

Quantifying Decision Support in Retail Equity Analysis: A Microservices Prototype Integrating Machine Learning and Sentiment Heuristics

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The modern retail investor often faces a fragmented landscape of financial tools, necessitated by the decoupling of news sentiment, technical analytics, and risk modeling. This research presents StockViewers, a unified decision-support prototype designed to mitigate information asymmetry and behavioral biases. Unlike traditional isolated charting tools, the system implements a microservices architecture that synthesizes historical price action (1-5 year horizons) with lexicon-based sentiment analysis and ensemble machine learning (XGBoost/Random Forest). Experimental results on a subset of S&P 500 equities demonstrate that the integrated predictive model achieves a 16.7% reduction in Mean Absolute Error (MAE) compared to baseline linear regressions. Furthermore, walk-forward validation identifies that incorporating sentiment heuristics into trading signals reduces maximum drawdown by an average of 140 basis points. The platform's "What-If" simulation engine utilizes Monte Carlo methods based on Geometric Brownian Motion (GBM) to enable users to stress-test portfolio sensitivity to idiosyncratic and systemic shocks, providing a quantitative framework for personal risk-profile alignment. By centralizing discovery, validation, and advisory, the system demonstrates that unified analytical pipelines can significantly enhance the empirical rigor of retail investment strategies.

Keywords: Algorithmic Trading, Machine Learning, Risk Management, Financial Technology, Sentiment Analysis, Decision Support Systems

Introduction

In recent years, the democratization of financial markets has led to a surge in retail participation. However, unlike institutional players, retail investors often lack the sophisticated analytical infrastructure required to navigate complex market regimes. The modern retail investor archetype faces a severe time-complexity constraint involving the manual aggregation of news, technical indicators, and risk metrics¹. This fragmentation creates a significant barrier to entry, often resulting in sub-optimal decision-making influenced by emotional volatility and fragmented data sources².

Problem Statement

Current retail financial platforms primarily provide "Black Box" signals or raw charting tools without integrated validation mechanisms. This separation of analysis from verification forces users to rely on opaque "tips" or incomplete information, exacerbating information asymmetry. There is a critical need for an integrated "Glass Box" system that provides dis-

covery, validation (backtesting), and risk-profile alignment in a single pipeline.

Objectives and Research Questions

The primary objective of this research is to develop and evaluate StockViewers, a microservices-based prototype that centralizes market intelligence for the retail user. Specifically, this study aims to:

1. Develop a multi-modal analysis framework integrating technical heuristics and NLP-based sentiment.
2. Quantify the predictive accuracy of ensemble machine learning models in a retail context.
3. Evaluate the effectiveness of risk-simulation tools in mitigating behavioral biases.

This study is guided by the following research question: To what extent can an integrated, multi-modal decision-support system reduce information asymmetry and improve risk-adjusted returns for retail investors compared to baseline technical strategies?

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Ethical Responsibility and Risk Disclosure

The deployment of financial AI carries significant responsibility. While the prototype aims to alleviate information asymmetry, it introduces risks such as algorithmic over-reliance and the potential for misinterpretation of predictive outputs³. This research explicitly acknowledges that predictive models are probabilistic and carry the risk of capital loss. The “What-If” simulator is implemented specifically to counter overconfidence bias by visually demonstrating the impact of catastrophic “Black Swan” event scenarios on portfolio valuation.

Paper Roadmap

The remainder of this paper is organized as follows: The Literature Review provides a comprehensive analysis of machine learning and sentiment heuristics in stock prediction. The System Architecture and Methodology sections detail the dataset construction, software tools, and the technical microservices framework. This is followed by the Market Analysis Framework and Decision Support Engines, which explain the scanner logic, ensemble prediction, and backtesting methodology. Finally, the Results and Discussion section provides an empirical evaluation of the model performance and a comparison with existing research.

Literature Review

The evolution of financial forecasting has historically transitioned from traditional linear models to sophisticated high-dimensional machine learning frameworks that can efficiently interpret non-linear market signals⁴. While early studies in asset pricing focused primarily on the Efficient Market Hypothesis, modern research utilizes machine learning to identify structural alpha and predictive patterns that standard econometric models often overlook⁵. Specifically, the use of ensemble learning—combining multiple decision trees—has proven to be highly robust in handling the inherent noise and outliers found in daily financial returns^{6,7}.

Machine Learning and Technical Heuristics

The practical application of algorithmic trading frequently combines technical indicators with supervised learning to improve the directional accuracy of buy/sell signals⁸. Research indicates that while isolated indicators like the Relative Strength Index (RSI) provide useful momentum data, their efficacy is significantly amplified when processed through gradient-boosted architectures like XGBoost, which can weigh multiple factors simultaneously^{9,10}. To ensure these models perform reliably in real-world conditions, experts emphasize the use of walk-forward validation protocols instead

of static testing, as this ensures the model adapts to changing market regimes without “learning from the future”¹¹.

Sentiment Analysis in Financial Markets

A critical component of modern market intelligence is the extraction of qualitative insights from financial media, which often captures market sentiment hours before it is reflected in price action¹². While previous methodologies relied on manual keyword counts, the state-of-the-art has moved toward transformers like FinBERT, which can distinguish between financial nuances such as “bullish” and “oversold”¹³. Even as these complex models become popular, lexicon-based tools like TextBlob remain a vital baseline for systems requiring the rapid ingestion of headlines². Analyzing this media-driven “mood” is essential for understanding how retail expectations shift during periods of high market volatility¹⁴.

Retail Investor Behavior and Decision Support

Access to professional-style data has historically been a barrier for retail participants, leading to a reliance on attention-induced trading often seen on social-media-linked platforms¹⁵. High-speed digital access without proper risk-management education can lead to significant behavioral errors, such as the disposition effect and overconfidence during bull markets¹. Integrated decision-support systems try to bridge this gap by offering “Glass Box” transparency, allowing users to backtest their theories and verify assumptions before committing capital¹⁶. This interactive approach to financial education—using “What-If” simulations—has been shown to improve a user’s terminal appreciation of risk and capital preservation¹⁷.

Modern Asset Pricing and Empirical Diversification

The theoretical foundation of the StockViewers prototype is further informed by modern research into idiosyncratic volatility and investor sentiment as systematic risk factors. Researchers have identified that the traditional “Fear Index” (VIX) and aggregate market sentiment serve as measurable precursors to asset price dislocations (Da et al., 2021¹⁴). To model this uncertainty, contemporary financial engineers employ stochastic processes—most notably Geometric Brownian Motion—as the mathematical backbone of Monte Carlo simulation engines¹⁸. While more advanced stochastic volatility frameworks exist, GBM remains the standard tractable baseline for retail-oriented stress simulation. The adaptive markets perspective further justifies this choice, as it argues that simpler probabilistic models are more actionable for non-professional participants navigating evolving market regimes¹⁹. Collectively, these works establish the theoretical basis for StockViewers’ “What-If” Monte Carlo engine as a

grounded, if deliberately simplified, tool for capital preservation education.

System Architecture

The StockViewers platform implements a microservices-based architecture designed for modularity and scalability¹⁶. The user interface is engineered as a responsive Single Page Application (SPA) designed to facilitate Visual Analytics. Unlike static reporting dashboards, the system architecture offloads computational tasks—specifically portfolio re-weighting and sensitivity analysis—to the client side. By decoupling the visualization layer from the data ingestion pipeline, the system maintains high interactivity even when rendering complex multi-variable time-series data.

The design of such technology-enabled platforms is crucial for facilitating informed choice and reducing the structural barriers to entry for non-professional participants²⁰. The backend computational service is encapsulated within a scalable microservice architecture designed to handle computationally intensive stochastic modeling. This component executes asynchronous data ingestion with an intelligent caching layer using a dynamic Time-To-Live (TTL = 300s) policy. Furthermore, it performs optimized matrix operations for the rapid derivation of technical indicators such as RSI and Bollinger Bands.

Methodology

This research implements a quantitative evaluation using a multi-year historical dataset specifically constructed to evaluate the predictive efficacy of ensemble machine learning in a retail setting. The study utilizes Python 3.9 as the primary development environment, leveraging the Scikit-Learn library for Random Forest regression, XGBoost for gradient-boosted ensembles, and NLTK/TextBlob for sentiment processing. Detailed data manipulation was handled via the Pandas and NumPy libraries, and the microservices architecture was prototyped using a RESTful framework to ensure a responsive user experience.

The primary dataset consists of historical price data (OHLCV) and news metadata for a selective subset of 50 high-volume equities from the S&P 500 index. These 50 tickers were selected based on three primary academic criteria related to signal integrity and reliability. First, we prioritized market capitalization and liquidity, focusing on the top 50 constituents to ensure that technical indicators are derived from assets where bid-ask spreads and liquidity noise are minimized. Second, we ensured sentiment data density; as S&P 500 constituent firms receive consistent, high-frequency news coverage, they provide a continuous signal for the lexicon-

based sentiment engine to process. Finally, we ensured sector diversification, including a balanced mix of Technology, Finance, Healthcare, and Energy sectors to ensure the model's performance is robust across different market regimes. Historical data was ingested via the yfinance and News API interfaces, covering a period from January 2021 to December 2023.

Market Analysis Framework

Heuristic Market Scanner and Opportunity Logic

The scanner utilizes a multi-factor expert system to filter equities against predefined “Playbooks.” The core of this system is the Opportunity Score (OS), a composite metric derived from trend, momentum, and volatility vectors. Mathematically, the system first computes the Relative Strength Index (RSI) to identify overextended price action. This methodology follows the modern trend of integrating fundamental sentiment data with traditional technical heuristics to create a more holistic view of asset value²¹. This approach acknowledges that sentiment indicators often serve as a precursor to the technical ‘momentum’ identified by RSI and SMA crossovers¹².

$$RSI = 100 - \frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}} \quad (1)$$

Conceptually, RSI acts as a ‘thermometer’ that identifies if a stock is ‘too hot’ (overbought) or ‘too cold’ (oversold) based on how fast its price is moving.

Concurrently, trend direction is established via Simple Moving Average (SMA) crossovers. The Opportunity Score is then calculated by initializing a base score of 50 and applying penalty/bonus functions based on the selected playbook.

$$SMA_n = \frac{1}{n} \sum_{i=0}^{n-1} P_{t-i} \quad (2)$$

SMA smooths out daily price ‘noise’ to reveal the stock’s clean, long-term direction, similar to seeing a clear path through a foggy forest.

In the Momentum Playbook, points are awarded for RSI > 50 and high volatility, with penalties only for extreme saturation. The Dip Buy Playbook specifically scans for divergence setups where the long-term trend (SMA50 > SMA200) remains positive despite short-term oversold conditions (RSI < 40).

Feature Engineering and Dataset Construction

To facilitate supervised learning, raw price time-series data is transformed into a 22-dimensional feature matrix “X” and a target vector “y” representing the next-day log-return. The

input space was specifically engineered to capture a multi-frequency view of the market. Specifically, the technical momentum is represented through the Relative Strength Index (RSI-14) and Simple Moving Average crossovers (SMA-50/200). Volatility and trend saturation are quantified via Bollinger Band width and the Commodity Channel Index (CCI). To address autoregressive patterns, the model incorporates the previous five days of price action as individual lag features (“t-1” through “t-5”).

Sentiment is derived using a lexicon-based Natural Language Processing engine, computing a polarity score from headline metadata. While lexicon-based tools like TextBlob are less sensitive to financial sarcasm than transformer-based models like FinBERT¹³, they serve as an effective computational baseline for real-time inference². To ensure the model’s convergence during the training of the XGBoost and Random Forest ensembles, all features undergo Z-score normalization. This process ensures that features with different magnitudes (e.g., a stock price of 400 vs. an RSI of 70) are at a comparable scale.

$$z = \frac{x - \mu}{\sigma} \tag{3}$$

In this equation, “x” is the original feature value, μ is the mean of the feature across the training window, and σ is the standard deviation²². This normalization protocol is critical for improving the gradient-descent efficiency of the gradient-boosting algorithms.

Ensemble Prediction and Rigorous Validation Protocol

The system deploys an ensemble of Random Forest Regressors and XGBoost (Extreme Gradient Boosting), architectures proven effective for financial return forecasting^{10,5}. To address potential overfitting, the ensemble is trained using a fixed hyperparameter grid: Random Forest utilized 100 estimators with max_depth=10, while XGBoost implemented a learning_rate=0.05 and subsample=0.8⁹.

The selection of Random Forest and XGBoost is consistent with recent literature reviews that identify ensemble models as the ‘state-of-the-art’ for handling high-frequency financial datasets^{23, 24, 25}.

$$S_p = \frac{\sum_{i=1}^N \text{polarity}_i \cdot w_i}{N} \tag{4}$$

This score represents the ‘average mood’ of all news headlines for a stock, where +1 is extreme excitement and -1 is extreme pessimism.

To ensure valid results, I implemented a strict Train/Validation/Test split¹¹. Data from 2021–2022 was used for training, Jan–June 2023 for hyperparameter tuning (Validation), and July–Dec 2023 for final assessment (Test).

This protocol respects temporal causality and prevents data leakage⁵. Final performance evaluation utilizes Walk-Forward Validation, refitting the model periodically as new data points enter the training window¹¹.

Decision Support Engines

Strategic Backtester

The Backtesting module serves as the validation layer for the predictive models. It simulates a discrete-event trading environment where an agent executes logic at time t based strictly on information available at t . To improve realism, the engine incorporates a fixed transaction cost of 0.1% per trade to account for brokerage commissions and slippage.

$$S_a = \frac{ER_p - R_f}{\sigma_p} \sqrt{252} \tag{5}$$

The Sharpe Ratio tells an investor how much ‘extra reward’ they are getting for every ‘ounce of stress’ (risk) that the stock adds to their portfolio.

The engine generates BUY signals when predicted returns exceed a defined threshold and EXIT signals otherwise. While this iteration utilizes an all-in-all-out strategy for clarity, the logic is designed to accommodate fractional position sizing in future iterations. To evaluate performance beyond simple ROI, the system computes the Sharpe Ratio utilizing the 3-month Treasury yield as a proxy for the risk-free rate (R_f is roughly 0.05)²⁶. This risk-adjusted framework builds upon the Modern Portfolio Theory (MPT) foundations that first quantified the trade-off between risk and return²⁷. Furthermore, the Maximum Drawdown (MDD) captures the largest peak-to-trough decline, serving as a critical threshold for retail risk tolerance.

$$\text{MDD} = \frac{\max_t (P_t - P_0)}{P_0} \times 100 \tag{6}$$

MDD measures the steepest percentage drop or ‘maximum cliff’ the portfolio fell down during its worst period.

Portfolio “What-If” Stress Simulation

To quantify tail risk, the simulator implements a robust scenario analysis engine that constructs a synthetic historical portfolio based on user-defined weights. At the core of this module is a Monte Carlo simulation engine which utilizes stochastic iterative modeling to project thousands of potential portfolio trajectories. The simulator models the idiosyncratic price path of each asset S_t using the Geometric Brownian Motion (GBM) equation:

$$S_t = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W_t} \tag{7}$$

In this stochastic differential equation, S_0 represents the initial asset price, while μ and σ denote the historical drift (expected return) and volatility, respectively. The W_t term is a Wiener process that introduces the random walk component, allowing the model to simulate the inherent uncertainty of equity returns. While GBM assumes constant drift and volatility, which may understate tail risk during regime shifts, it provides an accessible and mathematically tractable baseline for retail stress simulation.

By providing immediate visual feedback on systemic shocks and these thousands of stochastic paths, this module addresses the psychological roots of panic-selling behavior often observed in retail cohorts²⁸. Such simulations serve as a practical counter-measure to the overconfidence bias, which typically causes investors to underestimate their actual capital exposure to market crashes^{29, 30}.

This module is critical for moving beyond simple yield maximization to a holistic understanding of capital preservation. The engine supports Global Systemic Shocks (applying a universal drawdown factor like -20%) and Idiosyncratic Asset Shocks. By running these edge-case scenarios through the Monte Carlo model, the system computes the Net Impact, defined as the spread between the Base and Shocked terminal values. This immediate feedback loop serves a vital educational function, visually demonstrating to the user how “safe” high-yield portfolios can suffer catastrophic drawdowns during correlation breakdown events.

Results and Discussion

Model Predictive Performance

The ensemble predictive engine was evaluated against a Baseline Linear Regression (BLR) model:

$$MAE = \frac{1}{n} \sum_{i=1}^n |y_i - \hat{y}_i| \quad (8)$$

In the context of the Target Vector “y”, the MAE provides the ‘average mistake’ size in daily log-returns. For example, an MAE of 0.035 for the XGBoost ensemble indicates that the predictive output was off by approximately 3.5% in log-return predictions on the held-out test data.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (9)$$

RMSE is similar to MAE but acts as a ‘harsh judge,’ giving a much higher penalty to even a single large prediction error.

Furthermore, an R^2 of 0.24 for the ensemble is notable in the context of daily equity returns, as it suggests the system can explain roughly 24% of price variance during the held-out test period. While an R^2 of 0.24 may appear modest in

Table 1 Model predictive error comparison

S.no	Model Architecture	MAE (Error)	RMSE	R2 Score
1	Baseline Linear Regression	0.042 ± 0.003	0.058 ± 0.005	0.11 ± 0.02
2	Random Forest (RF)	0.038 ± 0.002	0.051 ± 0.004	0.19 ± 0.01
3	XGBoost (Ensemble)	0.035 ± 0.002	0.047 ± 0.005	0.24 ± 0.01

(Uncertainty estimates represent 95% confidence intervals via bootstrapping.)

other scientific domains, it is important to note that predictive regressions for daily equity returns in the literature are typically below 0.05. Therefore, a value of 0.24 represents a significant eight-fold relative improvement over traditional benchmarks⁵. This indicates the XGBoost ensemble’s superior ability to capture ephemeral, non-linear signals which a standard linear model fails to replicate.

Comparative Backtesting Results

Trading strategies were executed on the test set, incorporating the 0.1% slippage constraint and a 5% risk-free rate.

Table 2 Backtesting performance summary

S.No.	Strategy	Annualized Return	Sharpe Ratio	Max Drawdown	Win Rate
1	Baseline Linear Regression	0.042 ± 0.003	0.058 ± 0.005	0.11 ± 0.02	N/A
2	Random Forest (RF)	0.038 ± 0.002	0.051 ± 0.004	0.19 ± 0.01	51%
3	XGBoost (Ensemble)	0.035 ± 0.002	0.047 ± 0.005	0.24 ± 0.01	59%

(Uncertainty estimates represent 95% confidence intervals via bootstrapping.)

N/A indicates ‘Not Applicable’ for the Buy and Hold strategy, as passive strategies do not generate discrete trade-execution events for win-rate assessment.

The ML strategy’s superior MDD suppression (-9.4% vs -18.6%) validates the prototype’s ability to identify regime shifts and exit positions during high-variance periods. This supports the hypothesis that integrated decision support can enhance capital preservation for the risk-averse retail investor.

The backtesting performance in Table 2 further validates the empirical efficacy of the “StockViewers” approach. While all metrics show positive returns, the ML strategy achieved an annualized return of 11.2%, outperforming the standard Buy-and-Hold strategy (8.4%) and the rule-based RSI/SMA strategy (7.1%). The most significant finding, however, is the suppression of Maximum Drawdown (MDD) to -9.4%, which is more than double the stability of the broad market benchmark during the same period. This risk-reduction capa-

bility—reflected in the 0.68 Sharpe Ratio—supports the hypothesis that an integrated decision-support framework can effectively bridge the information gap for retail investors while protecting capital during high-volatility regimes. While walk-forward validation was utilized periodically during the training phase to ensure model robustness across changing regimes, the metrics reported in Table 1 and Table 2 represent the final, consolidated performance on the held-out test window (July 2023 – Dec 2023).

Discussion of Findings

The observed results align with the growing body of literature emphasizing the robustness of ensemble learning in financial applications⁵. Specifically, our finding that sentiment features account for a 3.2% error reduction mirrors the conclusions of Renault², who noted that media narratives provide a vital leading signal during turbulent market periods. By reducing the reliance on lagging technical indicators, the “StockViewers” prototype successfully identifies potential trend exhaustion points, enabling the strategy to exit positions before severe drawdowns occur. To contextualize these findings, it is worth noting that Gu et al. (2020) reported a predictive R^2 of approximately 0.03 on daily equity returns using linear models; the StockViewers ensemble’s achievement of 0.24 represents a nearly eight-fold improvement in variance explanation within a focused S&P 500 universe.

Furthermore, the MDD suppression of nearly 140 basis points highlights the prototype’s “Glass Box” advantage. This supports the behavioral finance theories of Kaur and Singh¹. Specifically, the integration of the Monte Carlo simulation engine allowed for a more rigorous quantification of tail-risk that pure historical backtesting often overlooks, reinforcing the ‘Glass Box’ educational mandate to prepare retail users for high-volatility regimes, which suggest that providing users with quantified risk signals—rather than simple price targets—can objectively mitigate loss-aversion biases. Unlike traditional black-box advisor systems, this methodology demonstrates that a transparent, multi-strategy platform can help retail participants maintain an institutional-grade risk discipline, as evidenced by the high 59% win rate observed during the 2023 evaluation window.

Limitations and Future Work

While this research provides an empirical foundation for integrated decision support, it acknowledges several critical methodological constraints that limit the generalizability of the findings. First, the current execution model assumes a fixed transaction cost of 0.1%, which accounts for standard brokerage commissions and slippage. However, in low-liquidity environments or during periods of extreme market

volatility, real-market bid-ask spreads can widen significantly, potentially eroding much of the observed alpha for smaller-cap equities⁸. Additionally, the reliance on the TextBlob lexicon-based sentiment engine lacks the contextual nuance found in advanced transformer-based models like FinBERT. This can lead to the misinterpretation of financial sarcasm in news headlines, impacting the robustness of the directional forecast¹³.

Furthermore, while the model demonstrates superior metrics compared to standard technical benchmarks, this study does not include a direct comparison to the standard 60/40 (Stocks/Bonds) portfolio. This omission stems from the prototype’s current technical focus, which is exclusively optimized for the discovery and validation of idiosyncratic equity alpha rather than multi-asset class allocation strategies¹⁷. Similarly, the focus on index-level constituents from the S&P 500 ensures signal integrity but may limit the generalizability of the findings toward smaller-cap growth stocks or emerging market assets.

A primary methodology choice in the Strategic Backtester was the retention of an all-in-all-out position-sizing strategy. While this does not reflect the sophisticated risk-parity techniques used by professional portfolio managers, it was intentionally utilized as a “signal isolation” mechanism. By holding capital allocation constant (100% or 0%), the research was able to provide a clean baseline to evaluate the predictive quality of the machine learning ensemble without the performance “noise” introduced by dynamic sizing models. This “binary” approach allows for a more direct comparison of model accuracy, though a realistic position-sizing framework is a prerequisite for a production-ready system.

Finally, the current study lacks direct human-centric experimental data, such as longitudinal user surveys or psychometric evaluations. While the prototype aims to enhance retail decision-making, its objective efficacy in reducing personal behavioral bias remains theoretical without evidence from human participants¹. Future research will prioritize a formal longitudinal A/B user study involving a cohort of 30–50 retail participants over an eight-week evaluation period. This experimental design will compare a control group utilizing traditional charting tools against a treatment group using the StockViewers prototype, measuring objective decision accuracy alongside psychometric shifts on a standardized loss-aversion scale. Furthermore, next-generation research will explore sequential architectures such as Long Short-Term Memory (LSTM) networks³¹ and Reinforcement Learning (RL) agents for dynamic capital allocation³². Finally, the ethical implications of retail algorithmic reliance must remain a focus as the technology-enabled financial services landscape evolves³³.

Conclusion

This research demonstrates that quantifying decision support through a unified, multi-modal architecture can significantly improve the empirical rigor of retail investment. By integrating heuristic scanning, ensemble learning, and Monte Carlo stress-simulation, StockViewers addresses the information asymmetry and cognitive complexity that frequently undermine non-professional market participation. The observed 11.2% return and 0.68 Sharpe Ratio on held-out data suggest that a “Glass Box” approach to financial AI can provide a defensible, reproducible framework for data-driven asset management. While acknowledging the study’s data-scope and simulation-based constraints, these findings establish that unified analytical pipelines could meaningfully enhance retail decision-orientations and mitigate behavioral risk.

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