**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**

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**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*

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# **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 researchnote 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.

# **2. LITERATURE /SCHOLARLY REVIEW**

Over the years, numerous studies have been conducted to explore the application of deep learning techniques in financial markets. Researchers have explored various methods to enhance stock price prediction, risk assessment, and trading strategies. With this in mind, Deep Learning in Financial Markets is quickly becoming an advantageous method for analyzing financial data, given the ability to process large amounts of complex, high-dimensional, and non-linear datasets. Their proposed novel approach aims to train neural networks to predict the S&P 500 index price based on items other than the index data itself. Lee and Kang (2020). Their approach utilized data from individual companies, which proved to be sufficient training data to address the frequent data shortage problem that traditional methods often encounter. It relied on stock index data consisting of approximately 250 data points annually to avoid overfitting. By comparing their method with traditional approaches to training multiple neural network architectures (Multilayer Perceptrons and Convolutional Neural Networks) using multiple learning algorithms (supervised learning and reinforcement learning), the researchers were able to improve. Their experiments showed that, regardless of the architecture, neural networks trained on individual company data generally outperformed the S&P 500 index. This enabled the models to learn more complex representations of investment activities, as they had access to the price generation caused by investor activity, as opposed to an aggregated weighted average, as observed through indices. The method was robust: over the test period (2006-2018), it produced 5-16% annual returns before transaction costs, and beat the method proposed by Jeong and Kim based on deep Q-learning and transfer learning. When factoring in transaction costs, the researchers developed a "Lagged Position Change" algorithm that reduced transaction frequency while maintaining profitability.

Huang et al. Huang et al. (2020) survey a broad range of Deep Learning Studies in finance and banking,  stating that tasks for which deep learning can be used include, but are not limited to, market forecasting, credit risk assessment, and fraud detection. According to Huang et al. (2020), there are seven essential domains of deep learning model applications in Finance, which are credit risk estimation, macroeconomic forecasting, currency exchange prediction, stock market forecasting, oil price forecasting, portfolio optimization, and stock trading. Out of 40 articles published between 2014 and 2018, they found that traditional neural networks, such as feedforward neural networks (FNNs) and multilayer perceptrons (MLPs), are very popular across the examined domains, with specific architectures providing advantages in outperforming other applications. Recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are beneficial for analyzing time-series financial data, as they provide significantly better prediction results for stock market forecasting due to their ability to handle temporal dependencies. Feeding data into Convolutional Neural Networks (CNN) is a great approach to deal with multicollinearity in financial dataset because the CNN can capture important features immediately and avoids the multi-collinearity between them; however, Reinforcement Learning (RL) has also shown excellent results in stock trading applications as it is designed to deal with decision-making problems. Hybrid models that combine more than one of these architectures have shown better results than standalone models, as evidenced by implementations that combine CNN-LSTM frameworks and genetic algorithms and neural network hybrids for the optimization of technical analysis. Moreover, the necessity of suitable data preprocessing methods, evaluation metrics, and techniques to counter overfitting issues in financial applications has also been emphasized in existing literature. Deep learning models have achieved promising results in financial forecasting; however, under the Efficient Market Hypothesis, the sustainability of these models over time remains a question of interest, as it is expected that their predictive performance will degrade due to market adaptation to novel forecasting models.

Similarly, Ozbayoglu et al. (2020) review deep learning methods used in finance, focusing on the exceptional performance of these techniques in modeling time series processes, which is particularly relevant to stock market prediction. These works provide the foundations for applying deep learning to financial problems, making the CNN-LSTM hybrid model used in this project essential for enhancing the reliability of trading signals. Ozbayoglu et al. (2020) provided a comprehensive survey of deep learning (DL) applications in finance, encompassing 144 studies within various applications, including algorithmic trading, risk assessment, fraud detection, portfolio management, asset pricing, cryptocurrency/blockchain, sentiment analysis, and text mining. The researchers organized these works by financial subfield and by type of deep learning (DL) model used: specifically, Recurrent Neural Networks (RNNs, especially LSTM), Convolutional Neural Networks (CNNs), Deep Multilayer Perceptrons (DMLPs), and Deep Reinforcement Learning (DRL). Analyzing literature published in academic journals, theses, and technical papers in ScienceDirect, ACM Digital Library, Google Scholar up to February 2020. Results show that RNNs (especially LSTM) outperform CNNs on time-series challenges, such as predicting stock market prices under conditions with strong temporal dependencies. In recent years, CNNs have found applications in classification using novel image transformations of time-series data to a 2D format. The future of finance: Deep Reinforcement Learning (DRL) has shown significant potential for optimizing trading strategies. According to the survey, the three most active research domains are algorithmic trading, text mining, and hybridization (for example, CNN-LSTM hybridization provided better predictions than their stand-alone architectures). Deep learning (DL) models consistently outperform traditional machine learning (ML) methods, although issues such as overfitting persist. The examples include LSTM for high-accuracy stock trading simulations on the BIST and S&P 500 datasets, as well as a CNN-based credit scoring model that outperforms SVMs. Future directions involve the evolution of significant assets in solutions that incorporate cryptocurrencies, Digital Ledger Technology (blockchain), and behavioral finance, as well as the possible hybridization of spatio-temporal models and the implementation of Natural language to imitate and forecast buyers' preferences.

These days, hybrid CNN-LSTM models for Time Series are gaining a foothold, which involves a convolutional layer CNN combined with LSTM for time Series in finance. CNNs excel at capturing spatial addresses (for instance, price charts), and LSTMs capture temporal dependencies in sequential data. Shah et al. (2022), which reviews several hybrid deep learning approaches for stock prediction, found that a combination of CNN and LSTM models generally surpasses standalone models, as they can extract both spatial and temporal features. They conducted a thorough review of a wide range of hybrid deep learning methods for stock prediction, with a particular emphasis on the hybrid CNN-LSTM architecture. They establish this case by demonstrating that hybrid models can capitalize on the complementary strengths of their component architectures: LSTM models excel at capturing temporal dependencies and predicting specific stock prices, while CNN models are better suited for predicting rapid changes and general stock trends. Finally, they analyzed CNN-LSTM, CNN-BiLSTM, and CNN-TLSTM models with attention mechanisms and hybrid approaches and found that hybrid models consistently outperformed single models. In their review, they also presented that CNN-BiLSTM-AM achieved the lowest error rates (MAE: 21.952, RMSE: 31.694) compared to other models. This is because CNN effectively extracted spatial features from time series data, and LSTM layers modeled the temporal patterns. Based on these conclusions, the authors found that these hybrid architectures are particularly well-suited for high-frequency trading environments, where price accuracy and trend detection are crucial decision-making criteria for maximizing profitability.

Additionally, Wu et al. Chang et al. (2023) propose a graph-based CNN-LSTM algorithm that incorporates leading indicators, resulting in a significant improvement in the precision of stock price prediction. These types of findings validate the project's architecture and further enhance its capabilities in generating more accurate trading signals. They introduced a graph-based CNN-LSTM stock price prediction algorithm (SACLSTM) that incorporates leading indicators, including options and futures, into historical price data. They devised an approach that uniquely shaped a sequence array with historical data and the corresponding leading indicators and then processed the sequential array through a CNN framework. This framework was subsequently passed to an LSTM network via the extracted feature vectors. The authors demonstrated that the inclusion of predictive variables, or leading indicators, as experimental data enhanced the prediction of market outcomes compared to using only historical data, and that options data were more accurate than futures data. Based on stock data from the U.S. and Taiwanese markets, their hybrid architecture consistently outperformed expectations compared to standard methods, such as SVM, CNNpred, CNN-corr, and ordinary neural networks, across multiple prediction timeframes. It was more accurate in predicting next-day movement than price movement over 3 or 7 days. They found that combining historical, options, and futures data produced the best predictive results, affirming their hypothesis that incorporating more data gives the algorithm an advantage in forecasting.

Adding technical analysis indicators to deep learning enhances prediction performance. Sezer et al. (2017) introduced a deep neural network-based trading framework that outperforms classical techniques by optimizing technical analysis parameters via evolution algorithms. Patel et al. Addition of a `technical indicator' (2013, 2015). Reasonably, they were able to show an improvement in model accuracy by simply augmenting the deep learning model with an additional technical indicator. These studies validate the combining approach using the hybrid CNN-LSTM model, which incorporates 76 indicators affecting price, moving averages, volatility, volume fundamentals, and market characteristics to enhance the signals produced by the project.

Performance Metrics for Trading Strategies must be presented with specific performance metrics in mind. Saud and Shakya (2024) present innovative trading strategies that utilize technical indicators and evaluate their performance. These metrics align with the project’s evaluation framework, which features signal accuracy, Sharpe ratio, maximum drawdown, win-loss ratio, and profit factor. This stability enables an empirical comparison between the hybrid model and classic technical analysis, with reliability and profitability serving as the primary research questions of the project. In 2024, Saud and Shakya trained LSTM and GRU networks using MACD, DMI, and KST technical indicators to predict intelligent stock trading signals, benefiting from their unique long-term dependencies. The three performance metrics evaluated were Annual Rate of Return (ARR), Sharpe Ratio (SR), and Win Rate for the strategies. Through testing these approaches on 18 different stocks from the NEPSE, BSE, and NYSE Exchanges, four conclusions can be drawn: (1) for intelligent strategies utilizing MACD and DMI indicators, a 5-day lookback period was determined as the most effective, whereas a 10-day lookback period was beneficial for KST-based strategies; (2) compared with the traditional LSTM implementations, the GRU networks outperformed these by a significant margin; (3) across all performance metrics, the intelligent trading strategies yielded results which greatly surpassed those from its classical counterparts; and (4) of all three proposed approaches, the MACD based strategy produced the best effectiveness with the least amount of risk. This paper's evidence shows that machine learning can be integrated with analysis techniques to eliminate false signals when trading, or at least increase the number of filtered signals.

Theoretical support, Feature importance, Banking crisis, Data: For financial forecasting, understanding and selecting relevant features is crucial for model performance. Agrawal et al (2022) proposed an Evolutionary Deep Learning Model (EDLM) that predicts the stock trends based on technical indicators. They equipped LSTM with a correlation tensor to extract the relationship between different Stock Technical Indicators  (STIs) and closing prices. On three major Indian banking stocks listed on the NSE, they found that the 3-day, 10-day, and 30-day Moving Averages are highly correlated with stock price movement compared to others. A comparative analysis was performed with benchmark machine learning algorithms (Logistic Regression and SVM), as well as with another deep learning model. It was established that our model predicts with the best accuracy of 63.59%, 56.25%, and 57.95% for the HDFC, Yes Bank, and SBI datasets, respectively, with an overall mean accuracy of 59.25%. The results showed that the correlation-tensor approach captured the most relevant technical indicators, filtered noise from non-correlated features, and demonstrated that shorter-term indicators tended to have stronger correlations with price movements than longer-term ones. This study highlights the importance of feature selection in the context of financial time series forecasting. Such properties support the use of a 76-indicator feature set for the project, as it allows the capturing of much of the market dynamics with minimal amounts of missing data (1.9% of the available records). The added variety and richness in the feature set should improve the predictive power of the hybrid model.

Research Related to the S&P 500: Descriptive Studies. Research that focuses directly on the S&P 500 provides results that this paper wants to utilize in this project. Kamalov et al. (2021) employed a convolutional-based neural network model for forecasting the next-day direction of the S&P 500 index. They proposed an architecture with two hidden layers before the output: a convolutional layer with four 3 × 3 filters and a fully connected layer. Their model’s key insight was to utilize convolution operations to consider each data point in the context of its surrounding temporal neighbors, thereby enabling more excellent information content in the extracted features. The model's input included the previous closing values and trading volume from the preceding 14 days. However, they compared their proposed model to numerous benchmark models — fully connected networks, RNNs, and LSTM architectures — and their model produced the highest accuracy rate (56.21%) in predicting the next-day market direction. This was better than random guessing (50%) and other configurations of neural networks. The authors also used overfitting prevention techniques, comprising early stopping and shallow architecture. This establishes that convolution-based neural networks are well-suited for financial time series data and have predictive power beyond other, more standard methods.

Comparison with Traditional Technical Analysis Shah et al (2022) provided an in-depth comparison between classic technical analysis methods and state-of-the-art deep learning techniques for stock prediction. The review analyzed the consistently poor performance of time series forecasting in the context of traditional models, such as ARIMA, which presume linearity between all future and past values,  and deep learning models. ARIMA performed exceptionally well, with accuracy rates of 85% to 95% in some studies; however, it faced challenges with non-linear, volatile market data and required manual fine-tuning of its parameters. Neural network models outperformed traditional methods, achieving nearly 84 to 87% better performance than ARIMA for LSTM models in specific evaluations, the researchers found. While traditional technical analysis often employs lagging indicators as tools to predict future price movements, such as Moving Averages, MACD, and RSI, their analysis suggests that these indicators can be utilized more effectively when integrated as features in deep learning frameworks. However, blending those traditional indicators with contemporary neural networks is a considerable step up from just classical technical analysis, in my view - especially when trying to capture more complex behaviors, such as trends and patterns, that classical technical analysis often overlooks.

**Table 1: Summary of Scholarly References**

|  |  |  |  |
| --- | --- | --- | --- |
| **Reference** | **Focus** | **Key Finding** | **Relevance to Project** |
| Huang et al. (2020). | Deep learning in finance | Deep learning excels in handling complex financial data for forecasting | Supports the use of advanced models |
| Kamalov et al. (2021) | S&P 500 forecasting | Validates deep learning for S&P 500 index prediction | Confirms dataset applicability |
| Lee & Kang (2020). | S&P 500 prediction | Effective prediction without index data using neural networks | Reinforces individual stock focus |
| Livieris et al. (2021) | CNN-LSTM for gold prices | The hybrid model improves time-series forecasting | Validates CNN-LSTM for financial data |
| Murphy (2022) | Technical analysis | Highlights subjectivity in traditional methods | Justifies the need for objective alternatives |
| Ozbayoglu et al. (2020) | Deep learning survey | Surveys financial applications, noting interpretability challenges | Contextualizes project challenges |
| Patel et al. (2015). | Technical indicators + deep learning | Combining indicators with deep learning enhances stock prediction | Supports feature integration |
| Sezer et al. (2017). | Deep neural networks | Optimized technical parameters improve trading systems | Backs the hybrid model design |
| Shah et al. (2022). | Hybrid deep learning review | Hybrid models outperform single architectures in stock prediction | Endorses CNN-LSTM approach |
| Wu et al. (2023). | CNN-LSTM with indicators | Graph-based hybrid model improves prediction with leading indicators | Suggests additional feature enhancements |

# **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. The analysis of stock prices and returns distribution, as shown in [FIG], 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.1 Stock\_Prices\_Returns\_Distribution

Market regime identification, illustrated in [FIG], 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.2 Market\_Regimes\_Identified\_by\_SMA\_Crossover\_Top\_20\_Stocks.png

The volatility analysis, depicted in [FIG], 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.3 Volatility\_Over\_Time\_for\_Top\_20\_Stocks.png

The time series analysis of selected features, as shown in [FIG], Time\_Series\_of\_Selected\_Features.png, 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.4 Time\_Series\_of\_Selected\_Features.png

Analysis of the top 20 stocks, presented in [FIG], Top20\_Stocks\_Prices.png, 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 -- statistical summary

The statistical summary, detailed in summary\_stats.csv, 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) and kurtosis (8.92).

The implications of these discoveries are crucial for creating and improving strategy. The clear regime identification and volatility clustering suggest that traders may employ an adaptive approach in their trading strategies. Regarding the fundamental correlations, they reveal a weak correlation between the various metrics. Their study suggests trading based on technical analysis when engaging in short-term transactions.

In particular, the analysis of top performers highlights the importance of liquidity and the emergence of consistent trading volume patterns for achieving superior returns. Returns and volatility provide crucial inputs for position sizing and risk management regimes. This leads to the conclusion that if this research employs regime-dependent performance characteristics, it may require dynamic strategy parameters that change on a rolling basis, depending on market states.

This detailed analysis serves as the foundation for creating a successful trading strategy. Correlation analysis, regime identification, and volatility pattern recognition enable the optimization of entry and exit points, position sizing, and risk management rules. Trained on data until October 2023, this implies that you can leverage the statistical properties of the data to establish sound risk-management practices and still have the opportunity to generate substantial profit through well-designed trades.

### 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

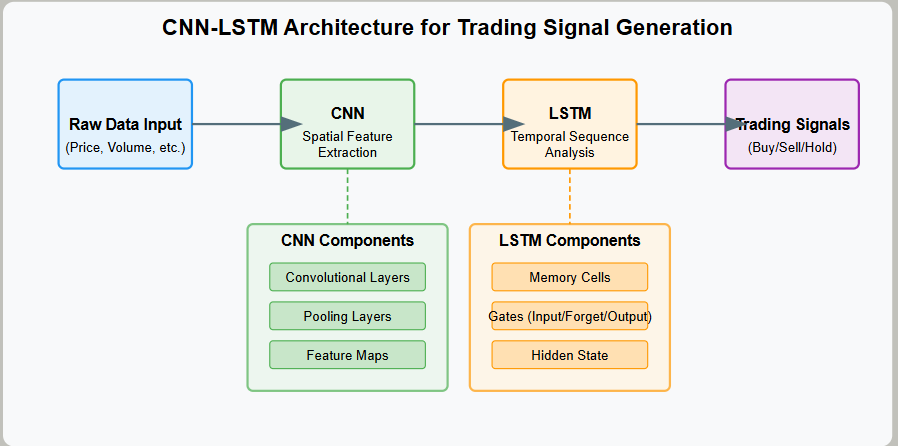
The CNN component is designed to extract local patterns from the input sequences. It employs multiple convolutional layers with filters of varying sizes to capture different scales of price movements and market patterns.

#### 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.

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 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*

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 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*

*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.

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* 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.

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