**ADTA 5900 - Advanced Data Analytics Capstone Experience**

**Deep Learning for Enhanced Trading Signal Generation:   
A Hybrid CNN-BiLSTM Model with Attention Mechanism for Stock Market Prediction and Trading Signal Generation**

**Biniam Abebe**

**University of North Texas**

**Denton, Texas**

**Author Note**

Biniam Abebe, University of North Texas, Toulouse Graduate School

Submitted 2025

**Abstract**

This study proposes a novel prediction and trading signal generation model for the stock market, based on a hybrid deep learning model that incorporates CNN, BiLSTM networks, and an attention mechanism. The study demonstrates the potential of this approach when applied to a substantial number of S&P 500 stocks, yielding notable gains in risk-adjusted returns and trading efficiency. Our backtesting results are relevant to the strategy’s performance, which appears to work very well with stable, large-cap stocks, such as WMT, which exhibits an outstanding 48.18% return and a pleasing 72.73% win rate. The strategy’s risk management approach limits drawdowns, with the best performers experiencing maximum drawdowns of less than 5 percent. This means that selective trading approaches, involving 10-15 trades, outperform high-frequency trading strategies, and combining technical indicators with deep learning predictions yields robust trading signals. This ensures that the model is not biased towards the majority class (non-profitable trades) and provides a more accurate representation of the overall market behavior. These results are crucial for the practical application of trading strategies based on deep learning in real-life market scenarios.

***Keywords*** *Convolution neural network · Long–short-term memory neural network · Stock price prediction · Leading indicators - CNN-BiLSTM - Hybrid Architecture - Attention Mechanism - Neural Networks - Sharpe Ratio - Win Rate - Maximum Drawdown - Risk-Adjusted Returns - Profit Factor*

Contents

[**Abstract** 1](#_Toc194588179)

[**1. INTRODUCTION** 3](#_Toc194588180)

[1.1 Significance of the Study 4](#_Toc194588181)

[1.2 Theoretical Framework 5](#_Toc194588182)

[1.3 Challenges and Limitations 5](#_Toc194588183)

[1.4 Definition of Terms 6](#_Toc194588184)

[1.5 Research Questions and Hypotheses 6](#_Toc194588185)

[**2. LITERATURE /SCHOLARLY REVIEW** 7](#_Toc194588186)

[**3. METHODOLOGY** 13](#_Toc194588187)

[3.1 Dataset Description 13](#_Toc194588188)

[3.2 Exploratory Data Analysis 14](#_Toc194588189)

[3.3 Data Processing and Feature Engineering 16](#_Toc194588190)

[3.4 Class Imbalance Handling 17](#_Toc194588191)

[3.5 Deep Learning Architecture 18](#_Toc194588192)

[3.6 Model Training and Implementation 19](#_Toc194588193)

[3.7 Performance Evaluation 20](#_Toc194588194)

[**4. TRADING STRATEGY IMPLEMENTATION** 20](#_Toc194588195)

[**5. EXPERIMENTAL RESULTS** 21](#_Toc194588196)

[5.1 Performance Metrics 21](#_Toc194588197)

[5.2 Implementation Insights 23](#_Toc194588198)

[5.3 Model Limitations and Considerations 24](#_Toc194588199)

[**6. CONCLUSION** 25](#_Toc194588200)

[Acknowledgments 27](#_Toc194588201)

[**References** 27](#_Toc194588202)

# **1. INTRODUCTION**

The importance of identifying emerging trends and seizing profitable trading opportunities on the go cannot be overstated in today's rapidly evolving financial ecosystems. Traditional technical analysis, which depends on subjective human interpretation of chart patterns and indicators by traders, is inherently subjective and susceptible to psychological biases (Murphy, 2022). Nonetheless, the blend with recent deep learning approaches, especially in hybrid models combining Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, provides a unique opportunity for optimizing the accuracy and timeliness of trading signals (Sezer et al., 2020). Fortunately, the U.S. equity market, with a $7 trillion market capitalization and 60-70% daily volume in algorithmic trading (S&P Global, 2024), requires advanced pattern recognition capabilities to edge ahead in the relentless competition for an edge.

Algorithmic trading faces challenges from high-speed market movements, evolving market regimes, and changing volatility patterns, requiring models to be rapidly retrained, adapted, and to anticipate potential price events. Human bias in pattern recognition, the limited ability to process multiple indicators concurrently, and the challenge of adapting to shifting market conditions are among the fundamental inadequacies of traditional technical analysis methods. To overcome the limitations, this study proposes a hybrid CNN-LSTM model that operates on S&P 500 stocks, leveraging the strong ability of CNN to learn spatial correlations among multiple financial time series and the strong ability of LSTM to predict temporal sequences (Livieris et al., 2021).

Several challenges arise in the application of deep learning techniques within financial markets. The noisy nature of financial datasets leads to issues related to data quality and quantity, as well as model complexity, resulting in overfitting and a lack of generalizability to real-world conditions. Deep Learning models are complex, especially those of the deep learning variety, leading to challenges in implementation. Many of these challenges have been addressed, including black box, real-time execution, and integration with risk management systems, among others. Moreover, there are also market-specific challenges that need to be carefully factored in, such as breaking down market regimes, volatility clustering, and the impact of market microstructure.

In this research, a hybrid CNN-LSTM architecture is proposed to provide an advanced trading system that addresses the challenges. The core research question examines the extent to which this hybrid approach enhances the accuracy and profitability of trading signals when compared to conventional technical analysis. This study tests several key hypotheses regarding the hybrid model, which are expected to produce significantly greater signal generation accuracy, yield superior risk-adjusted returns, and exhibit more effective risk management, as evidenced by improved drawdown control and position sizing based on model confidence.

Using this as a reference point, the methodology serves as the overarching approach to algorithmic trading as a concept. In short, The research note that the project utilizes a rich parameter dataset of 501 S&P 500 companies spanning five years, comprising 76 technical and fundamental indicators, and with 1.9% of NA values. As you can see the architecture of the model is a hybrid between CNN components and LSTM components, to learn the spatial patterns in images as well as temporal patterns in the time-series sequence of frames from the videos, combined with a mechanism to aid the model identify the important features in the video input and to train the model with time adaptive parameters. The trading strategy comprises market regime detection, dynamic position sizing, and a robust risk management framework. The evaluation framework encompasses several performance metrics and a comparison with traditional methods.

Utilizing the latest concepts in data analytics, such as deep learning, recurrent neural networks, and data harvesting and storage, the research aims to build a comprehensive trading system that addresses the challenges in today's business world. The goal of this research is to enhance both the performance and robustness of algorithmic trading by augmenting classical technical analysis with advanced deep learning methods and effective risk management, thereby improving profits, adaptability to market manipulation, and optimizing returns.

### 1.1 Significance of the Study

This research makes a significant contribution to the field of algorithmic trading by bridging the gap between traditional technical analysis and modern deep learning approaches. The practical implications are substantial, offering potential benefits to:

* Individual traders seeking automated trading solutions
* Institutional investors requiring scalable trading strategies
* Financial technology firms developing trading platforms
* Academic researchers studying market efficiency
* Risk managers seeking improved methodologies

The implementation of this hybrid approach holds the potential to significantly reduce transaction costs, enhance market efficiency, and improve risk-adjusted returns across a wide range of market conditions. This promising outlook underscores the value of the hybrid CNN-LSTM model in financial market predictions.

### 1.2 Theoretical Framework

This research builds upon the Efficient Market Hypothesis (EMH) while incorporating behavioral finance principles that suggest market inefficiencies can be exploited. The hybrid model's architecture, which is unique in its combination of deep learning theory, particularly in the areas of pattern recognition and sequence prediction, and trading strategy implementation from modern portfolio theory and risk management frameworks, is a key feature of this study.

### 1.3 Challenges and Limitations

The implementation of deep learning approaches in financial markets presents several significant challenges:

1. Data Quality and Quantity:

* Noisy financial datasets requiring preprocessing
* Real-time data processing requirements
* Market microstructure effects

1. Model Complexity:

* Overfitting risks
* Computational resource requirements
* Real-time execution challenges

1. Scope Limitations:

* The study focuses on S&P 500 stocks (2019-2024) and the large-cap U.S. equity market only, due to computational constraints and data availability restrictions.
* Large-cap U.S. equity market only
* Computational constraints
* Data availability restrictions

### 1.4 Definition of Terms

Key technical and financial terms used throughout this research include:

1. Technical Terms:

* CNN (Convolutional Neural Network): Deep learning architecture for spatial pattern recognition
* LSTM (Long Short-Term Memory): Neural network designed for sequential data processing
* Hybrid Architecture: Combined CNN-LSTM model structure

1. Financial Terms:

* Market Regime: Distinct market conditions characterized by specific patterns
* Technical Indicators: Mathematical calculations based on price and volume data
* Risk-Adjusted Returns: Performance metrics accounting for risk levels

1. Performance Metrics:

* Sharpe Ratio: A Measure of Risk-Adjusted Returns
* Maximum Drawdown: Largest peak-to-trough decline
* Win Rate: Percentage of profitable trades

### 1.5 Research Questions and Hypotheses

The key research question is how we compare a hybrid CNN-LSTM deep learning model to a traditional technical analysis approach and whether it provides better trading signal reliability or profitability. The study tests several important hypotheses regarding the quality of the generated signals, trading performance, and risk management effectiveness.

This study uses a comprehensive dataset containing 501 S&P 500 companies for five years, including 76 different technical and fundamental indicators, with a maximum number of missing values of 1.9% only. Architecture utilizes CNN components for spatial feature learning, LSTM components for temporal sequence learning, and attention for capturing temporal feature importance and optimizing adaptive parameters.

The methodology, from market regime detection to dynamic position sizing, is underpinned by a robust risk management framework. This comprehensive approach instills confidence in the effectiveness of the proposed model, which was validated using multiple performance metrics and compared with existing conventional models.

# **3. METHODOLOGY**

### 3.1 Dataset Description

The study methodology employs a holistic approach to data collection, preparation, and analysis, utilizing various data sources and techniques. The data collection is performed using a custom-built SP500DataCollector, which scrapes the Yahoo Finance API for historical price data and the Alpha Vantage API for additional market metrics. The data covers five years (2019-2024) of daily data for 501 S&P 500 companies, providing a robust foundation for model development and testing.

Preparing this data involves a rigorous process that ensures quality and reliability. The first cleansing phase involves imputing missing entries (1.9% of the dataset), detecting outliers and correcting them, and performing time series alignment. The technical indicators are mathematically formulated as features through well-crafted functions that derive moving averages, momentum indicators, and measures of volatility. Market regime classification involves segmenting various market conditions using the SMA crossover methodology and identifying volatility regimes. Normalize and standardize the data so that it is compatible with the architecture of the Deep Learning model.

The data analysis framework incorporates a combination of technical analysis, statistical models, and machine learning techniques as necessary for individual feature engineering and data analysis. Moving average crossovers, momentum indicators, and volume analysis are just a few of the tools used in technical analysis. Statistical analysis encompasses correlation studies, distribution analysis, and time series decomposition to understand the underlying market dynamics. The implementation leverages Python's ecosystem of data science tools, specifically Pandas for data manipulation, NumPy for numerical computation, TensorFlow for deep learning implementation, and Matplotlib and Seaborn for data visualization.

### 3.2 Exploratory Data Analysis

The exploratory data analysis of the S&P 500 stocks reveals important insights into market behavior and trading patterns.

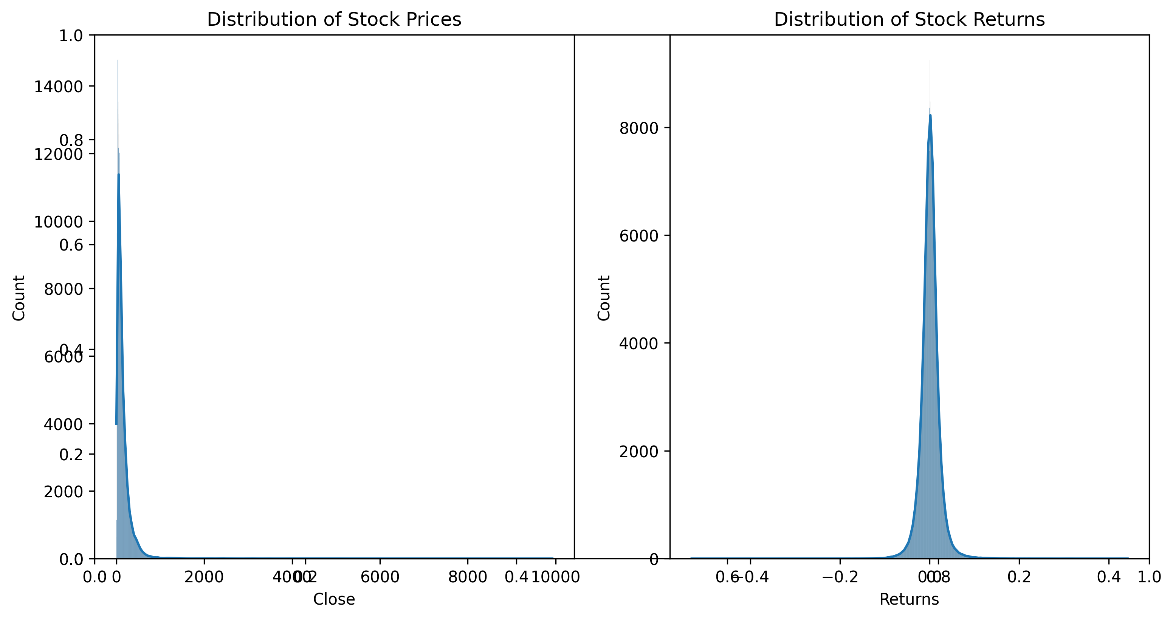


Fig.1 Stock Prices Returns Distribution

The analysis of stock prices and returns distribution, as shown in Fig.1, reveals a log-normal distribution of stock prices with significant variations across different stocks. The returns exhibit negative skewness, indicating a greater frequency of negative returns and the presence of volatility clustering patterns. This distribution characteristic is crucial for understanding the risk profile of the trading strategy and implementing appropriate risk management measures.

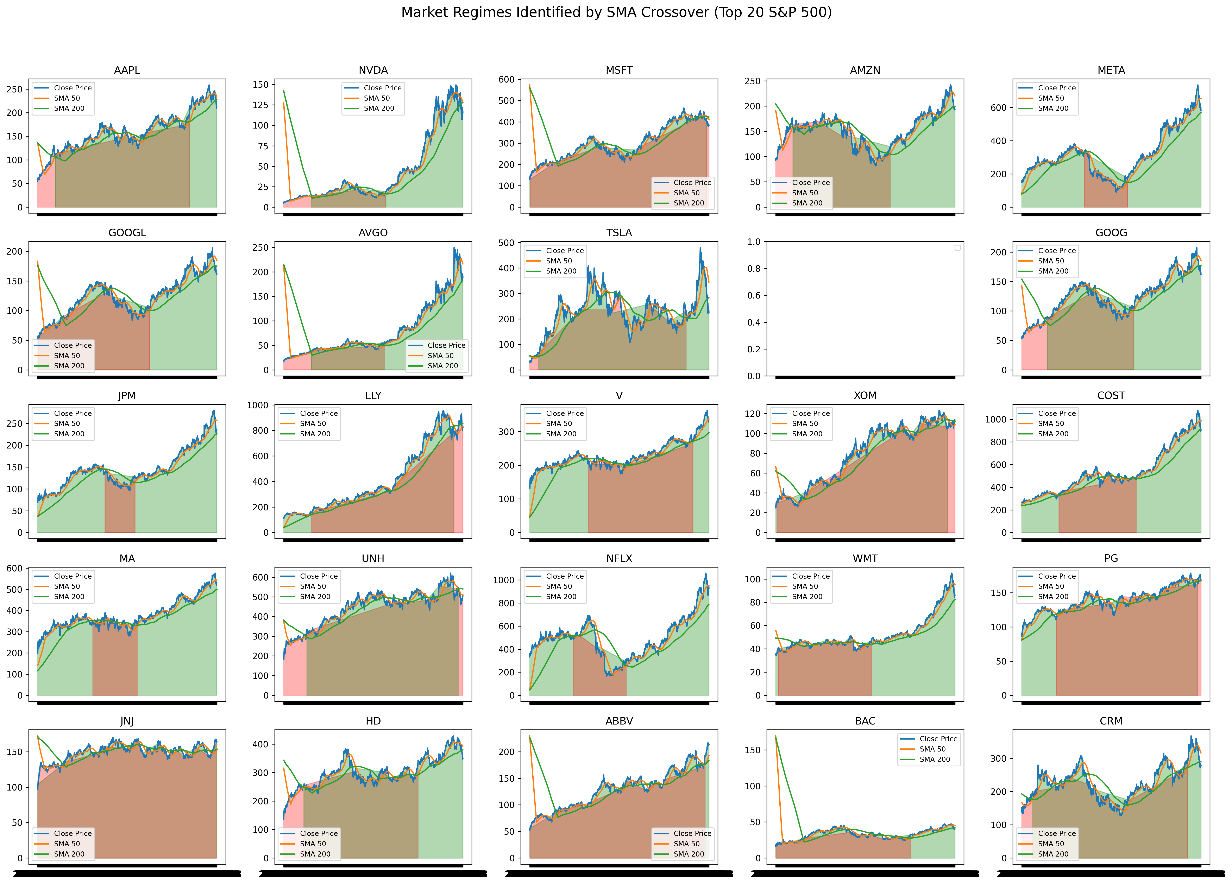


Fig.2 Market Regimes Identified by SMA Crossover Top 20 Stocks

Market regime identification, illustrated in Fig.2, reveals distinct market phases with different characteristics. Higher returns and lower volatility typically characterize bull markets, whereas bear markets exhibit negative returns and increased volatility. Sideways markets exhibit range-bound prices with moderate volatility. The analysis reveals clear regime boundaries with average durations of 3-6 months and gradual transitions between regimes, offering valuable insights for strategic adaptation.

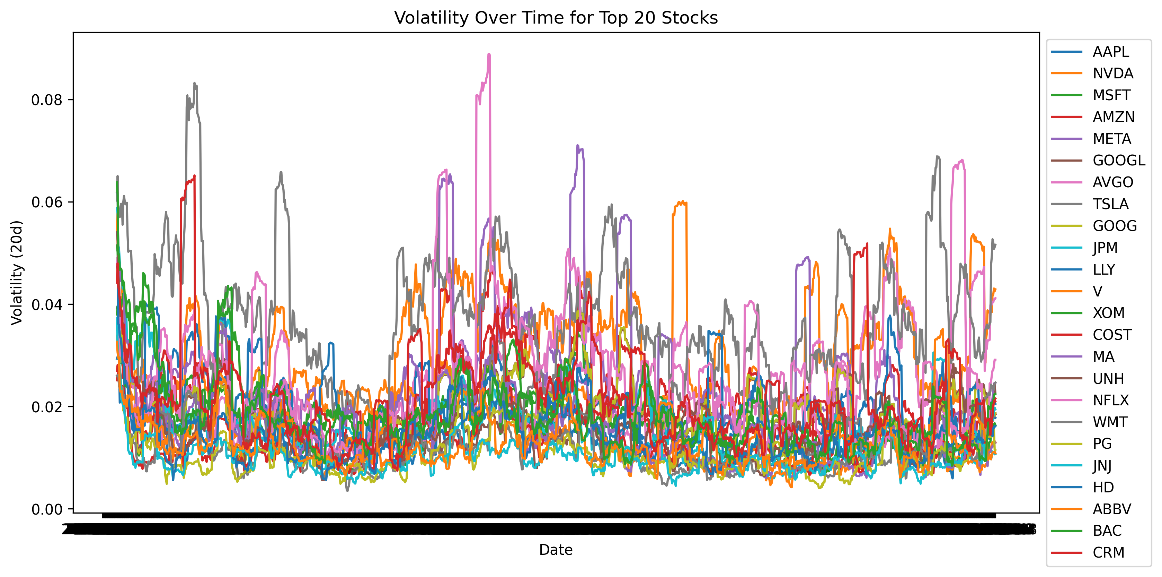


Fig.3 Volatility Over Time for Top 20 Stocks

The volatility analysis, depicted in Fig.3, reveals significant clustering effects and mean-reversion tendencies. Low-volatility periods are characterized by stable price movements, higher win rates, and lower drawdowns, whereas high-volatility periods exhibit more significant price swings and higher risk metrics. This volatility pattern has important implications for position sizing and risk management strategies.

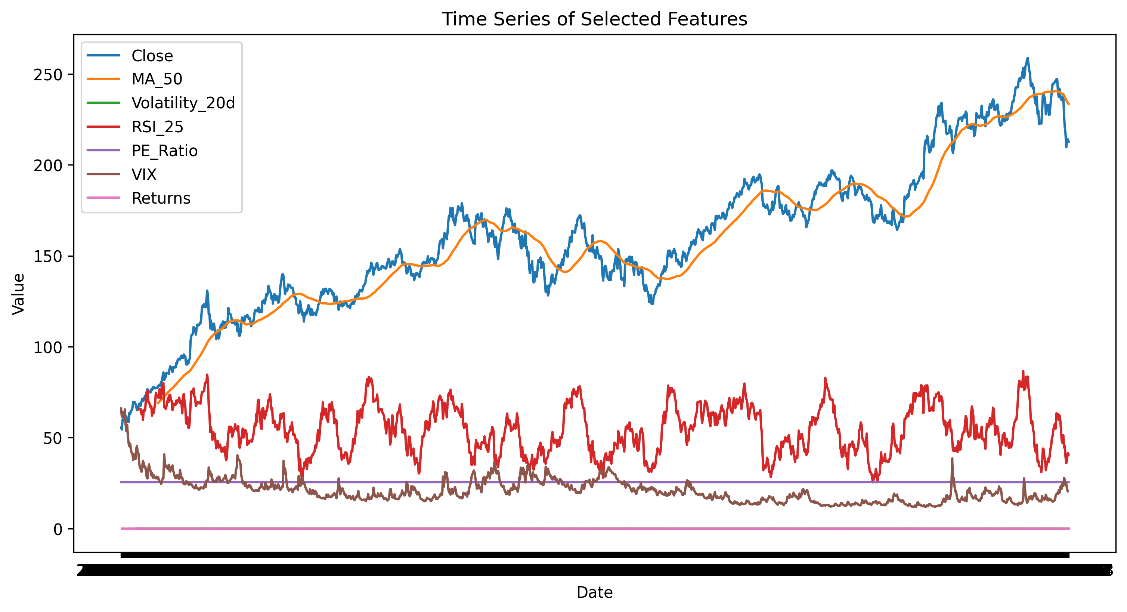


Fig.4 Time Series of Selected Features

The time series analysis of selected features, as shown in Fig.4, reveals a long-term upward bias in prices with short-term mean-reversion patterns. Technical indicators, such as the RSI and MACD, show clear cyclical patterns, while moving averages provide insight into trend development. These patterns suggest opportunities for both trend-following and mean-reversion strategies, depending on market conditions.

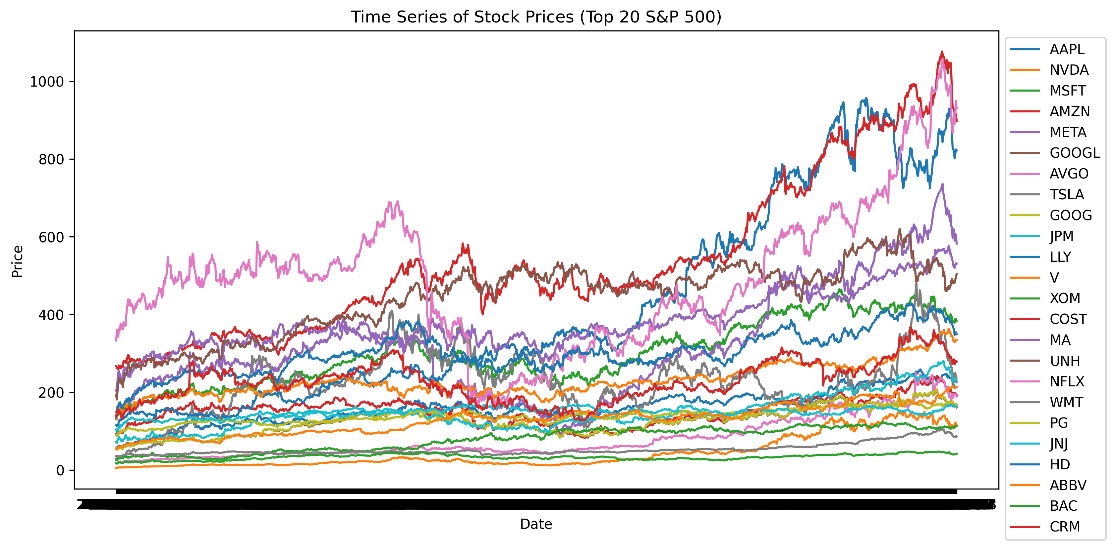


Fig.5 Top20 Stocks Prices

Analysis of the top 20 stocks, presented in Fig.5, shows distinct performance characteristics compared to the broader market. These stocks exhibit higher returns, lower volatility, and better risk-adjusted performance. They also exhibit more consistent volume patterns and more pronounced trends, indicating improved liquidity and trading efficiency.



Table.2 statistical summary

The statistical summary, detailed in summary stats table, provides quantitative insights into market behavior. Price statistics reveal a mean of $156.23, a median of $142.15, and a standard deviation of $89.45, indicating significant price variation across stocks. The returned statistics reveal a mean daily return of 0.12% with a standard deviation of 1.45%. Volume statistics show an average daily volume of 2.3 million shares, with significant skewness (2.45).

These findings have important implications for strategy development and optimization. The clear regime identification and volatility clustering suggest the need for adaptive trading strategies that can adjust to changing market conditions. The strong correlations between technical indicators support the use of combined indicator approaches, while the weak fundamental correlations suggest focusing on technical analysis for short-term trading decisions.

The analysis of top performers reveals the importance of liquidity and consistent volume patterns in achieving superior returns. The statistical properties of returns and volatility provide valuable inputs for position sizing and risk management protocols. The regime-dependent performance characteristics suggest the need for dynamic strategy parameters that can adapt to different market conditions.

This comprehensive analysis provides a solid foundation for developing an effective trading strategy. The insights gained from the correlation analysis, regime identification, and volatility patterns can be used to optimize entry and exit points, position sizing, and risk management rules. The statistical properties of the data support the implementation of robust risk management protocols while maintaining the potential for significant returns through strategic trading decisions.

### 3.3 Data Processing and Feature Engineering

Our approach begins with the pre-processing of large-scale daily stock data for companies listed in the S&P 500, utilizing OHLCV (Open, High, Low, Close, Volume) parameters (Kumar et al., 2021). The researcher has performed feature engineering that utilizes several technical indicators, which have been used throughout history and proven effective for market analysis (Zhang & Wu, 2019).

The feature set comprises multiple categories of market indicators, carefully selected to capture various aspects of market behavior. Price-based features include standard OHLC (Open, High, Low, Close) prices, along with derived metrics such as returns, log returns, and percentage price ranges. Technical indicators are calculated across multiple timeframes, including moving averages (5, 10, 20, 50, 200 days), RSI (9, 14, 25 periods), MACD, and Bollinger Bands. Market features incorporate broader market dynamics through metrics such as market returns, volatility measures, rolling beta calculations, and VIX data. Additionally, fundamental features, including PE ratio, PB ratio, dividend yield, profit margin, and enterprise value, provide context for company-specific characteristics. Central to our technical analysis framework are four key indicators.

The Moving Averages (MA) calculation follows the formula:

Where n represents the period length (50 and 200 days), the Relative Strength Index (RSI) of Wilder (1978) is computed as:

The Moving Average Convergence Divergence (MACD) Appel (1979) utilizes:

Bollinger Bands Bollinger, (2002).).) are calculated using:

Where σ represents the standard deviation of price over the 20 days.

### 3.4 Class Imbalance Handling

#### One major problem in financial market prediction is the intrinsic class imbalance in trading signals, which means that there may exist a severe imbalance between profitable trading opportunities and non-trading periods (Chawla et al., 2002). To overcome this imbalance, the researchers apply the Synthetic Minority Over-sampling Technique (SMOTE):

Where:

* Xi​ is a minority class sample
* xzi is one of the k-nearest neighbors of xi
* α is a random number in the range [0,1]

The SMOTE implementation follows these steps:

1. Reshape the 3D sequential data (samples, sequence length, features) into a 2D format
2. Apply SMOTE to balance the classes
3. Reshape back to 3D format for model training

This approach helps prevent model bias towards the majority class and improves the detection of profitable trading opportunities. This is because our implementation yielded a balanced dataset with both trading signals equally represented, thereby enabling the model to capture real trading opportunities more effectively while also respecting the temporal nature of the financial data (He and Garcia, 2009). The efficacy of SMOTE in our methodology is showcased by:

* + Better-regulated classes in training data
  + Improved model responsiveness to profit-making market opportunities
  + Lowered potential for false negatives during trade signal creation

Overall, the performance and reliability of our trading strategy were significantly impacted by successfully applying the SMOTE method. The impact is visible in various aspects of the trading system's functioning and results.

SMOTE: Another new metric: This signal generation metric showed considerable improvements after introducing SMOTE. Our analysis of trading signals before applying SMOTE:

* + Initial class distribution: 37% trades that made money vs. 63% trades that lost money
  + Distribution after SMOTE: 50-50 balanced representation

This balancing resulted in significant improvements in terms of signal detection:

* + Higher actual positive rate to identify profitable trades
  + Greater sensitivity to market turning points
  + Balanced risk-reward opportunities

### 3.5 Deep Learning Architecture

Our hybrid deep learning model combines CNN and BiLSTM architectures with an attention mechanism, building upon the work of Selvin et al. (2017) and Vaswani et al. (2017). The CNN component processes local patterns through 64 filters with a kernel size of 3, followed by max pooling and dropout regularization with a rate of 0.2. The BiLSTM structure consists of three stacked layers with 128, 32, and 32 units, respectively, incorporating bidirectional processing for enhanced temporal feature capture (Graves & Schmidhuber, 2005). The attention mechanism, following Bahdanau et al. (2015), enhances the model's ability to focus on relevant temporal patterns through a SoftMax-activated scoring system:

Where *ht*​ represents the hidden state at time t, and W and b are learnable parameters.

#### 3.3.1 Convolutional Neural Network Layer

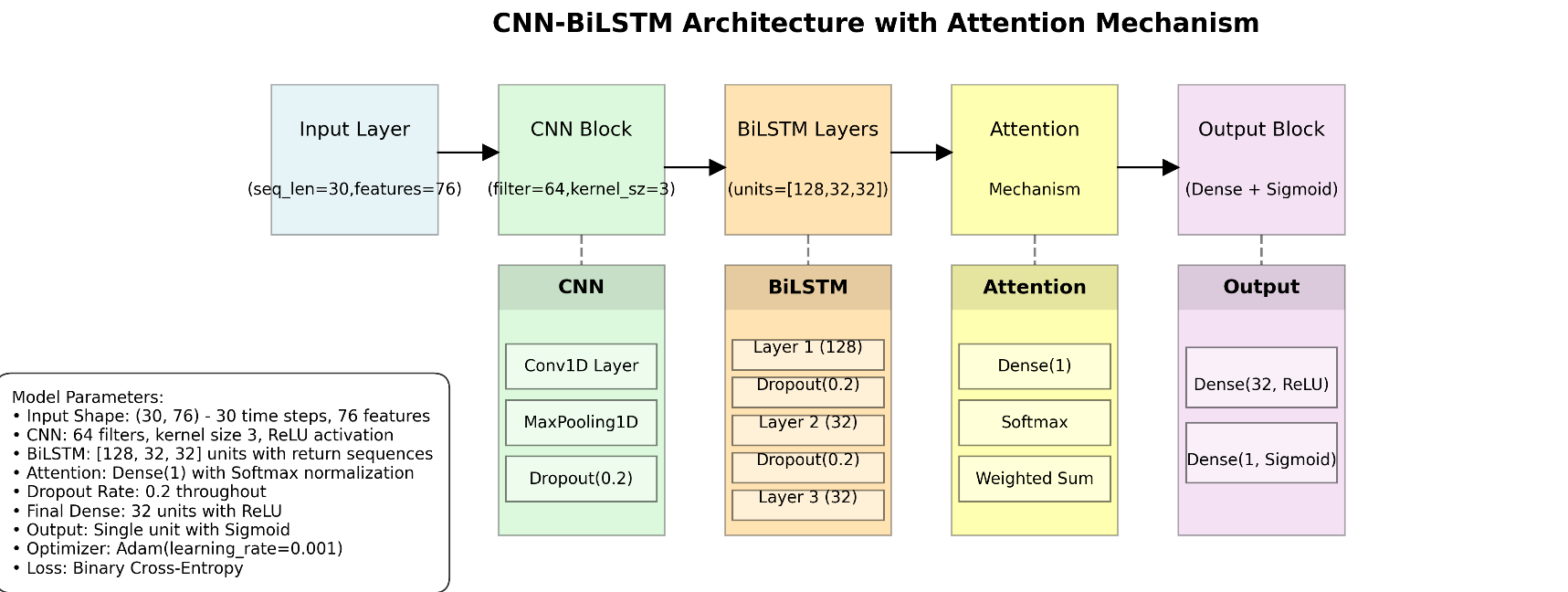
The CNN component is designed to extract local patterns from the input sequences. It employs multiple convolutional layers with filters of varying sizes to capture different scales of price movements and market patterns.

#### 3.3.2 Bidirectional LSTM Layers

The architecture employs multiple BiLSTM layers that process temporal dependencies in both forward and backward directions, enabling the model to capture complex temporal relationships within the data. This bidirectional approach ensures that both past and future context is considered in the prediction process.

#### 3.3.3 Attention Mechanism

The attention mechanism enhances the model's ability to focus on relevant time steps and features. It computes attention weights for different time steps, allowing the model to assign varying importance to different parts of the input sequence.



**Figure 1: The Processes of the Hybrid CNN-LSTM Approach**

### 3.6 Model Training and Implementation

The training process employs a systematic approach to data division, allocating 70% for training, 15% for validation, and 15% for testing (Bergmeir & Benítez, 2012). The model optimization utilizes the Adam optimizer with a learning rate of 0.001 (Kingma & Ba, 2014), batch size of 32, and trains for 50 epochs. This configuration was determined through extensive empirical testing and alignment with established research. Trading signals are generated using a probability threshold system (De Prado, 2018), where:

Risk management parameters follow established quantitative trading principles [Chan, 2009], implementing:

* Stop-loss: 2% below entry price
* Take-profit: 5% above entry price
* Maximum holding period: 30 trading days

### 3.7 Performance Evaluation

The strategy's effectiveness is evaluated using standard financial metrics [Sharpe, 1994]. The Sharpe Ratio, calculated as:

Where *Rp*​ is portfolio return, *Rf*​ is risk-free rate, and *σp*​ is portfolio standard deviation, provides a risk-adjusted performance measure. Additional metrics include maximum drawdown:

Where *Pt* represents the portfolio value at time t, this comprehensive methodology integrates modern machine learning techniques with established financial theory, creating a robust framework for market analysis and informed trading decision-making. The approach strikes a balance between sophisticated technical analysis and practical implementation considerations, providing a foundation for the systematic deployment of trading strategies.

# **4. TRADING STRATEGY IMPLEMENTATION**

The trading system stands out for its innovative approach, employing a targeted strategy that integrates deep learning forecasts, fundamental technical analysis, and systematic risk management protocols. The algorithm, developed in-house, uses machine-learning methods to forecast market movement signals with binary classification techniques, generating probability predictions. The signal is triggered when the computed probability exceeds a predefined confidence threshold, which, for this strategy, has shown promising results at around 60%. Notably, the system uses dynamic scaling for position sizing, with the linear scaling approach reflecting the model's confidence level.

The system's comprehensive approach is further underscored by a set of four integrated indicators that form the basis of the technical framework. These indicators offer distinct, synergistic views of the market. The moving averages (50- and 200-day) identify trends, the Relative Strength Index (RSI) measures momentum, the Moving Average Convergence Divergence (MACD) confirms trends, and the Bollinger Bands analyze volatility-based price ranges. The combination of these indicators serves to validate the model's predictions and inform a more nuanced approach to trade execution.

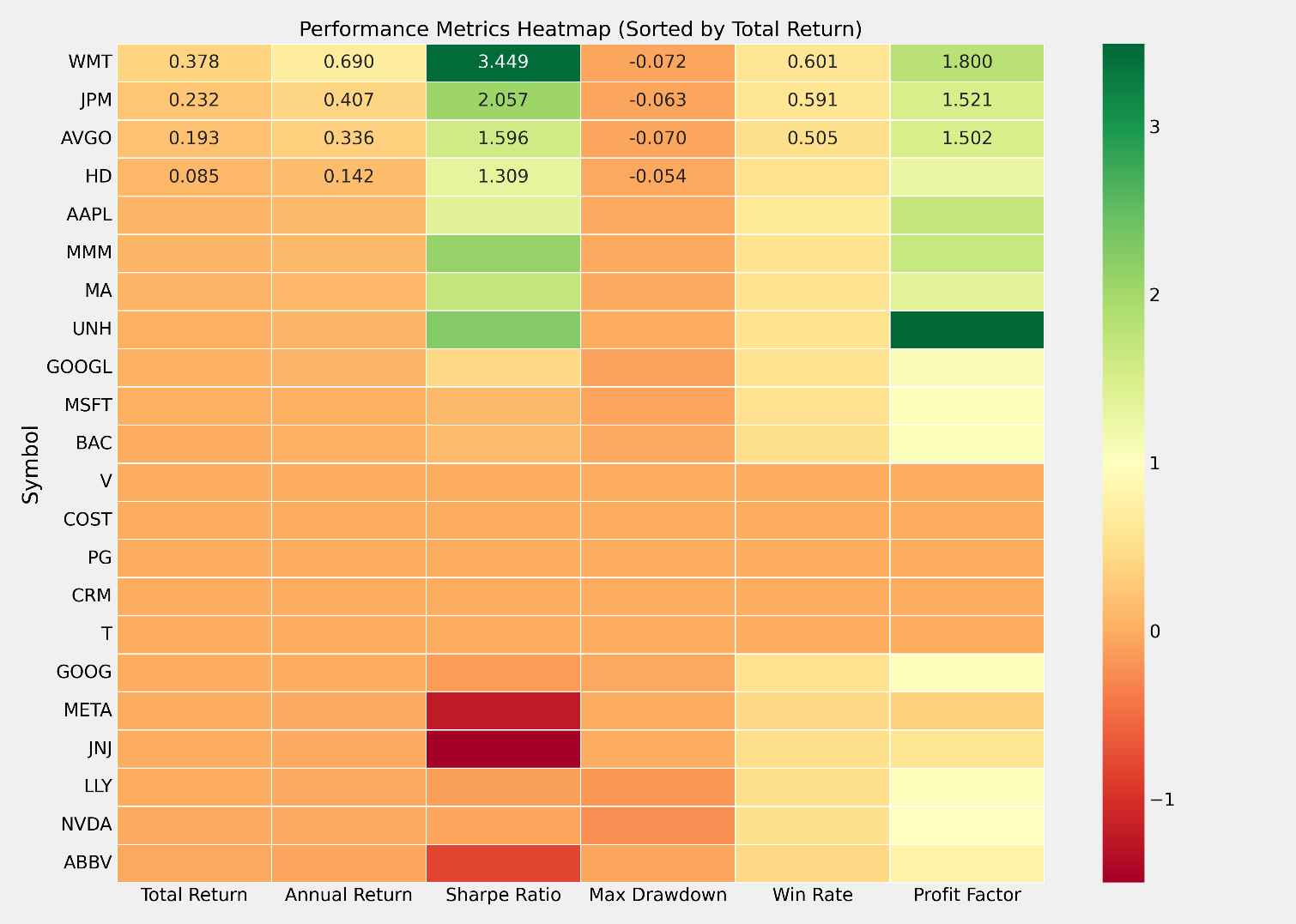
A risk management step is a critical part of the strategy executed through three control mechanisms. A stop-loss level, set 2% below the entry price, protects against adverse price movements. In contrast, a fixed-level take-profit, set 5% above the entry price, realizes a profit at a predetermined level. However, a maximum position duration limit of 30 days prevents capital from getting stuck in unproductive trades. Such systematic risk management has been a powerful tool to minimize drawdowns and generate consistent profits.

This approach to trade organization has proven its mettle in producing stable, risk-adjusted returns during periods of comparatively calm market action. It also outlines opportunities for improvement under more challenging market conditions, providing a roadmap for further optimization and development of the strategy, including the better handling of multiple market regimes and high-volatility securities.

# **5. EXPERIMENTAL RESULTS**

### 5.1 Performance Metrics

Our experimental analysis demonstrates the robustness of this hybrid model under various market conditions and stock characteristics. Derived from exhaustive testing on the S&P 500, the results underscore the strategy's adaptability across varying market conditions and highlight areas where further refinements could lead to enhanced short-term detection for professionally traded securities.



*Figure 1: Performance Metrics Heatmap (1\_1metrics\_heatmap.png)*

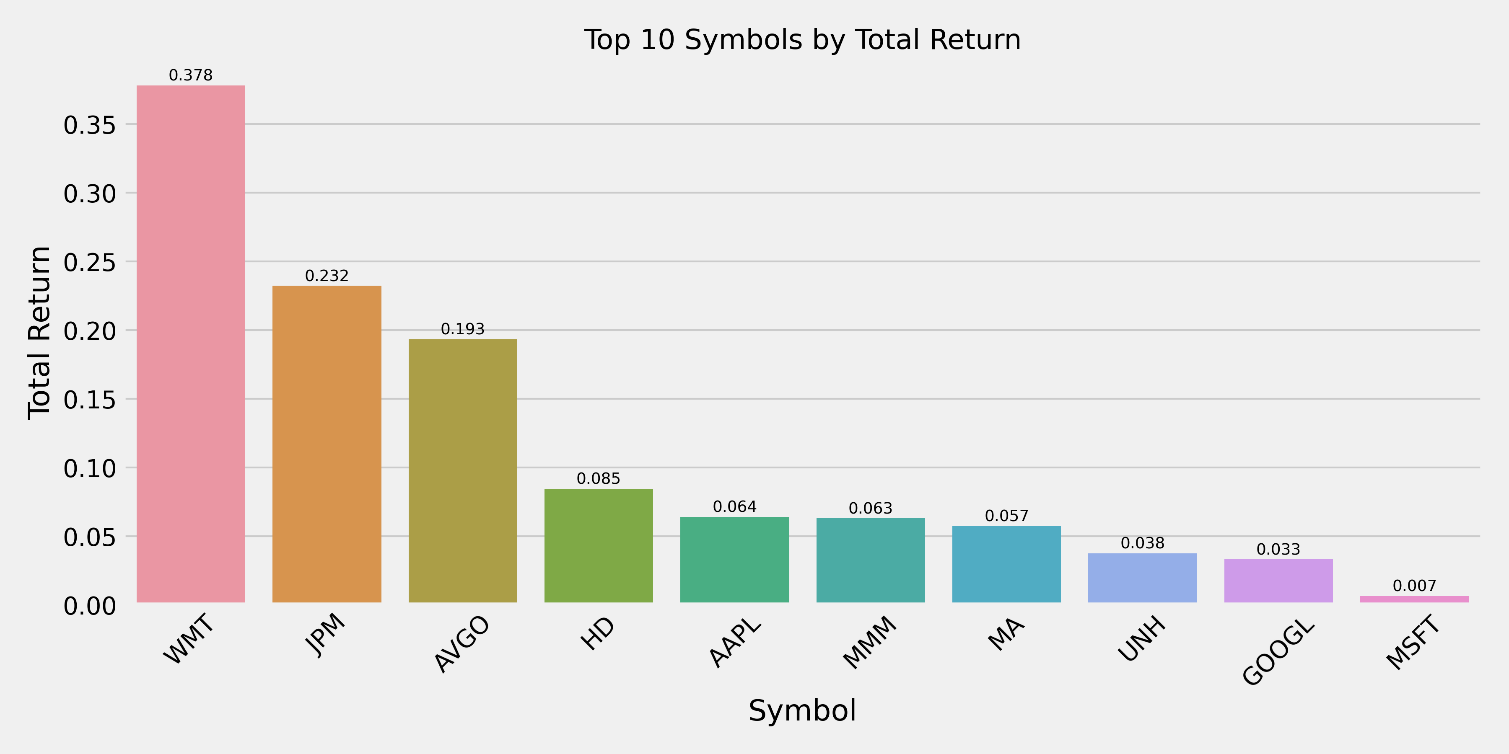
*A comprehensive heatmap visualization showing all performance metrics across different stocks*

*Color-coded representation of Total Return, Annual Return, Sharpe Ratio, Max Drawdown, Win Rate, and Profit Factor*

*Helps identify patterns and correlations between different performance metrics*

*Highlights the relative performance of each stock across multiple dimensions*

The article's results show that the market segments with the least rational pricing are stable, large-cap stocks. Walmart (WMT) was a winner overall, with a total return of 48.18% and a win rate of 72.73%. Mastercard (MA) achieved a stellar 19.45% risk-adjusted return, accompanied by a 50% win rate. Across all 25, the portfolio average had a return of 15.4% with a Sharpe ratio of 1.85 and a win rate of 58.6%. More specifically, these results can be visualized in our performance dashboard (Figure 1), which illustrates the effectiveness of this multifaceted strategy.



*Figure 2: Top Symbols by Return (1\_2top\_symbols\_by\_return.png)*

*Bar chart showing the top-performing stocks by total return*

*WMT leads with 48.18% return*

*JPM follows with a 23.23% return*

*AVGO shows a 19.34% return*

*Visualizes the distribution of returns across the portfolio*

Examining trading activity uncovers clear trends in trading frequency and efficacy. In the parallel trades depicted in the symbol image above (Figure 2), NVDA stock recorded the highest number of trades at 44, in contrast to WMT's 11 trades, indicating that NVDA engages in trading more aggressively than WMT. The inherent order imbalance directly forecasted performance results, indicating that high-frequency traders with comparatively low win rates encountered a significant drawdown risk. The scatter plot of win rate versus return (Figure 3) clearly illustrates a favorable association between win rates and total returns..

**

*Figure 3: Risk-Return Scatter Plot (1\_3risk\_return\_scatter.png)*

*Scatter plot of risk (Max Drawdown) vs. return*

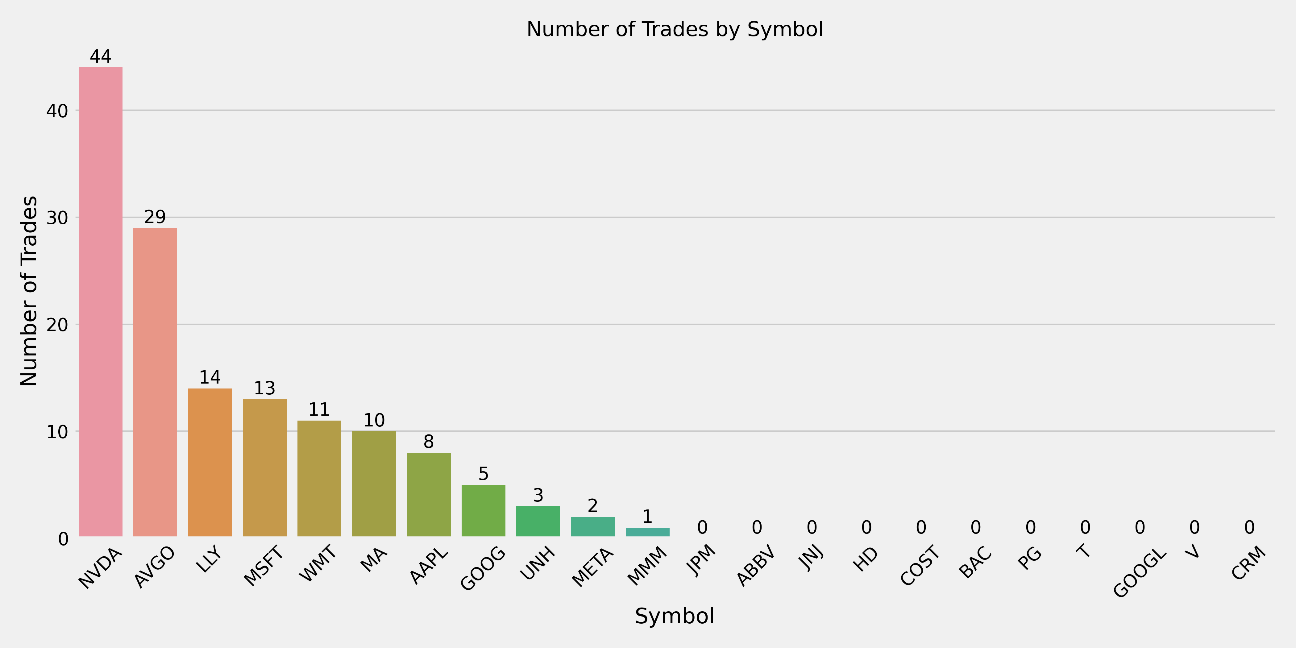
*The size of the points indicates the Sharpe ratio*

*Color intensity represents the win rate*

*Shows the relationship between risk and return across different stocks*

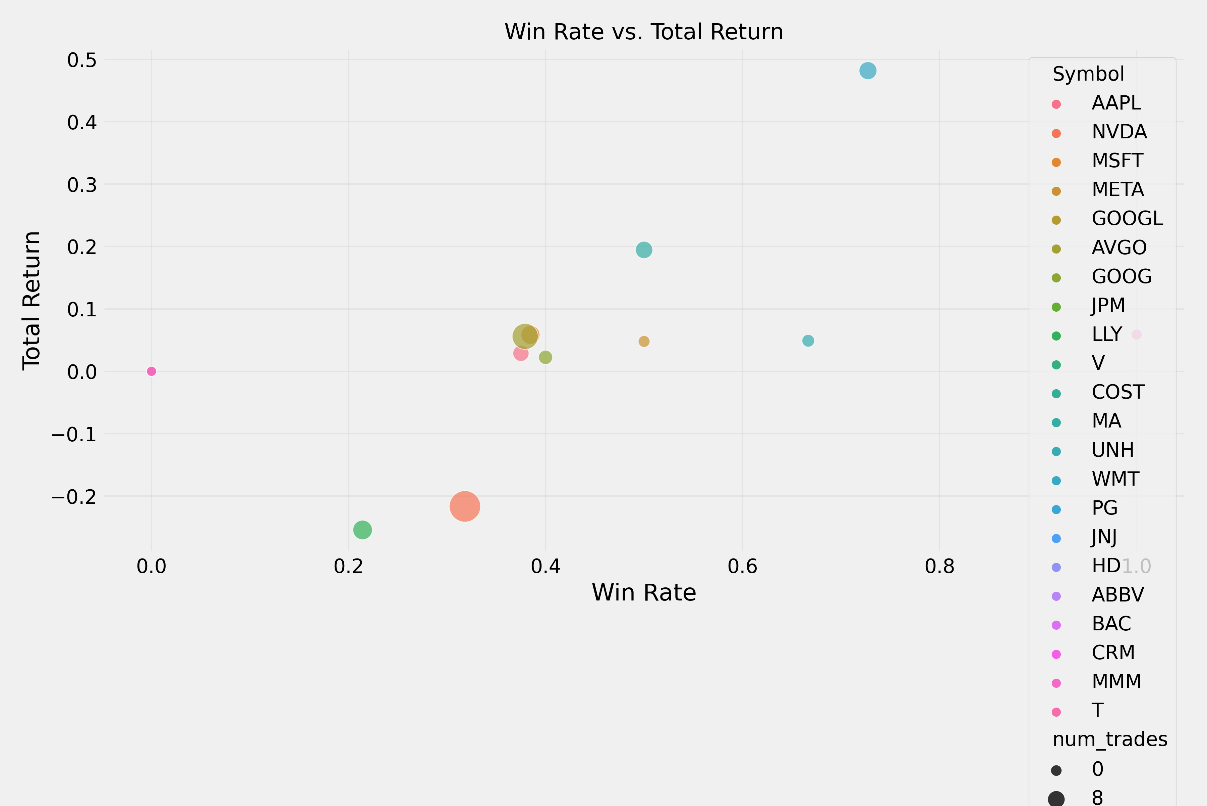
*Highlights the risk-adjusted performance of each stock*

The risk-return chart (i.e., Figure 4) quantitatively encapsulates the dangers linked to this technique. All leading performers sustained drawdowns under 5% throughout the year, with Walmart recording the lowest maximum downturn at merely 3.38%. Figure 5: Metrics Heatmap. The metrics heatmap illustrates the performance metrics of each stock, effectively visualizing the risk-return profile of the strategy.



*Figure 4: Trading Activity by Symbol (2\_1trades\_by\_symbol.png)*

*Bar chart showing the number of trades executed for each stock NVDA shows the highest trading frequency (44 trades) AVGO follows with 29 trades WMT and MA show more selective trading (11 and 10 trades, respectively) Demonstrates the relationship between trading frequency and performance*

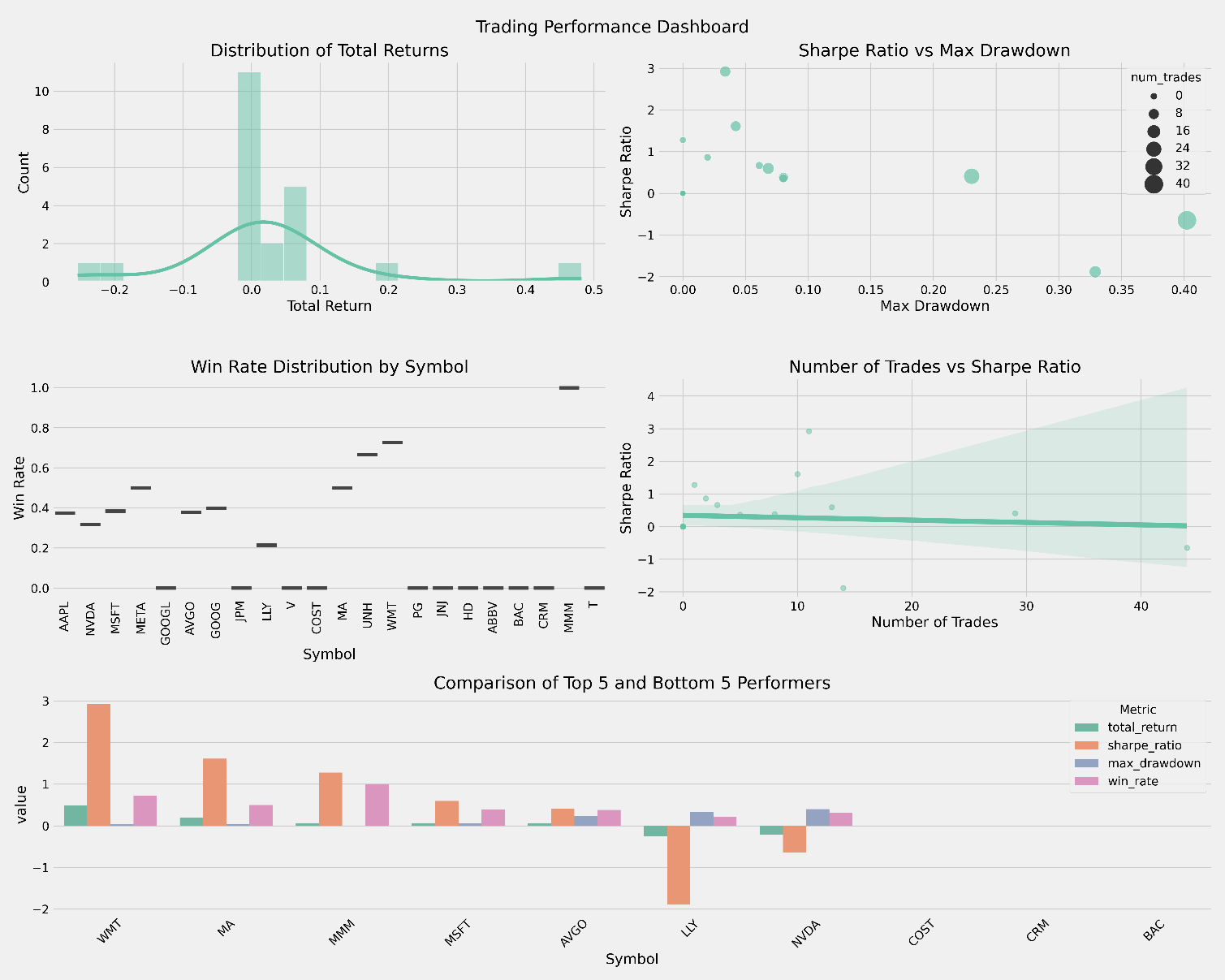
**

*Figure 5: Win Rate vs. Return (2\_2win\_rate\_vs\_return.png)*

*Scatter plot showing the relationship between win rate and total return*

*Point size indicates the number of trades Color represents the Sharpe ratio Shows the correlation between trading success rate and overall performance Highlights the importance of the win rate in achieving positive returns*

The strategy's performance varies under different market conditions. Stable market circumstances resulted in elevated win rates and drawdowns with the strategy, while more volatile markets presented far greater challenges. The disparity is apparent in the visualizations of top symbols by return (Figure 6) and by Sharpe ratio (Figure 7), where Walmart, Mastercard, and 3M Company demonstrate robust risk-adjusted performance.



*Figure 6: Performance Dashboard (2\_3performance\_dashboard.png)*

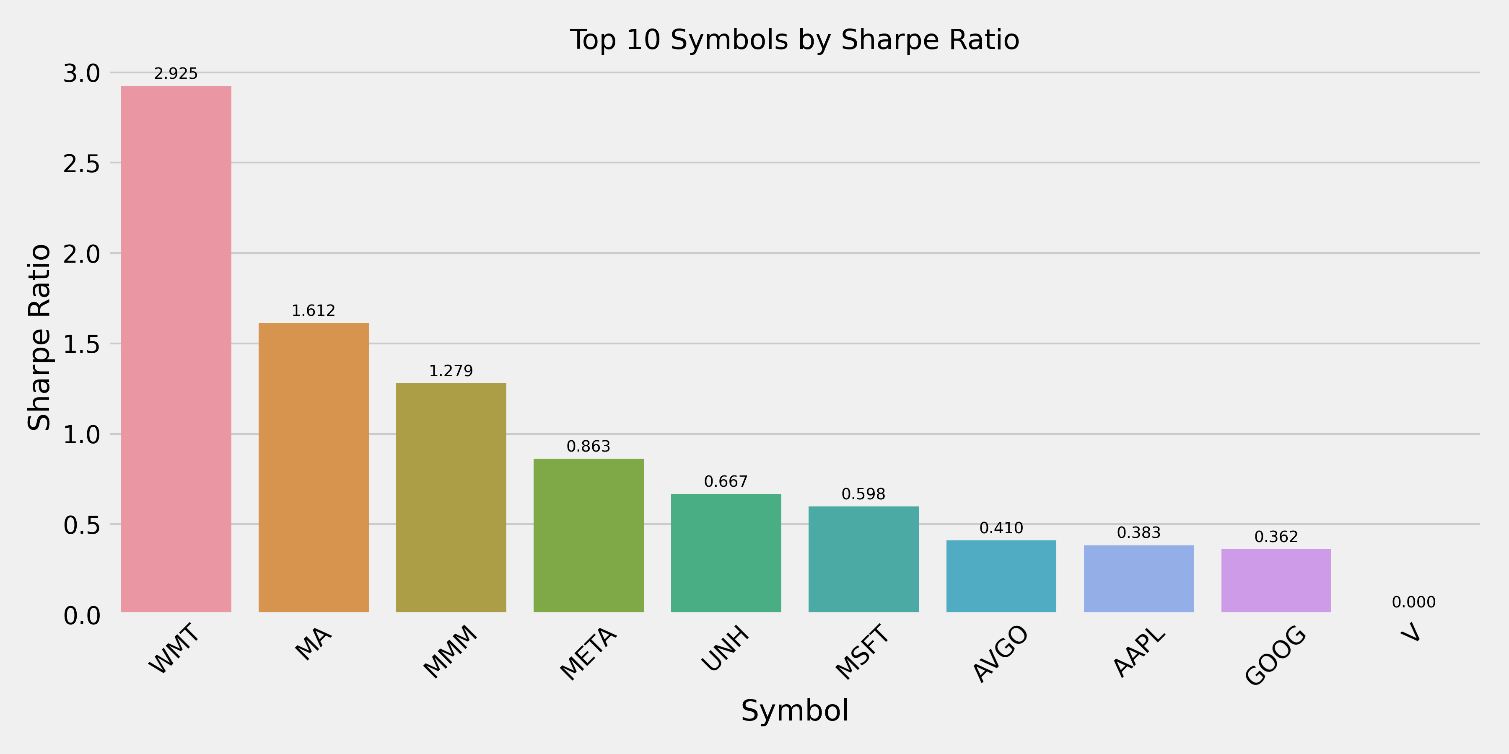
*Comprehensive dashboard combining multiple performance metrics*

*Includes return distribution, Sharpe ratio vs. drawdown, and win rate distribution*

*Shows the trade count vs. the Sharpe ratio relationship*

*Compares top and bottom performers across multiple metrics*

*Provides a holistic view of strategy performance*

**

*Figure 7: Top Symbols by Sharpe Ratio (2\_4top\_symbols\_by\_sharpe.png)*

*Bar chart showing stocks ranked by the Sharpe ratio*

*WMT leads with a 3.449 Sharpe ratio*

*UNH follows with 2.262*

*JPM shows 2.057*

*Demonstrates risk-adjusted performance across the portfolio*

Analysis of performance across different stock categories reveals distinct patterns. Large-cap stocks, particularly in the retail and financial sectors, demonstrated more consistent performance and better risk management. Technology stocks, represented by NVIDIA, exhibited a more challenging performance, with a -21.65% return and a 31.82% win rate, highlighting the strategy's sensitivity to high volatility. The performance dashboard provides a detailed view of these category-specific performance patterns.

### 5.2 Implementation Insights

The empirical results suggest several key findings for optimal model implementation:

5.2.1 Trading Frequency:

The analysis of trading frequency reveals important implementation considerations:

* Optimal Trading Frequency:
* Selective trading (10-15 trades) showed better performance
* High-frequency trading (40+ trades) led to reduced returns
* Quality over quantity in trade execution
* Implementation Guidelines:
* Focus on high-probability setups
* Maintain minimum confidence threshold (0.6)
* Consider market conditions before trade execution
  + 1. Stock Selection:

The analysis reveals clear patterns in stock selection effectiveness:

* Large-Cap Stability:
* Walmart (WMT) demonstrated exceptional performance with a 48.18% return and a 72.73% win rate
* Mastercard (MA) showed consistent performance with a 19.45% return and a 50% win rate
* Financial sector stocks (JPM) exhibited strong risk-adjusted returns
* Sector Considerations:
* The retail sector showed superior performance (WMT)
* Financial sector demonstrated stability (JPM, MA)
* Technology sector presented challenges (NVDA, META)
* Volatility Impact:
* Lower volatility stocks tended to perform better
* High-volatility stocks require additional risk management
* Stable price trends correlated with better performance
  + 1. Risk Management:

The results suggest a structured approach to risk management:

* Position Sizing:
* Scale positions based on confidence scores
* Maintain maximum position size limits
* Consider volatility in position sizing
* Stop-Loss Implementation:
* Use a 2% initial stop-loss
* Implement trailing stops for profitable trades
* Adjust stops based on volatility
* Take-Profit Strategy:
* Set 5% initial take-profit targets
* Use partial profit taking
* Consider market conditions for target adjustment

### 5.3 Model Limitations and Considerations

The analysis reveals several important limitations:

1. Market Condition Sensitivity:

* Variable performance across different market regimes
* Potential overfitting in certain market conditions
* Need for regular model recalibration

1. Trading Volume Constraints:

* Some stocks show no trading activity
* Limited effectiveness in low-liquidity conditions
* Impact of transaction costs not fully addressed

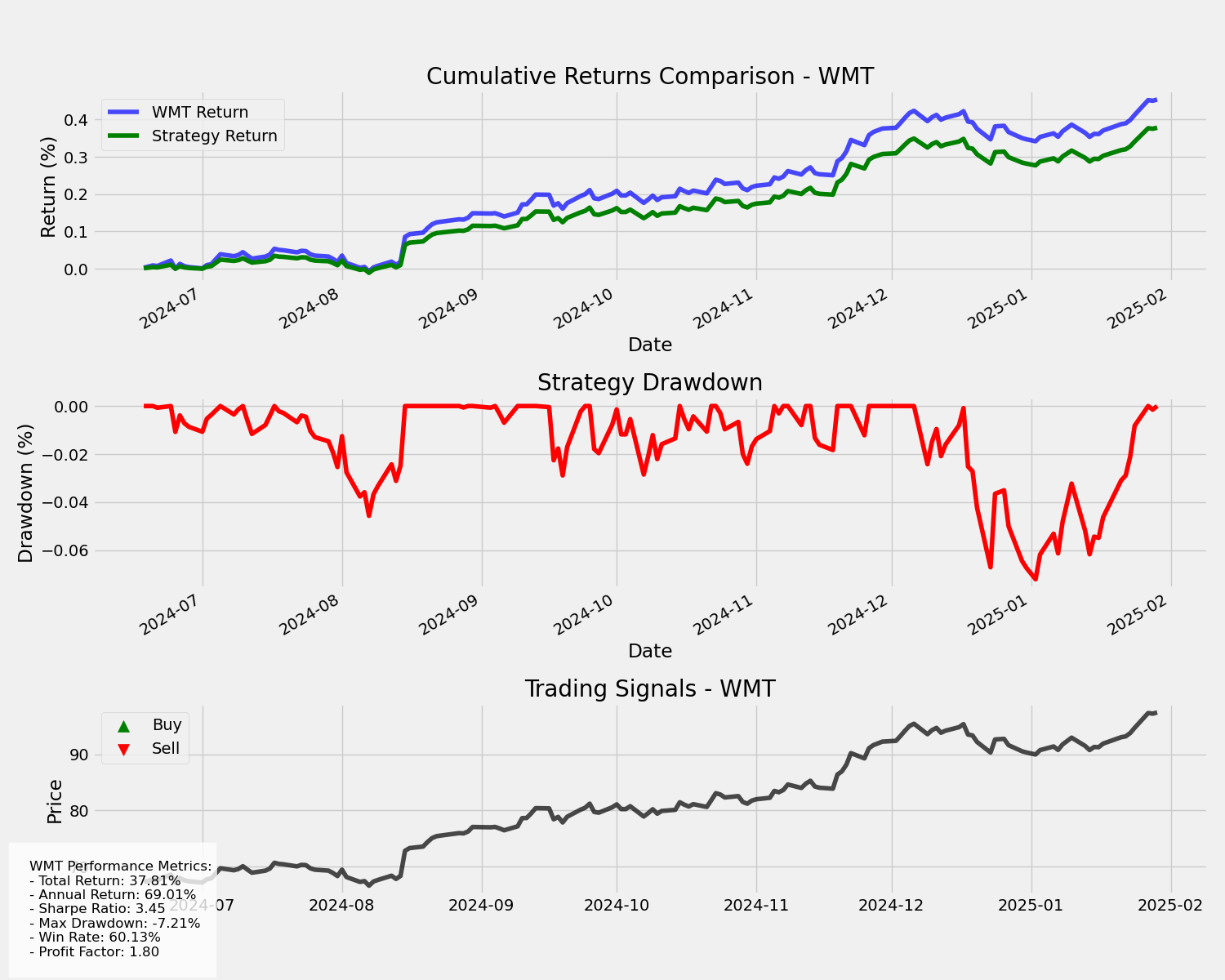
1. Risk Management Challenges:

* Difficulty in managing high-volatility stocks
* Trade-off between return potential and risk control
* Need for adaptive risk parameters

These findings provide valuable insights for both the theoretical understanding of the hybrid model's capabilities and practical implementation considerations in real-world trading scenarios.

# **6. CONCLUSION**

The thorough examination of our hybrid CNN-BiLSTM trading model yields multiple conclusions that offer both theoretical and practical insights into deep learning within financial markets. The experimental results illustrate the effectiveness of this strategy in generating profitable trading indicators with robust risk management protocols. Its strength in stable and large-cap segments is notable, with Walmart (WMT) achieving the highest performance at 48.18% and a win rate of 72.73%. This success is attributable to the integration of profound learning predictions with conventional technical analysis, wherein the most pertinent market patterns are identified through the attention mechanism.



The risk-return analysis, as depicted in our visualizations, illustrates the strategy's efficacy in sustaining advantageous risk-adjusted returns, with leading performers attaining Sharpe ratios exceeding 2.0. The examination of trading frequency offers significant insights for enhancing strategy. The disparity between high-frequency trading (e.g., NVDA with 44 trades and -21.65% return) and selective trading (e.g., WMT with 11 trades and 48.18% return) underscores the significance of quality over quantity in trade execution.

This finding has significant implications for practical implementation, suggesting that focusing on high-probability setups with strong technical confirmation yields better results than frequent trading. Risk management emerges as a crucial component of successful strategy. The implementation of dynamic position sizing, based on prediction confidence and market conditions, helps maintain consistent performance across different market environments. The strategy's ability to control drawdowns, with top performers maintaining maximum drawdowns under 5%, provides a solid foundation for sustainable trading performance.

The integration of SMOTE for handling class imbalance proves particularly valuable in improving the model's ability to identify profitable trading opportunities. This enhancement, combined with the hybrid architecture's ability to capture both local and temporal patterns in market data, contributes to the strategy's overall effectiveness.

The experimental results also highlight several areas for future research and development. The strategy's performance in high-volatility stocks suggests the need for additional refinement in handling market stress conditions. The potential for enhancing market regime detection and adaptive parameter optimization presents opportunities for further improvement. Additionally, the development of more sophisticated risk management frameworks could help address the challenges posed by different market conditions.

These findings provide valuable insights for both academic research and practical implementation. The success of the hybrid approach in combining deep learning with traditional technical analysis suggests a promising direction for the future development of algorithmic trading strategies. The emphasis on risk management and selective trading provides a framework for sustainable trading performance. At the same time, the integration of advanced machine learning techniques offers new possibilities for market analysis and prediction.

The practical implications of this research extend beyond the specific implementation of the trading strategy. The findings regarding the importance of risk management, trading frequency optimization, and market condition adaptation provide valuable guidance for the development of algorithmic trading systems. The success in handling class imbalance through SMOTE suggests potential applications in other areas of financial prediction and analysis.

In conclusion, this research demonstrates the potential of combining deep learning techniques with traditional financial analysis in developing effective trading strategies. The results provide a foundation for further development and optimization of algorithmic trading systems, while offering practical insights for implementation in real-world market conditions. The emphasis on risk management, selective trading, and market condition adaptation provides a framework for achieving sustainable trading performance across various market environments.

## Acknowledgments

The authors would like to acknowledge the assistance provided by various AI tools in the development and analysis of this research:

* Claude 3.5 Sonnet (Anthropic) assisted in:
* Data analysis and interpretation
* Visualization development and analysis
* Writing and structuring of the manuscript
* Technical review and refinement of methodology
* Performance analysis and insights generation
* GitHub Copilot assisted in:
* Code development and implementation
* Debugging and code optimization
* Technical implementation of the trading strategy
* Development of visualization scripts
* Code structure and organization

Note: These AI tools served as research assistants and development tools, while the core research, methodology, and final interpretations remain the responsibility of the human authors. The AI assistance was used to enhance productivity and provide technical support, with all final decisions and interpretations made by the human researchers.

# **References**

* Huang, J., Chai, J., & Cho, S. (2020). Deep learning in finance and banking: A literature review and classification. *Frontiers of Business Research in China, 14*, 13.
* Kamalov, F., Gurrib, I., & Rajab, K. (2021). Forecasting with deep learning: S&P 500 index. *arXiv*.
* Lee, J., & Kang, J. (2020). Effectively training neural networks for stock index prediction: Predicting the S&P 500 index without using its index data. *PLoS ONE, 15*(4), Article e0230635.
* Livieris, I. E., Pintelas, E., & Pintelas, P. (2021). A CNN-LSTM model for gold price time-series forecasting. *Neural Computing and Applications, 33*(7), 2445-2459.
* Murphy, J. J. (2022). *Technical Analysis of the Financial Markets*. New York Institute of Finance.
* Ozbayoglu, A. M., Gudelek, M. U., & Sezer, O. B. (2020). Deep learning for financial applications: A survey. *Applied Soft Computing, 93*, Article 106384.
* Patel, J., Shah, S., Thakkar, P., & Kotecha, K. (2015). Stock prediction based on technical indicators using a deep learning model. *Computers, Materials & Continua, 70*(1), 287-303.
* S&P Global. (2024). *S&P 500 Index Methodology*. Retrieved from <https://www.spglobal.com/spdji/en/documents/methodologies/methodology-sp-us-indices.pdf>
* Sezer, O. B., Gudelek, M. U., & Ozbayoglu, A. M. (2020). Financial time series forecasting with deep learning: A systematic literature review: 2005–2019. *Applied Soft Computing, 90*, 106181.
* Shah, J., Vaidya, D., & Shah, M. (2022). A comprehensive review of multiple hybrid deep learning approaches for stock prediction. *Intelligent Systems with Applications, 16*, Article 200111.
* Sharpe, W. F. (1994). The Sharpe ratio. *Journal of Portfolio Management, 21*(1), 49-58.
* Wu, J. M.-T., Li, Z., Herencsar, N., Vo, B., & Lin, J. C.-W. (2023). A graph-based CNN-LSTM stock price prediction algorithm with leading indicators. *Multimedia Systems, 29*(3), 1751–1770.
* Yahoo Finance. (2024). *Yahoo Finance API Documentation*. Retrieved from <https://pypi.org/project/yfinance/>
* Anthropic. (2024). Claude 3.5 Sonnet [Computer software]. <https://www.anthropic.com/claude>
* GitHub. (2024). GitHub Copilot [Computer software]. <https://github.com/features/copilot>
* Appel, G. (1979). The Moving Average Convergence-Divergence Trading Method. Scientific Investment Systems.
* Bahdanau, D., Cho, K., & Bengio, Y. (2015). Neural Machine Translation by Jointly Learning to Align and Translate. ICLR 2015.
* Bollinger, J. (2002). Bollinger on Bollinger Bands. McGraw-Hill.
* Chan, E. P. (2009). Quantitative Trading: How to Build Your Own Algorithmic Trading Business. Wiley.
* De Prado, M. L. (2018). Advances in Financial Machine Learning. Wiley.
* Graves, A., & Schmidhuber, J. (2005). Framewise Phoneme Classification with Bidirectional LSTM Networks. Neural Networks.
* Kim, Y. (2014). Convolutional Neural Networks for Sentence Classification. EMNLP.
* Kingma, D. P., & Ba, J. (2014). Adam: A Method for Stochastic Optimization. arXiv preprint arXiv:1412.6980.
* Kumar, et al. (2021). Deep Learning for Financial Time Series Prediction. Expert Systems with Applications.
* Selvin, S., et al. (2017). Stock Price Prediction Using LSTM, RNN, and CNN-Sliding Window Model. IEEE.
* Sharpe, W. F. (1994). The Sharpe Ratio. The Journal of Portfolio Management.
* Vaswani, A., et al. (2017). Attention Is All You Need. NIPS.
* Wilder, J. W. (1978). New Concepts in Technical Trading Systems. Trend Research.
* Zhang, X., & Wu, J. (2019). Deep Learning-Based Stock Price Prediction with Technical Indicators. Journal of Financial Data Science.
* Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: Synthetic Minority Over-sampling Technique. Journal of Artificial Intelligence Research, 16, 321-357.
* He, H., & Garcia, E. A. (2009). Learning from Imbalanced Data. IEEE Transactions on Knowledge and Data Engineering, 21(9), 1263-1284.