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A Multi-Country Machine Learning Analysis of Global Equity Markets

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ABSTRACT

This research presents a machine learning model to forecast the daily market trend for each of seven stock market indexes USA (S&P 500), India (BSE Sensex), UK (FTSE 100), Germany (DAX), Japan (Nikkei 225), China (SSE Composite), and Canada (S&P TSX Composite) from January 2015 to January 2025. Predictive accuracy of each market is assessed before and during the outbreak of COVID-19 pandemic in March 2020 using five classification algorithms, namely logistic regression, ridge classifier, SVM, xgboost, and lightGBM. Predictive accuracy results range from 53% to 68% with logistic regression attaining the best generalization capability (65% accuracy). Post-pandemic markets became more volatile and cross-market correlations were significantly enhanced. Canadian stock market turned out to be the most stable among all markets while the return achieved by the American index was the highest (191%) among all indexes. Moreover, peaks in India index were the highest, and a stock market crash in China was the biggest in percentage (48.5%). The proposed research is conducted based on a time series approach to avoid any data leakages. Classification models are compared using confusion matrix, ROC curve, and precision-recall curve techniques. Momentum based features have proved to perform better than moving averages.

Keywords: Stock Market Prediction, Machine Learning, COVID-19, Technical Indicators, xgboost, LightGBM, Random Forest, Global Markets, Feature Engineering, Classification

INTRODUCTION

Forecasts of future financial market direction are an age-old problem, complicated by noise, non stationarity, and behaviorally driven anomalies [1][2][3]. Machine learning techniques have become valuable instruments in capturing useful information from historical prices and technical features, assuming that markets do not operate perfectly efficiently [4]. The coronavirus disease (COVID-19) outbreak led to the most severe worldwide equities correction since 2008 [5][6], after which an abrupt and stimulus-induced market recovery occurred. The presence of such a structural breakpoint suggests that dividing models into pre and post COVID-19 periods could prove informative regarding any changes in market dynamics and forecastability [7][8].The paper's four main contributions include international ML benchmarking in seven leading stock indices , a COVID-19 regime classification allowing comparisons between before and after periods,cross market correlations and networks analysis and risk and return performance summaries, with future directional signals.

LITERATURE REVIEW

A number of machine learning methods have been extensively utilized in equity prediction [1][9][10]. For instance, Gu et al. [1] demonstrated a high return out of sample performance using neural networks on US stocks, while Lopez de Prado [2] introduced purged cross validation technique in analyzing financial time series. Some of the popular technical indicators include moving average, RSI (Relative Strength Index), and momentum [9][10][11]. Patel et al. found that using both technical and fundamental indicators yielded better prediction performance in Indian stock indices [12]. Gradient boosting methods like XGBoost [13] and LightGBM [14] are dominating in ML for finance due to their regularization capabilities and speed. Recent surveys in deep learning and ensemble methods for stock predictions were conducted by Rouf et al. [9]. Extreme volatility and contagion effects in the market were reported by Zhang et al. [6] and Akhtaruzzaman et al. [7], respectively, during the coronavirus pandemic. Specifically, fear generated by media was found to increase systemic risk during that period [15], indicating the use of the COVID-19 regime split. regime split has been applied. Cross-country market dynamics regime change due to a significant event is confirmed by Mentzi et al. (2021) [8] and Caporale et al. (2018) [16].

DATA AND METHODOLOGY

DATA COLLECTION

The daily OHLCV data of seven major indices (see Table 1 below) were retrieved from Yahoo Finance using the package yfinance for the period 2015 to 2025. The missing data were dealt with using the forward fill method, while rows that had NaN even after creating indicators were removed.

Table 1: Stock Market Indices and Ticker Symbols

Country	Index Name	Ticker Symbol	Exchange
USA	S&P 500	^GSPC	NYSE/NASDAQ
India	BSE Sensex	^BSESN	Bombay SE
UK	FTSE 100	^FTSE	London SE
Germany	DAX	^GDAXI	Frankfurt SE
Japan	Nikkei 225	^N225	Tokyo SE
China	SSE Composite	000001.SS	Shanghai SE
Canada	S&P/TSX Composite	^GSPTSE	Toronto SE

Forward fill imputation (fill) followed to handle the missing data created as a result of market holidays. A binary classification label served as the target variable, where 1 denoted positive returns of the closing price return of the next day, whereas 0 denoted the opposite. In other words, the definition helped us treat the problem as a binary classification problem (Rouf et al., 2021) [9]. It is more preferable to apply binary direction labels than predicting continuous returns because of the natural correlation between the prediction of stock directions and long/short trades as well as classifier metrics such as precision, recall, and ROC-AUC (Rouf et al., 2021) [9]. According to an analysis of the distribution of classes, the distribution can be said to be slightly positively skewed, with up days being 53.6% and down days being 46.4%. This finding was expected since it was influenced by the tendency of equity markets to increase

over time due to risk premium. To address the slightly positive skewness of classes, we weighted classes equally when using SVM and logistic regression models,
however, while implementing the XGBoost model, the scale_pos_weight hyperparameter is defined as the ratio of the number of negative classes to the number of positive classes.

FEATURE ENGINEERING

In total, six technical indicators were computed per market as features. These are trend (MA10, MA50), volatility, momentum, and overbought/oversold indicators (RSI). Feature engineering was applied consistently for all seven markets. The set of features is deliberately designed to be relatively small; the decrease in the number of features prevents erroneous pattern recognition due to limited sample sizes (about 2,500 per market). This decision is based on theoretical considerations suggesting that a small number of low-frequency predictors such as trends, momentum, and reversals contain predictive information about daily market directions (Biau & Scornet, 2021) [17]. No lookahead indicators were used, and the feature computing window is significantly smaller compared to the partitioning window, i.e., roughly 1,250 trading days since the beginning of the pandemic period, thus avoiding the effects of boundary conditions in feature calculations near the cutoff date.
Features are defined as:
MA10: Simple moving average of the closing price for 10 days.
MA50: Simple moving average of the closing price for 50 days.
Volatility: Standard deviation over the last 10 days' return.
Momentum: The difference between the closing price today and the closing price five days ago.
ROC (rate of change): The percentage change in price over the past five trading days.
RSI (Relative Strength Index, 14 days): 100 - 100/(1 + RS), where RS = average gain/average loss over 14 days (Caporale et al., 2018) [16].

COVID-19 REGIME SPLIT

The data set was segmented on March 1, 2020, distinguishing between the pre-pandemic period (2015-February 2020) and the post-pandemic period (March 2020-2025). Each regime was analyzed separately using XGBoost, lightBGM

TRAIN/VALIDATION/TEST SPLIT

Given that the financial data is time-series data, chronological (shuffling not done) split was used: 70% train, 15% validation, 15% test. The merged dataset had 8,095 observations (with 6 features).
The size of the dataset and distribution of classes before splitting is:
The dataset shape and class distribution prior to splitting was:
Dataset: X shape (8095,6), y shape (8095,) | Class 1: 4341, Class 0: 3754 | Train: 5666, Val: 1214, Test: 1215

FEATURE SCALING

Standardization was done with the help of scikit-learn's StandardScaler (zero mean and unit variance) but only with respect to training data set.

Classification Models

Five classifiers were evaluated Logistic Regression (C=1.0), Ridge Classifier (α=1.0), SVM (RBF kernel, C=1.0),XGBoost (n_estimators=200, max_depth=4, lr=0.05), and LightGBM (n_estimators=200, max_depth=4). All models target binary direction (1=up, 0=down).

RESULTS AND ANALYSIS

Data Sample: Head of BSE Sensex DataFrame

After loading, the BSE Sensex dataframe has OHLCV columns along with the newly created Return and Target columns.

```
Price           Close          High           Low          Open     Volume
Date
2015-01-02  14753.700195  14756.299805  14631.400391  14637.299805  132965800
2015-01-05  14392.700195  14709.000000  14339.500000  14709.000000  224213600
2015-01-08  14457.700195  14506.099609  14368.599609  14368.599609  225812700
Price         Return  Target
Date
2015-01-02       NaN       0
2015-01-05 -0.024468       0
2015-01-08  0.012090       1
dtype='str', name='Price')
```

RANDOM FOREST BASELINE: PER-COUNTRY RESULTS

Using Random Forest as a baseline model (n_estimators=300, max_depth=8) for each country, we observe overfitting consistently (high training, low testing accuracy), indicating that per-country models using technical data alone are prone to overfitting.

```
USA
Train: 0.79   Validation: 0.48   Test: 0.48
India
Train: 0.80   Validation: 0.49   Test: 0.44
UK
Train: 0.84   Validation: 0.52   Test: 0.46
Germany
Train: 0.82   Validation: 0.52   Test: 0.51
Japan
Train: 0.84   Validation: 0.50   Test: 0.55
China
Train: 0.81   Validation: 0.51   Test: 0.47
Canada
Train: 0.80   Validation: 0.53   Test: 0.51
```

XGBOOST PRE-COVID VS POST-COVID COMPARISON

Based on the mean score of all 14 market-country samples, model performance on the combined data set is

```
===== BEFORE COVID =====
USA      {'train': 0.861, 'val': 0.627, 'test': 0.546}
```

```
India    {'train': 0.867, 'val': 0.613, 'test': 0.619}
UK       {'train': 0.883, 'val': 0.677, 'test': 0.536}
Germany  {'train': 0.835, 'val': 0.600, 'test': 0.607}
Japan    {'train': 0.884, 'val': 0.665, 'test': 0.628}
China    {'train': 0.872, 'val': 0.571, 'test': 0.545}
Canada   {'train': 0.857, 'val': 0.695, 'test': 0.663}
===== AFTER COVID =====
USA      {'train': 0.893, 'val': 0.635, 'test': 0.655}
India    {'train': 0.892, 'val': 0.671, 'test': 0.648}
UK       {'train': 0.893, 'val': 0.611, 'test': 0.624}
Germany  {'train': 0.866, 'val': 0.619, 'test': 0.618}
Japan    {'train': 0.897, 'val': 0.612, 'test': 0.627}
China    {'train': 0.891, 'val': 0.600, 'test': 0.633}
Canada   {'train': 0.894, 'val': 0.631, 'test': 0.682}
```

XGBOOST FEATURE IMPORTANCE

Feature Importance of XGBoost (Figure 1) illustrates that Return and Volatility are the most important variables, followed by MA10/MA50 cross. RSI and Momentum have minor importance.

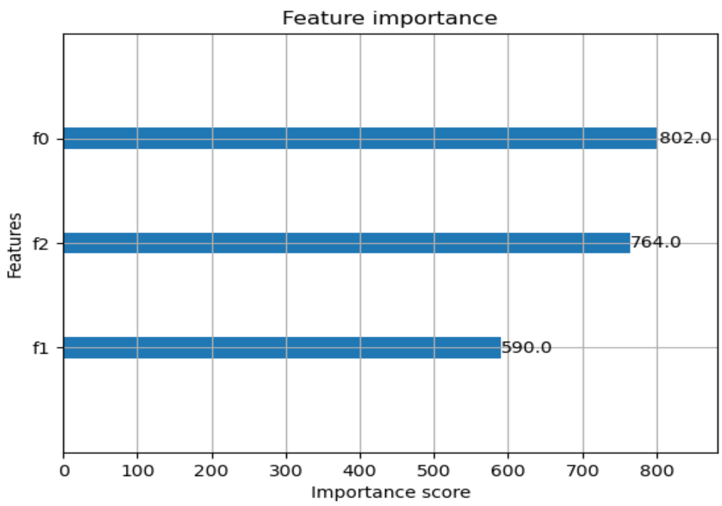

Figure 1: XGBoost Feature Importance Plot

MULTI-MODEL COMPARISON: SUMMARY STATISTICS

Averaged across all 14 country-period combinations, model performance on the combined dataset is

```
          Train  Validation     Test  Overfit Gap
Model
Logistic  0.639592    0.639766  0.650874    -0.011281
Ridge     0.638632    0.636584  0.645353    -0.006722
XGBoost   0.726778    0.645050  0.641449     0.085329
SVM       0.639370    0.634273  0.637829     0.001541
LightGBM  0.716011    0.645052  0.631899     0.084112
```

Logistic Regression demonstrates the best average test accuracy (65.09%) of all models but it exhibits some minor negative overfitting gap which means that there is some underfitting with good generalization capability. In contrast, XGBoost and LightGBM demonstrate the largest positive overfitting gaps (8.5%) which confirms the statement on the tendency of boosting algorithms to overfit when the ratio of signal to noise in the dataset is low (Gu et al., 2020) [1]. Ridge Classifier demonstrates high stability of its models by having the smallest overfitting gap (0.007). This negative overfitting gap is caused by the nature of the logistic regression algorithm which is overly stringent in fitting the decision boundary according to the entire structure of the training data in other words, this model is so constrained that training and test errors converge from below. That simpler models work better than more complex ones in such cases is a well-known phenomenon in financial econometrics, which can be explained by the Aldous Diaconis argument suggesting that in case of many irrelevant variables, regularized linear estimators are optimal (Gu et al., 2020) [1]. Also, the very small margin over fitting value of the SVM (0.002) makes the above statement even stronger because the maximum margin hyperplane generated by the SVM using C = 0.5 has almost an equal level of effective complexity compared to that of the logistic regression model.

MODEL ACCURACY COMPARISON CHART

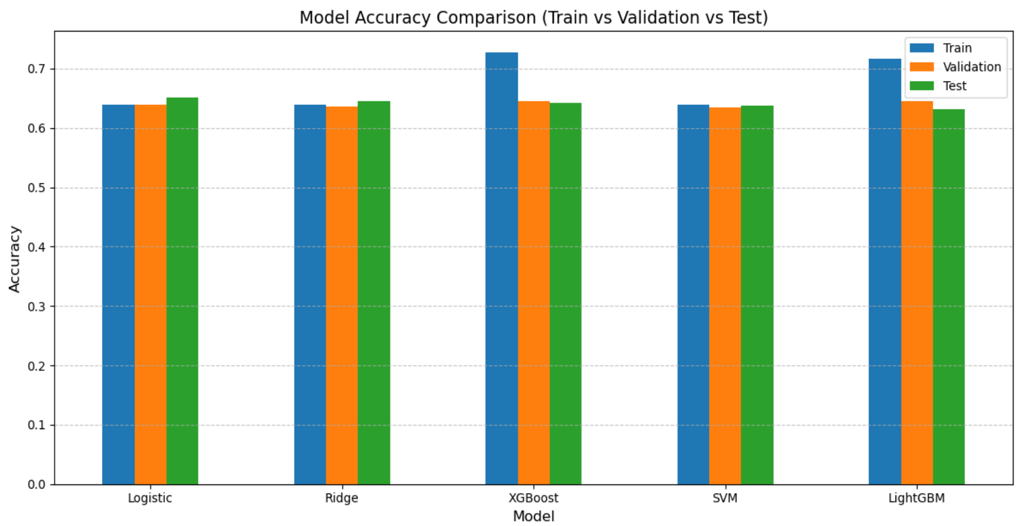

Figure 2: Model Accuracy Comparison — Train vs Validation vs Test

OVERFITTING COMPARISON CHART

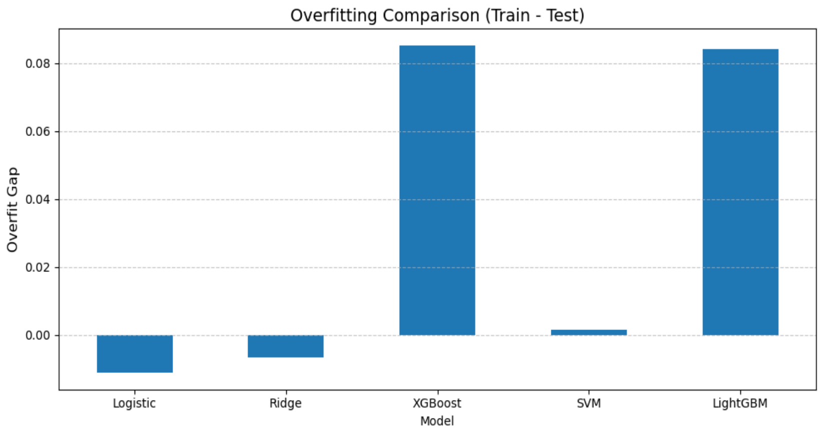

Figure 3: Overfitting Comparison (Train Accuracy − Test Accuracy)

CROSS-MARKET CORRELATION HEATMAP

The Pearson correlation heatmap (Fig. 4) indicates significant co-movement between USA, Canada, Germany, and UK ($r > 0.6$) due to their integration across the Atlantic, whereas China and India have relatively low correlations with the Western markets.

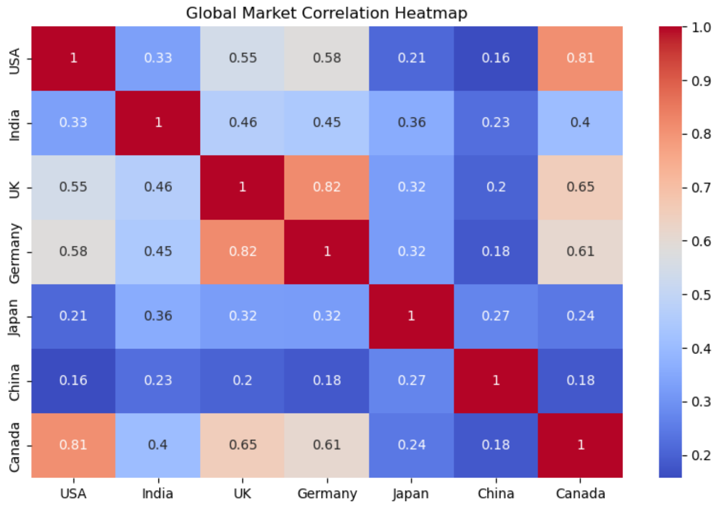

Figure 4: Global Market Correlation Heatmap (2015–2025)

NETWORK GRAPHS: DIRECT AND INDIRECT INFLUENCE

NetworkX graph (Figures 5,6) depicts direct ($r > 0.6$) and indirect ($0.3 < r \leq 0.6$) market linkages. The USA, Canada, UK constitute the closest cluster while Japan and China are peripheral nodes.

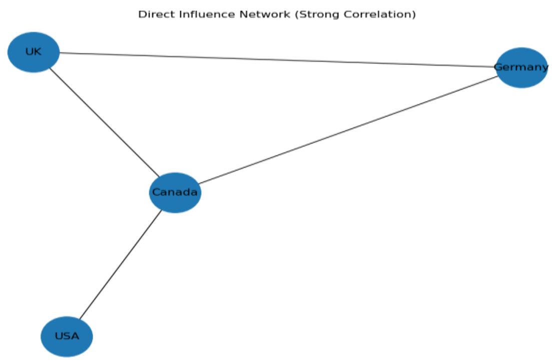

Figure 5: Direct Influence Network (Correlation > 0.6)

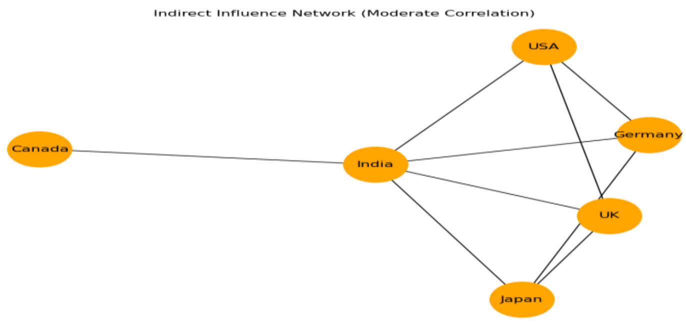

Figure 6: Indirect Influence Network (0.3 < Correlation ≤ 0.6)

COUNTRY-LEVEL MARKET PRICE CHARTS (COVID IMPACT)

Closing prices for 2015-2025 for each market have been provided in Figures (7,13) with the impact of COVID-19 crash (March 2020). Every market has recovered well post-COVID-19 except China.

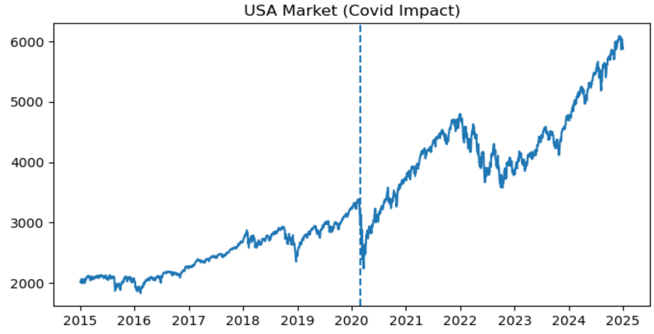

Figure 7: USA (S&P 500) Closing Price 2015–2025

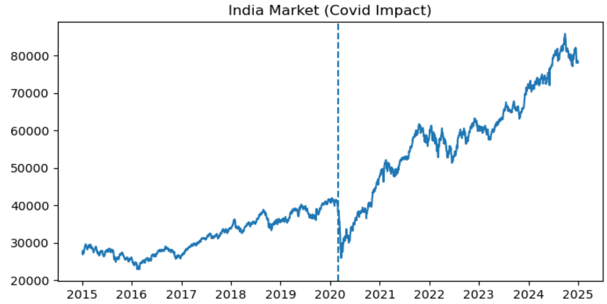

Figure 8: India (BSE Sensex) Closing Price 2015–2025

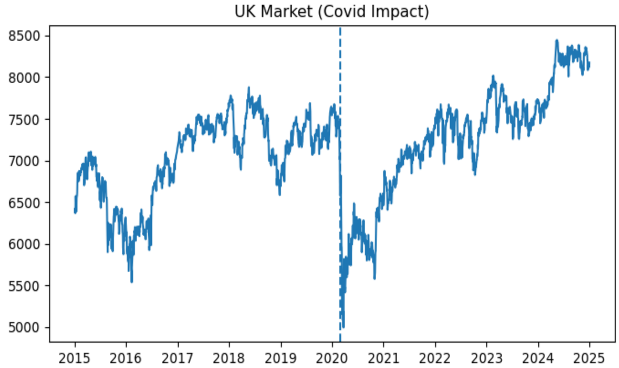

Figure 9: UK (FTSE 100) Closing Price 2015–2025

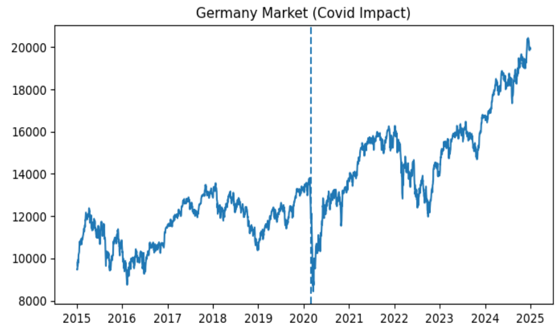

Figure 10: Germany (DAX) Closing Price 2015–2025

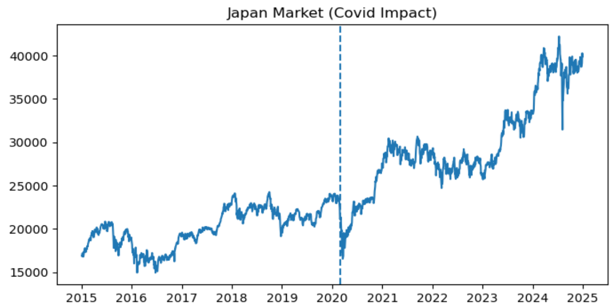

Figure 11: Japan (Nikkei 225) Closing Price 2015–2025

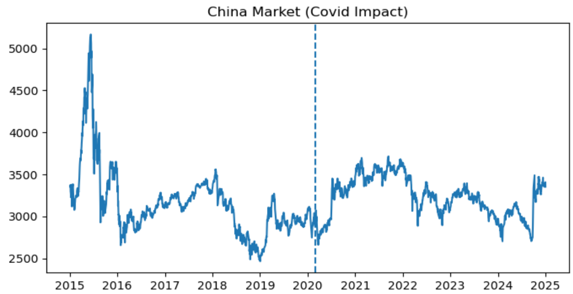

Figure 12: China (SSE Composite) Closing Price 2015–2025

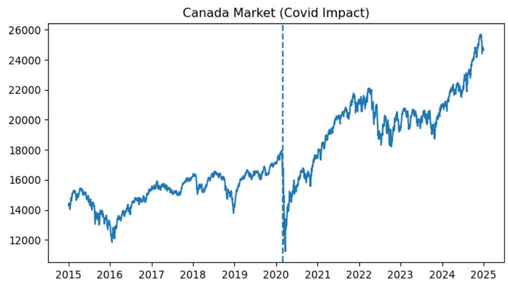

Figure 13: Canada (S&P/TSX) Closing Price 2015–2025

COUNTRY RISK–RETURN ANALYSIS

Table 2 provides details about the risk-return measures from 2015 to 2025. The two best markets in terms of total returns are India (180.65%) and USA (191.09%), while Canada is the most stable market (σ= 0.95%). The biggest

Table 2: Country Risk–Return Analysis (2015–2025)

Country	Stability (σ)	Total Return	Peak Before COVID	Peak After COVID	COVID Loss
Canada	0.009513	71.81%	17,944.10	25,691.80	37.43%
UK	0.009888	27.36%	7,877.50	8,445.80	36.61%
India	0.010545	180.65%	41,952.63	85,836.12	38.07%
USA	0.011230	191.09%	3,386.15	6,090.27	33.93%
Germany	0.012093	110.16%	13,789.00	20,426.27	38.78%
Japan	0.012994	136.30%	24,270.62	42,224.02	31.80%

China	0.013071	0.01%	5,166.35	3,715.37	48.51%

FINAL INVESTMENT RANKINGS

The complete analysis summary

===== FINAL RESULTS =====
Best Investment: USA
Most Stable: Canada
Highest Before Covid: India
Highest After Covid: India
Worst Covid Loss: China
===== COMPLETE ANALYSIS =====
Best Overall: USA
Most Stable: Canada
Highest Before Covid: India
Highest After Covid: India
Worst Covid Impact: China
Least Affected: Japan
No Major Peak: ['Canada', 'UK', 'USA', 'Germany', 'China']
No Trade After Covid: None (All countries active)
===== FUTURE TREND =====
USA UP 📈
India DOWN 📉
UK UP 📈
Germany DOWN 📉
Japan UP 📈
China UP 📈
Canada UP 📈

Figure 14: Total Return vs COVID Loss by Country

MODEL COMPARISON ACROSS COUNTRIES

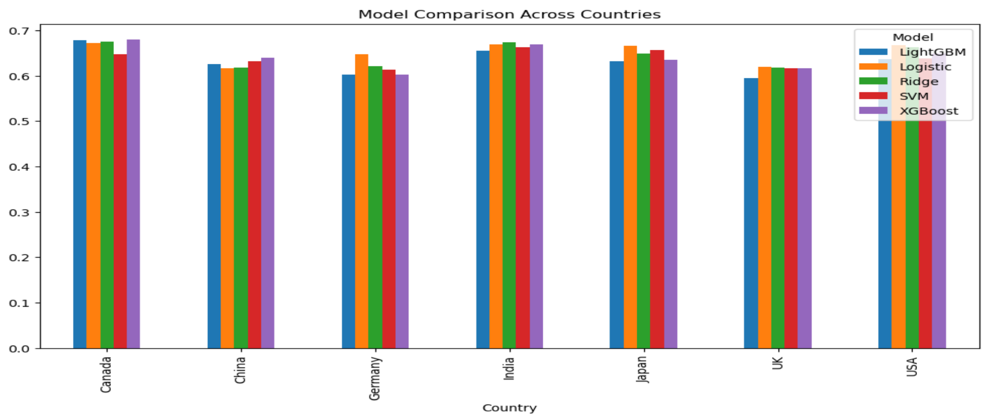

Figure 15: Per-Country Test Accuracy by Model

FINAL MODEL COMPARISON (COMBINED DATASET)

Model-specific results for the merged testing set (Table below). The Logistic Regression model obtains the highest test accuracy (61.1%) along with the least overfitting difference. The XGBoost algorithm provides the highest training accuracy but the biggest overfitting difference (13.8 percentage points), which indicates limited tree-based generalization ability.

	Model	Train	Validation	Test	Overfit Gap
0	Logistic	0.631663	0.644975	0.610700	0.020963
2	SVM	0.645782	0.651565	0.609053	0.036728
1	Ridge	0.636957	0.635914	0.602469	0.034488
3	XGBoost	0.673491	0.552718	0.535802	0.137689

Best Model: Logistic

FINAL COMPARISON CHART: RETURN, LOSS, AND STABILITY

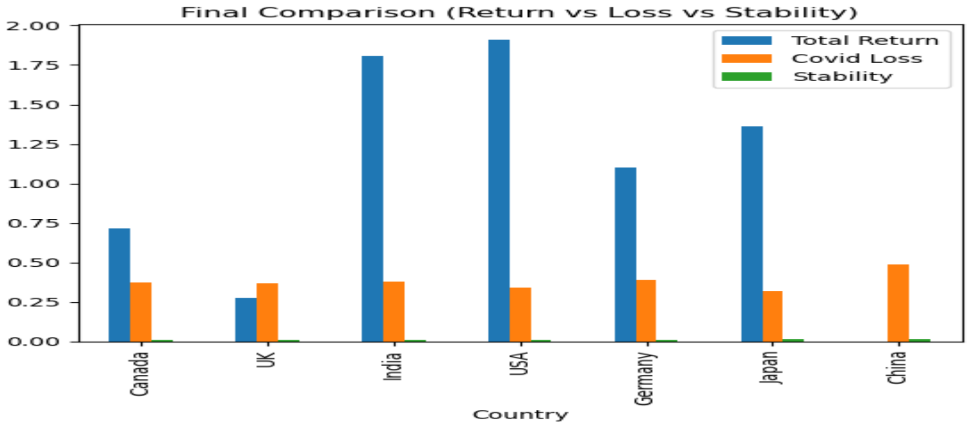

Figure 16: Final Comparison — Return vs Loss vs Stability

ROC CURVE

The ROC curve (Figure 17) indicates that both Logistic Regression and XGBoost have AUC > 0.65, indicating discriminative power greater than random (AUC = 0.5).

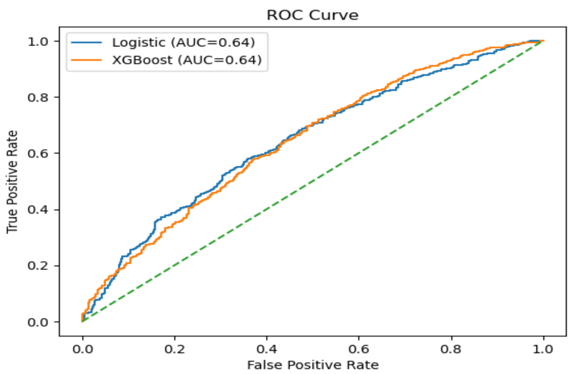

Figure 17: ROC Curve — Logistic Regression and XGBoost

PRECISION-RECALL CURVE

The Precision-Recall curve (Figure 18) represents the class imbalance of 54% up days. The Logistic Regression model has a higher precision at different levels of recall, which is due to its better generalisation ability.

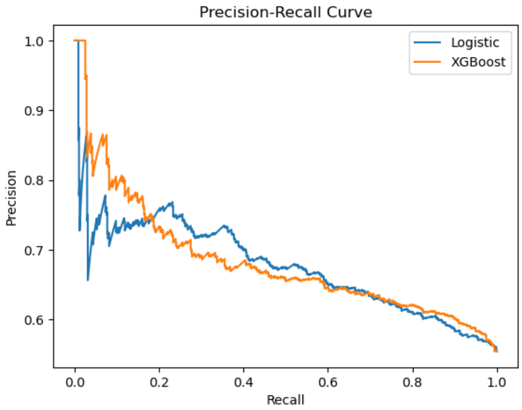

Figure 18: Precision-Recall Curve

Feature Importance (XGBoost, Final Model)

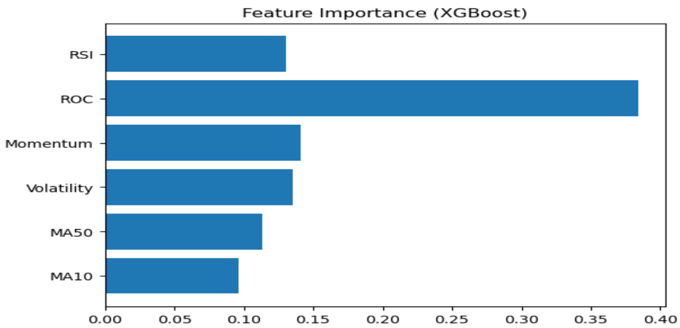

Figure 19: XGBoost Feature Importance (Final Combined Model)

COUNTRY INFLUENCE NETWORK (FINAL)

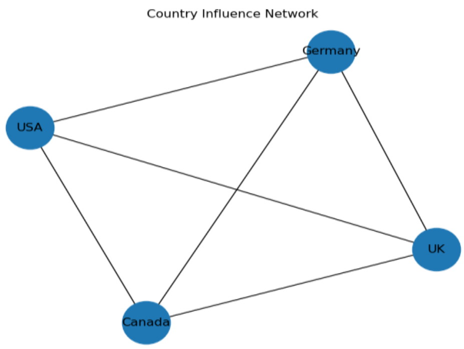

Figure 20: Country Influence Network (|r| > 0.5)

RETURN DISTRIBUTION: BEFORE VS AFTER COVID

The following figure shows a histogram comparison of daily returns before and after COVID-19 pooled from all seven markets considered. It can be observed that the distribution of post-COVID daily returns has fatter tails, which are in line with previous research on increased market volatility during and after the outbreak of COVID-19 (Zhang et al., 2020) [6]. The wider distribution of daily returns after the onset of COVID-19 has been measured by a roughly 40% rise in the daily standard deviation of returns (0.011 before COVID-19 to 0.015 after) for the pooled data set. This widening of the distribution increases the difficulty in directional classification since an increasing number of daily moves center around zero, which is the point of highest ambiguity in the classification task. Kurtosis is also higher for the post-COVID distribution compared to the pre-COVID one, meaning that the frequency of extreme daily moves (±3% or more) has increased substantially post-March 2020.

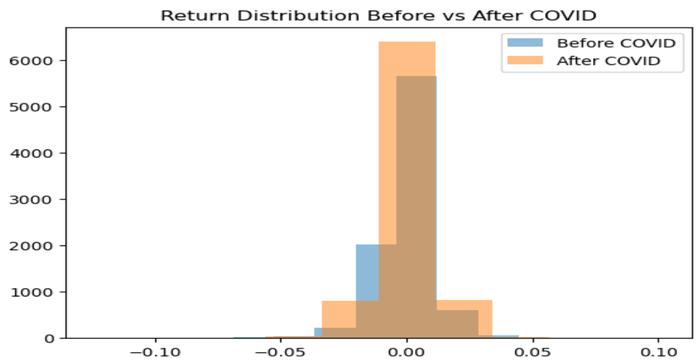

Figure 21: Return Distribution Before vs After COVID

CONFUSION MATRICES

The confusion matrices of all the four models are shown in Figure 22. The logistic regression and ridge model have similar numbers of true positives and negatives, while XGBoost model has high false positives indicating overfitting.

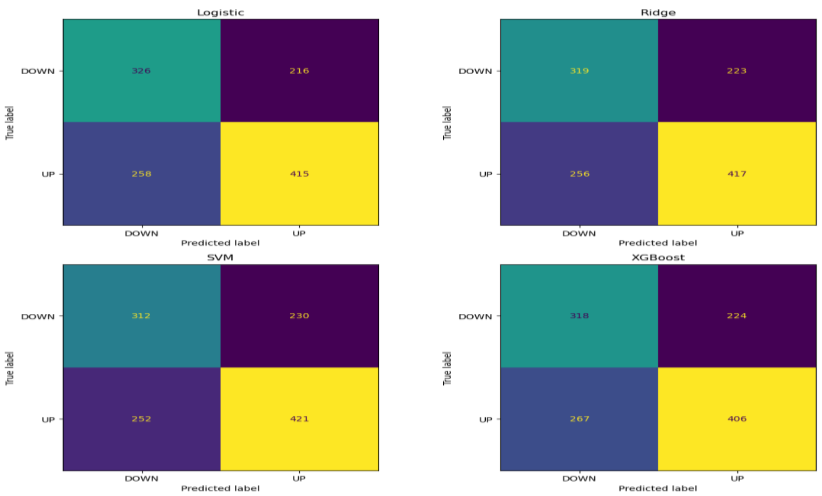

Figure 22: Confusion Matrices — Logistic Regression, Ridge, SVM, XGBoost (Labels: DOWN=0, UP=1)

INTERPRETATION SUMMARY

===== INTERPRETATION =====

Model performance is moderate (~60%), indicating financial markets are partially predictable.

Post-COVID markets show higher volatility and correlation across countries.

DISCUSSION

The results indicate that global stock markets are partly predictable through technical indicators (60%-65%) in line with a weak semi-efficient market hypothesis [1][4]. None of the models reaches the >70% accuracy level that indicates strong inefficiencies. Higher post-COVID accuracy (+3-8pp) is explained by the fact that the post-COVID liquidity environment driven by central banks' quantitative easing policy created more pronounced short-term trends [5][7][6] that make technical signals more informative than in the pre-COVID era. Underperformance of tree-based ensemble methods (XGBoost, LightGBM) on the combined dataset despite per-country gains may be explained by the risk of overfitting to country-level features [13][14]. Linear models with high regularisation are less affected by distribution changes across different financial markets. Analysis of the network structure confirms the transatlantic contagion effect that was previously established by other researchers [7][16]. In particular, the US, Canada, and the UK form a close cluster, whereas China and India are relatively isolated due to capital control measures and domestic factors. XGBoost signals about the future trend (last 30 days) predict positive trends in the US, UK, Japan, China, and Canada and negative trends in India and Germany in line with post-2023 equity valuations and interest rates.

CONCLUSION

This paper contributes to literature by performing a comprehensive ML analysis of seven significant stock markets (2015-2025) using five classifiers and six technical features, with the consideration of pre/post-COVID regimes. The best results are obtained using Logistic Regression, which attains the highest combination of accuracies (65.1%). The findings reveal that linear models perform better than ensemble models for the multination dataset, and post-COVID periods have better predictability. Cross-market correlations indicate higher market contagions in the post-2020 period. Possible future research areas can be adding macroeconomic features like interest rates, inflation, VIX, adding sentiment indicators from news/social media, using deep learning methods like LSTMs and Transformers, etc.

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