movements?



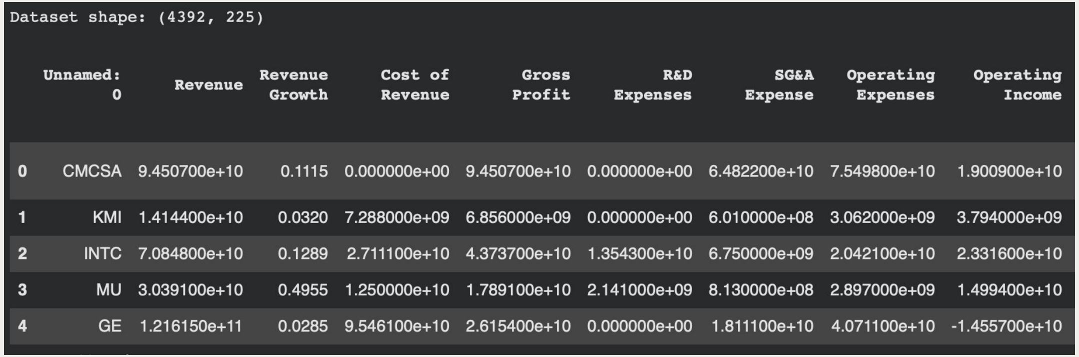
Data Overview

Source: Kaggle 200+ Financial Indicators of US stocks (2014-2018)

- 4,392 US companies
- 225 financial variables

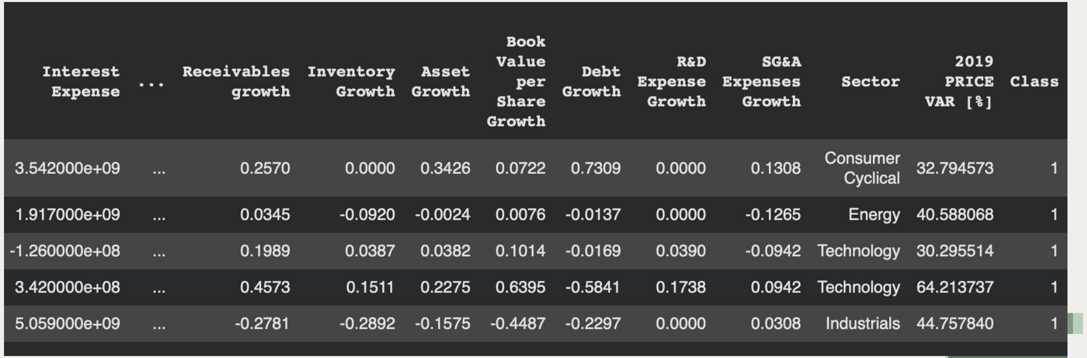
Target:

- Class 1: Price increased (610)
- Class 0: Price decreased (269)



```
Dataset shape: (4392, 225)
```

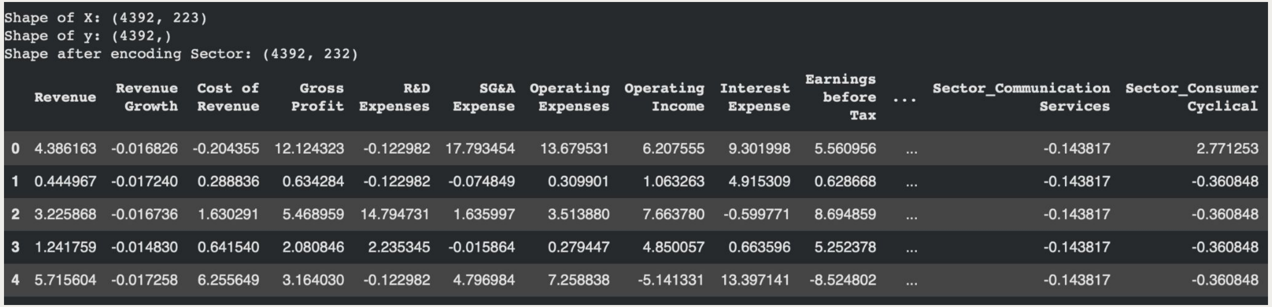
	Unnamed: 0	Revenue	Revenue Growth	Cost of Revenue	Gross Profit	R&D Expenses	SG&A Expense	Operating Expenses	Operating Income
0	CMCSA	9.450700e+10	0.1115	0.000000e+00	9.450700e+10	0.000000e+00	6.482200e+10	7.549800e+10	1.900900e+10
1	KMI	1.414400e+10	0.0320	7.288000e+09	6.856000e+09	0.000000e+00	6.010000e+08	3.062000e+09	3.794000e+09
2	INTC	7.084800e+10	0.1289	2.711100e+10	4.373700e+10	1.354300e+10	6.750000e+09	2.042100e+10	2.331600e+10
3	MU	3.039100e+10	0.4955	1.250000e+10	1.789100e+10	2.141000e+09	8.130000e+08	2.897000e+09	1.499400e+10
4	GE	1.216150e+11	0.0285	9.546100e+10	2.615400e+10	0.000000e+00	1.811100e+10	4.071100e+10	-1.455700e+10



Interest Expense	...	Receivables growth	Inventory Growth	Asset Growth	Book Value per Share Growth	Debt Growth	R&D Expense Growth	SG&A Expenses Growth	Sector	2019 PRICE VAR [%]	Class
3.542000e+09	...	0.2570	0.0000	0.3426	0.0722	0.7309	0.0000	0.1308	Consumer Cyclical	32.794573	1
1.917000e+09	...	0.0345	-0.0920	-0.0024	0.0076	-0.0137	0.0000	-0.1265	Energy	40.588068	1
-1.260000e+08	...	0.1989	0.0387	0.0382	0.1014	-0.0169	0.0390	-0.0942	Technology	30.295514	1
3.420000e+08	...	0.4573	0.1511	0.2275	0.6395	-0.5841	0.1738	0.0942	Technology	64.213737	1
5.059000e+09	...	-0.2781	-0.2892	-0.1575	-0.4487	-0.2297	0.0000	0.0308	Industrials	44.757840	1

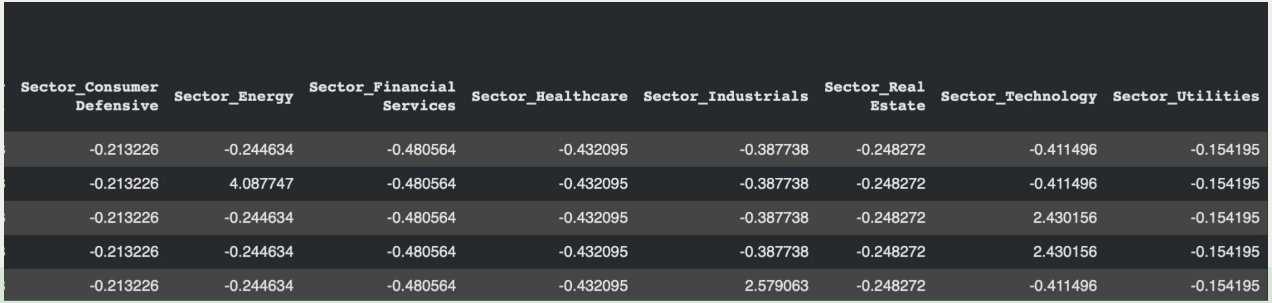
Preprocessing

1. Median imputation for missing values
2. One-hot encode Sector
3. Standardize features



```
Shape of X: (4392, 223)
Shape of y: (4392,)
Shape after encoding Sector: (4392, 232)
```

	Revenue	Revenue Growth	Cost of Revenue	Gross Profit	R&D Expenses	SG&A Expense	Operating Expenses	Operating Income	Interest Expense	Earnings before Tax	...	Sector_Communication Services	Sector_Consumer Cyclical
0	4.386163	-0.016826	-0.204355	12.124323	-0.122982	17.793454	13.679531	6.207555	9.301998	5.560956	...	-0.143817	2.771253
1	0.444967	-0.017240	0.288836	0.634284	-0.122982	-0.074849	0.309901	1.063263	4.915309	0.628668	...	-0.143817	-0.360848
2	3.225868	-0.016736	1.630291	5.468959	14.794731	1.635997	3.513880	7.663780	-0.599771	8.694859	...	-0.143817	-0.360848
3	1.241759	-0.014830	0.641540	2.080846	2.235345	-0.015864	0.279447	4.850057	0.663596	5.252378	...	-0.143817	-0.360848
4	5.715604	-0.017258	6.255649	3.164030	-0.122982	4.796984	7.258838	-5.141331	13.397141	-8.524802	...	-0.143817	-0.360848

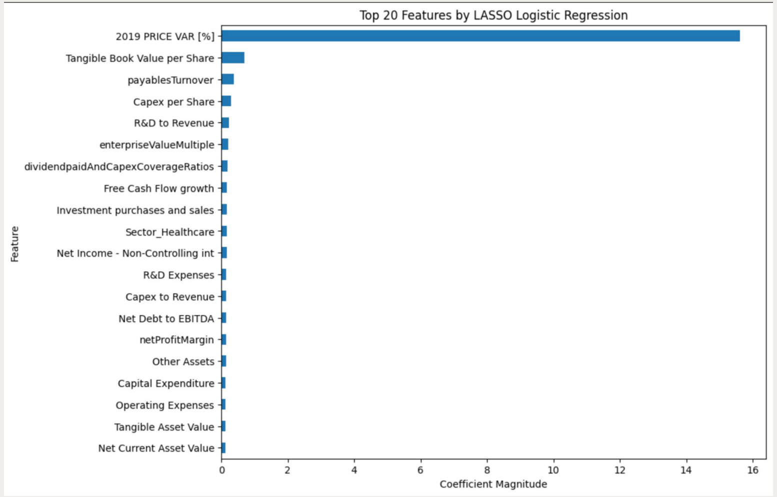


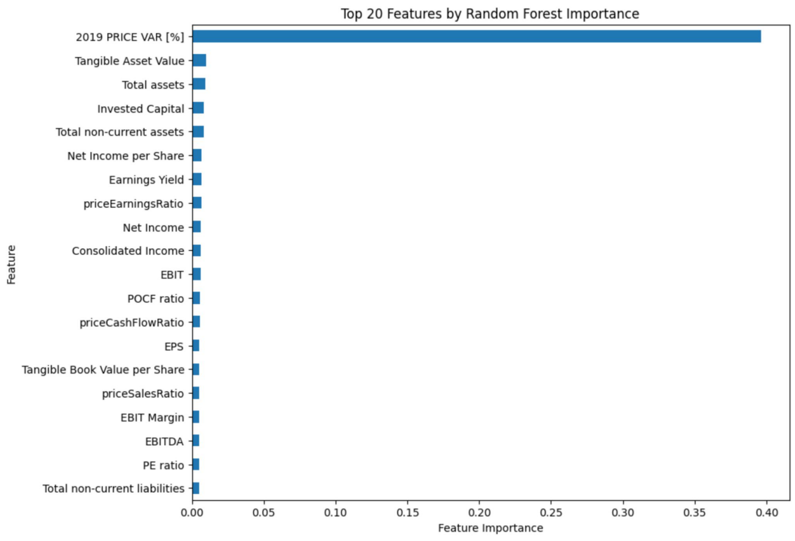
Sector_Consumer Defensive	Sector_Energy	Sector_Financial Services	Sector_Healthcare	Sector_Industrials	Sector_Real Estate	Sector_Technology	Sector_Utilities
-0.213226	-0.244634	-0.480564	-0.432095	-0.387738	-0.248272	-0.411496	-0.154195
-0.213226	4.087747	-0.480564	-0.432095	-0.387738	-0.248272	-0.411496	-0.154195
-0.213226	-0.244634	-0.480564	-0.432095	-0.387738	-0.248272	2.430156	-0.154195
-0.213226	-0.244634	-0.480564	-0.432095	-0.387738	-0.248272	2.430156	-0.154195
-0.213226	-0.244634	-0.480564	-0.432095	2.579063	-0.248272	-0.411496	-0.154195

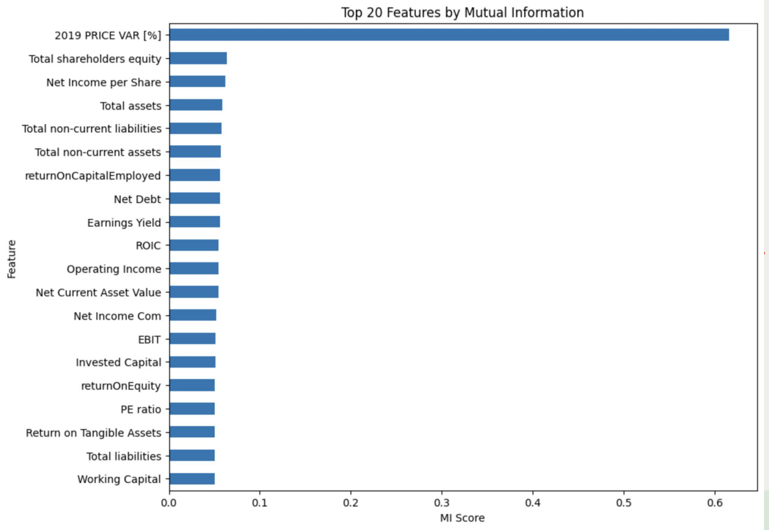
Feature Selection 1

Three methods:

- Mutual Information
- Random Forest Feature Importance
- LASSO Regression



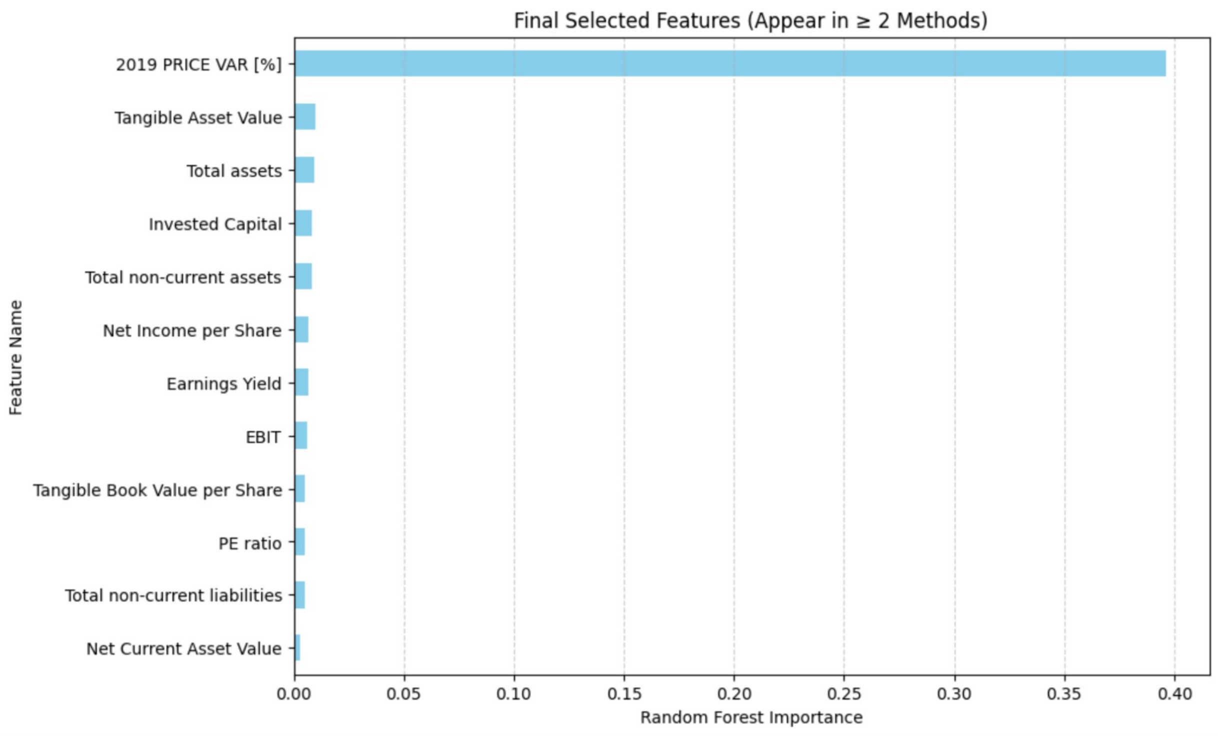




Feature Selection

Criteria: Feature must appear in ≥2 methods

Result: 12 features selected



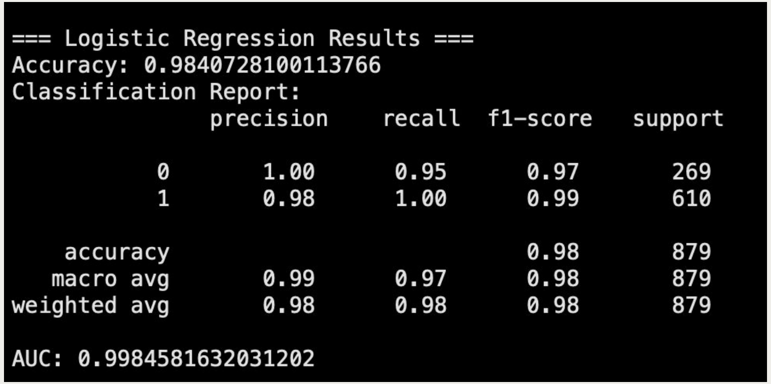
Problem Discovered: Data Leakage

The feature `2019 PRICE VAR [%]` directly measures the stock's percentage price change in 2019. The target variable `Class` also depends on whether the stock increased in 2019.

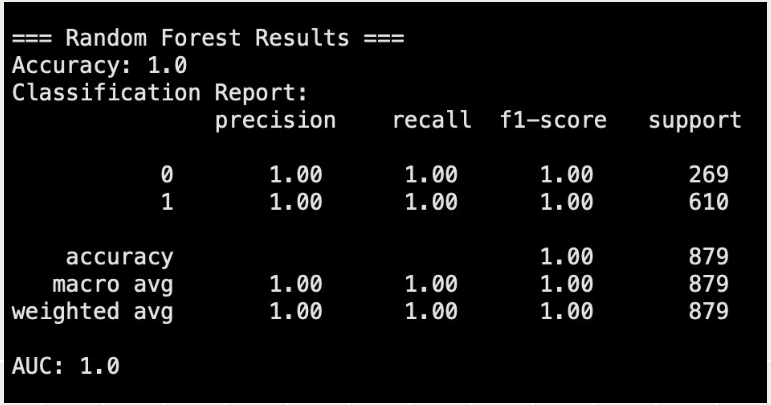
Using this feature introduces **data leakage**, because the model has access to the future outcome it is supposed to predict.

This caused unrealistically high performance.

To correct this, we remove `2019 PRICE VAR [%]` from the dataset and redo the feature selection and model training steps.



```
=== Logistic Regression Results ===
Accuracy: 0.9840728100113766
Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.95      0.97       269
           1       0.98      1.00      0.99       610

    accuracy                           0.98       879
   macro avg       0.99      0.97      0.98       879
weighted avg       0.98      0.98      0.98       879

AUC: 0.9984581632031202
```

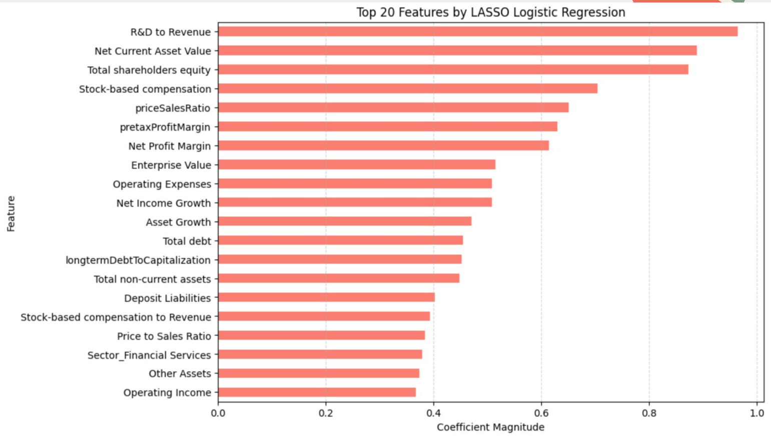


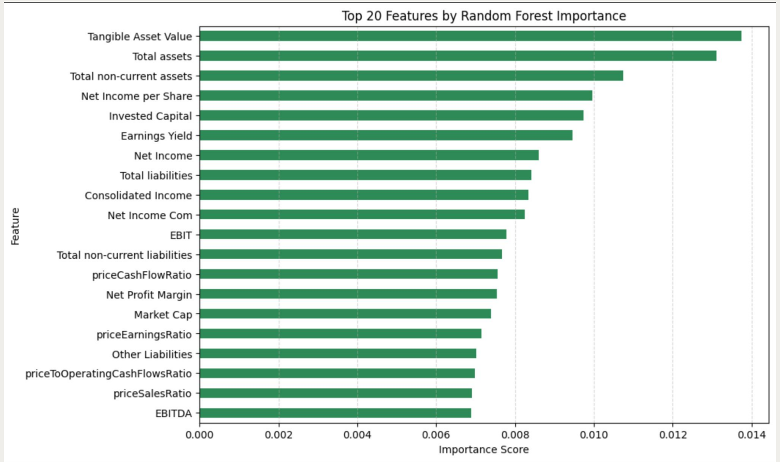
```
=== Random Forest Results ===
Accuracy: 1.0
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       269
           1       1.00      1.00      1.00       610

    accuracy                           1.00       879
   macro avg       1.00      1.00      1.00       879
weighted avg       1.00      1.00      1.00       879

AUC: 1.0
```

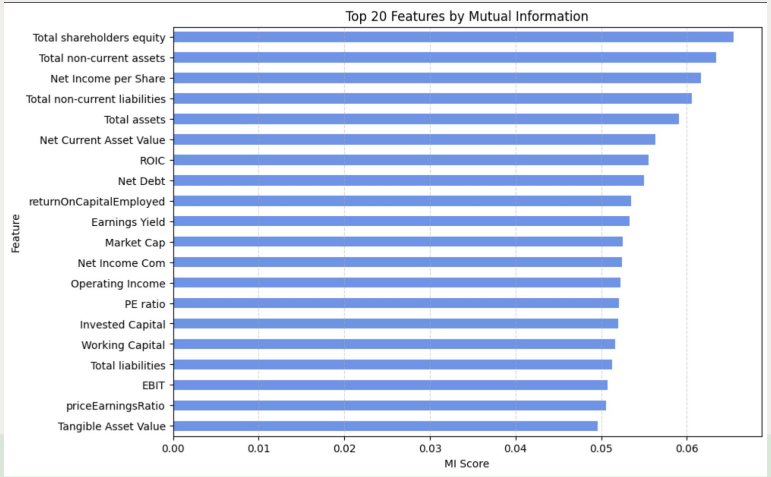
Feature Selection 2

Three methods:

- Mutual Information
- Random Forest
- LASSO Regression



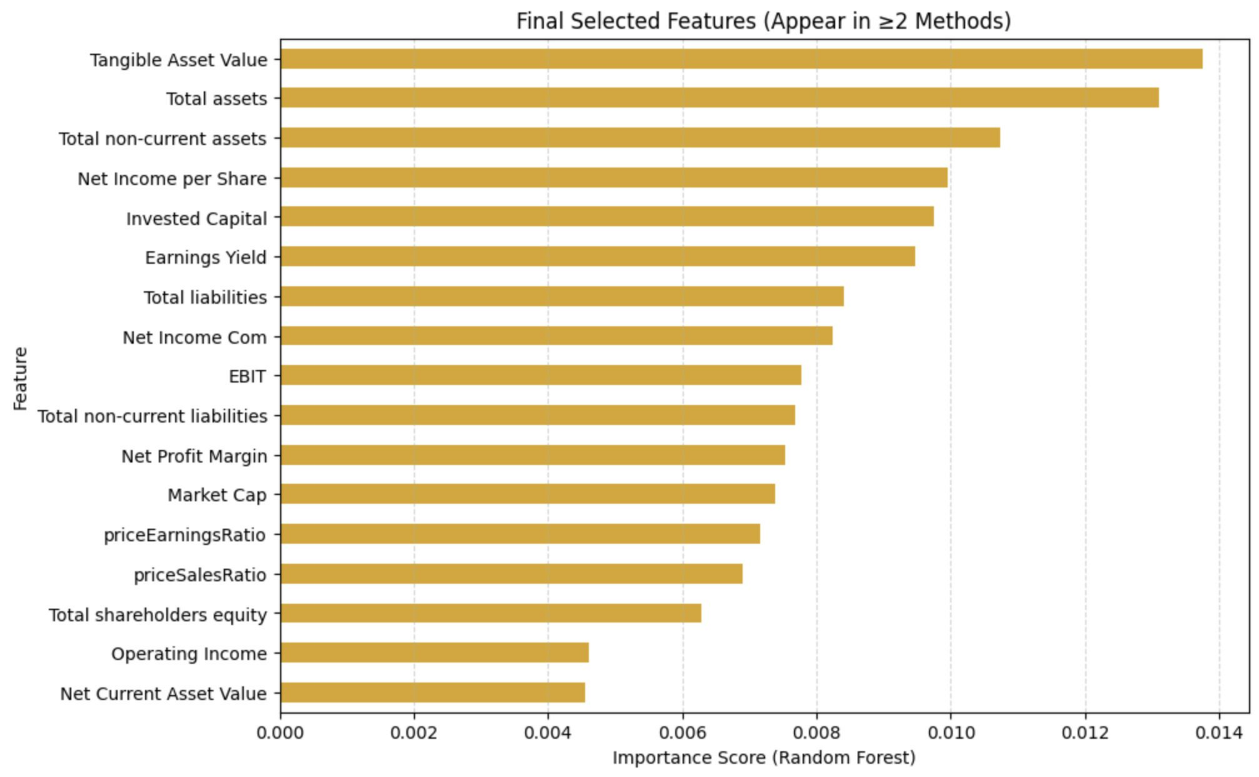




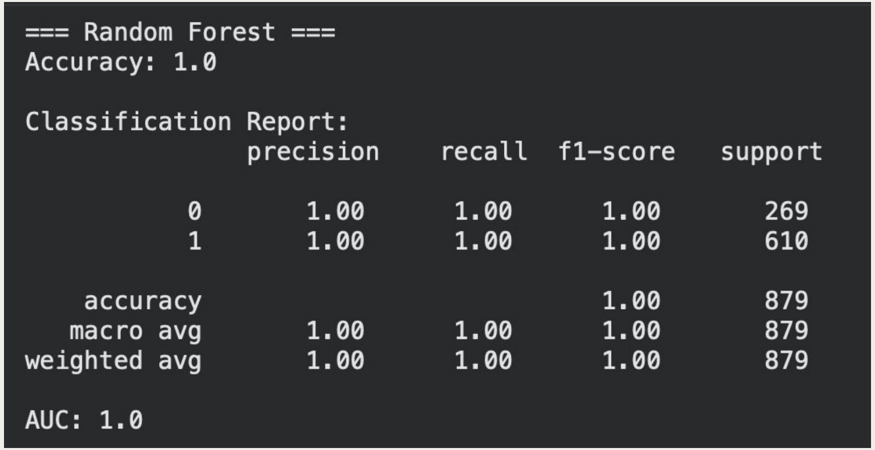
Feature Selection 2

Criteria: Feature must appear in ≥2 methods

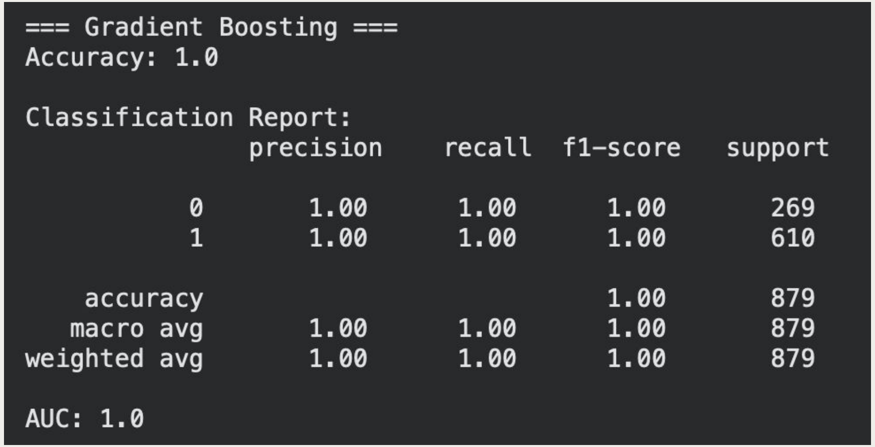
Result: 17 features selected



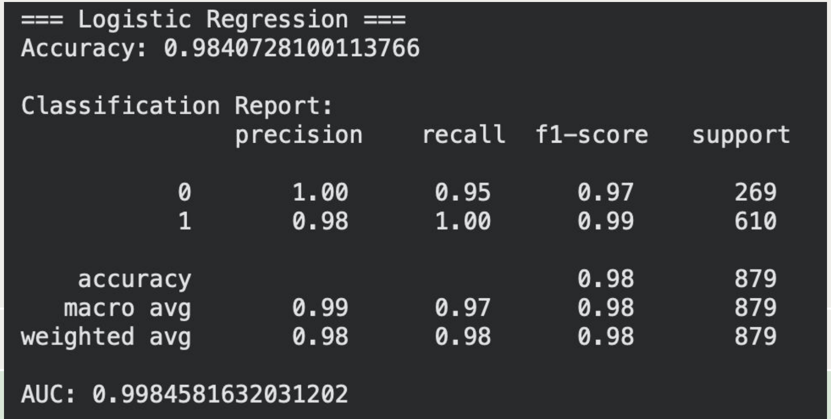
Data Leakage, Again



```
=== Random Forest ===
Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       269
           1       1.00      1.00      1.00       610

    accuracy                           1.00       879
   macro avg       1.00      1.00      1.00       879
weighted avg       1.00      1.00      1.00       879

AUC: 1.0
```



```
=== Gradient Boosting ===
Accuracy: 1.0

Classification Report:
               precision    recall  f1-score   support

           0       1.00      1.00      1.00       269
           1       1.00      1.00      1.00       610

    accuracy                           1.00       879
   macro avg       1.00      1.00      1.00       879
weighted avg       1.00      1.00      1.00       879

AUC: 1.0
```

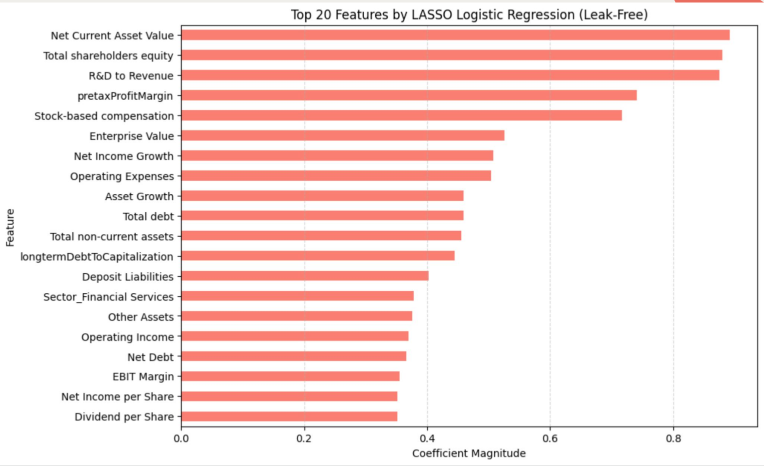


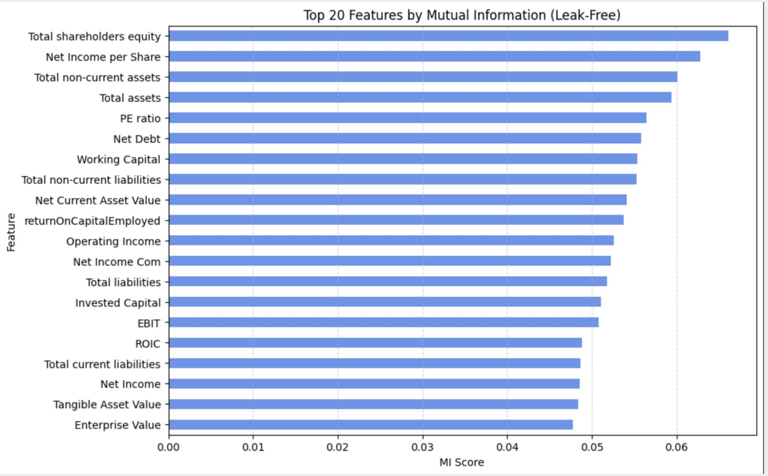
```
=== Logistic Regression ===
Accuracy: 0.9840728100113766

Classification Report:
               precision    recall  f1-score   support

           0       1.00      0.95      0.97       269
           1       0.98      1.00      0.99       610

    accuracy                           0.98       879
   macro avg       0.99      0.97      0.98       879
weighted avg       0.98      0.98      0.98       879

AUC: 0.9984581632031202
```

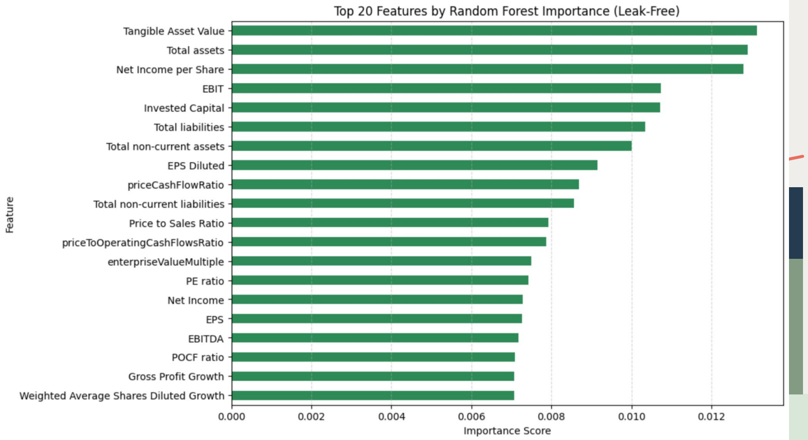
Feature Selection 3

Three methods:

- Mutual Information
- Random Forest
- LASSO Regression



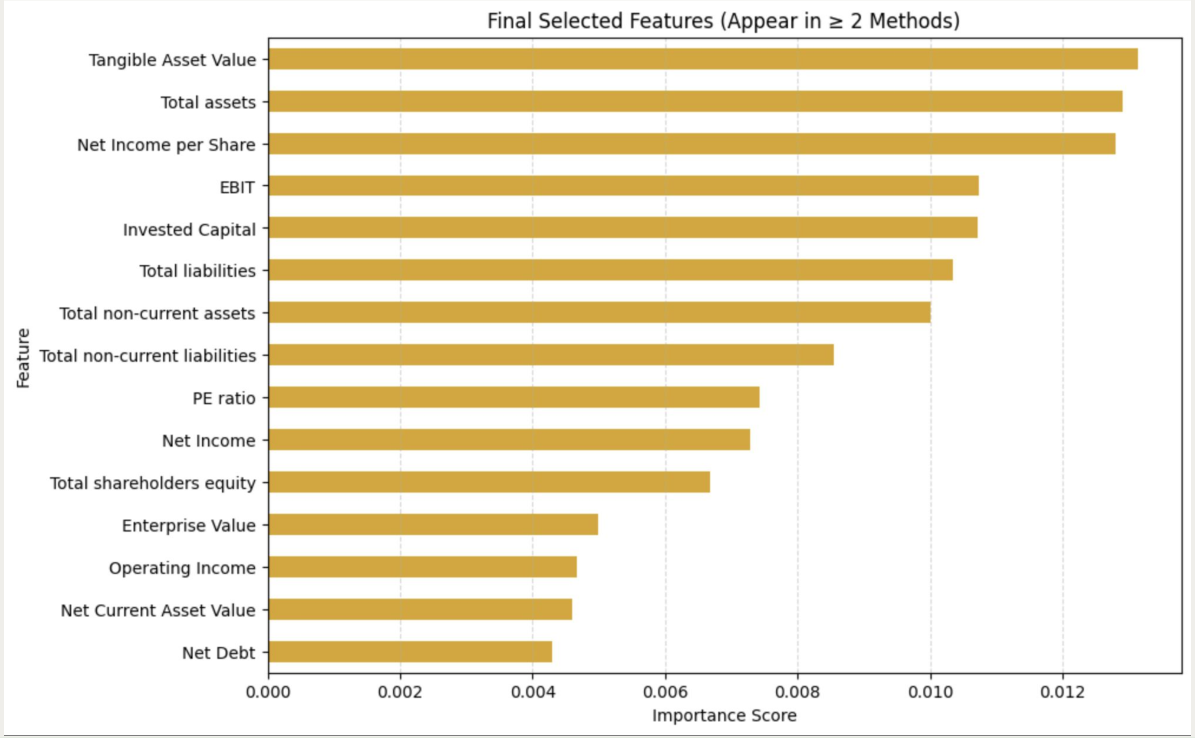




Feature Selection 3

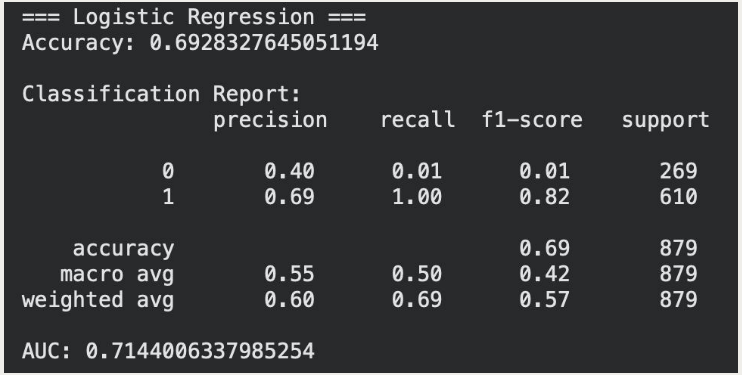
Criteria: Feature must appear in ≥2 methods

Result: 15 features selected

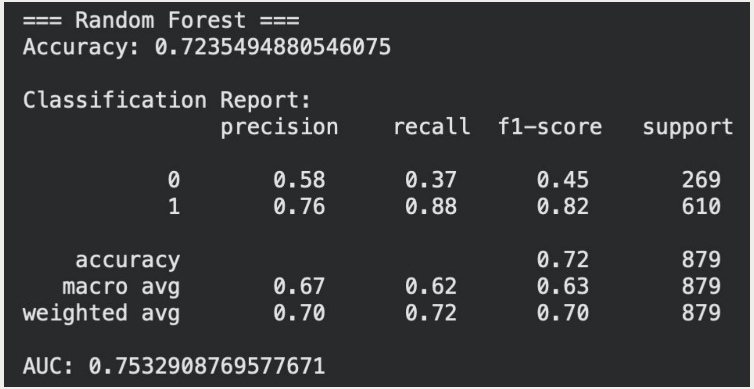


Results

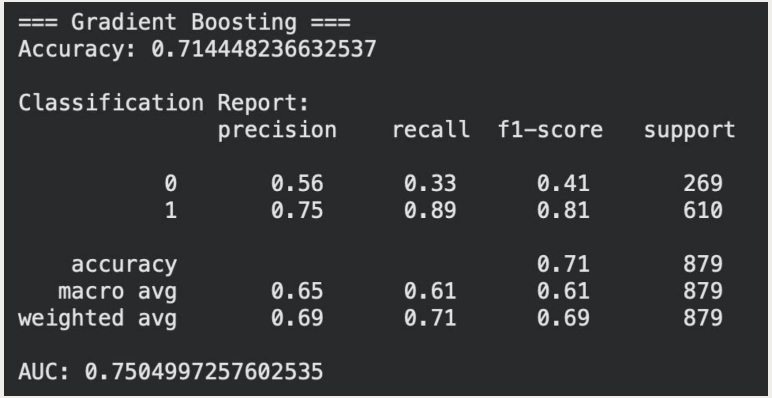
- Logistic Regression struggles with class 0 because the dataset is moderately imbalanced (more class 1 stocks).
- Random Forest and Gradient Boosting significantly outperform Logistic Regression, showing better ability to capture nonlinear relationships in financial data.
- AUC values around 0.75 indicate the models have moderate predictive power, which is expected in real-world stock prediction problems.



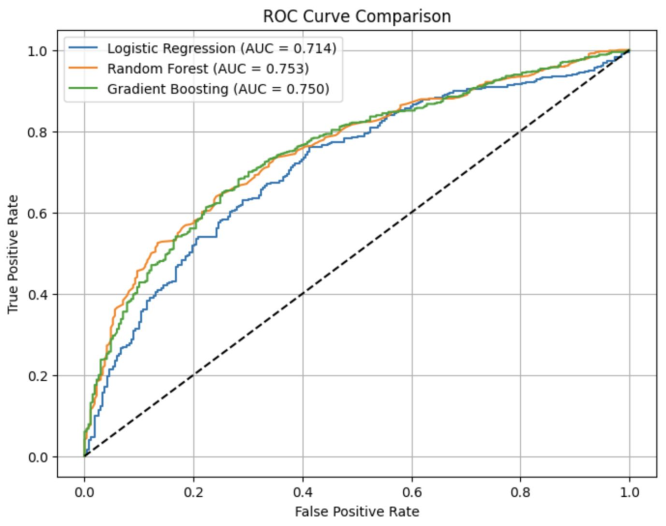
```
=== Logistic Regression ===
Accuracy: 0.6928327645051194

Classification Report:
              precision    recall  f1-score   support

           0       0.40      0.01      0.01       269
           1       0.69      1.00      0.82       610

    accuracy                           0.69       879
   macro avg       0.55      0.50      0.42       879
weighted avg       0.60      0.69      0.57       879

AUC: 0.7144006337985254
```



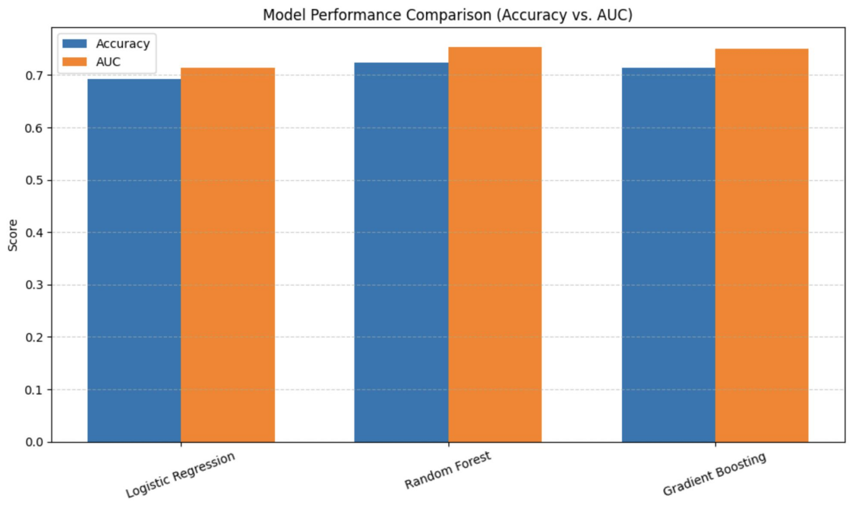
```
=== Random Forest ===
Accuracy: 0.7235494880546075

Classification Report:
              precision    recall  f1-score   support

           0       0.58      0.37      0.45       269
           1       0.76      0.88      0.82       610

    accuracy                           0.72       879
   macro avg       0.67      0.62      0.63       879
weighted avg       0.70      0.72      0.70       879

AUC: 0.7532908769577671
```



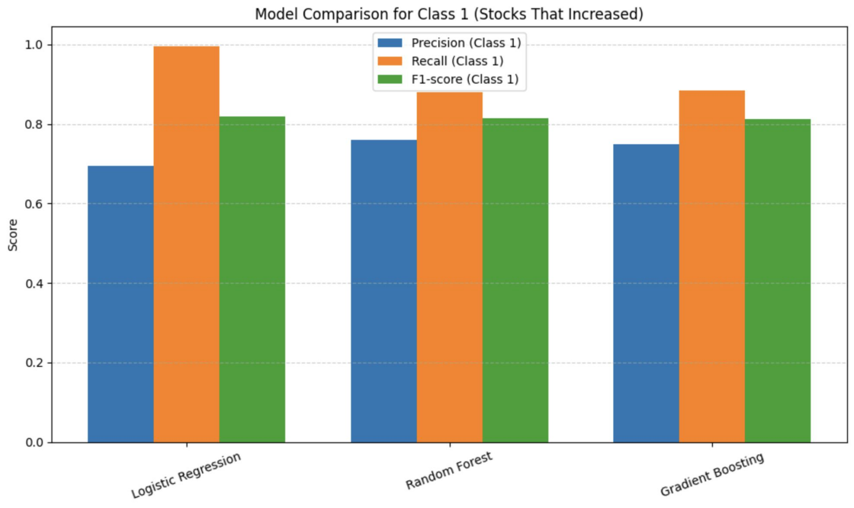
```
=== Gradient Boosting ===
Accuracy: 0.714448236632537

Classification Report:
              precision    recall  f1-score   support

           0       0.56      0.33      0.41       269
           1       0.75      0.89      0.81       610

    accuracy                           0.71       879
   macro avg       0.65      0.61      0.61       879
weighted avg       0.69      0.71      0.69       879

AUC: 0.7504997257602535
```



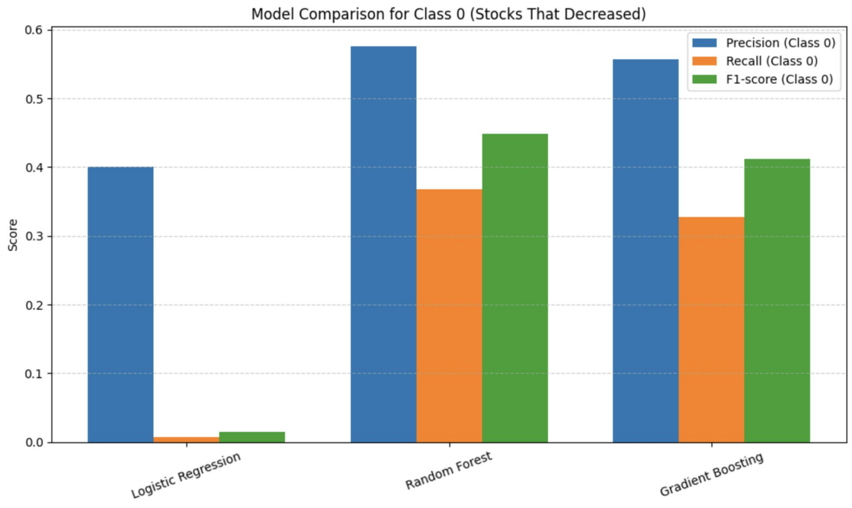
ROC Curve Comparison



Model Performance Comparison (Accuracy vs. AUC)



Model Comparison for Class 1 (Stocks That Increased)



Model Comparison for Class 0 (Stocks That Decreased)

Future Work

Handle class imbalance:

- SMOTE, class weights, threshold tuning

Try advanced models:

- XGBoost, LightGBM

Add external data:

- Market trends, macro indicators

Conclusion

What we built:
A leak-free stock prediction model using only accounting data

What we learned:
Data leakage can hide in plain sight, rigorous validation is critical

What we achieved:

- Random Forest: 72.4% accuracy, 0.753 AUC
- Realistic, reproducible results
- Deep understanding of the methodology

Thank You!

Questions?