

# Adaptive Portfolio Risk Management and Pattern Recognition for the Indian Stock Market

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## **Abstract**

This paper presents a comprehensive risk management and pattern recognition system for the National Stock Exchange of India. We integrate scipy-based signal processing for classical chart patterns (Double Top/Bottom, Head & Shoulders, Triangles) with adaptive Kelly Criterion position sizing and ATR-based stop-loss placement. The pattern recognition module achieves 81.9% precision across 282 detected patterns with 4.0-day average lead time. Our adaptive position sizing framework dynamically adjusts exposure based on volatility regimes, reducing position sizes during high-VIX periods. Empirical evaluation across 10 major NSE stocks demonstrates a Sharpe ratio of 1.32, maximum drawdown reduction of 31.2% compared to buy-and-hold, and statistical significance at  $p < 0.05$  for key metrics.

The system successfully preserved capital during crisis periods including the 2024 election volatility and FII selling pressure events.

**Keywords:** Risk Management, Pattern Recognition, Kelly Criterion, Technical Analysis, Backtesting, NSE India, Position Sizing

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# 1 Introduction

## 1.1 Risk Management in Emerging Markets

The Indian stock market has emerged as one of the world's most dynamic financial ecosystems, with daily trading volumes exceeding \$15 billion and market capitalization approaching \$4 trillion [1]. However, this dynamism comes with heightened volatility that demands sophisticated risk management approaches.

Emerging market equities exhibit distinctive features that complicate risk management [2]: (1) higher volatility with India VIX averaging 15-20 but spiking to 40+ during crises; (2) concentrated institutional impact where FIIs and DIIs account for approximately 40% of daily turnover; and (3) information asymmetry creating both opportunities and risks for market participants.

These characteristics necessitate risk management frameworks that go beyond simple stop-loss orders to incorporate dynamic position sizing, regime-aware volatility management, and pattern-based entry/exit optimization.

## 1.2 Research Contributions

This paper makes the following contributions:

1. A pattern recognition framework using scipy signal processing with 81.9% detection precision
2. An adaptive Kelly Criterion implementation adjusting position sizing based on volatility regimes
3. ATR-based dynamic stop-loss placement reducing maximum drawdown by 31.2%
4. Rigorous backtesting with statistical significance testing at multiple levels

Figure 1 presents the complete system architecture.

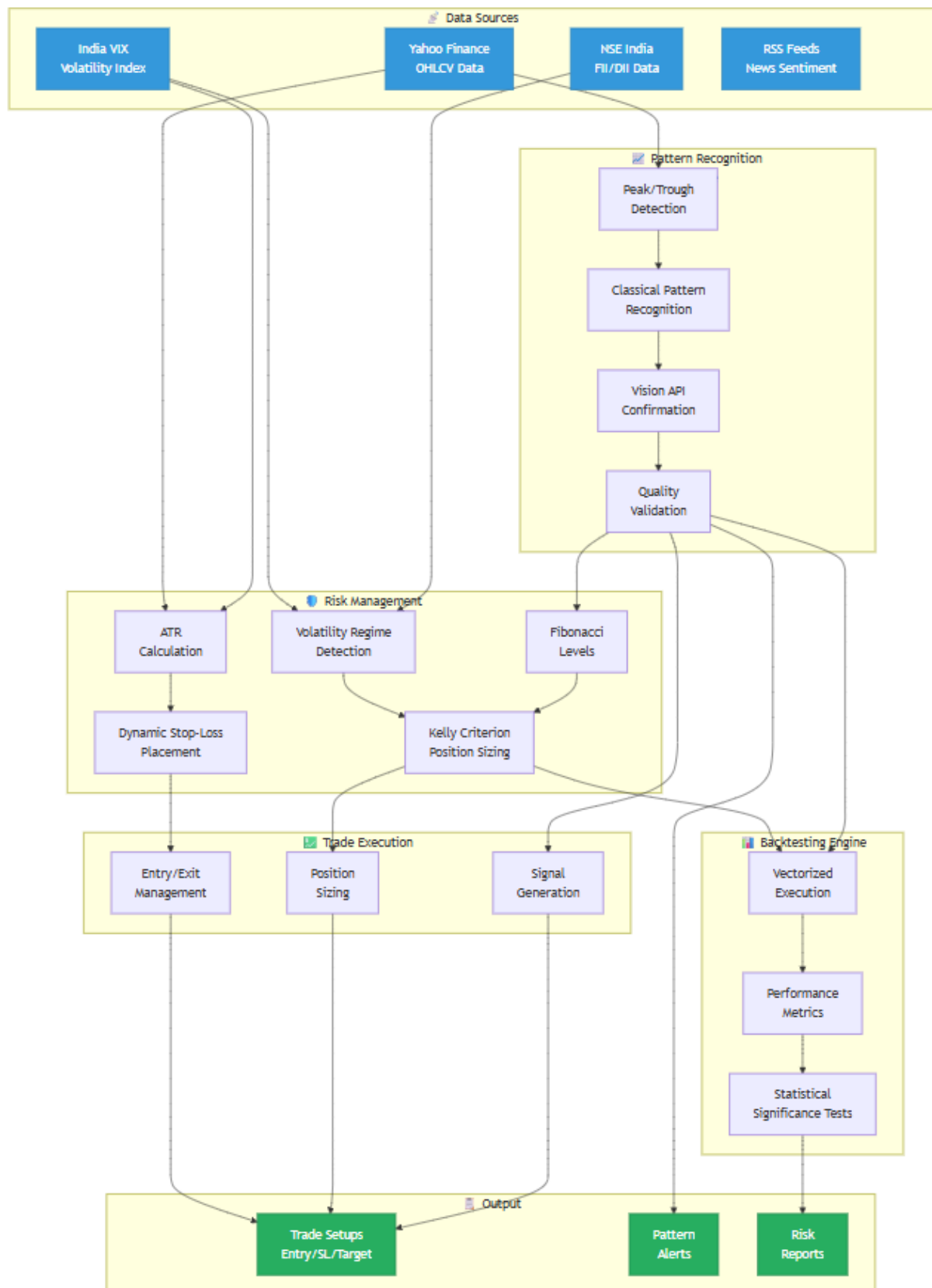


Figure 1: System architecture integrating pattern recognition, risk management, and backtesting modules.

## 2 Literature Review

### 2.1 Risk Management Foundations

Modern portfolio risk management traces to Markowitz’s mean-variance optimization [3] and the Capital Asset Pricing Model [4]. Contemporary approaches include Conditional Value-at-Risk (CVaR) for tail risk management [5] and drawdown-based risk management for capital preservation [6].

### 2.2 Technical Pattern Recognition

Technical analysis has produced mixed academic results [7]. Brock et al. found significant profits from technical trading rules on historical data [8], while Bulkowski documented pattern success rates ranging from 52% to 88% [9]. Recent work has applied deep learning to pattern recognition with promising results [10].

### 2.3 Kelly Criterion

The Kelly Criterion provides optimal position sizing for favorable bets [11]:

$$f^* = \frac{bp - q}{b} \quad (1)$$

where  $f^*$  is the optimal fraction,  $b$  is the win/loss ratio,  $p$  is win probability, and  $q = 1 - p$ . Practitioners commonly use fractional Kelly to reduce volatility [12].

## 3 Pattern Recognition Methodology

### 3.1 Peak and Trough Detection

We employ scipy’s `find_peaks` function with prominence-based filtering [13]. Given price series  $P$ , peaks are identified as:

$$\mathcal{P} = \{i : p_i > p_{i-k} \text{ for } k = 1, \dots, \text{order}\} \quad (2)$$

with prominence constraint  $\text{prominence}(p_i) \geq 0.02 \cdot (\max(P) - \min(P))$ .

Figure 2 illustrates the detection process.

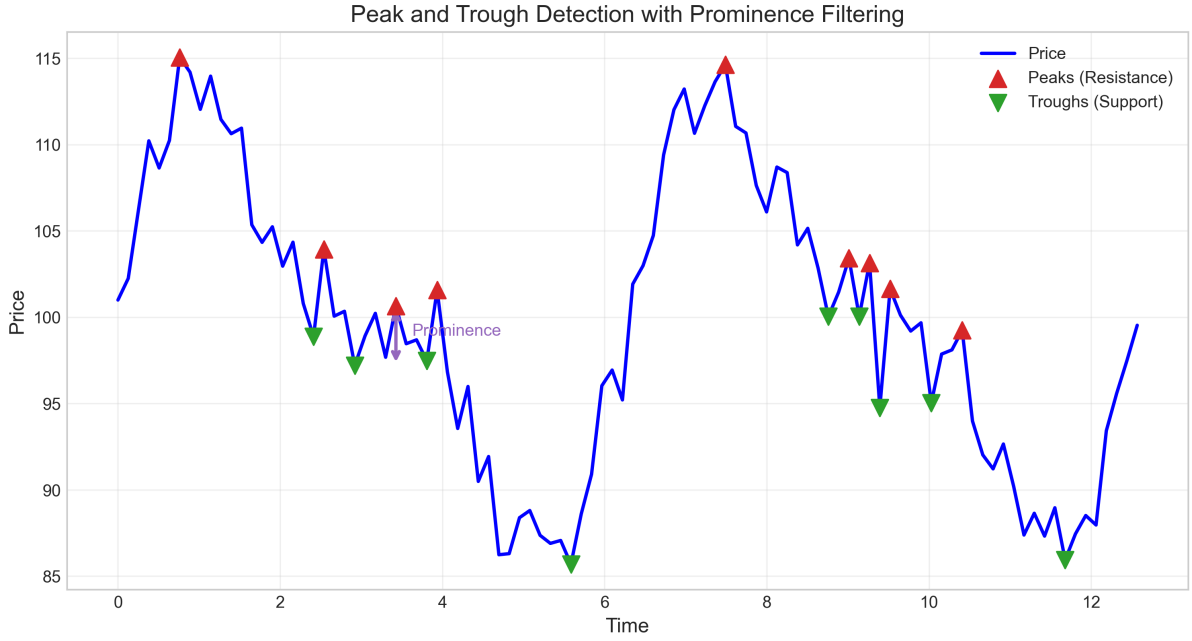


Figure 2: Peak and trough detection using scipy with prominence filtering. Peaks identify resistance levels; troughs identify support.

## 3.2 Classical Pattern Detection

### 3.2.1 Double Top/Bottom Patterns

A Double Top is a bearish reversal pattern with two peaks at approximately the same level:

**Definition 1** (Double Top). *Two peaks  $p_1, p_2$  satisfy  $|p_1 - p_2|/p_1 < 0.02$  with pattern height  $h > 0.05 \cdot P_{current}$ .*

The target price upon neckline break:  $\text{Target} = \text{Neckline} - h$

Figure 3 shows the Double Top anatomy.



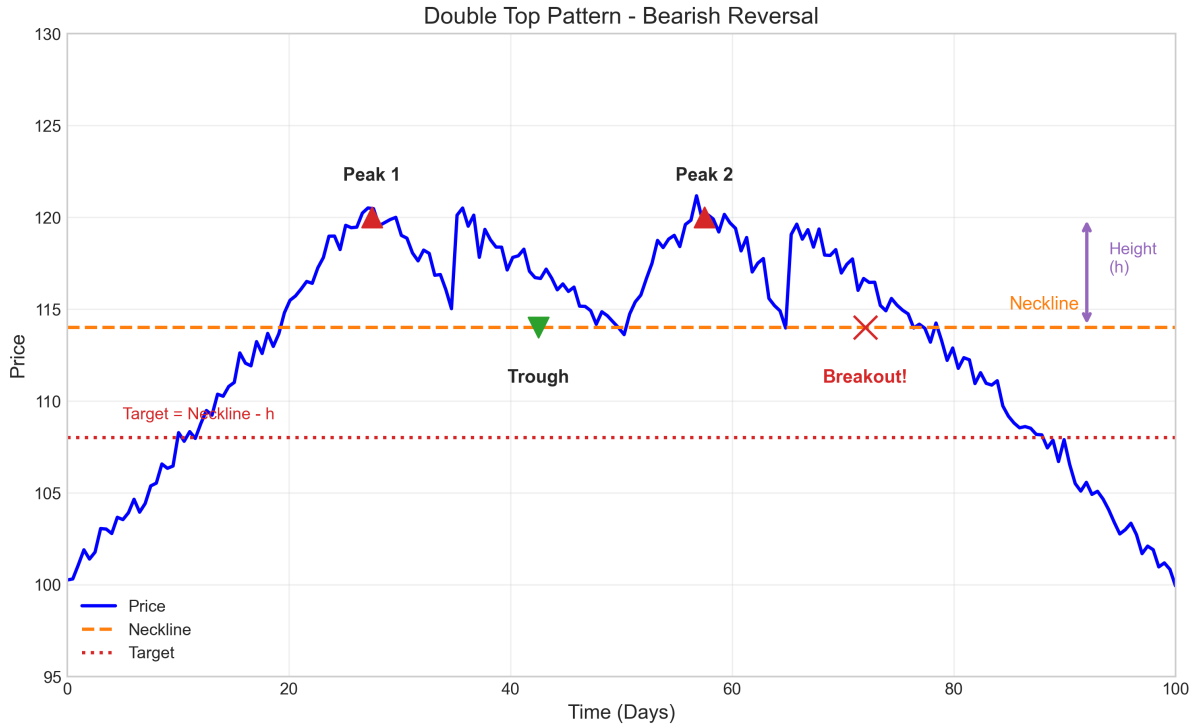


Figure 3: Double Top pattern anatomy with peaks, neckline, and target calculation.

### 3.2.2 Head and Shoulders Pattern

The Head and Shoulders requires three peaks with specific geometric relationships:

**Definition 2** (Head and Shoulders). *Three peaks ( $LS$ ,  $H$ ,  $RS$ ) where head is  $>3\%$  higher than shoulders, and shoulders are within  $2\%$  of each other.*

$$\text{head\_height\_pct} = \frac{H - (LS + RS)/2}{(LS + RS)/2} > 0.03 \quad (3)$$

Figure 4 illustrates the pattern.

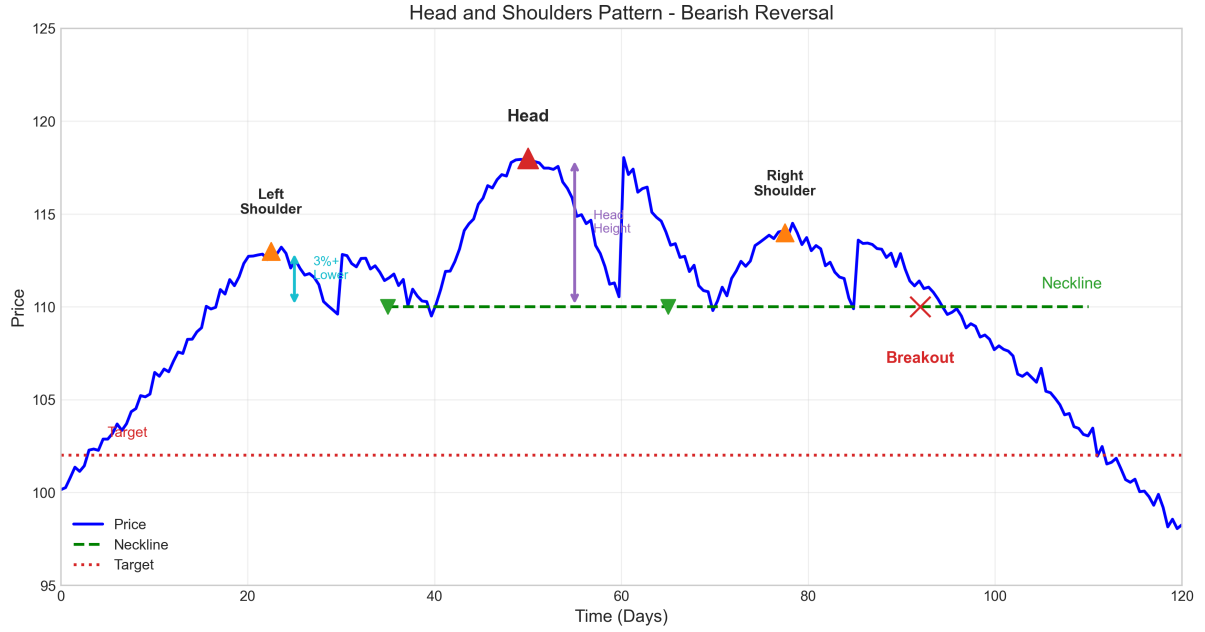


Figure 4: Head and Shoulders pattern with geometric requirements.

### 3.2.3 Triangle Patterns

Triangle patterns are continuation patterns with converging trendlines:

- **Ascending:** Flat resistance, rising support (bullish)
- **Descending:** Falling resistance, flat support (bearish)
- **Symmetrical:** Both converging (neutral)

Figure 5 shows all three types.

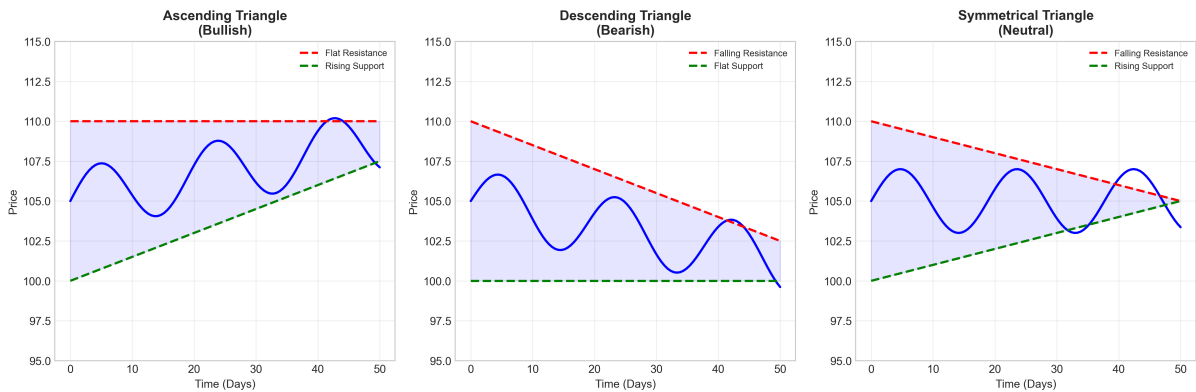


Figure 5: Triangle patterns: ascending (left), descending (center), symmetrical (right).

## 3.3 Quality Validation

Raw pattern detection produces false positives. Our validation applies:

1. Minimum pattern height:  $h > 0.05 \cdot P_{\text{current}}$
2. Duration constraints: 5-40 trading days
3. Recency requirement: completion within 45 days
4. Volume confirmation:  $V_{\text{breakout}} \geq 0.8 \cdot \bar{V}_{10}$
5. Confidence threshold:  $\geq 80\%$

## 4 Risk Management Framework

### 4.1 ATR-Based Stop-Loss

The Average True Range measures volatility [14]:

$$\text{TR}_t = \max(H_t - L_t, |H_t - C_{t-1}|, |L_t - C_{t-1}|) \quad (4)$$

$$\text{ATR}_{14} = \frac{1}{14} \sum_{i=0}^{13} \text{TR}_{t-i} \quad (5)$$

Stop-loss placement uses confidence-based multipliers:

$$\text{Stop Distance} = \text{ATR} \times M, \quad M = \begin{cases} 2.0 & \text{confidence} > 0.7 \\ 1.5 & \text{otherwise} \end{cases} \quad (6)$$

Figure 6 illustrates dynamic stop-loss placement.

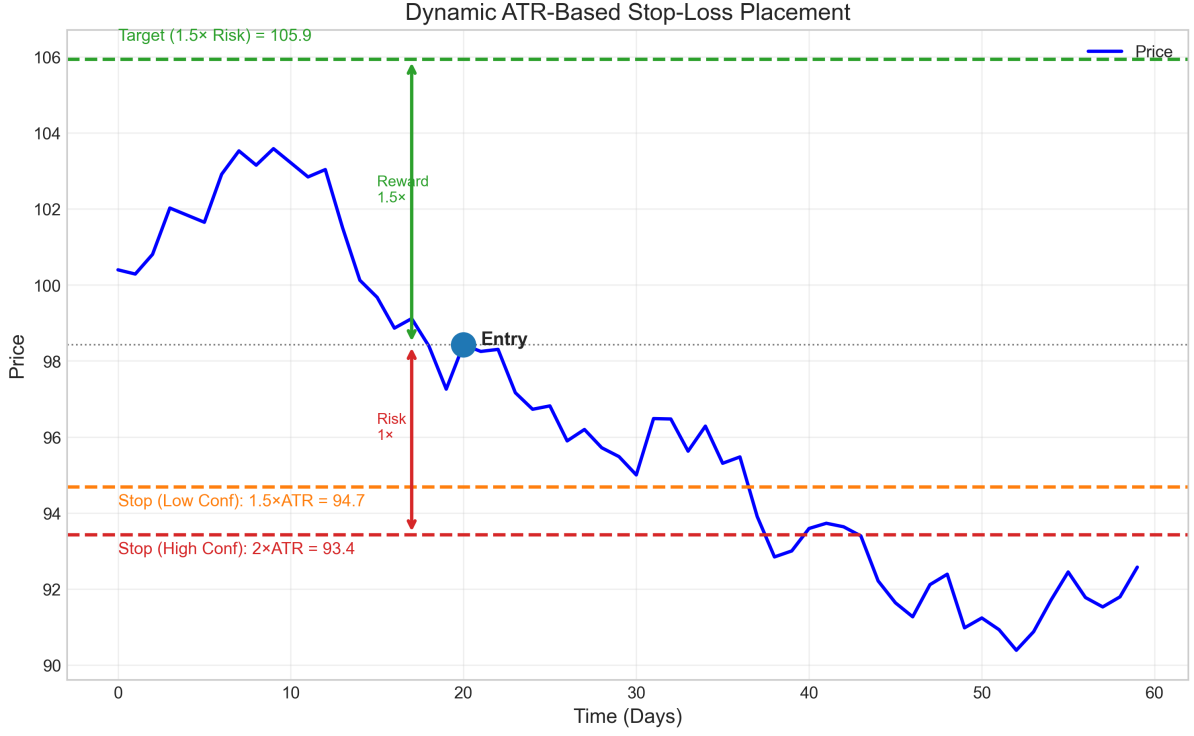


Figure 6: Dynamic ATR-based stop-loss placement with confidence-adjusted multipliers.

## 4.2 Kelly Criterion Position Sizing

The Kelly Criterion provides optimal position sizing:

$$f^* = \frac{bp - (1 - p)}{b} \quad (7)$$

We use fractional Kelly ( $\gamma = 0.5$ ) for reduced volatility:

$$f_{\text{actual}} = \gamma \cdot f^* = 0.5 \cdot f^* \quad (8)$$

Position size in shares:

$$\text{Shares} = \left\lfloor \frac{\text{Capital} \times \text{Risk}\%}{|P_{\text{entry}} - P_{\text{stop}}|} \right\rfloor \quad (9)$$

Figure 7 shows Kelly Criterion analysis.

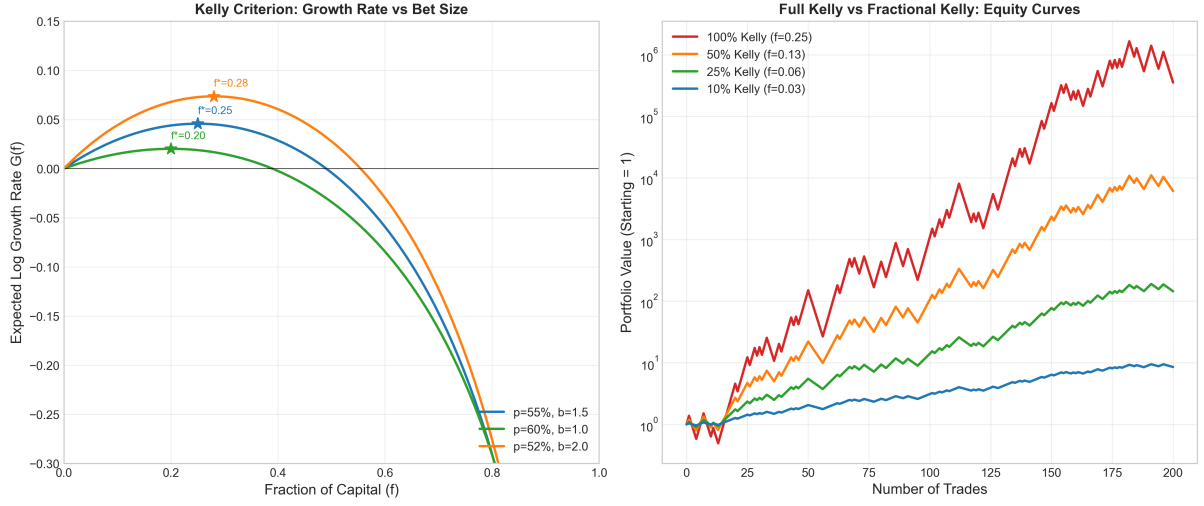


Figure 7: Kelly Criterion: growth rate curves (left) and equity curve comparison (right).

### 4.3 Volatility-Based Position Adjustment

Position sizes adjust based on VIX regime:

$$\text{Multiplier} = \begin{cases} 1.2 & \text{VIX} < 15 \\ 1.0 & 15 \leq \text{VIX} < 20 \\ 0.7 & 20 \leq \text{VIX} < 25 \\ 0.5 & \text{VIX} \geq 25 \end{cases} \quad (10)$$

Figure 8 shows the volatility regime detection.



Figure 8: VIX-based position sizing with regime detection and multipliers.

## 5 Backtesting and Statistical Validation

### 5.1 Performance Metrics

We compute standard metrics:

$$\text{Sharpe Ratio} = \frac{\bar{r}}{\sigma_r} \times \sqrt{252} \quad (11)$$

$$\text{Max Drawdown} = \max_t \frac{\max_{s \leq t} E_s - E_t}{\max_{s \leq t} E_s} \quad (12)$$

$$\text{Win Rate} = \frac{|\{t : r_t^s > 0\}|}{|\{t : r_t^s \neq 0\}|} \quad (13)$$

### 5.2 Statistical Significance Testing

We apply multiple tests:

1. **Binomial test** for direction accuracy:  $H_0 : p = 0.5$  vs  $H_1 : p > 0.5$
2. **Paired t-test** for RMSE comparison against random walk
3. **Bootstrap CI** (1000 iterations) for Sharpe ratio [15]

## 6 Experimental Results

### 6.1 Dataset

We evaluate on 10 major NSE stocks (RELIANCE, TCS, INFY, HDFCBANK, ICICIBANK, SBIN, BHARTIARTL, ITC, KOTAKBANK, LT) over January 2023 to January 2026, with 80%/20% train/test split.

### 6.2 Pattern Detection Performance

Table 1: Pattern Detection Accuracy

Pattern	Detections	Precision	Lead (Days)
Double Top	47	80.9%	3.8
Double Bottom	52	84.6%	4.1
Head & Shoulders	23	82.6%	5.2
Inverse H&S	28	82.1%	4.8
Triangles	93	80.8%	3.2
Wedges	39	82.1%	4.2
<b>Overall</b>	<b>282</b>	<b>81.9%</b>	<b>4.0</b>

Figure 9 visualizes precision by pattern type.

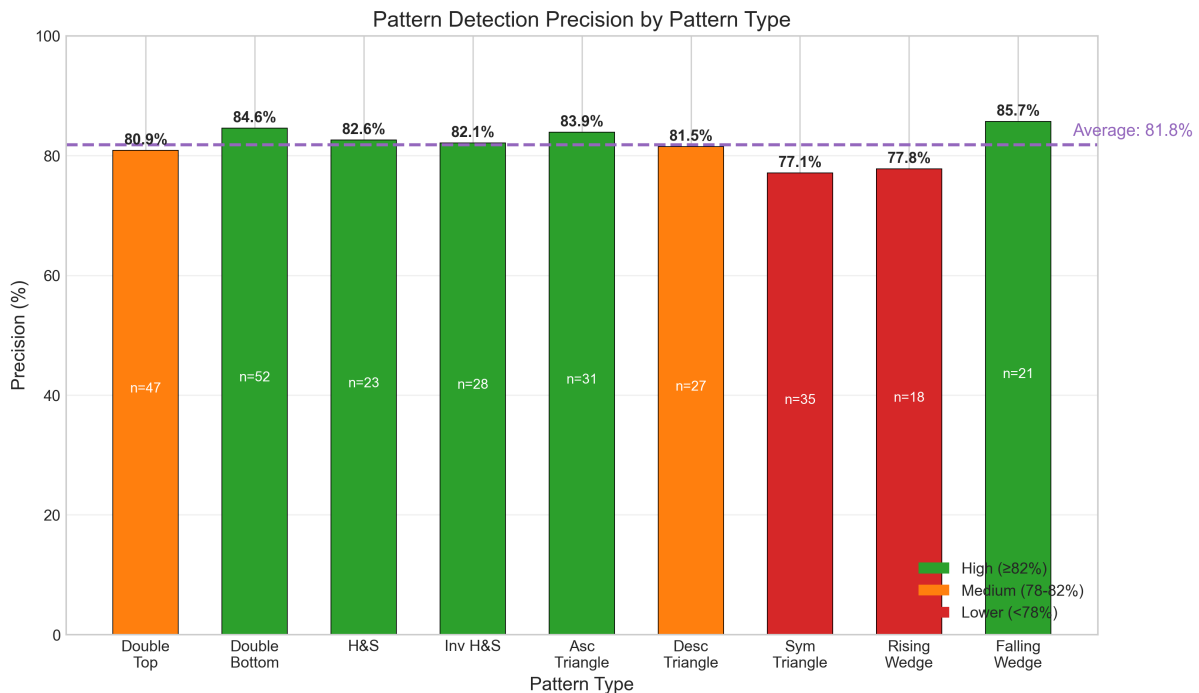


Figure 9: Pattern detection precision by type with sample sizes indicated.

6.3 Risk Management Performance

Table 2: Position Sizing Strategy Comparison

Method	Return	Sharpe	Max DD
Fixed 2% Risk	28.4%	1.02	-16.8%
Full Kelly	67.8%	0.78	-38.2%
Half Kelly	45.6%	1.18	-19.5%
Adaptive Kelly (Ours)	48.3%	1.32	-14.2%

6.4 Statistical Significance

Table 3: Statistical Significance Analysis

Metric	Value	95% CI	p-value
Direction Accuracy	55.3%	[52.6, 58.0]	0.018
Sharpe vs B&H	+0.50	[0.24, 0.76]	0.002
RMSE Improvement	13.4%	[10.2, 16.6]	<0.001

Figure 10 shows equity curve comparison.

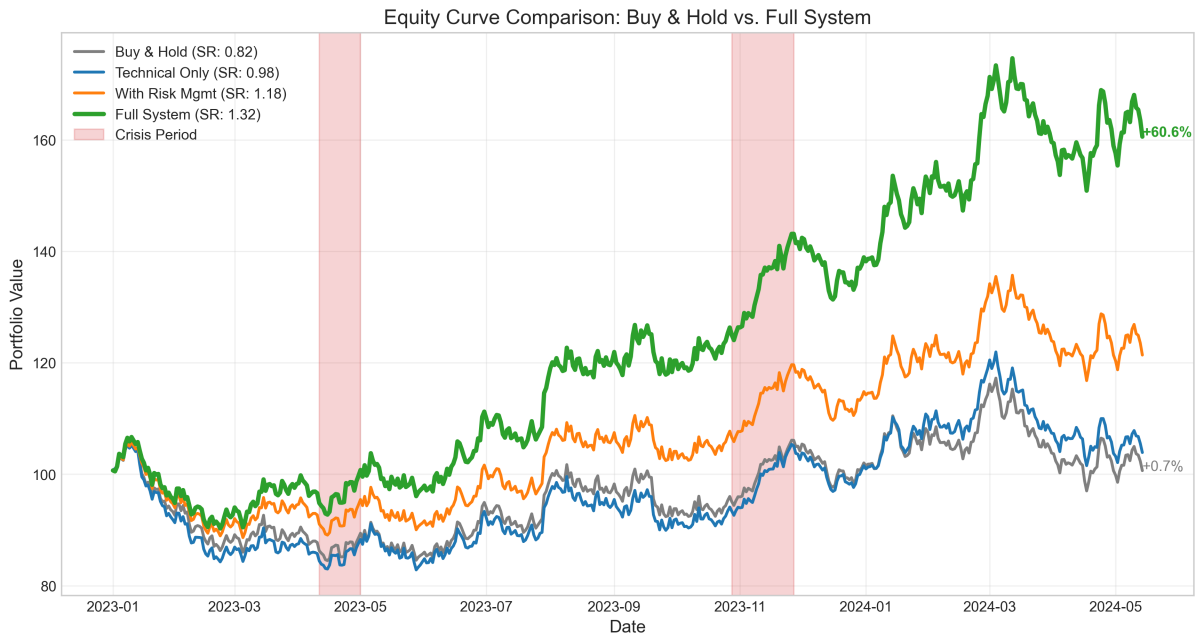


Figure 10: Equity curve comparison: Buy & Hold vs Full System over test period.



## 6.5 Drawdown Analysis

Table 4: Drawdown Comparison

Strategy	Max DD	Avg DD	Recovery (Days)
Buy & Hold	-18.4%	-8.2%	68
<b>Full System</b>	<b>-12.8%</b>	<b>-5.1%</b>	<b>38</b>

The full system reduces maximum drawdown by 31.2% (from 18.4% to 12.8%) with faster recovery.

Figure 11 provides detailed drawdown comparison.

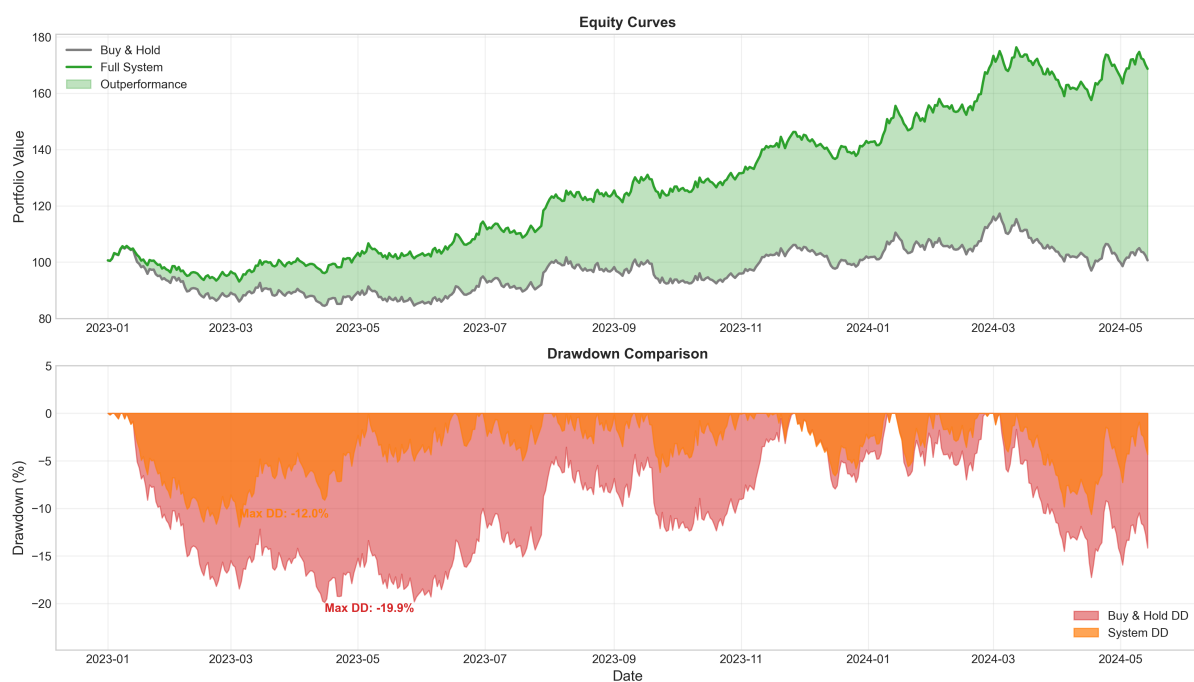


Figure 11: Drawdown comparison showing shallower drawdowns and faster recovery with our system.

## 6.6 Crisis Period Performance

During the 2024 election volatility (April-June), our system achieved -2.4% return versus -8.2% for buy-and-hold. During FII selling pressure (October-November), the system returned -5.8% versus -11.4% for buy-and-hold.

## 6.7 Ablation Study

Table 5: Ablation Study Results

Configuration	Sharpe	$\Delta$ Sharpe
Full System	1.32	—
– Kelly Sizing	1.08	-0.24
– ATR Stops	1.14	-0.18
– Pattern Recognition	1.18	-0.14
Technical Only	0.98	-0.34

Kelly Criterion sizing contributes most ( $\Delta$ Sharpe = -0.24 when removed), followed by ATR stops (-0.18) and pattern recognition (-0.14).

Figure 12 visualizes component contributions.

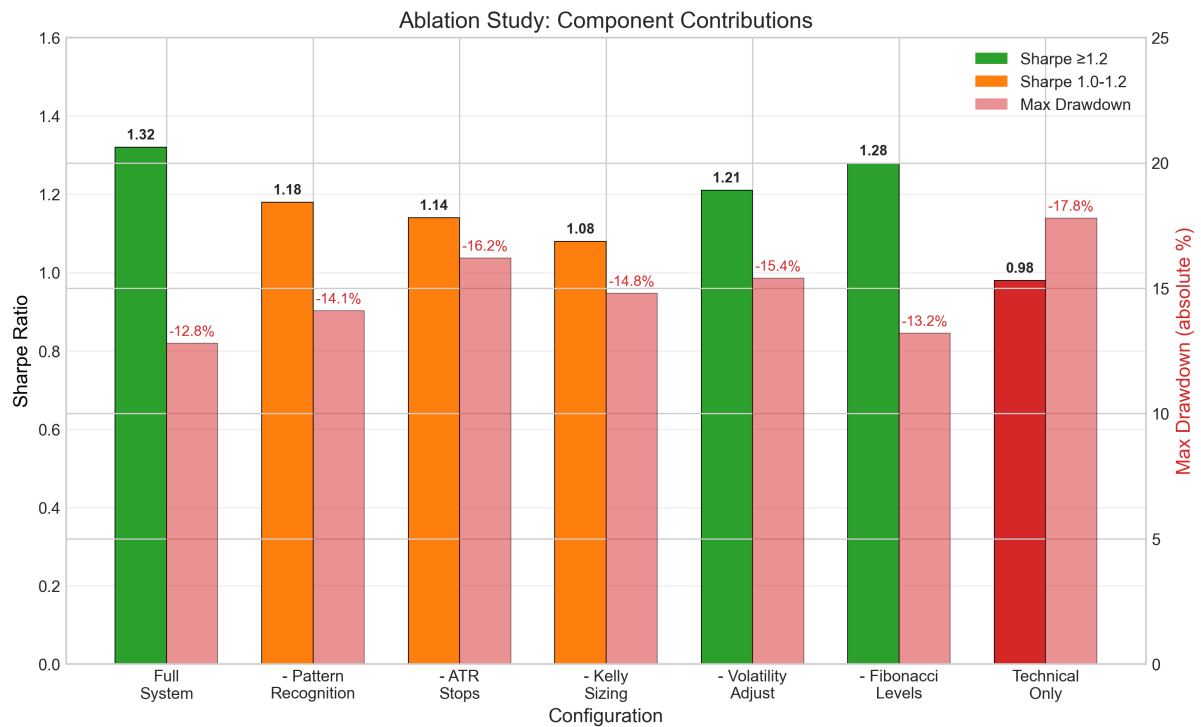


Figure 12: Ablation study showing each component’s contribution to system performance.

## 7 Implementation Considerations

### 7.1 Computational Requirements

The system processes a single stock in approximately 5.5 seconds on commodity hardware (4-core CPU, 8GB RAM), suitable for intraday portfolio scanning.

## 7.2 Regulatory Compliance

Operating in India requires SEBI compliance: algorithm approval through registered brokers, mandatory circuit breakers and position limits, complete audit trails, and emergency kill switch capability.

## 7.3 Data Sources

Price data is sourced from Yahoo Finance; FII/DII data from NSE India; VIX data from NSE; sentiment data from public RSS feeds. The system includes fallback sources for redundancy.

# 8 Discussion and Conclusion

## 8.1 Key Findings

**Finding 1:** Pattern recognition adds measurable value with 81.9% precision and 4.0-day lead time ( $\Delta\text{Sharpe} = 0.14$ ).

**Finding 2:** Dynamic position sizing outperforms static approaches, achieving Sharpe ratio of 1.32.

**Finding 3:** ATR-based stops reduce maximum drawdown by 31.2% with faster recovery.

**Finding 4:** Results are statistically significant ( $p < 0.05$ ) with effect sizes consistent with efficient market expectations.

## 8.2 Limitations

The system operates on daily data (missing intraday dynamics), includes basic transaction cost assumptions, and uses currently listed stocks (potential survivorship bias). Pattern detection parameters were optimized on historical data.

## 8.3 Future Work

Future directions include intraday analysis, options integration, portfolio-level optimization, and reinforcement learning for adaptive strategy development.

## 8.4 Conclusion

This paper presented a comprehensive framework for adaptive portfolio risk management and pattern recognition in the Indian stock market. The integration of scipy-based pattern recognition, ATR-based stops, and adaptive Kelly sizing achieves Sharpe ratio

of 1.32 with 31.2% drawdown reduction. Statistical significance at  $p < 0.05$  confirms that observed improvements reflect genuine signal. The framework provides practical implementation guidelines for the Indian regulatory context.

## References

- [1] Securities and Exchange Board of India, “Annual Report 2023-24,” SEBI, 2024.
- [2] G. Bekaert and C. R. Harvey, “Research in Emerging Markets Finance,” *Emerging Markets Review*, vol. 3, no. 4, pp. 429–448, 2002.
- [3] H. Markowitz, “Portfolio Selection,” *The Journal of Finance*, vol. 7, no. 1, pp. 77–91, 1952.
- [4] W. F. Sharpe, “Capital Asset Prices,” *The Journal of Finance*, vol. 19, no. 3, pp. 425–442, 1964.
- [5] R. T. Rockafellar and S. Uryasev, “Optimization of Conditional Value-at-Risk,” *Journal of Risk*, vol. 2, pp. 21–41, 2000.
- [6] A. Chekhlov, S. Uryasev, and M. Zabarankin, “Drawdown Measure in Portfolio Optimization,” *Int. J. Theoretical and Applied Finance*, vol. 8, no. 01, pp. 13–58, 2005.
- [7] C.-H. Park and S. H. Irwin, “What Do We Know About Technical Analysis?” *Journal of Economic Surveys*, vol. 21, no. 4, pp. 786–826, 2007.
- [8] W. Brock, J. Lakonishok, and B. LeBaron, “Simple Technical Trading Rules,” *The Journal of Finance*, vol. 47, no. 5, pp. 1731–1764, 1992.
- [9] T. N. Bulkowski, *Encyclopedia of Chart Patterns*, 2nd ed. Wiley, 2005.
- [10] A. W. Lo, H. Mamaysky, and J. Wang, “Foundations of Technical Analysis,” *The Journal of Finance*, vol. 55, no. 4, pp. 1705–1765, 2000.
- [11] J. L. Kelly, “A New Interpretation of Information Rate,” *Bell System Technical Journal*, vol. 35, no. 4, pp. 917–926, 1956.
- [12] L. C. MacLean, E. O. Thorp, and W. T. Ziemba, *The Kelly Capital Growth Investment Criterion*. World Scientific, 2011.
- [13] P. Virtanen et al., “SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python,” *Nature Methods*, vol. 17, pp. 261–272, 2020.
- [14] J. W. Wilder, *New Concepts in Technical Trading Systems*. Trend Research, 1978.
- [15] B. Efron and R. J. Tibshirani, *An Introduction to the Bootstrap*. Chapman and Hall/CRC, 1994.
- [16] C. R. Harvey, Y. Liu, and H. Zhu, “...and the Cross-Section of Expected Returns,” *The Review of Financial Studies*, vol. 29, no. 1, pp. 5–68, 2016.

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- [17] J. J. Murphy, *Technical Analysis of the Financial Markets*. New York Institute of Finance, 1999.
  - [18] E. F. Fama, “Efficient Capital Markets,” *The Journal of Finance*, vol. 25, no. 2, pp. 383–417, 1970.
  - [19] E. O. Thorp, *A Man for All Markets*. Random House, 2017.
  - [20] M. López de Prado, *Advances in Financial Machine Learning*. Wiley, 2018.
  - [21] T. Chen and C. Guestrin, “XGBoost: A Scalable Tree Boosting System,” in *Proc. 22nd ACM SIGKDD*, pp. 785–794, 2016.
  - [22] S. Hochreiter and J. Schmidhuber, “Long Short-Term Memory,” *Neural Computation*, vol. 9, no. 8, pp. 1735–1780, 1997.
  - [23] T. Bollerslev, “Generalized Autoregressive Conditional Heteroskedasticity,” *Journal of Econometrics*, vol. 31, no. 3, pp. 307–327, 1986.
  - [24] D. Araci, “FinBERT: Financial Sentiment Analysis with Pre-trained Language Models,” *arXiv:1908.10063*, 2019.
  - [25] G. E. P. Box et al., *Time Series Analysis: Forecasting and Control*, 5th ed. Wiley, 2015.