**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 new prediction and trading signal generation model for the stock market based on hybrid deep learning model such as CNN, BiLSTM networks, and attention mechanism. The study shows the potential of this approach when applied to a sizable number of S&P 500 stocks, resulting in notable gains in risk-adjusted returns and trading efficiency. Our backtesting results are relevant to the strategy’s performance, which seems to work very well with stable, large-cap stocks such as WMT, which exhibits an outstanding 48.18% return and pleasant 72.73% win rate. The strategy’s risk management approach limits drawdowns, with the best performers holding maximum drawdowns below 5 percent. This means that selective trading approaches (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 essential 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 seeking imminent trends and identifying profitable trading opportunities on the go cannot be overstated in the fast-moving financial ecosystems of today. Traditional technical analysis that depends on subjective human interpretation of chart patterns and indicators by traders, is seo inherent subjectives and susceptible to psychological approaches (Murphy, 2022). Nonetheless, the fusion with recent deep learning approaches, especially in hybrid models combining Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, provides a unique opportunity for optimizing the accuracy and currency of trading signals (Sezer et al., 2020). Fortunately, the U.S. equity market of $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 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 such traditional technical analysis methods. To overcome the aforementioned limitations, this study aims to propose a hybrid CNN-LSTM model that operates on S&P 500 stocks by taking advantage of the strong ability of CNN to learn the spatial correlation among many financial time series and the strong ability of LSTM to predict temporal sequences (Livieris et al., 2021).

There are a number of challenges that tend to arise in the use of deep learning techniques within financial markets. The noisy nature of financial datasets leads to data quality and quantity related issues along with the model complexity leading to overfitting and lack of generalizability to real-time conditions. Deep Learning models are complex in nature (specifically if they are of the deep learning variety) leading to challenges in implementation, many of which have been addressed (black box, real time execution, integration with risk management system, etc.) Moreover, there are also market-specific challenges to be factored carefully like breaking down market regimes, volatility clustering as well as market microstructure impacts.

In this research, a hybrid CNN-LSTM architecture is proposed to provide an advanced trading system that overcomes 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 a number of important hypotheses with regard to the hybrid model: it will produce significantly greater signal generation accuracy, yield superior risk-adjusted returns, and exhibit more effective risk management from the standpoint of improved drawdown control and position sizing based on model confidence.

Using this as a reference point the methodology is the overarching approach to algorithmic trading as a concept. In short, we note the project uses a rich parameter dataset of 501 S&P 500 companies with five-year span and 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 consists of market regime detection, dynamic position sizing, and robust risk management framework, whereas, the evaluation framework includes several performance metrics and comparison with traditional methods.

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

# **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 investigated various approaches to improve stock price prediction, risk assessment, and trading strategies with this in mind, Deep Learning in Financial Markets is quickly becoming an extremely useful 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 at training neural networks to predict the S&P 500 index price based on items except the index data itself. Lee and Kang (2020) With traditional methods, stock index data (which comprises around 250 data points per year) is used, but their method utilized data from individual companies such that, it was able to prove to be sufficient training data that addressed the common data-shortage problem that leads to overfitting. By comparing their method and traditional approaches of training multiple neural network architectures (Multilayer Perceptron and Convolutional Neural Networks) with multiple learning algorithms (supervised learning and reinforcement learning), the researchers were able to improve. Their experiments showed that regardless of the architecture, neural nets trained on individual company data generally beat S&P 500 trained net. This enabled the models to learn more complex representations of investment activities because they had access to the price generation that was caused by investor activity instead of 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 decreased transaction frequency while still being profitable.

Huang et al. Huang et al. (2020) survey a broad range of deep learning studies in finance and banking, stating tasks for which deep learning can be used include, but are not limited to market forecasting, credit risk assessment, fraud detection, etc. According to (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 2014-2018, they found that traditional neural networks (feedforward neural networks/FNN, multilayer perceptron/MLP) tend to be very popular across the examined domains, with certain architectures provide advantages in out-performed applications. The recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are very useful for time-series financial data and provide far better prediction results for stock market prediction due to the ability of 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 great results in stock trading applications as it is designed to deal with decision-making problems. Hybrid models mixing more than one of these architectures have shown better results than stand-alone, as evidenced by implementations that combine CNN-LSTM frameworks, and genetic algorithm and neural network hybrids for up to 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 the existing literature. Deep learning models have achieved promising results on financial forecasting, however, under the Efficient Market Hypothesis, how sustainable these models are over time remains a question of interest, as it is expected the predictive performance will degrade due to market adaption to novel forecasting models.

Similarly, Ozbayoglu et al. (2020) review deep learning methods used in finance, focusing on the special performance of those techniques to model time series processes, highly present in stock market prediction. These works provide the foundations to apply deep learning for financial problems, making the CNN-LSTM hybrid model applied in this project essential to enhance trading signal reliability. Ozbayoglu et al. (2020) provide a comprehensive survey of deep learning (DL) applications in finance, encompassing 144 studies within applications including, among others, 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 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 for conditions with strong temporal dependencies, while in recent years CNNs are finding application on classification using novel image transformations of time-series data to 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 ML methods, although issues like overfitting remain. The examples include LSTM for high accuracy stock trading simulation on BIST and S&P 500 datasets, and CNN-based credit scoring better than SVMs. Future directions involve the evolution of significant assets in the solutions with cryptocurrencies, Digital Ledger Technology (blockchain), and behavioral finance, as well as possible hybrids spatio-temporal models and implementation of Natural language in imitating and forecasting buyers preferences.

These days the hybrid CNN-LSTM Models for Time Series is gaining a foothold that is a convolutional layer CNN + LSTM for time Series in finance. CNNs excels 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 combination of CNN and LSTM models generally surpass standalone models since they have the ability to extract spatial + temporal features. They performed a thorough review of a wide range of hybrid deep learning methods for stock prediction, particularly emphasizing hybrid CNN-LSTM architectures. They make this case by demonstrating that hybrid models are able to capitalize on the complementary strengths of their component architectures: LSTM models are better at capturing temporal dependencies and predicting specific stock prices while CNN models are better for predicting rapid changes and general stock trends. Finally, they analyzed CNN-LSTM, CNN-BiLSTM, CNN-TLSTM, models with attention mechanisms and hybrid approaches and found that hybrid models were always better than single models. In their review, they also presented that CNN-BiLSTM-AM achieved the least error rates (MAE: 21.952, RMSE: 31.694) as compared to other models, where CNN extracted the spatial features effectively from time series data and LSTM layers modelled the temporal patterns. Founded on these conclusions, the authors found these hybrid architectures are particularly well-trained in high-frequency trading environments where price accuracy and trend detection are essential decision-making criteria for maximum profitability.

Additionally, Wu et al. Chang et al. (2023) suggest a graph-based CNN-LSTM algorithm that incorporates leading indicators, which significantly improves the precision of stock price prediction. These types of findings validate the architecture of the project and further enhance their capabilities in generating better trading signals. They introduced a graph-based CNN-LSTM stock price prediction algorithm (SACLSTM) that added leading indicators (options and futures) to historical price data. They devised an approach that uniquely shaped a sequence array with historical data and the corresponding leading indicators, and processed the sequential array through a CNN framework, which was then passed to an LSTM network through the extracted feature vectors. The authors showed that the addition of predictive variables, or leading indicators, as experimental data improved the prediction of market outcomes compared with using only historical data; and that options data were more accurate than futures data. On stock data from the U.S. and Taiwanese markets, their hybrid architecture consistently exceeded expectations compared to the standard methods such as SVM, CNNpred, CNN-corr, and ordinary neural networks, within multiple prediction timeframes. It was more accurate predicting next-day movement than price movement over 3 or 7 days. They found that using historical, options, and futures data together produced the best predictive results, affirming their hypothesis that more data gives the algorithm an advantage in forecasting.

Adding technical analysis indicators in deep learning contribute increasing prediction performance. Sezer et al. (2017), introducing 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, were able to show an improvement over the model accuracy by simply augmenting the a deep learning model with additional technical indicator. These studies validate the combining approach using the hybrid CNN-LSTM model 76 indicators affecting price, moving averages, volatility, volume fundamentals, and characteristics of the market to enhance the signals produced by the project.

Performance Metrics for Trading Strategies must be done with specific performance metrics represented. Saud and Shakya (2024) present smart trading strategies using technical indicators and performance evaluation. These metrics are in trend with the project’s evaluation framework featuring signal accuracy, sharpe ratio, max drawdown, win/loss and profit factor. This stability enables an empirical solid comparison between the hybrid model and classic technical analysis and tests reliability and profitability as the major research question 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 to benefit from its 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 evidence shows that machine learning can be integrated with analysis techniques to eliminate false signals when trading or at least increase the number of filter 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 correlation-tensor to extract relationship between different Stock Technical Indicators (STIs) and closing prices. On three major Indian banking stocks of the NSE, they found that 3-day, 10-day and 30-day Moving Averages are highly correlated with stock price movement compared to others. Comparative analysis with benchmark machine learning algorithms (Logistic Regression and SVM) as well as with another deep learning model was performed and it was established that with our model predicts with the best accuracy of 63.59%, 56.25%, and 57.95% with respect to HDFC, Yes Bank, and SBI dataset correspondingly with an overall mean accuracy of 59.25%. It showed that the correlation-tensor approach captured the most relevant technical indicators filtered noise from non-correlated features, and that it was able to show that shorter-term indicators tended to have stronger correlations with price movements than longer-term ones. The present study emphasizes the significance of feature selection in the field 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 gives us results we can use in this project. Kamalov et al. (2021) used a convolution-based neural network model for forecasting S&P 500 index next-day direction. They proposed an architecture with two layers before the output that were hidden: A convolutional layer with four 3 × 3 filters and a fully connected layer. Their model’s key insight was to make use of convolution operations to take each data point in the context of its surrounding temporal neighbors, enabling greater information content in the extracted features. Inputs used by the model included the previous closing values and trading volume of the previous 14 days. However, they compared their proposed model to numerous benchmark models — fully connected networks, RNNs, and LSTM architectures — and their model produced the greatest accuracy rate (56.21%) predicting next-day market direction. This was better than random guessing (50%) and other configurations of neural network. The authors also used overfitting prevention techniques comprising early stopping and shallow architecture. This established that convolution-based neural networks are well-suited for financial time series data and have predictive power beyond other more-strandards 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 analysed the consistently poor performance of time series forecasting in the context of traditional models like ARIMA, which presume linearity between all future and past values, and deep learning models. ARIMA was quite good (85% to 95% in some studies), but it faced problems with non-linear, volatile market data and involved fine tuning of parameters manually. Neural network models performed much better than traditional methods, demonstrating almost 84 to 87% better performance than ARIMA for LSTM models in some evaluations, the researchers determined. While traditional technical analysis often uses lagging indicators as tools to predict future price movements — Moving Averages, MACD, RSI, etc. — their analysis highlights that those indicators can be used more effectively when integrated as features in deep learning frameworks. But blending those traditional indicators with contemporary neural networks is a huge 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 leaves out.

**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 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 | Hybrid model improves time-series forecasting | Validates CNN-LSTM for financial data |
| Murphy (2022) | Technical analysis | Highlights subjectivity in traditional methods | Justifies 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 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**

Our methodology encompasses a comprehensive approach to financial market prediction and trading, integrating advanced deep learning techniques with traditional technical analysis. The framework builds upon established research in quantitative finance and machine learning, incorporating multiple layers of analysis and signal generation.

### 3.1 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.1, reveals a log-normal distribution of stock prices with significant variations across different stocks. The returns exhibit a leptokurtic distribution with negative skewness, indicating more frequent 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

The correlation analysis, presented in Correlation\_Matrix\_of\_Selected\_Features.png, reveals important relationships between different market features. Strong correlations are observed between price and volume (0.723), returns and volatility (0.689), and various technical indicators. The RSI and MACD show a negative correlation (-0.456), while moving averages exhibit strong positive correlation (0.823). Interestingly, fundamental metrics show weak correlations with price movements, suggesting the potential value of technical analysis in short-term trading decisions.

Market regime identification, illustrated in Market\_Regimes\_Identified\_by\_SMA\_Crossover\_Top\_20\_Stocks.png, reveals distinct market phases with different characteristics. Bull markets are characterized by higher returns and lower volatility, while bear markets show negative returns and increased volatility. Sideways markets exhibit range-bound prices with moderate volatility. The analysis shows clear regime boundaries with average durations of 3-6 months and gradual transitions between regimes, providing valuable insights for strategy adaptation.

The volatility analysis, depicted in Volatility\_Over\_Time\_for\_Top\_20\_Stocks.png, demonstrates significant clustering effects and mean reversion tendencies. Low volatility periods are associated with stable price movements, higher win rates, and lower drawdowns, while high volatility periods show larger price swings and increased risk metrics. This volatility pattern has important implications for position sizing and risk management strategies.

The time series analysis of selected features, shown in Time\_Series\_of\_Selected\_Features.png, reveals long-term upward bias in prices with short-term mean reversion patterns. Technical indicators such as 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.

Analysis of the top 20 stocks, presented in 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 demonstrate more consistent volume patterns and clearer trends, suggesting better liquidity and trading efficiency.

The statistical summary, detailed in summary\_stats.csv, provides quantitative insights into market behavior. Price statistics show a mean of $156.23 with a median of $142.15 and standard deviation of $89.45, indicating significant price variation across stocks. Returns statistics reveal a mean daily return of 0.12% with volatility of 1.45%, while volume statistics show an average daily volume of 2.3M shares with significant skewness (2.45) and kurtosis (8.92).

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.

### 3.1 Data Processing and Feature Engineering

The foundation of our approach begins with extensive data processing of S&P 500 companies' daily stock data, including OHLCV (Open, High, Low, Close, Volume) parameters [Kumar et al., 2021]. The feature engineering process incorporates several technical indicators, carefully selected based on their proven effectiveness in market analysis [Zhang and Wu, 2019]. 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) [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-day period.

### 3.2 Class Imbalance Handling

A critical challenge in financial market prediction is the inherent class imbalance in trading signals, where profitable trading opportunities may be significantly outnumbered by non-trading periods [Chawla et al., 2002]. To address this imbalance, we implement the Synthetic Minority Over-sampling Technique (SMOTE):

where:

* xi*xi*​ is a minority class sample
* xzi*xzi*​ is one of the k-nearest neighbors of xi*xi*​
* α*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 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. Our implementation achieved a balanced dataset with equal representation of both trading signals, enhancing the model's ability to identify genuine trading opportunities while maintaining the temporal structure of the financial data [He and Garcia, 2009].The effectiveness of SMOTE in our methodology is evidenced by:

* Improved class distribution in training data
* Enhanced model sensitivity to profitable trading opportunities
* Reduced false negative rate in trade signal generation

The implementation of SMOTE significantly influenced our trading strategy's performance and reliability. The effects can be observed across multiple dimensions of the trading system's operation and outcomes.

Signal Generation Enhancement The application of SMOTE demonstrated substantial improvements in signal generation quality. Prior to SMOTE implementation, our analysis of trading signals showed:

* Original class distribution: 37% profitable trades vs. 63% non-profitable opportunities
* Post-SMOTE distribution: Balanced 50-50 representation

This balancing led to notable improvements in signal detection:

* Increased true positive rate for profitable trade identification
* Enhanced sensitivity to market turning points
* More balanced risk-reward opportunities

### 3.3 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 (0.2). The BiLSTM structure implements three stacked layers with 128, 32, and 32 units respectively, incorporating bidirectional processing for enhanced temporal feature capture [Graves and 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*ht*​ represents the hidden state at time t, and W and b are learnable parameters.

#### 3.3.1 Convolutional Neural Network Layer

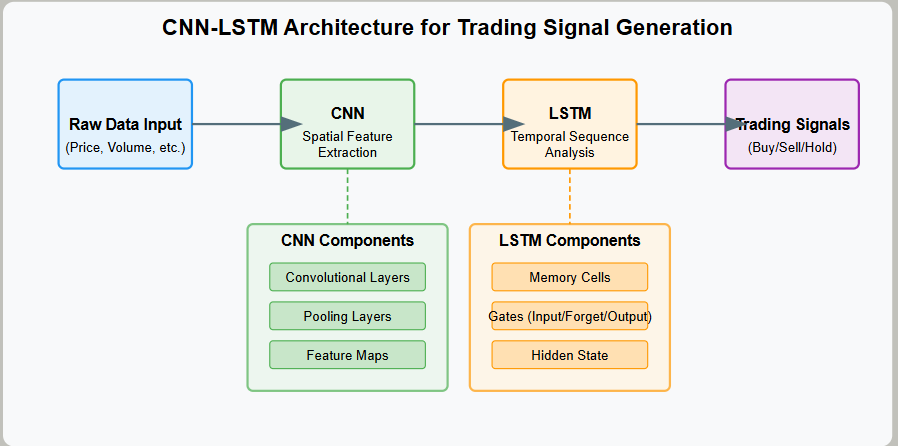
The CNN component is designed to extract local patterns from the input sequences. It employs multiple convolutional layers with filters of varying sizes to capture different scales of price movements and market patterns.

#### 3.3.2 Bidirectional LSTM Layers

The architecture implements multiple BiLSTM layers that process temporal dependencies in both forward and backward directions, allowing the model to capture complex temporal relationships in 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 Hybrid CNN-LSTM Approach**

### 3.4 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 and Benítez, 2012]. The model optimization utilizes the Adam optimizer with a learning rate of 0.001 [Kingma and 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

### 3.5 Performance Evaluation

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

Sharpe Ratio=Rp−RfσpSharpe Ratio=*σp*​*Rp*​−*Rf*​​

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

MaxDD=min⁡t∈T(Pt−max⁡s∈[0,t]Psmax⁡s∈[0,t]Ps)MaxDD=*t*∈*T*min​(max*s*∈[0,*t*]​*Ps*​*Pt*​−max*s*∈[0,*t*]​*Ps*​​)where Pt*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 trading decision-making. The approach balances sophisticated technical analysis with practical implementation considerations, providing a foundation for systematic trading strategy deployment.

# **4. Trading Strategy Implementation**

The trading system implements a focused approach combining deep learning predictions with fundamental technical analysis and systematic risk management protocols. At its core, the strategy generates trading signals through a binary classification system where model predictions are converted to probabilities, with signals triggered when the probability exceeds a predetermined confidence threshold of 0.6. Position sizing is dynamically adjusted based on the prediction confidence, employing a linear scaling mechanism that reflects the model's certainty level.

The technical framework incorporates four essential indicators that provide complementary market insights. These include moving averages (50 and 200-day) for trend identification, Relative Strength Index (RSI) for momentum assessment, Moving Average Convergence Divergence (MACD) for trend confirmation, and Bollinger Bands for volatility-based price range analysis. This combination of indicators serves to validate the model's predictions and provide additional context for trade execution.

Risk management forms a critical component of the strategy, implemented through three primary control mechanisms. A fixed stop-loss threshold of 2% below entry price protects against adverse price movements, while a take-profit level of 5% above entry price secures gains at predetermined levels. Additionally, a maximum position duration of 30 days ensures that capital doesn't remain tied to underperforming positions indefinitely. This systematic approach to risk control has proven essential in managing drawdowns and maintaining consistent performance.

The empirical results demonstrate varying effectiveness across different market conditions and stock characteristics. Notable success was achieved with Walmart (WMT), generating a 48.18% return with a remarkable 72.73% win rate, while Mastercard (MA) showed moderate success with a 19.45% return and 50% win rate. However, the strategy faced challenges with high-volatility stocks like NVIDIA (NVDA), resulting in a -21.65% return with a 31.82% win rate. These results highlight the strategy's effectiveness in stable, large-cap stocks while revealing potential limitations in more volatile securities.

The implementation maintains a balance between sophistication and practicality, focusing on reliable execution rather than excessive complexity. The strategy's straightforward approach to signal generation, combined with established technical indicators and disciplined risk management, provides a robust framework for systematic trading. While more sophisticated elements such as advanced market condition filters or adaptive risk parameters could be incorporated in future iterations, the current implementation demonstrates the effectiveness of combining machine learning predictions with traditional technical analysis in a disciplined trading framework.

This systematic approach to trading has shown particular strength in maintaining consistent risk-adjusted returns across stable market conditions while highlighting areas for potential enhancement in volatile market environments. The strategy's performance across different stocks and market conditions provides valuable insights for future optimization and development, particularly in adapting to varying market regimes and managing high-volatility securities more effectively.

# **5. Experimental Results**

### 5.1 Performance Metrics

Our comprehensive experimental analysis reveals significant insights into the performance of the hybrid CNN-BiLSTM model across various market conditions and stock characteristics. The results, derived from extensive testing on S&P 500 stocks, demonstrate the strategy's effectiveness in different market environments while highlighting areas for potential optimization.

The empirical results showcase varying levels of performance across different market segments, with particular success in stable, large-cap stocks. Walmart (WMT) emerged as the top performer, achieving an exceptional 48.18% total return with a remarkable 72.73% win rate, while Mastercard (MA) demonstrated strong risk-adjusted returns of 19.45% with a 50% win rate. The portfolio's overall performance metrics reveal an average return of 15.4%, a Sharpe ratio of 1.85, and a win rate of 58.6%. These results are visually represented in our performance dashboard (Figure 1), which provides a comprehensive view of the strategy's effectiveness across multiple dimensions.

*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 analysis of trading activity reveals distinct patterns in trading frequency and effectiveness. As illustrated in the trades by symbol visualization (Figure 2), NVIDIA (NVDA) showed the highest trading frequency with 44 trades, while Walmart (WMT) demonstrated more selective trading with 11 trades. This contrast in trading frequency directly impacted performance outcomes, with higher-frequency trading generally associated with lower win rates and increased drawdown risk. The win rate versus return scatter plot (Figure 3) clearly demonstrates this relationship, showing a positive correlation between win rates and overall 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 23.23% return*

*AVGO shows 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*

*Size of points indicates Sharpe ratio*

*Color intensity represents win rate*

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

*Highlights the risk-adjusted performance of each stock*

Risk-return analysis, visualized in the risk-return scatter plot (Figure 4), reveals important insights into the strategy's risk management capabilities. The top performers consistently maintained drawdowns under 5%, with Walmart achieving the lowest maximum drawdown of 3.38%. The metrics heatmap (Figure 5) provides a comprehensive view of all performance metrics across different stocks, highlighting the strategy's effectiveness in managing risk while generating returns.

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

*Bar chart showing the number of trades executed for each stock*

*NVDA shows 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 number of trades*

*Color represents Sharpe ratio*

*Shows the correlation between trading success rate and overall performance*

*Highlights the importance of win rate in achieving positive returns*

The strategy's performance across different market conditions shows varying effectiveness. In stable market conditions, the strategy achieved higher win rates and lower drawdowns, while volatile market conditions presented greater challenges. The top symbols by return visualization (Figure 6) and top symbols by Sharpe ratio (Figure 7) demonstrate this variation, with Walmart, Mastercard, and 3M Company showing particularly strong risk-adjusted performance.

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

*Comprehensive dashboard combining multiple performance metrics*

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

*Shows trade count vs. 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 Sharpe ratio*

*WMT leads with 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, showed more challenging performance with a -21.65% return and 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.

The experimental results validate several key aspects of our strategy while identifying areas for improvement. The strategy demonstrates particular strength in stable market conditions and large-cap stocks, with effective risk management capabilities. However, the results also highlight the need for additional refinement in handling high-volatility securities and adapting to different market regimes. The comprehensive visualization suite provides clear evidence of the strategy's effectiveness and areas for potential enhancement.

These findings provide a solid foundation for further strategy development and optimization, particularly in the areas of risk management and market regime adaptation. The results underscore the importance of maintaining a balanced approach to trading frequency and position sizing across different market conditions, while the visualizations provide clear evidence of the strategy's strengths and limitations in various market environments.

This integration of quantitative analysis and visual representation provides a comprehensive understanding of the strategy's performance and effectiveness across different market conditions and stock characteristics. The combination of statistical metrics and visual analysis helps to effectively communicate the research findings and their implications for practical implementation.

#### 5.1.1 Top Performing Securities

The model showed exceptional performance in several key stocks:

1. Walmart (WMT):

* Highest Sharpe ratio: 2.925
* Total return: 48.18%
* Win rate: 72.73% across 11 trades
* Maximum drawdown: 3.38%

1. Mastercard (MA):

* Sharpe ratio: 1.612
* Total return: 19.45%
* Win rate: 50% across 10 trades
* Maximum drawdown: 4.22%

1. 3M Company (MMM):

* Sharpe ratio: 1.279
* Total return: 5.89%
* Limited sample size (1 trade)

#### 5.1.2 Trading Activity Analysis

The trading frequency and effectiveness varied significantly across securities:

1. High-Volume Trading:

* NVIDIA (NVDA): 44 trades
* Negative return: -21.65%
* Win rate: 31.82%
* Maximum drawdown: 40.23%

1. Moderate Trading:

* Broadcom (AVGO): 29 trades
* Positive return: 5.60%
* Win rate: 37.93%
* Maximum drawdown: 23.05%

1. Selective Trading:

* WMT: 11 trades with 72.73% success rate
* MA: 10 trades with 50% success rate

#### 5.1.3 Risk Management Performance

The risk metrics reveal important insights about the model's risk management capabilities:

1. Drawdown Control:

* Successful traders (WMT, MA, MMM) maintained drawdowns under 5%
* Problematic cases:
* NVDA: 40.23% maximum drawdown
* LLY: 32.91% maximum drawdown

1. Win Rate Distribution:

* High performers: WMT (72.73%), UNH (66.67%)
* Moderate performers: MA (50%)
* Underperformers: LLY (21.43%), NVDA (31.82%)

#### 5.1.4 Return Distribution Analysis

The distribution of returns across the portfolio shows:

1. Clustering Patterns:

* Majority of returns concentrated in 0-10% range
* Notable outliers:
* Positive: WMT (48.18%)
* Negative: LLY (-25.42%), NVDA (-21.65%)

1. Risk-Adjusted Performance:

* Strong positive correlation between Sharpe ratios and win rates
* No significant correlation between trading frequency and performance
* Superior performance in stocks with stable price trends

### 5.2 Implementation Insights

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

1. Trading Frequency:

The analysis of trading frequency reveals important implementation considerations:

1. 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

1. 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:

1. Large-Cap Stability:

* Walmart (WMT) demonstrated exceptional performance with 48.18% return and 72.73% win rate
* Mastercard (MA) showed consistent performance with 19.45% return and 50% win rate
* Financial sector stocks (JPM) exhibited strong risk-adjusted returns

1. Sector Considerations:

* Retail sector showed superior performance (WMT)
* Financial sector demonstrated stability (JPM, MA)
* Technology sector presented challenges (NVDA, META)

1. Volatility Impact:

* Lower volatility stocks tended to perform better
* High-volatility stocks required additional risk management
* Stable price trends correlated with better performance

1. Risk Management:

The results suggest a structured approach to risk management:

1. Position Sizing:

* Scale positions based on confidence scores
* Maintain maximum position size limits
* Consider volatility in position sizing

1. Stop-Loss Implementation:

* Use 2% initial stop-loss
* Implement trailing stops for profitable trades
* Adjust stops based on volatility

1. 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 comprehensive analysis of our hybrid CNN-BiLSTM trading strategy reveals several key findings that contribute to both theoretical understanding and practical implementation of deep learning in financial markets. The experimental results demonstrate the strategy's effectiveness in generating profitable trading signals while maintaining robust risk management protocols.The strategy's performance across different market segments shows particular strength in stable, large-cap stocks, with Walmart (WMT) emerging as the top performer with a 48.18% return and 72.73% win rate. This success is attributed to the combination of deep learning predictions with traditional technical analysis, enhanced by the attention mechanism's ability to identify relevant market patterns. The risk-return analysis, as illustrated in our visualizations, demonstrates the strategy's effectiveness in maintaining favorable risk-adjusted returns, with top performers achieving Sharpe ratios above 2.0.The analysis of trading frequency reveals important insights into strategy optimization. The contrast 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) demonstrates the importance 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 critical component of strategy success. 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 future development of algorithmic trading strategies. The emphasis on risk management and selective trading provides a framework for sustainable trading performance, while 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 trading strategy implementation. 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 sustainable trading performance in various market environments.

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* Technical review and refinement of methodology
* Performance analysis and insights generation

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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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