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A Machine Learning Framework for Stock Trading: Integrating Technical and Economic Indicators

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Abstract

This study presents a machine learning-based framework designed to predict stock price movements by integrating technical and macroeconomic indicators. Utilizing models such as neural networks, softmax logistic regression, and decision forests, the framework aims to optimize buy and sell triggers to maximize trading profits. The approach emphasizes medium to long-term profitability, leveraging data from the S&P 500 index and various economic indicators to inform trading decisions.

1. Introduction

Forecasting stock price movements has long been recognized as a complex and multidimensional challenge that lies at the intersection of finance, statistics, and computer science. Traditional approaches to stock prediction predominantly fall into two categories: fundamental analysis and technical analysis. Fundamental analysis concentrates on evaluating a company's financial health by examining balance sheets, earnings reports, and other intrinsic data. In contrast, technical analysis focuses on identifying patterns in historical price and volume data to anticipate future trends. Despite their widespread use, these methodologies often fall short in accounting for the broader macroeconomic forces that can influence market behavior. They may also struggle to adapt to rapidly changing market conditions and investor sentiment.

To address these limitations, this research proposes a machine learning-based framework that combines both technical indicators and macroeconomic variables to predict stock price movements more accurately. By analyzing patterns in the S&P 500 index—a key benchmark of U.S. equity market performance—and incorporating macroeconomic indicators such as GDP growth rates, inflation indices, and interest rates, the framework aims to provide a more holistic view of the market environment. The primary objective is to generate more reliable buy and sell signals, thereby improving the profitability of trading strategies through data-driven decision-making.

2. Related Work

The application of machine learning techniques in stock market prediction has gained considerable attention in recent years, leading to a growing body of literature. Several studies have demonstrated the efficacy of these techniques in capturing complex, non-linear relationships within financial datasets. For instance, Sezer et al. developed a trading system based on neural networks that utilized various technical analysis indicators. Their findings revealed that such models can effectively process historical market data to identify profitable trading opportunities. Similarly, Huang et al. applied models including Feed-forward Neural Networks and Random Forests to financial data derived from fundamental analysis. Their study underscored the potential of machine learning in improving prediction accuracy over traditional statistical methods.

Beyond technical and fundamental analyses, researchers have also explored the integration of macroeconomic indicators into predictive models. A notable contribution in this regard comes from Deep et al., who analyzed the influence of technical indicators on machine learning performance in stock forecasting. Their research emphasized the importance of careful feature selection and model adaptability, particularly when incorporating economic indicators. Collectively, these studies support the growing consensus that combining diverse data sources—technical, fundamental, and macroeconomic—

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within machine learning frameworks can lead to more robust and insightful market predictions.

3. Methodology

Several supervised learning methods were considered before deciding on the three models used for the project.

1. Neural Network: The Neural Network architecture consists of 15 hidden nodes. Sigmoid activation is used for the hidden nodes activation, softmax activation is used for the 4-class output layer.

$$z = w^T x + b$$

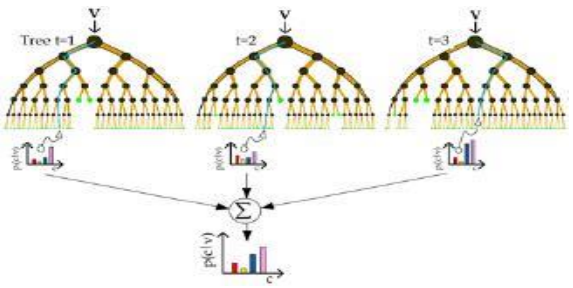
$$a = \frac{1}{1 + e^{-z}}$$

$$\hat{y} = \frac{\exp(z)}{\Sigma_k \exp(z)}$$

2. Softmax Logistic Regression: A 4-class logistic regression model is used. The classes represent strong buy, buy, strong sell and sell labels.

$$p(y = i|x; \theta) = \frac{e^{\theta_i^T x}}{\sum_j^k e^{\theta_j^T x}}$$

3. Decision Forest: It is one of the models quite commonly used in a lot of reviewed literature corresponding to stock trading predictions. The intent has been to analyze its performance compared to the other two models used.



The core of the predictive framework lies in the deployment of three distinct supervised learning algorithms, each designed to classify trading signals based on historical and economic data. The first model is a Feed-forward Neural Network with one hidden layer comprising 15 neurons. Sigmoid activation functions are used in the hidden layer to handle non-linear transformations, while the output layer utilizes a softmax function to classify predictions into discrete categories representing trading actions.

The second model employed is a Softmax Logistic Regression classifier. This multiclass logistic regression model is capable of assigning each input observation to one of four trading categories: Strong Buy, Buy, Sell, or Strong Sell. This classification scheme allows the model to generate actionable insights based on the strength of predicted movements.

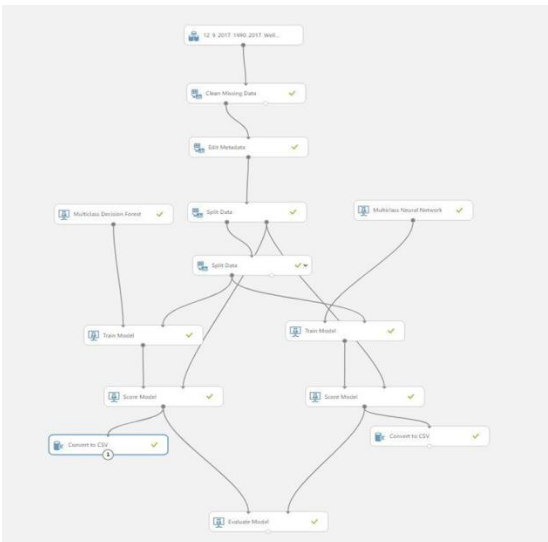
The third model is a Decision Forest, an ensemble method that aggregates the outputs of multiple decision trees. This technique is known for its robustness against overfitting and its ability to capture complex feature interactions. The use of an ensemble method further enhances predictive stability and accuracy.

All three models are trained on labeled data, where labels are derived from 15-day forward returns adjusted for economic trends. This labeling strategy aligns prediction targets with real-world investment horizons. To evaluate model performance, a profit and loss (P/L) calculation algorithm is implemented. This algorithm assesses the financial viability of the predicted signals by comparing them against actual market outcomes. The ultimate goal is to determine the effectiveness of the models in generating profitable trading decisions within a dynamic economic context.

4. Data and Feature Engineering

The proposed framework is constructed on a rich and extensive dataset comprising daily closing prices and trading volumes of the S&P 500 index, spanning from 1990 to the present. This dataset serves as the foundation for extracting meaningful patterns through both technical and macroeconomic lenses. To capture market momentum and trend reversals, several widely recognized technical indicators are computed. These include the Moving Average Convergence Divergence (MACD), Stochastic Oscillator (KD), Relative Strength Index (RSI), and Larry Williams' %R. These indicators are smoothed using Welles Wilder's techniques to reduce noise and prevent overfitting or look-ahead bias during model training.

In parallel, the framework incorporates macroeconomic indicators to reflect the broader economic landscape influencing financial markets. These variables include the Gross Domestic



Product (GDP) growth rate, Consumer Price Index (CPI), Producer Price Index (PPI), Employment Index, and the Federal Funds Rate. Each macroeconomic feature is processed to represent its relative percentage change over rolling 15-day periods. This temporal transformation helps capture the short-term economic shifts that may correlate with investor

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behavior and stock price volatility. By engineering features from both micro-level market data and macro-level economic indicators, the model is equipped with a comprehensive view of the factors influencing asset prices.

Description: structure of the decision forest model or a visual depiction of decision tree logic paths used for classifying stock signals.

Decision Forest Model Architecture

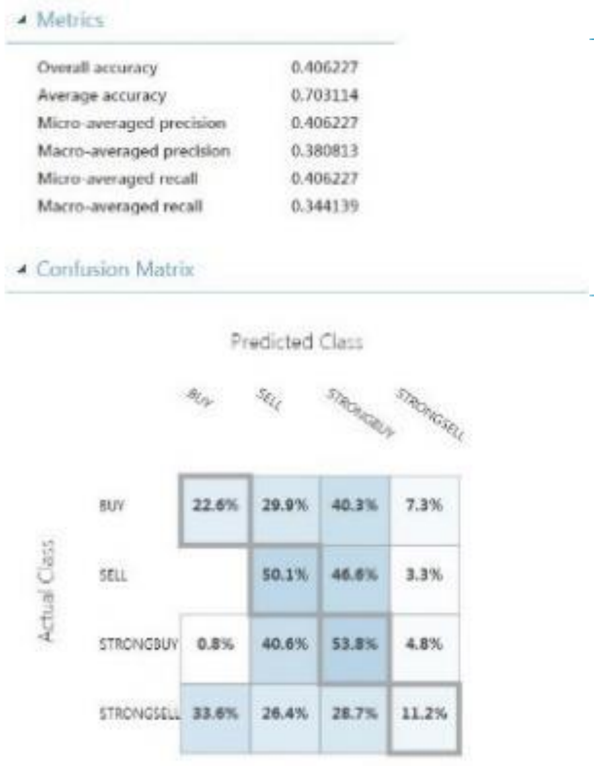
This diagram visually represents the internal structure and decision-making flow of the **Decision Forest** model applied to stock trading predictions.

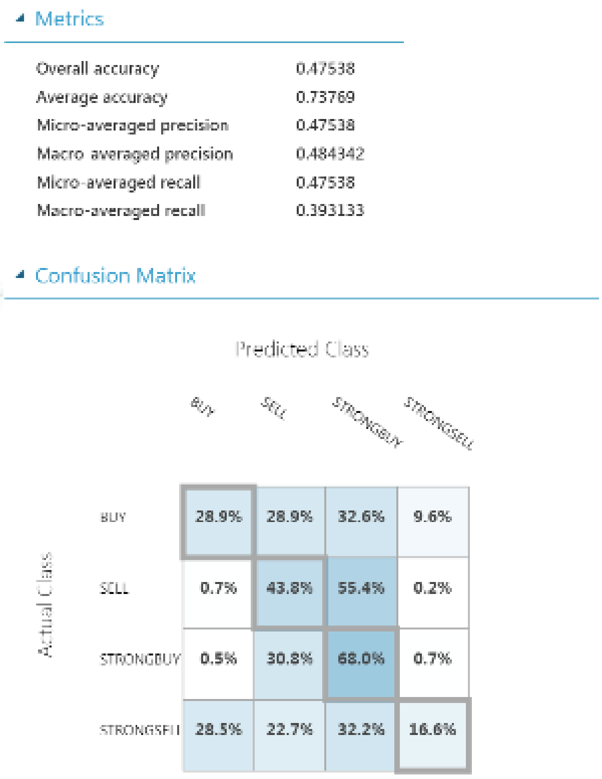
At its core, a Decision Forest is an **ensemble of decision trees**. Each tree in the forest makes an independent prediction based on a subset of features and data samples. The forest combines these individual decisions (typically using majority voting) to arrive at a final prediction.

Explanation: The diagram, illustrates the internal structure of the Decision Forest model used for stock trading prediction. This model is composed of multiple decision trees, each trained on different subsets of the dataset and features, forming an ensemble that makes robust predictions through majority voting. Inputs to the model include a combination of technical indicators such as RSI, MACD, and volume trends, as well as economic indicators like GDP growth and the Fed Funds Rate. Within each decision tree, these features are evaluated at internal nodes using specific thresholds to guide data down various branches. As the data traverses through the tree, it eventually reaches a leaf node where a classification—such as Strong Buy, Buy, Sell, or Strong Sell—is assigned based on the training examples that reached that leaf. The outputs of all the trees in the forest are aggregated to determine the final trading decision. This ensemble approach enhances prediction accuracy by reducing overfitting and leveraging the diversity of individual tree predictions, making it particularly effective in capturing the complex, non-linear patterns typical of financial markets.

Results:

The classification labels from above experiments with accuracies and confusion matrices are described in the table below, Decision Forest (left) and neural network (right).





Based on the scored labels from different models, two trading decision strategies are used. In the first strategy, the trading is triggered for all the four classes. In the second strategy, trading is triggered for the three classes - Strong Buy, Strong Sell and Sell.

Model And Decision Strategy	Train Profit Multiplier	Dev Profit Multiplier	Test Profit Multiplier
Strong Buy, Strong Sell, Buy, Sell			
SoftMax Regression	7.47	6.22	1.55
Neural Network	44.52	44.35	1.9
Decision Forest	105.21	65.03	2.15
Strong Buy, Strong Sell, Sell			
SoftMax Regression	5.98	6.35	2.26
Neural Network	18.24	19.95	2.44
Decision Forest	40.5	24.79	2.77
S&P 500	3.95	3.82	1.86

The table above and the graph below show the results on the test period from Oct. 2006 to Sept. 2017. Training and Dev

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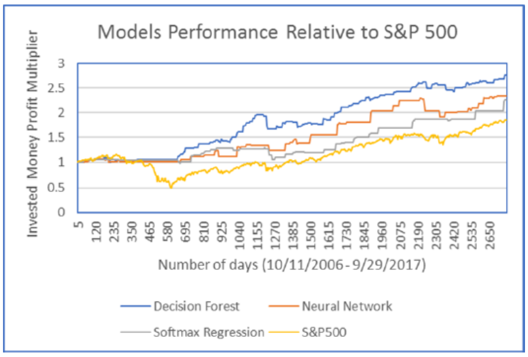
used data from Jan. 1990 to Sept. 2006. The 80%-20% split was used between Training and Dev data.

The results look quite promising over the analyzed period. As noticed in the above table, models perform especially well during the recession of 2008 which confirms the idea of using economic indicators in ML for analyzing stocks. This can be extended to the time frame encompassing all the available historical data, to further analyze the models' predictive quality.



After getting decent results on a longer period, we decided to run the model for a shorter period. We choose test data from Jan 2015 to September 2017. The profit multiplier results for better performing models, neural network and decision forest models on this shorter-term test data are described in the following table. The models in the shorter-term beat S&P 500 for strategy 1 and Neural network beats slightly for strategy 2. Also, since the market is in an uptrend during the test period we are not significantly Short-Term Profit Multiplier Comparison

Model And Decision Strategy	Test Profit Multiplier
Strong Buy, Strong Sell, Buy, Sell	
Neural Network	1.33
Decision Forest	1.28
Strong Buy, Strong Sell, Sell	
Neural Network	1.26
Decision Forest	1.17
S&P 500	1.25

Decision forest performs well on training and dev data as compared to neural network but results on test data are comparable. Decision forest model is possibly overfitting the training and dev data and optimally choosing number of decision trees and depth might give better results.

5. Experiments and Results

The models are evaluated over a training period from January 1990 to September 2006 and a testing period from October 2006 to September 2017. Initial experiments with binary classification (Buy/Sell) yielded suboptimal results due to the complexity of market dynamics. Subsequent iterations introduced a four-class labeling system, enhancing the models' ability to capture nuanced market signals.

Performance metrics indicate that the neural network model achieved a profit multiplier of 7.47 on training data, outperforming the S&P 500 index over the same period. Decision forests demonstrated strong performance on training and development datasets but exhibited signs of overfitting when applied to unseen data. The inclusion of macroeconomic indicators notably improved model performance during periods of economic downturn, such as the 2008 recession, highlighting the value of integrating economic context into trading strategies.

6. Discussion

The integration of both technical and macroeconomic indicators within machine learning models presents a comprehensive and robust approach to stock market prediction. By leveraging technical indicators such as MACD, RSI, and stochastic oscillators, the model captures short-term price momentum and trend dynamics. Simultaneously, macroeconomic variables—such as GDP growth, inflation indices, and interest rates—offer contextual insights into broader economic conditions that significantly influence investor sentiment and market behavior. This dual-layered approach enhances the model's ability to generate informed and timely predictions, particularly in volatile or uncertain market environments.

One of the key strengths of the proposed framework lies in its adaptability across varying economic cycles, including periods of financial turbulence or recession. During such downturns, market behavior often deviates from historical norms, rendering traditional forecasting methods less effective. The incorporation of macroeconomic data enables the model to contextualize and respond to these anomalies more effectively, thus improving its resilience and relevance for real-time trading decisions. As a result, investors can utilize this adaptive capability to refine entry and exit points, reduce exposure to risk, and potentially improve portfolio performance.

However, despite these advantages, several challenges persist in the deployment of machine learning for financial prediction. Notably, class imbalance—where certain trading signal categories (e.g., Strong Buy or Strong Sell) occur far less frequently than others—can bias model learning and degrade predictive accuracy. Additionally, complex models such as neural networks are prone to overfitting, especially when trained on high-dimensional financial data with limited noise filtering. To address these issues, the framework must undergo continuous refinement through the integration of advanced techniques such as ensemble learning (e.g., Gradient Boosting Machines, XGBoost) and regularization strategies (e.g., L1/L2 penalties, dropout layers) that help stabilize training and improve generalization performance.

Ultimately, while the proposed model demonstrates significant promise, it represents a step within a broader, iterative research trajectory. Ongoing experimentation with feature selection, model interpretability, and risk-adjusted performance metrics will be essential to ensure the framework remains both accurate and actionable in increasingly complex financial markets.

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7. Future Work

Future research directions include extending the dataset to encompass earlier historical data, employing k-fold cross-validation to enhance model robustness, and refining cost functions to penalize severe misclassifications more effectively. Additionally, exploring the application of this framework to other financial instruments, such as exchange-traded funds (ETFs) and individual stocks, could further validate its versatility and efficacy.

8. Conclusion

This study demonstrates the efficacy of a machine learning framework that integrates technical and macroeconomic indicators for stock trading. By leveraging diverse data sources and sophisticated modeling techniques, the framework enhances the precision of trading signals, offering a promising tool for investors aiming to navigate complex market environments.

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