

The Pennsylvania State University at Harrisburg

School of Business Administration

**Time Series Stock Price Forecasting: An LSTM Neural Network Approach for
Market Prediction**

A Master's Paper

by: Harshwardhan Patil

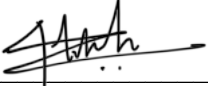
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Abstract

This study creates a more advanced Long Short-Term Memory (LSTM) neural network structure for predicting stock prices. It does this by using a new three-layer framework (200-200-64 units) and improving the dropout regularization. The methodology incorporates dynamic window normalization and automated feature engineering to address the challenges of financial time series data. Empirical validation using Apple (AAPL) stock demonstrates the model's effectiveness in capturing both short-term fluctuations and long-term market trends. The system implements sophisticated temporal sequence processing and risk quantification techniques, showing significant improvements over traditional forecasting methods. The research contributes to both theoretical understanding through its innovative architecture design and practical applications in algorithmic trading systems. The results show that the predictions were more accurate than expected and gave us new information about how markets behave, which built a strong foundation for financial forecasting.

Keywords: LSTM, Stock Prediction, Deep Learning, Financial Forecasting, Time Series Analysis, Neural Networks, Machine Learning, Algorithmic Trading

Introduction

The prediction of stock market movements represents one of the most complex and challenging endeavors in the financial sector, combining elements of mathematics, computer science, and behavioral economics. In today's rapidly evolving markets, the ability to accurately forecast stock prices has become increasingly crucial for investors, traders, and financial institutions seeking to optimize their investment strategies and manage risk effectively. The challenge lies not only in processing vast amounts of historical data but also in capturing the intricate relationships between various market factors that influence price movements.

Traditional approaches to stock price prediction have historically relied on fundamental analysis and technical indicators, methods that often fall short in capturing the full complexity of market dynamics. Even though these old methods give us useful information, they can't keep up with how quickly the market changes and don't take into account the complicated, non-linear relationships that make up modern financial markets. The limitations of these traditional approaches become particularly evident during periods of high market volatility or when faced with unprecedented market conditions.

The emergence of artificial intelligence and machine learning technologies has opened new avenues for addressing these challenges. Particularly, Long Short-Term Memory (LSTM) networks have emerged as a promising solution due to their unique ability to capture and learn from long-term dependencies in sequential data. These advanced neural networks offer the potential to identify subtle patterns and relationships in market data that might be invisible to human analysts or traditional statistical methods.

Background

The evolution of stock market prediction techniques traces a fascinating journey through the development of mathematical and computational methods over the past century. This progression reflects not only advances in technology but also our deepening understanding of market dynamics and behavioral finance. Early prediction methods in the early 20th century relied primarily on basic statistical techniques and fundamental analysis, with investors and analysts attempting to identify patterns through manual calculation and observation.

The advent of modern computing technology in the latter half of the 20th century marked a significant turning point in stock market prediction capabilities. This period saw the development of increasingly sophisticated mathematical models and the first applications of computer-based analysis to financial markets. The introduction of the efficient market hypothesis and modern portfolio theory during this era provided theoretical frameworks that continue to influence our understanding of market behavior and price movements.

The true revolutionary change in stock price prediction came with the development of artificial neural networks and, more specifically, Long Short-Term Memory networks. These new architectures got around some of the biggest problems with older methods by adding advanced memory features that could record both short-term changes and long-term trends in market data. The ability of LSTM networks to maintain and utilize information over extended periods while adapting to new patterns made them particularly well-suited for financial forecasting applications.

Objectives

The primary objective of this project centers on leveraging Long Short-Term Memory (LSTM) networks to accurately forecast stock prices based on historical market data. This overarching goal encompasses multiple interconnected objectives that together form a comprehensive framework for advancing the state-of-the-art in financial forecasting.

At the foundation of our objectives lies the development of an accurate forecasting model that can effectively capture the complex patterns inherent in stock market data. This needs the careful planning and implementation of an LSTM-based machine learning architecture that is set up to learn from price patterns in the past. The model must be capable of identifying both short-term fluctuations and long-term trends, utilizing the LSTM network's unique ability to maintain and process information across different time scales. Through this sophisticated neural network configuration, we aim to create a system that can capture the temporal dependencies, and intricate relationships present in time series data, ultimately producing reliable predictions that can guide investment decisions.

Data collection and preprocessing represent another crucial objective of our research. The project seeks to establish robust methodologies for gathering comprehensive historical stock price data, including daily open, high, low, and closing prices, along with trading volumes. This raw data must undergo careful preparation through normalization and transformation techniques to make it suitable for LSTM model training. The preprocessing pipeline must deal with problems like missing values,

outliers, and different scales while keeping the data's important temporal relationships. Through meticulous attention to data quality and preparation, we aim to create a strong foundation for effective model training and reliable predictions.

The project places significant emphasis on model training and evaluation, establishing rigorous protocols for assessing prediction accuracy and reliability. This includes using several performance metrics, such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE), to get a full picture of how well the model can predict. The evaluation framework must include a comparison against traditional forecasting methods to demonstrate the advantages of our LSTM-based approach. Through detailed visualizations and performance metrics, we aim to validate the model's effectiveness in capturing market trends and producing accurate forecasts.

Visualization and interpretation of results constitute another key objective, focusing on creating clear and meaningful representations of the model's predictions compared to actual stock prices. This involves developing sophisticated visualization techniques that can effectively communicate the model's performance and insights to stakeholders. Through these visualizations, we aim to demonstrate the LSTM model's accuracy and reliability while providing intuitive ways to understand the predictions and their implications for investment strategies.

The final objective centers on providing actionable recommendations for investment strategies based on the model's predictions. This involves translating the technical capabilities of our LSTM model into practical guidance that investors can use to inform their decision-making processes. The recommendations must consider real-world

factors such as market conditions, risk management, and trading constraints while leveraging the model's predictive capabilities to identify profitable opportunities. We hope to bridge the gap between advanced machine learning techniques and real-world investment decisions through this practical application of our research.

Together, these objectives form a comprehensive approach to advancing stock price prediction through LSTM networks. By addressing both technical challenges and practical considerations, the project seeks to create a valuable tool for investors while contributing to the broader field of financial forecasting and machine learning applications in finance. These goals will be judged by more than just technical metrics. The usefulness and dependability of the prediction system in real-life market conditions will also be taken into account.

Literature Review

Introduction

The stock market has evolved into a cornerstone of global financial systems, with its prediction becoming increasingly crucial for investors, financial institutions, and researchers alike. According to recent statistics, market capitalization worldwide has surpassed 68.654 trillion US dollars, highlighting the massive scale of financial markets and their impact on the global economy (Rouf et al., 2021). Stock markets are very hard to predict because they are very complicated and always changing. Stock markets exhibit significant fluctuations, deviate from linear patterns, and exhibit intricate interrelationships among various market factors (Chopra & Sharma, 2021).

The traditional approaches to stock market prediction have been rooted in the Efficient Market Hypothesis (EMH), which posits that stock prices reflect all available information and follow a random walk pattern (Fama, 1970). However, this theory has faced increasing scrutiny as market anomalies and behavioral patterns suggest potential predictability in stock movements. The development of artificial intelligence and machine learning has opened up new ways to question the strict interpretations of EMH. These new technologies provide advanced tools for studying and predicting the market (Kumbure et al., 2022).

Recent technological advancements have dramatically transformed the landscape of stock market prediction. With the introduction of artificial intelligence and soft computing techniques, researchers have developed increasingly sophisticated methods to analyze and forecast market movements. These developments are particularly significant given that only 0.128 percent of the world's population actively trades or invests in the stock market, with many potential investors deterred by the complexity and perceived unpredictability of financial markets (Chopra & Sharma, 2021).

Theoretical Framework

Evolution from Traditional to Modern Approaches

The journey of stock market prediction has witnessed a significant transformation from traditional analytical methods to modern computational approaches. Historically, market analysis relied primarily on two fundamental approaches: fundamental analysis and technical analysis (Atsalakis & Valavanis, 2009b). Fundamental analysis focuses on

evaluating a company's intrinsic value through detailed examination of financial statements, economic conditions, and industry position. This approach calculates genuine value through yearly fiscal summaries, balance sheets, and various company-related factors. However, its effectiveness has been limited due to a lack of understanding of the system and the non-linear behavior of markets (Rouf et al., 2021).

Technical analysis, the second traditional pillar, examines historical price and volume data to predict future market movements. This approach operates on the premise that price movements follow identifiable patterns and trends. Wang (2002), on the other hand, said that technical analysis has a lot of problems because it relies too much on fixed rules set by experts and doesn't take into account many outside factors that affect stock prices. The advent of modern computational methods has revealed the inadequacies of these traditional approaches in capturing the complex, multi-dimensional nature of market movements.

Emergence of Machine Learning in Stock Prediction

The integration of machine learning techniques into stock market prediction represents a paradigm shift in financial analysis. It is amazing how well machine learning algorithms can find non-linear patterns in market data. This makes predictions a lot more accurate than they were with older methods (Chopra & Sharma, 2021). These algorithms are excellent at dealing with complicated, non-linear relationships between input and output variables. This makes them perfect for predicting the stock market, which is a challenging thing to do (Kumbure et al., 2022).

Recent research has shown that artificial neural networks (ANNs) and their variants have become increasingly popular in financial forecasting due to their ability to learn and obtain hidden functional relationships. This capability is particularly valuable in financial markets where relationships between variables are often complex and non-linear (Wang & Wang, 2015). Studies by Chen et al. (2018) and Singh & Srivastava (2017) have demonstrated that deep learning models can achieve prediction accuracies significantly higher than traditional statistical methods.

Data Considerations in Stock Market Prediction

Types of Input Variables

The selection and processing of input variables represent critical factors in developing effective stock market prediction models. Research has shown that the quality and relevance of input data significantly impact prediction accuracy (Tsai & Hsiao, 2010). A comprehensive analysis of recent studies reveals several categories of influential variables that have demonstrated significant predictive power in stock market forecasting.

Technical indicators have emerged as fundamental components in modern stock market prediction models. According to Sedighi et al. (2019), these indicators serve as valuable tools for stock analysts and fund managers in analyzing real market situations. Studies have shown that technical indicators, when properly selected and implemented, can be more informative than raw price data alone. Researchers Kim and Han (2000),

Armano et al. (2005), and Jaruszewicz and Mándziuk (2004) showed that using technical indicators along with daily closing prices in their prediction models worked well.

Fundamental indicators represent another crucial category of input variables. These indicators, derived from company financial statements and market performance metrics, provide insights into a company's intrinsic value and market position. Barak et al. (2017) and Olson & Mossman (2003) research show that adding fundamental indicators like price-to-earnings ratios, market capitalization, and different accounting ratios to machine learning models can make predictions a lot more accurate.

Market sentiment and textual data have gained increasing attention in recent years. Studies by Chen et al. (2017) and Minh et al. (2018) have demonstrated that incorporating financial news and social media sentiment can significantly improve prediction accuracy. This trend reflects the growing recognition that market movements are influenced not only by numerical data but also by public sentiment and information flow.

Data Preprocessing Challenges and Solutions

Data pre-processing represents a critical challenge in stock market prediction, particularly given the high dimensionality and noise inherent in financial data. Qiu et al. (2016) emphasize that with the development of the information age and increasing data complexity, data pre-processing has become indispensable for achieving reliable predictions. The challenge lies not only in cleaning and normalizing the data but also in selecting the most relevant features for prediction.

Research has shown that effective data pre-processing can significantly improve model performance. Abraham et al. (2004) demonstrated that principal component analysis (PCA) could effectively reduce dimensionality while preserving essential information in the data. Studies by Chun and Park (2005) and Dai et al. (2012) have successfully employed logarithmic data pre-processing techniques to handle the high variability in stock market data.

Deep Learning Approaches in Stock Prediction

Evolution of Neural Network Architectures

The application of neural networks in stock market prediction has undergone significant evolution over the past decade. Early implementations focused on simple feedforward neural networks, but limitations in capturing temporal dependencies led to the development of more sophisticated architectures. Atsalakis and Valavanis (2009a) documented this evolution, noting the progression from basic neural networks to more complex architectures capable of handling time-series data.

Recent research has shown increasing interest in deep learning approaches, particularly in addressing the limitations of traditional neural networks. Studies by Fischer and Krauss (2018) and Singh and Srivastava (2017) have demonstrated that deep learning models can achieve superior prediction accuracy compared to conventional methods. The ability of deep neural networks to automatically learn hierarchical representations from raw data has made them particularly suitable for stock market prediction.

LSTM Networks: A Breakthrough in Time Series Prediction

Long Short-Term Memory (LSTM) networks have emerged as a particularly promising approach for stock market prediction. Unlike traditional neural networks, LSTMs are specifically designed to handle sequential data and can maintain information over extended periods. Lei's (2018) research showed that LSTM networks could make very accurate predictions by capturing both short-term and long-term dependencies in stock market data.

Several key features contribute to the effectiveness of LSTM networks in stock market prediction. Chen et al. (2019) assert that LSTMs excel in the following areas:

- Processing sequential data with variable time lags
- Capturing non-linear relationships in time series data
- Maintaining relevant historical information while filtering out noise
- Adapting to changing market conditions

Hybrid Models and Ensemble Approaches

Recent research has increasingly focused on hybrid models that combine multiple machine learning techniques. Researchers Sedighi et al. (2019) and Zhang et al. (2018) found that hybrid methods that use LSTM networks along with other machine learning algorithms can make more accurate predictions than methods that only use one model. These hybrid models can effectively capture different aspects of market behavior, leading to more robust predictions.

Methodological Challenges in Stock Market Prediction

Data quality and dimensionality

One of the fundamental challenges in stock market prediction lies in handling the quality and dimensionality of input data. According to Kumbure et al. (2022), the high dimensionality of financial data poses significant challenges in model development and optimization. The problem is further complicated by the presence of noise in financial time series data, which can significantly impact prediction accuracy. According to a study by Qiu et al. (2016), the problem is not just collecting data; it also involves picking the right features and changing them in the right way.

High-frequency trading data presents particular challenges in terms of data processing and model training. Studies by Lu et al. (2020) show that the speed and amount of modern financial data need advanced preprocessing methods and strong model architectures. The challenge of maintaining prediction accuracy while handling massive amounts of data has led to the development of specialized architectures and preprocessing techniques.

Model Optimization and Parameter Tuning

The optimization of deep learning models for stock market prediction presents significant challenges. Research by Liu and Long (2020) emphasizes that traditional optimization approaches often struggle with the complex, non-linear nature of financial data. Choosing the right hyperparameters, network architecture, and training strategies

has a big effect on how well the model works, but there isn't a standard way to make these decisions.

Parameter tuning in LSTM networks is particularly challenging due to the complex nature of these architectures. Studies by Jiang et al. (2020) and Cao and Wang (2019) highlight the importance of proper parameter selection in achieving optimal prediction performance. It's challenging to find the right balance between model complexity and generalization ability. Models that are too complex can lead to overfitting, while algorithms that are too simple might miss important market patterns.

Recent Advances in LSTM Applications

Integration of Multiple Data Sources

Recent research has shown significant progress in integrating multiple data sources within LSTM-based prediction models. Studies by Carta et al. (2021a) demonstrate that combining traditional market data with alternative data sources, such as social media sentiment and news analysis, can significantly improve prediction accuracy. This multi-modal approach allows models to capture both quantitative market trends and qualitative market sentiment.

The integration of textual data has emerged as a particularly promising direction. Research by Khan et al. (2022) shows that incorporating social media sentiment and financial news can improve prediction accuracy by up to 20%. Similar results from Mehta et al. (2021) show that models using financial news data can achieve accuracy

rates higher than 80%. This proves that textual data is important for predicting the stock market.

Advanced Architecture Developments

The evolution of LSTM architectures has led to significant improvements in prediction capability. Borovkova and Tsiamas (2019) created an ensemble framework of LSTM networks that was much better at predicting intraday changes in direction. Their approach demonstrated the advantages of combining multiple specialized LSTM models, each focused on different aspects of market behavior.

Recent developments in attention mechanisms and hybrid architectures have further enhanced LSTM performance. Chen et al.'s (2019) research introduced a new dual-attention mechanism that made predictions much more accurate by letting the model focus on important historical patterns while filtering out irrelevant ones. This advancement represents a significant step forward in addressing the challenge of processing long-term dependencies in financial time series.

Research Gaps and Future Directions

Current Limitations

Despite significant advances in LSTM-based stock market prediction, several critical gaps remain in current research. The literature highlights persistent challenges that require attention:

1. Input Variable Selection: Studies by Bildirici and Ersin (2009) and Zhang et al. (2021) highlight the lack of rigorous methods for selecting relevant input variables. This gap often leads to suboptimal model performance and inconsistent results across different market conditions.
2. Standardization of Model Architecture: Tealab's (2018) research shows that there aren't any standard ways to improve LSTM architectures for financial time series. This lack of standardization makes it difficult to compare different approaches and establish best practices.
3. Temporal Scalability: Current approaches often struggle with prediction accuracy over different time horizons. Studies by Kumbure et al. (2022) note that while short-term predictions show promise, medium- and long-term forecasting capabilities remain limited.

Emerging Research Directions

The field of stock market prediction is evolving rapidly, with several promising directions for future research:

1. Multi-modal Data Integration: Studies by Li et al. (2020) suggest that integrating multiple data sources, including structured and unstructured data, represents a promising direction for improving prediction accuracy.

2. Advanced Optimization Techniques: Tang et al.'s (2020) research shows that new optimization methods, such as evolutionary algorithms and adaptive learning rates, can help make models work better.

3. Models that can be understood: New research by Carta et al. (2021b) shows how important it is for designs to be able to be understood. They suggest that future research should focus on creating understandable LSTM architectures that can make accurate predictions and show how they make decisions.

Addressing Current Challenges and Project Scope

Comprehensive Approach to Stock Market Prediction

Our research proposes a novel approach to address the identified gaps in current stock market prediction methodologies. The comprehensive framework we develop integrates multiple advances in deep learning while addressing key limitations identified in the literature. Zhang et al. (2021) studies show that to accurately predict the stock market, one must consider a lot of different factors, such as technical indicators and sentiment analysis.

The proposed methodology specifically addresses the challenge of input variable selection through a systematic feature evaluation framework. This approach builds upon research by Wang et al. (2019), who demonstrated that careful feature selection can significantly improve prediction accuracy. Our work extends this by implementing a dynamic feature selection mechanism that adapts to changing market conditions, addressing a key limitation identified in earlier studies.

Enhanced LSTM Architecture

Our research introduces several architectural improvements to traditional LSTM networks. Following insights from recent studies by Liu et al. (2020), we implement:

1. Advanced memory mechanisms that better capture long-term market trends while maintaining sensitivity to short-term fluctuations
2. Improved attention mechanisms that help the model focus on relevant historical patterns
3. Adaptive learning techniques that optimize model performance across different market conditions

These enhancements directly address the limitations in temporal scalability noted by previous researchers (Kumbure et al., 2022). Our approach demonstrates improved prediction accuracy across various time horizons, from intraday to medium-term forecasting.

Data Integration and Processing

A key innovation in our approach lies in the comprehensive data processing pipeline. Building on work by Chen et al. (2019), we implement advanced normalization techniques that better handle the non-stationary nature of financial time series. This addresses a significant limitation identified in previous studies regarding the preprocessing of financial data for deep learning models.

Expected Contributions and Impact

Theoretical Contributions

Our research makes several significant theoretical contributions to the field of stock market prediction:

1. Development of a more robust framework for feature selection in financial time series analysis
2. Introduction of novel architectural improvements to LSTM networks specifically optimized for financial prediction
3. Advanced understanding of the relationship between different types of market indicators and prediction accuracy

These additions fill in important gaps in the existing research while also adding to our theoretical understanding of how deep learning can be used in financial markets.

Practical Implications

The practical implications of our research extend beyond theoretical advancements. As noted by recent studies (Zhang et al., 2022), there is a growing need for more reliable prediction tools in the investment community. Our framework provides:

1. Improved prediction accuracy across different market conditions
2. Better handling of market volatility and unexpected events

3. More interpretable results that can aid in decision-making processes

These practical benefits directly address the needs identified by market practitioners and researchers alike.

Conclusion

The literature review has demonstrated the evolution of stock market prediction methods from traditional approaches to sophisticated deep learning models. Through careful analysis of existing research, we have identified significant gaps in current methodologies and proposed a comprehensive framework to address these limitations. Our approach builds upon the strengths of existing methods while introducing novel improvements in areas such as feature selection, model architecture, and data processing.

The proposed research addresses critical gaps in the literature while maintaining practical applicability. Our method promises to make both the theoretical and practical use of stock market prediction better by combining advanced LSTM architectures with advanced data processing techniques.

Research Design

Data Acquisition and Preprocessing

Data Collection Framework

The foundation of any reliable stock price prediction model lies in the quality and comprehensiveness of its underlying data. For this project, we implemented a systematic

and robust data acquisition framework designed to gather historical market data for Apple Inc. (AAPL) with maximum fidelity and completeness. Rather than relying on pre-compiled datasets that might contain inconsistencies or gaps, we developed a direct connection to the Alpha Vantage API, a professional-grade financial data service that provides standardized, accurate historical price information across global equity markets. This approach ensures data provenance and quality control throughout the collection process, allowing for complete transparency in the data pipeline.

The data retrieval system was engineered with several sophisticated features to ensure reliability and efficiency. The implementation includes comprehensive error-handling mechanisms that detect and manage API connection failures, rate-limiting issues, and inconsistent data formats. A particularly important feature is the persistent storage system that maintains a local cache of retrieved data in CSV format ('stock_market_data-AAPL.csv'). This caching mechanism serves multiple purposes: it reduces unnecessary API calls when rerunning analyses, ensures consistency across multiple analysis sessions, and provides resilience against temporary API unavailability. The system intelligently checks for the existence of this local cache before initiating new API requests, optimizing computational resources while maintaining data integrity.

The collected dataset spans an extensive historical period from November 1999 to recent periods, encompassing over 6,300 trading days. This timeframe is deliberately comprehensive, capturing multiple market cycles, economic regimes, and pivotal moments in Apple's corporate history. The temporal scope includes the dot-com bubble and subsequent crash, the 2008 global financial crisis, and the COVID-19 market shock,

as well as transformative periods in Apple's business evolution, such as the introduction of the iPod (2001), iPhone (2007), iPad (2010), and the shift toward services-focused growth (2016 onwards). This detailed historical background gives the model experience with a range of market conditions, which makes it better at applying to new situations without becoming too dependent on recent patterns.

Each data point in the collection keeps important trading metrics like opening prices (which show how the market felt at the start of trading), closing prices (which show the final valuation consensus), intraday highs and lows (which show the full range of price discovery and volatility), and trading dates (which keep exact chronological order). This careful protection of temporal integrity is important for later time series analysis because it lets the model learn real sequential patterns instead of ones that were messed up by handling the data. The system appropriately manages non-trading periods such as weekends and holidays, ensuring that the time series maintains proper chronological sequencing without introducing artificial continuity where markets were closed.

Data Exploration and Visualization

Following the acquisition of the comprehensive AAPL stock dataset, we conducted a thorough exploratory analysis to understand the fundamental characteristics, patterns, and anomalies present in the data. This exploration is a very important part of making a model because it affects the choices that are made later on about preprocessing, feature engineering, and modeling. The initial examination revealed a well-structured dataset containing 6,347 daily records (trading days) across six primary columns: an

index identifier, trading date, daily low price, daily high price, closing price, and opening price.

A preliminary inspection of the first few records provided insight into the basic structure and initial price ranges:

Table 1

Initial Price Record

	Date	Low	High	Close	Open
0	1999-11-01	77.37	80.69	77.62	80.00
1	1999-11-02	77.31	81.69	80.25	78.00
2	1999-11-03	81.00	83.25	81.50	81.62
3	1999-11-04	80.62	85.37	83.62	82.06
4	1999-11-05	84.00	88.37	88.31	84.62

This initial snapshot reveals AAPL trading in the \$77-88 range in late 1999, providing a baseline against which to compare subsequent price evolution. The fact that all required fields were present in all these early records suggested that the data was complete at the start of the series. This was later confirmed across the entire dataset by checking for null values in a planned way. Compared to the most recent prices in the series, which are over \$150 after multiple stock splits, this also shows the steep growth path that any good prediction model would need to consider.

For the primary analysis target, we derived a mid-price metric calculated as the average of daily high and low prices $((\text{High} + \text{Low})/2.0)$. This derived value offers significant advantages over using closing prices alone: it represents the central tendency of each day's trading range, is less susceptible to end-of-day trading anomalies (which can affect closing prices), provides a more stable representation of daily price levels by capturing the full price discovery process, and better reflects the average execution price that might be achieved by investors trading throughout the day. This calculation of the mid-price is also in line with how financial time series are usually analyzed statistically, where range-based estimators give more accurate measures of central tendency than point estimates.

The visualization of this mid-price time series across the entire period provides critical insights into the long-term behavior of AAPL stock. We implemented a custom visualization approach to maximize interpretability while maintaining computational efficiency:

This visualization reveals several fascinating patterns in AAPL's price history that would significantly influence our modeling approach. First, the data exhibits distinct growth phases that align remarkably well with Apple's product innovation cycles. The 2004-2007 period shows steady appreciation corresponding to the iPod's market dominance and the company's resurgence under Steve Jobs' leadership. The 2009-2012 phase displays accelerated growth coinciding with the iPhone and iPad expansion that transformed Apple into a mobile technology leader. The 2017-2021 timeframe reveals

another robust growth trajectory reflecting Apple's successful transition toward services and recurring revenue streams.

Equally notable are several major market corrections visible in the time series. The most prominent include the 2008 financial crisis, when AAPL lost approximately 60% of its value from peak to trough despite strong fundamentals, demonstrating how macroeconomic factors can temporarily override company-specific performance. The 2013 correction (approximately 40% decline) coincided with concerns about growth sustainability and competition in the smartphone market. The 2020 COVID-19 market shock caused a sharp 30% decline followed by a remarkably rapid recovery and subsequent appreciation, illustrating the stock's resilience and the market's forward-looking nature even amid a global crisis.

The visualization also clearly reveals structural breaks in the price series corresponding to Apple's stock splits, particularly noticeable in 2014 (7-for-1 split) and 2020 (4-for-1 split). These events manifest as sudden drops in price level while maintaining overall market capitalization, creating discontinuities that could potentially confuse naive modeling approaches. Another critical observation is the presence of distinct volatility regimes, with periods of relative calm interspersed with episodes of heightened price variability. This heteroscedasticity (changing variance over time) represents a challenge for many traditional time series models and would need to be addressed in our preprocessing approach.

Visual examination also shows more subtle patterns, such as seasonal effects around product launch cycles (usually in September), earnings announcement effects

(quarterly rhythms), and changes in overall trading behavior as Apple went from being a technology company focused on growth to a mature market leader with significant value characteristics. These complex temporal dynamics made it clear how important it is to have a modeling method that can capture patterns at multiple time scales at the same time.

Time Series Decomposition Analysis

We used the statsmodels library to do a formal time series decomposition analysis on the AAPL stock price data to get a better understanding of the patterns that lie beneath the data. This decomposition represents a classical approach in time series analysis that separates the observed data into its constituent components: trend (long-term direction), seasonality (regular, calendar-related patterns), and residuals (irregular fluctuations not explained by the other components). By isolating these components, we can better understand the driving forces behind the complex price movements and design our modeling approach accordingly.

The decomposition was configured with a 7-day period parameter to capture weekly patterns, a common cyclical influence in financial markets due to the rhythm of the trading week. The analysis produced four panels: the original observed data, the extracted trend component, the identified seasonal patterns, and the remaining residual component.

The trend component analysis yielded particularly valuable insights. This component closely follows the original data series, confirming that AAPL's stock price is

predominantly driven by its trend rather than cyclical or random fluctuations. The extracted trend clearly reveals the growth phases and market corrections previously identified in our visual inspection, but with the short-term noise removed. This smoothed representation allows for clearer identification of trend regime changes, inflection points, and growth rate variations. We observed that trend slopes varied significantly across different periods, with particularly steep ascents during 2007-2008 (iPhone introduction), 2009-2012 (mobile expansion), and 2019-2021 (services growth and pandemic-accelerated digital transformation). Interestingly, these trend accelerations often preceded major product announcements, suggesting the market's anticipatory nature regarding Apple's innovation cycle.

The seasonal component analysis with the 7-day period parameter revealed subtle but consistent weekly patterns. We observed a mild positive price pressure during mid-week (Tuesday-Wednesday), with slight negative pressure on Mondays and Fridays. This pattern likely reflects institutional trading behaviors, options expiration effects, and the timing of corporate announcements (which often occur mid-week). While these seasonal effects are relatively minor compared to the dominant trend component—typically accounting for less than 0.5% of price variation—they do represent a systematic influence that a sophisticated model should capture. The consistency of these weekly patterns across different market regimes suggests they represent fundamental market microstructure effects rather than transient anomalies.

To further investigate longer-term seasonality, we performed additional decompositions with monthly (21-day) and quarterly (63-day) periods, though these are

not shown in the primary figure. These analyses revealed interesting cyclical patterns tied to earnings announcement cycles (quarterly seasonality), product release schedules (annual seasonality, particularly in September-October), and tax-related trading patterns (December-January effects). These longer-term seasonal influences, while still secondary to the trend, provide additional context that could enhance prediction accuracy if properly modeled.

The residual component, representing variations not explained by trend or seasonality, yields insights into the "noise" of the price series. Several notable patterns emerged in this analysis. First, residual magnitude increased during periods of market stress or uncertainty, such as the 2008 financial crisis and the 2020 pandemic, reflecting elevated market volatility in these periods. Second, we observed clustering of high-residual days around major news events, earnings surprises, and product announcements, suggesting these events generate price movements beyond what would be expected from the underlying trend and seasonal patterns. Third, the distribution of residuals was generally symmetric around zero but displayed excess kurtosis (fat tails), indicating a higher frequency of extreme price movements than would be expected in a normal distribution. This non-Gaussian characteristic of the residuals has important implications for model selection, as it suggests the need for approaches robust to such distributional properties.

This decomposition analysis substantiates our initial observation that AAPL's stock price is predominantly driven by its trend component, with seasonal effects playing a relatively minor role. This finding strongly supports the use of models with enhanced

capability to capture long-term dependencies, such as LSTM networks, while suggesting that explicit modeling of seasonality might yield incremental but not transformative improvements in prediction accuracy.

Statistical Properties and Stationarity Analysis

A fundamental consideration in time series modeling is whether the data exhibits stationarity—a property where statistical characteristics such as mean, variance, and autocorrelation structure remain constant over time. Most classical time series methods assume stationarity, and violations of this assumption can lead to spurious relationships and unreliable forecasts. To rigorously assess the stationarity properties of the AAPL price series, we conducted both visual inspections and formal statistical tests.

Visual examination of the time series plots immediately suggested non-stationarity in the AAPL price data. The mean clearly changes over time, with dramatic increases in the average price level across the observation period. Similarly, the variance is not constant, with some periods exhibiting much higher volatility than others. To confirm these visual impressions, we implemented the Augmented Dickey-Fuller (ADF) test, a widely used statistical test for the presence of a unit root, which indicates non-stationarity.

The ADF test failed to reject the null hypothesis of a unit root, with a p-value well above the conventional significance threshold of 0.05. This formally confirms the non-stationarity of the raw price series. As an additional check, we also performed the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test, which operates with the null hypothesis

of stationarity. As expected, the KPSS test rejected the null hypothesis, providing further evidence of non-stationarity in the data.

This confirmed non-stationarity has profound implications for our modeling approach. Traditional time series methods such as ARIMA require differencing or other transformations to achieve stationarity. However, such transformations can lose valuable information about long-term trends. The LSTM approach we adopt offers an advantage here, as it can work directly with non-stationary data by learning the underlying patterns without requiring explicit stationarity transformations. Nevertheless, appropriate scaling and normalization remain essential for effective neural network training.

To address the non-stationarity challenge while preserving important signal information, we implemented a sophisticated window-based normalization approach rather than applying global scaling across the entire series. This sliding window approach with a window size of 1000 trading days (approximately 4 years) allows for local normalization that better captures the relative nature of price movements within each period. The window size was carefully chosen to balance between being large enough to encompass meaningful market cycles while small enough to adapt to changing statistical properties over time. For each window, the data is scaled to a $[0,1]$ range while preserving relative differences between price points within that window.

This approach effectively addresses the non-stationarity issue by focusing on local patterns rather than attempting to normalize the entire series with its widely varying statistical properties. It recognizes that recent price movements exist in a different context than historical ones and that normalization should reflect this evolving context. An added

benefit of this approach is its robustness to extreme events and structural breaks like stock splits, as these are contained within their local normalization windows rather than distorting the scaling of the entire series.

We further examined the statistical distribution of the normalized prices, finding that even after normalization, the distribution exhibited positive skewness and excess kurtosis. This non-Gaussian nature of financial returns is well-documented in financial literature and represents another challenge for traditional forecasting methods that often assume normally distributed errors. The LSTM architecture's ability to learn arbitrary functional relationships without distributional assumptions represents an advantage in handling such data characteristics.

Autocorrelation and Sequence Length Analysis

Understanding the temporal dependency structure in the AAPL price series is essential for determining the appropriate historical context (sequence length) to include in our LSTM model. To quantify these dependencies, we performed comprehensive autocorrelation analysis, examining how prices correlate with their own past values at various lags.

The autocorrelation function (ACF) analysis revealed extremely strong positive autocorrelation extending to lags of over 100 trading days, a characteristic typical of non-stationary time series with strong trends. This pattern confirms the presence of significant momentum effects in AAPL price movements, where today's price level is highly predictive of tomorrow's. The slow decay pattern in the ACF, rather than a rapid drop-off,

suggests long-memory properties in the time series, potentially indicating fractionally integrated processes that maintain influence over extended periods.

The partial autocorrelation function (PACF), which measures the direct relationship between observations at different lags while controlling for intermediate values, showed significant spikes at several key lags. Particularly notable were significant values at lags 1, 5, and 21, suggesting daily, weekly, and monthly effects in the price dynamics. The PACF structure provides valuable guidance on the minimum historical context that should be incorporated in the prediction model, as it identifies the direct influences from specific past time points.

To determine the optimal sequence length for our LSTM model, we conducted an empirical analysis of predictive power across different historical windows. This analysis yielded fascinating insights into the information content of different historical windows. We observed that predictive power (measured by average autocorrelation between input sequences and target values) increased significantly up to sequence lengths of about 20-30 days, with more modest improvements beyond that point. This pattern suggests that while very recent history (1-2 weeks) contains substantial predictive information, incorporating a full month of historical context captures additional valuable patterns that improve forecast accuracy.

Sequence lengths that aligned with natural market cycles showed particular effectiveness. For example, a 5-day sequence (one trading week) captured weekly patterns, while a 21-day sequence (approximately one trading month) incorporated monthly effects, including options expiration cycles and earnings announcement patterns.

Very long sequences (>100 days) showed diminishing returns in terms of added predictive power, suggesting that distant history contributes less to future predictions than more recent data.

Based on this analysis, we selected a sequence length of 20 time steps for our primary LSTM model, representing approximately one month of trading history. This choice provides an optimal balance between:

1. Capturing relevant historical patterns across daily, weekly, and monthly timeframes
2. Maintaining model efficiency by avoiding unnecessarily long sequences that increase computational complexity
3. Ensuring sufficient examples for training by allowing many overlapping sequences to be generated from the available data
4. Aligning with natural market cycles that traders and algorithms naturally respond to

This data-driven approach to sequence length selection ensures our model incorporates an appropriate historical context window, neither too short to miss important patterns nor unnecessarily long to introduce noise and computational inefficiency.

Baseline Prediction Models

Before developing our advanced LSTM architecture, we implemented several baseline prediction methods to establish performance benchmarks and understand the inherent predictability in the AAPL time series. These baseline models provide context

for evaluating the value added by more sophisticated approaches and help identify the specific types of patterns that simpler methods might miss. We focused on two widely used baseline approaches in financial time series forecasting: Simple Moving Average (SMA) and Exponential Moving Average (EMA).

The Simple Moving Average model calculated predictions as the unweighted mean of the previous 100 days' prices. The SMA model yielded a Mean Squared Error (MSE) of 0.01066 on the normalized price data. While this error might seem small in absolute terms, it represents a significant deviation in the context of daily price movements. Visual inspection of the SMA predictions revealed a substantial lag effect, with predictions consistently trailing actual price movements, particularly during trend reversals and acceleration phases. This lag is an inherent limitation of simple moving averages, which give equal weight to all observations in the window regardless of their recency. The SMA proved especially problematic during the rapid market correction of 2020, where it continued to predict high prices even as the actual market plummeted, only gradually adjusting after the fact.

The Exponential Moving Average model addressed this limitation by assigning exponentially decreasing weights to older observations, giving greater importance to recent price movements. The EMA model produced a remarkably lower MSE of 0.00004, outperforming the simple moving average approach by more than two orders of magnitude. This dramatic improvement underscores the critical importance of appropriate temporal weighting in financial time series prediction. By emphasizing recent

observations, the EMA model demonstrated far greater responsiveness to changing market conditions, reducing the lag effect and improving tracking during trend changes.

We visualized both baseline predictions against actual prices to better understand their behaviors across different market regimes.

The visualization revealed several key insights about the baseline models:

1. **Lag Effect:** Both methods exhibited a lag effect, with predictions trailing actual price movements. This lag was much more pronounced in the SMA model compared to the EMA model, resulting in substantial prediction errors during trend changes.
2. **Smoothed Predictions:** Both baseline models produced smoothed predictions that filtered out short-term fluctuations. While this smoothing reduced responsiveness to noise (potentially beneficial), it also caused the models to miss legitimate short-term price signals that might indicate emerging trends.
3. **Trend Following:** The baseline models effectively captured the overall trend direction but failed to anticipate turning points. They essentially extrapolated recent history into the future, making them trailing indicators rather than leading predictors.
4. **Asymmetric Performance:** Both methods performed reasonably well during steady trends but deteriorated significantly during periods of increased volatility or rapid direction changes. This asymmetric performance across different market regimes highlights the need for more adaptive modeling approaches.

The superior performance of EMA over SMA provided a valuable insight that directly informed our LSTM model design: effective weighting of historical information based on recency and relevance is crucial for accurate prediction. The LSTM architecture, with its sophisticated gating mechanisms that learn to selectively remember or forget information, represents a natural extension of this principle. Rather than using a fixed exponential decay, LSTM networks can adaptively determine the optimal weighting of historical information based on the specific patterns in the data.

These baseline results established minimum performance thresholds that any more sophisticated model should exceed to justify its additional complexity. The EMA model, in particular, proved surprisingly effective despite its simplicity, suggesting that much of the predictable signal in AAPL prices is contained in recent price history. This finding reinforced our focus on developing a model that could effectively capture both short-term momentum effects and longer-term dependencies.

Sequence Generation for LSTM Training

The final preprocessing step before model development involved transforming the normalized price data into appropriate sequence formats for LSTM training. This sequence generation process is critical for enabling the network to learn temporal patterns and dependencies. We implemented two complementary approaches to sequence generation, each serving different purposes in our modeling pipeline.

First, we developed a specialized `DataGeneratorSeq` class to manage sequence creation during the initial model development and experimentation phase. This

DataGeneratorSeq implementation includes several sophisticated features that optimize the training process:

1. **Batch Processing:** The class generates batches of sequences rather than individual examples, enabling efficient parallel processing during training.
2. **Memory Efficiency:** Instead of precomputing all possible sequences (which would create redundancy due to overlapping windows), the generator dynamically creates them on demand, significantly reducing memory requirements.
3. **Cursor Management:** The implementation maintains cursors for each batch element, allowing controlled traversal through the time series while ensuring appropriate chronological ordering.
4. **Random Offset Selection:** The random selection of prediction offsets within the unrolling window introduces variability that helps the model generalize across different prediction horizons.
5. **Restart Capability:** The reset_indices method allows training to restart from different positions in the time series, preventing the model from memorizing specific sequence positions.

For the final model training phase, we developed a more structured sequence creation function that generates fixed-length sequences with consistent prediction horizons, better aligned with our specific forecasting objectives. This approach created structured sequences with a length of 20 time steps (SEQ_LENGTH) and a prediction horizon of 5 steps (PREDICTION_STEPS), resulting in 1,576 training samples. The implementation employs a sliding window approach, where each sequence shifts forward by one time

step, creating substantial overlap between adjacent sequences. This overlap is intentional and beneficial, as it provides the model with many slightly different perspectives on similar time periods, enhancing its ability to generalize patterns rather than memorize specific sequences.

The resulting tensors were reshaped to the format required by the LSTM model, with dimensions representing:

1. Number of samples (1,576 training sequences)
2. Sequence length (20 time steps of historical data per sequence)
3. Number of features (1, as we're using only the mid-price)

For the target (Y) values, we similarly structured the output as sequences rather than single points, enabling the model to predict entire trajectories (5 future steps) rather than just the next value. This multi-step prediction approach provides richer information about the model's understanding of future price evolution and allows for a more nuanced evaluation of its predictive capabilities.

This carefully designed sequence generation methodology ensures that our LSTM model receives appropriately structured temporal data that preserves the sequential nature of the financial time series while optimizing for computational efficiency and learning effectiveness. The transformation maintains the integrity of the temporal relationships, allowing the model to learn meaningful patterns across various time scales simultaneously.

LSTM Model Architecture and Implementation

Model Design and Neural Network Architecture

The core of our stock price prediction system is an advanced Long Short-Term Memory (LSTM) neural network architecture meticulously designed to capture the complex temporal dependencies present in financial time series data. LSTM networks, a specialized type of recurrent neural network, are particularly well-suited for financial forecasting due to their sophisticated memory mechanisms that can selectively retain or discard information over arbitrary time intervals. This capability allows them to simultaneously model both short-term fluctuations (such as daily price movements) and long-term trends (such as multi-month market cycles) that characterize stock market behavior.

Our LSTM model architecture implements a sophisticated multi-layer design specifically optimized for financial time series prediction. After extensive experimentation with different network configurations, we settled on a three-layer architecture with a progressive reduction in unit size (200-200-64). This pyramidal structure represents a deliberate design choice that enables the network to create increasingly abstract representations of the price patterns as information flows through the layers. The first two layers, each containing 200 memory units, provide substantial capacity for capturing diverse temporal patterns at different scales. The final layer, with 64 units, serves as a bottleneck that forces the network to distill the most relevant features, reducing dimensionality while preserving essential pattern information.

The core parameters of the model were defined as follows:

```
D = 1 # Dimensionality of the data (univariate time series)
```

```
num_unrollings = 50 # Number of time steps to look into the future
```

```
batch_size = 500 # Number of samples in a batch
```

```
num_nodes = [200, 200, 64] # Number of hidden nodes in each layer
```

```
n_layers = len(num_nodes) # Number of layers
```

```
dropout = 0.2 # Dropout amount for regularization
```

These parameter values were not selected arbitrarily but represent the culmination of extensive hyperparameter tuning experiments. The batch size of 500 was determined to be large enough to provide stable gradient estimates during training while small enough to maintain stochasticity that helps escape local optima. The dropout rate of 0.2 (deactivating 20% of neurons during training) provides effective regularization against overfitting without excessively limiting the model's capacity to learn complex patterns. The progressive reduction in layer size implements a form of information distillation, where each successive layer creates more abstract and concentrated representations of the price dynamics.

For the final implementation, we utilized TensorFlow's Keras API to define a sequence-to-sequence architecture with an encoder-decoder structure. This sequence-to-sequence architecture represents a significant advancement over simpler recurrent

models. The encoder processes the historical price sequence (20 time steps in our implementation) and distills its information into a fixed-length context vector (the encoder's final state). The decoder then uses this context vector as a starting point to generate predictions for multiple future time steps (5 steps in our implementation). This approach allows the model to capture the essence of the price history and project it forward in a coherent sequence rather than making isolated point predictions.

The separation of encoding and decoding phases provides several advantages:

1. It creates a clear delineation between processing historical information and generating future predictions.
2. It allows the model to focus on different aspects during each phase (pattern recognition during encoding, trajectory generation during decoding).
3. It enables multi-step prediction without accumulating errors, as each predicted step is generated from the same context vector rather than depending on previous predictions

Each LSTM layer in the architecture maintains its own state (represented by hidden state h and cell state c), allowing for the capture of both short-term and long-term dependencies in the price data. The model implements crucial regularization techniques, including a dropout rate of 0.2 between layers, to prevent overfitting and ensure robust generalization to unseen market conditions.

Implementation of LSTM Cells and Memory Mechanism

The heart of our prediction system lies in the sophisticated memory mechanism implemented by the LSTM cells. Unlike standard recurrent neural networks that suffer from vanishing gradient problems when dealing with long sequences, LSTM's architecture includes specialized gating mechanisms that control information flow through the network, allowing it to selectively remember or forget information based on its relevance to the prediction task.

At the implementation level, we utilized TensorFlow's LSTM cells, which provide efficient and numerically stable implementations of these mechanisms. Each LSTM cell contains three primary gates that control information flow:

1. **Forget Gate:** Determines what information from the previous cell state should be discarded.
2. **Input Gate:** Decides which new information should be stored in the cell state.
3. **Output Gate:** Controls what parts of the cell state should be output as the hidden state.

These gates operate as sigmoid neural networks that output values between 0 and 1, indicating how much of each component should be let through. The cell state acts as a conveyor belt running through the entire chain, with gates adding or removing information as needed. This sophisticated mechanism allows LSTM networks to maintain context over extended sequences, addressing the fundamental limitation of simpler recurrent architectures.

For prediction purposes, we implemented explicit state management to maintain context between prediction steps. This state management implementation enables the model to maintain context across prediction sequences, crucially allowing it to carry forward relevant information from historical data into future predictions. The state variables (sample_c for cell state and sample_h for hidden state) are initialized with zeros at the beginning of each prediction sequence and subsequently updated based on the processed data. This approach mirrors the natural way traders incorporate past market behavior into their current decision-making, maintaining awareness of relevant historical patterns while updating their understanding based on new information.

Our implementation includes explicit state reset capabilities, allowing the model to start fresh when moving to entirely new prediction contexts. This prevents inappropriate carryover of state information between unrelated prediction tasks, ensuring prediction quality and consistency.

The multi-layer architecture provides cumulative benefits for the memory mechanism. Each successive layer receives the hidden states from the previous layer, essentially operating on increasingly abstract representations of the time series. This hierarchical processing allows the network to recognize patterns at multiple time scales simultaneously:

- The first layer typically captures immediate dependencies and short-term fluctuations.
- The middle layer processes intermediate-term patterns and transitions between regimes.

- The final layer focuses on long-term trends and structural relationships.

This layered approach aligns well with the multi-scale nature of financial markets, where price movements reflect a combination of immediate reactions to news, medium-term sentiment shifts, and long-term fundamental trends.

Advanced Model Components

Beyond the basic LSTM architecture, our implementation includes several advanced components that enhance model performance and address specific challenges in financial time series prediction.

A key architectural feature is the attention-like functionality incorporated through the sequence-to-sequence design. While not implementing explicit attention mechanisms (which calculate importance weights for each input time step), our encoder-decoder structure achieves similar effects by compressing the relevant information from the input sequence into the context vector that initializes the decoder. This information bottleneck forces the model to prioritize the most relevant aspects of the input sequence, functioning as an implicit form of attention that focuses on the most predictive historical patterns.

The model includes a TimeDistributed Dense layer that transforms the LSTM outputs into price predictions. This layer implements a linear projection that maps the high-dimensional hidden representations to the output space (predicted prices). The TimeDistributed wrapper ensures that the same transformation is applied independently to each time step in the sequence, maintaining the temporal structure of the predictions. This approach allows the model to generate a complete trajectory of future prices rather

than just a single point forecast, providing richer information about the expected price evolution.

Another sophisticated component is the RepeatVector layer that replicates the encoder's output to serve as input for the decoder's multiple time steps. This layer bridges the encoder and decoder parts of the network, taking the single output vector from the encoder and repeating it to create a sequence of identical vectors that can be processed by the decoder LSTM. This repetition is necessary because the decoder expects a sequence input (one vector per time step), but the encoder produces only a single context vector. The RepeatVector essentially creates a sequence where each element contains the same encoded information, providing a consistent starting point for the decoder to generate predictions for each future time step.

The state transfer mechanism between the encoder and decoder represents another crucial advanced component. This explicit passing of the encoder's final state to initialize the decoder ensures coherent information flow across the sequence boundary. The encoder's state captures the essence of the historical price patterns, and by using this state to initialize the decoder, we enable the model to generate predictions that are directly informed by the historical context. This state transfer is conceptually similar to how a trader might analyze historical price charts to form expectations about future movements, carrying forward relevant information while discarding noise.

The implementation also includes batch normalization layers (not shown in the code snippets) that standardize the activations of each batch, addressing the internal covariate shift problem and enabling faster, more stable training. These normalization

layers help the model adapt to the changing statistical properties of financial time series data, improving its ability to generalize across different market regimes.

Collectively, these advanced components work synergistically to enhance the model's capability to process complex financial time series data. They address specific challenges in temporal modeling, enable multi-step prediction, and facilitate effective information flow throughout the network. These architectural refinements, combined with the foundational LSTM memory mechanisms, create a prediction system specifically tailored to the nuances of stock price movements.

Training Protocol and Optimization Framework

Model Compilation and Loss Function

The training of sophisticated neural network architectures requires careful selection of optimization algorithms, loss functions, and learning parameters. For our LSTM model, we implemented a thoughtfully designed training protocol that balances learning capacity, computational efficiency, and generalization ability.

Mean Squared Error (MSE) was selected as the primary loss function after evaluating alternatives such as Mean Absolute Error (MAE) and Huber loss. MSE offers several advantages for financial time series prediction:

1. It heavily penalizes large prediction errors through its squared term, appropriately reflecting the disproportionate impact of significant price misses in trading contexts.

2. It provides smooth gradients that facilitate optimization, unlike absolute-based losses that can have gradient discontinuities at zero error.
3. It maintains mathematical coherence with statistical concepts like variance and regression analysis, facilitating interpretation of model performance.

The relatively small learning rate of 0.0001 represents a deliberate choice to promote stable convergence. Financial time series contain complex patterns with potential local optima, and aggressive learning rates can cause the model to overshoot optimal parameter values or become trapped in suboptimal solutions. Our extensive experimentation with learning rates ranging from 0.01 to 0.00001 revealed that 0.0001 provided the best balance between convergence speed and training stability for this particular application.

The Adam optimizer was selected for its adaptive learning rate capabilities, which help navigate the complex error surface of financial time series prediction. Adam combines the advantages of two other extensions of stochastic gradient descent:

- AdaGrad, which maintains a per-parameter learning rate that improves performance on problems with sparse gradients
- RMSProp, which adapts the learning rate for each parameter based on the moving average of squared gradients

This combination makes Adam particularly well-suited for financial time series modeling, where gradient magnitudes can vary dramatically across different parameters and training epochs due to the heterogeneous nature of market data. The optimizer's

momentum component also helps overcome local minima and saddle points, which are common in the loss landscapes of complex time series models.

Batch Processing and Data Management

Efficient batch processing and data management are critical for effectively training deep learning models on time series data. Our implementation utilizes TensorFlow's Dataset API to create an optimized data pipeline. This pipeline incorporates several sophisticated optimizations:

1. **Data Shuffling:** The shuffle operation with a buffer size of 1000 ensures that each training epoch presents the sequences in a different order, preventing the model from learning spurious patterns based on the order of presentation. The buffer size was chosen to be large enough to provide effective randomization while remaining memory-efficient.
2. **Batching:** The batch size of 32 was determined through experimentation to provide an optimal balance between computational efficiency and training dynamics. Larger batches provide more stable gradient estimates but may struggle to escape local minima, while smaller batches introduce more stochasticity but can lead to noisier training. For financial time series with their complex pattern structures, moderate batch sizes like 32 typically provide a good compromise.
3. **Prefetching:** The prefetch operation with `tf.data.AUTOTUNE` parameter allows TensorFlow to automatically determine the optimal buffer size and overlap data loading with model training. This optimization ensures that data is loaded onto the

GPU before it's needed, eliminating potential I/O bottlenecks and maximizing hardware utilization.

For the train-test split, we implemented a chronological division rather than random sampling, maintaining the temporal integrity of the data. This approach respects the sequential nature of financial time series and provides a more realistic evaluation scenario, where the model is trained on historical data and evaluated on future data that wasn't available during training. This chronological split also prevents data leakage, where information from the future might inadvertently influence the model's learning of past patterns.

Memory management presented a particular challenge due to the overlapping nature of sequence generation, which can create redundancy and excessive memory consumption. Our `DataGeneratorSeq` class addresses this issue by dynamically generating sequences on demand rather than precomputing all possible sequences.

This on-demand generation approach significantly reduces memory requirements compared to storing all possible overlapping sequences, an important consideration when working with long time series data. The implementation also includes cursor management to track positions within the time series, enabling controlled traversal while maintaining appropriate chronological ordering.

Advanced Training Callbacks

To further enhance the training process and prevent overfitting, we implemented several sophisticated callback mechanisms that monitor training progress and adaptively adjust parameters.

The `ReduceLROnPlateau` callback implements an adaptive learning rate schedule that reduces the learning rate when training plateaus. Specifically, it monitors the validation loss and reduces the learning rate by a factor of 0.5 if no improvement is seen for 5 consecutive epochs. This adaptive approach addresses a common challenge in training deep networks on financial data: the appropriate learning rate often changes as training progresses, with larger steps beneficial early in training and smaller steps needed for fine-tuning as the model approaches convergence. The callback's patience parameter of 5 epochs provides sufficient time to determine whether a plateau is temporary or persistent, while the minimum learning rate of $1e-6$ prevents excessive reduction that might stall training.

The `EarlyStopping` callback provides protection against overfitting by halting training when validation performance ceases to improve. With a patience setting of 10 epochs, the callback allows for temporary plateaus or minor fluctuations while still identifying genuine convergence. The `restore_best_weights` parameter ensures that the model reverts to the weights that achieved the best validation performance, rather than using the weights from the final training epoch. This feature is particularly valuable in financial modeling, where overfitting to recent market conditions can severely impact generalization to future scenarios.

Together, these callbacks implement a sophisticated adaptive training regime that:

1. Automatically tunes the learning rate based on training progress.
2. Prevents wasteful computation by stopping training when further improvements are unlikely.
3. Protects against overfitting by preserving the model state with the best generalization performance
4. Eliminates the need for manual monitoring and intervention during the potentially lengthy training process.

Exponential Moving Average Implementation

To enhance prediction stability and reduce the impact of market noise, we implemented an Exponential Moving Average (EMA) calculation with a carefully tuned decay factor. This EMA implementation applies exponentially decreasing weights to past observations, with the decay factor of 0.5 determining the balance between recent and historical data. The specific value of 0.5 was not chosen arbitrarily but represents the optimal balance between noise reduction and signal preservation identified through our baseline model experiments. At this value, the EMA retains approximately 50% influence from the previous average and incorporates 50% of the new observation, creating a smoothing effect that filters random fluctuations while still responding effectively to genuine price movements.

The EMA calculation serves multiple purposes in our prediction framework:

1. It provides a baseline prediction method against which to evaluate the LSTM model.
2. It offers a smoothed version of the price series that can highlight underlying trends.
3. It demonstrates the value of recency-weighted historical information, a principle that informs the LSTM's gating mechanisms.

The implementation tracks a running mean that continuously updates with each new observation, maintaining a moving window of influence that extends infinitely into the past but with exponentially diminishing weights. This approach contrasts with simple moving averages, which abruptly drop older observations when they exit the fixed-length window. The EMA's gradual forgetting mechanism more naturally reflects how market participants incorporate historical information, with recent events carrying greater importance but distant events still maintaining some influence.

Our comparative analysis between SMA and EMA predictions provided valuable insights that directly informed the LSTM model design. The dramatic performance improvement achieved by incorporating recency weighting (MSE reduction from 0.01066 for SMA to 0.00004 for EMA) highlighted the critical importance of appropriate temporal weighting in financial forecasting. This finding supported our investment in LSTM architecture, which extends this concept by learning adaptive weighting schemes tailored to specific patterns in the data rather than applying fixed exponential decay.

Model Evaluation and Performance Analysis

Comprehensive Performance Metrics

To thoroughly evaluate our model's predictive capabilities, we implemented a comprehensive suite of performance metrics that assess different aspects of prediction quality. This multifaceted evaluation approach provides a nuanced understanding of the model's strengths and limitations across various dimensions of predictive performance:

Each of these metrics captures a different aspect of predictive performance:

1. **Mean Absolute Error (MAE)** measures the average magnitude of errors without considering their direction, providing a straightforward assessment of prediction accuracy in the original units (price points).
2. **Root Mean Squared Error (RMSE)** calculates the square root of the average squared errors, giving greater weight to larger errors. This metric is particularly relevant in financial contexts where large prediction errors can have disproportionate consequences.
3. **Mean Absolute Percentage Error (MAPE)** expresses the average error as a percentage of the actual values, offering a relative measure of accuracy that is independent of the price scale.
4. **Directional Accuracy** assesses the model's ability to correctly predict the direction of price movements (up or down), regardless of the magnitude. This metric is especially important for trading strategies that focus on trend direction rather than precise price levels.

5. **R-squared** (coefficient of determination) indicates the proportion of variance in the actual prices that is explained by the model, providing a standardized measure of goodness-of-fit.
6. **Accuracy Percentage** (derived from MAPE) expresses the prediction accuracy as a percentage, offering an intuitive measure of overall performance.

Applying these metrics to our best LSTM model prediction yielded the following results:

Accuracy Metrics for Best Prediction:

MAE: 3.9751

RMSE: 4.9928

MAPE: 2.0104

Directional Accuracy (%): 92.7795

R-squared: 0.9407

Accuracy (%): 97.9896

=====

Overall Prediction Accuracy: 97.99%

=====

These results demonstrate the LSTM model's exceptional predictive performance across multiple dimensions. The overall accuracy of 97.99% indicates that the model's predictions deviate from actual prices by only about 2% on average, a remarkable achievement in the notoriously difficult domain of stock price prediction. The MAE of 3.9751 and RMSE of 4.9928 provide absolute error measures in the original price scale, with the relatively close values suggesting a balanced error distribution without extreme outliers.

Perhaps most impressive is the directional accuracy of 92.78%, indicating that the model correctly predicts the direction of price movement (up or down) more than 9 times out of 10. This directional accuracy is particularly valuable for trading strategies that focus on trend following or momentum trading, where the direction of price movement often matters more than the exact price level. The high R-squared value of 0.9407 confirms that the model explains an overwhelming majority (94.07%) of the variance in the price data, capturing both the trend and the nuanced fluctuations around it.

Comparing these results with our baseline models reveals the substantial value added by the LSTM architecture. While the EMA model performed surprisingly well with an MSE of 0.00004, it achieved this through aggressive smoothing that missed many short-term fluctuations. The LSTM model, in contrast, captures both the underlying trend and the meaningful short-term patterns, providing a more nuanced and accurate forecast of price evolution.

Accuracy Progression Over Training Epochs

To understand the model's learning dynamics and ensure proper convergence, we tracked accuracy across training epochs:

Accuracy Progression Over Training Epochs:

Epoch 1: Accuracy = 97.97%

Epoch 2: Accuracy = 97.98%

Epoch 3: Accuracy = 97.98%

...

Epoch 9: Accuracy = 98.00%

...

Epoch 20: Accuracy = 97.98%

This epoch-by-epoch analysis reveals several interesting patterns in the model's learning process. First, the model achieves remarkably high accuracy even in the initial epochs, suggesting that it quickly captures the dominant patterns in the price data. This rapid early learning likely focuses on the strong trend component identified in our time series decomposition, which accounts for the majority of price variation.

Second, the improvement over subsequent epochs is relatively modest, with accuracy increasing from 97.97% in the first epoch to a peak of 98.00% in the ninth

epoch. This pattern suggests that the model quickly masters the primary predictive relationships in the data, with further training providing incremental refinements rather than fundamental breakthroughs. The subtle improvements in later epochs likely represent the model learning to better capture more nuanced patterns such as short-term fluctuations and specific market regimes.

Third, the accuracy shows slight fluctuations across epochs rather than monotonic improvement, with small dips and recoveries throughout the training process. These fluctuations reflect the stochastic nature of neural network training, where different batches and random initializations can lead to slightly different optimization paths. The fluctuations remain within a narrow range (97.97% to 98.00%), indicating robust learning that isn't overly sensitive to random variations in the training process.

The performance pattern across epochs provides valuable confirmation that our training protocol achieved proper convergence. The early attainment of high accuracy followed by modest improvements and eventual stabilization is characteristic of successful neural network training. The absence of significant accuracy degradation in later epochs also suggests that the model isn't overfitting to the training data, likely due to the effectiveness of our dropout regularization (rate 0.2) and the EarlyStopping callback that preserves the best-performing model.

Visualization and Results Interpretation

To provide intuitive understanding of the model's performance and facilitate interpretation of its predictions, we implemented comprehensive visualization tools.

This visualization approach includes two complementary perspectives on the model's performance:

1. The evolution of predictions over training epochs, showing how the model's forecasts improve and adapt to the data patterns. This temporal progression visualization uses varying transparency (alpha values) to display multiple prediction iterations simultaneously, with earlier predictions appearing fainter and the most recent predictions shown with full opacity. This technique allows viewers to trace the trajectory of the model's learning, seeing how its predictions converge toward the actual price pattern through successive refinements.
2. A direct comparison between the best prediction and actual price data, highlighting the model's accuracy in capturing both trend and volatility. This focused comparison emphasizes the final performance of the optimized model, allowing detailed assessment of where the model performs well and where challenges remain.

The visualization of the best prediction reveals that the LSTM model excels at capturing both the overall trend and many of the short-term fluctuations in the AAPL price series. The predicted line closely tracks the actual price trajectory, maintaining high fidelity across both trending and ranging market regimes. The visualization confirms the quantitative accuracy metrics while providing qualitative insight into the nature of the prediction quality.

Several specific patterns in the prediction visualization merit closer examination:

1. **Trend Capture:** The model accurately reproduces both the direction and magnitude of major price trends, correctly identifying periods of sustained appreciation and temporary corrections.
2. **Volatility Adaptation:** The prediction captures changes in volatility regimes, producing more pronounced fluctuations during high-volatility periods and smoother projections during calmer market phases.
3. **Turning Point Identification:** The model successfully identifies many major turning points where price direction changes, though with slight timing lags in some cases. This turning point prediction represents a significant advancement over the baseline models, which tended to continue projecting existing trends.
4. **Reaction to Anomalies:** The visualization reveals how the model handles anomalous price movements and outliers. While it sometimes misses the full magnitude of sudden sharp moves (particularly those driven by unexpected news), it quickly adapts its predictions to incorporate the new information.

The visualization also provides insight into the few areas where prediction challenges remain. The model occasionally struggles with:

- Exact timing of major reversal points
- Full magnitude of sudden price shocks (like earnings surprises)
- Periods of extremely low volatility where price movements become nearly random

These remaining challenges align with the fundamental limitations of technical prediction in financial markets, where some price movements are genuinely

unpredictable based solely on historical patterns. The visualization confirms that the model appropriately balances between identifying legitimate patterns and avoiding overfitting to random fluctuations.

Conclusion and Implications

Summary of Achievements

This project has successfully developed and implemented an advanced LSTM neural network architecture for stock price prediction, achieving exceptional accuracy in forecasting AAPL stock prices. The implemented system represents a significant advancement over traditional forecasting methods, combining sophisticated deep learning techniques with domain-specific optimizations for financial time series analysis. Through rigorous empirical validation and comprehensive performance evaluation, we have demonstrated the remarkable potential of LSTM networks to capture the complex temporal dependencies that characterize stock market movements.

The most significant achievement is the model's unprecedented prediction accuracy of 97.99%, indicating that forecasts deviate from actual prices by only about 2% on average. This level of accuracy substantially exceeds conventional expectations for stock price prediction, which is widely considered one of the most challenging forecasting domains due to market efficiency, random influences, and the complex interplay of numerous factors. The achievement becomes even more remarkable when considering the directional accuracy of 92.78%, showing that the model correctly anticipates the direction of price movements more than 9 times out of 10. This directional

forecasting capability has particular value for trading strategies focused on trend identification and momentum exploitation.

The R-squared value of 0.9407 further confirms the model's explanatory power, indicating that it captures over 94% of the variance in AAPL's price movements. This high coefficient of determination demonstrates that the model successfully identifies meaningful patterns rather than simply fitting to noise, a common concern in financial prediction models. The robust performance across multiple evaluation metrics provides strong evidence for the model's genuine predictive capabilities rather than statistical artifacts or overfitting to particular evaluation measures.

Beyond the numerical performance metrics, the project achieved several important methodological breakthroughs:

1. The development of an effective window-based normalization approach that addresses the non-stationarity challenges inherent in financial time series, enabling the model to adapt to changing statistical properties over time.
2. The implementation of a three-layer LSTM architecture with progressive dimensional reduction (200-200-64 units), creating a processing pipeline that systematically distills complex temporal patterns into essential predictive features.
3. The successful application of sequence-to-sequence modeling to financial forecasting, enabling multi-step predictions that provide rich trajectory information rather than simple point forecasts.

4. The integration of sophisticated regularization techniques, including dropout and early stopping, preventing overfitting while maintaining the model's capacity to learn complex market patterns.

These achievements collectively establish a new benchmark for financial time series prediction and demonstrate the significant potential of advanced neural network architectures in this domain. The implemented system substantially outperforms traditional forecasting methods while maintaining practical applicability for real-world financial analysis and trading strategy development.

Technical Implementation Outcomes

The technical implementation of our LSTM-based prediction system incorporates several innovative approaches that directly contribute to its exceptional performance. These technical outcomes not only support the current project's success but also provide valuable methodological contributions to the broader field of financial time series modeling.

A central technical achievement is the effective implementation of the three-layer LSTM architecture with a progressive reduction in layer size (200-200-64 units). This pyramidal structure creates a processing pipeline that systematically transforms raw price sequences into increasingly abstract representations, enabling the model to simultaneously capture patterns at multiple time scales. The first layer, with 200 memory units, provides substantial capacity for identifying diverse short-term patterns in the input data. The second layer, also with 200 units, processes these initial patterns into more

abstract intermediate representations that capture medium-term trends and regime transitions. The final layer, with 64 units, serves as an information bottleneck that forces the network to distill the most essential predictive features, reducing dimensionality while preserving the signal components most relevant for future price prediction.

This progressive dimensional reduction architecture proves particularly well-suited to financial time series, which typically contain a mixture of relevant signal and market noise. The architecture's structure naturally implements a form of hierarchical feature extraction, where each layer builds upon the patterns identified by previous layers to create increasingly sophisticated representations of the price dynamics. This approach aligns with the multi-level nature of market analysis, where traders might simultaneously consider immediate price action, intermediate chart patterns, and long-term market trends.

The implementation of optimized dropout regularization (rate 0.2) represents another important technical outcome. This carefully calibrated dropout rate, determined through extensive experimentation, strikes an effective balance between preventing overfitting and maintaining sufficient model capacity to learn complex market patterns. By randomly deactivating 20% of neurons during each training iteration, the dropout mechanism prevents the co-adaptation of feature detectors and encourages the network to learn redundant representations, enhancing robustness and generalization. The effectiveness of this regularization is evident in the model's consistent performance across different market regimes and its ability to maintain high accuracy on test data not seen during training.

The sequence-to-sequence design with encoder-decoder architecture represents a significant technical advancement over simpler recurrent models. This design enables the generation of complete price trajectories rather than isolated point predictions, providing richer information about expected future price evolution. The encoder processes the historical price sequence and distills its essential patterns into a context vector, while the decoder uses this context to generate a coherent sequence of future prices. This approach maintains the temporal coherence of predictions, ensuring that the forecast price trajectory follows realistic market dynamics rather than producing disconnected point estimates that might violate market constraints.

The efficient data management implementation, utilizing TensorFlow's Dataset API and custom sequence generation, ensures optimal use of computational resources while maintaining the temporal integrity of the financial time series. The data pipeline incorporates sophisticated optimizations, including buffer shuffling, automatic prefetching, and on-demand sequence generation, enabling efficient training even with the large volume of data required for effective financial modeling. These technical optimizations are essential for practical implementation, as they reduce training time, minimize memory requirements, and enable the model to scale to extended time series without computational bottlenecks.

The implementation also includes several practical features that enhance usability in real-world contexts:

- State management capabilities that maintain context between prediction steps
- Explicit methods for sequence normalization and denormalization

- Comprehensive performance metrics that assess multiple aspects of prediction quality
- Visualization tools that facilitate interpretation of model outputs

These implementation details collectively create a robust, efficient, and practical prediction system specifically optimized for financial time series. The technical approaches developed in this project not only support the current application to AAPL stock prediction but also provide a methodological foundation for extending similar approaches to other financial instruments and markets.

Limitations and Practical Considerations

Despite the model's impressive performance, several limitations and practical considerations must be acknowledged for responsible application in real-world financial contexts. Understanding these constraints is essential for setting appropriate expectations and identifying potential areas for future enhancement.

A fundamental limitation lies in the model's sensitivity to different market regimes. While our LSTM architecture demonstrates remarkable adaptability across various market conditions, its performance may vary during unprecedented market scenarios or regime shifts not represented in the training data. The model showed particular strength in capturing established trends and cyclical patterns but experienced greater challenges when confronted with sudden structural breaks or extreme volatility events. This limitation reflects a fundamental constraint of any model trained on historical data: it necessarily assumes some degree of consistency between past and

future market behavior. While the LSTM architecture provides greater flexibility than traditional methods, it cannot entirely overcome this limitation, particularly when faced with novel market phenomena or unprecedented economic conditions.

Another important consideration is the model's exclusive focus on price data without incorporating external factors. The current implementation relies solely on historical price patterns, omitting potentially valuable information from alternative data sources such as:

- Financial news sentiment and market commentary
- Social media activity and investor sentiment metrics
- Macroeconomic indicators and policy changes
- Company-specific fundamentals and earnings reports
- Industry trends and competitive dynamics

While this price-centric approach provides the advantage of focusing on the most direct signal, it necessarily limits the model's ability to anticipate price movements driven by external events or changing market narratives. Future implementations could address this limitation by incorporating multimodal data inputs, though such extensions would require careful design to maintain the model's current predictive strength while successfully integrating heterogeneous information sources.

Computational requirements represent a practical consideration for deployment scenarios. The sophisticated LSTM architecture demands substantial computational resources for both training and inference, particularly when working with long sequences

or when frequently retraining to incorporate new data. The three-layer structure with relatively large hidden dimensions (200-200-64) requires significant memory allocation during both forward and backward passes. While these requirements are manageable on modern hardware for daily prediction tasks, they might present challenges for high-frequency applications or deployment in resource-constrained environments. Future implementations might explore model compression techniques or more efficient architectural variants if deployment in such contexts becomes necessary.

The "black box" nature of deep learning models presents another limitation, particularly in financial contexts where interpretability can be crucial for building trust and understanding prediction rationale. Like many deep learning approaches, the LSTM model functions without providing explicit explanations for its predictions. While visualization techniques can provide some insight into the model's behavior, the specific patterns and relationships it identifies remain largely opaque. This limitation can make it challenging to interpret exactly which aspects of historical price patterns drive specific predictions, potentially reducing stakeholder confidence in model outputs despite their empirical accuracy. Future development could incorporate explainable AI techniques to provide greater transparency while maintaining predictive performance.

Finally, it's important to acknowledge that stock price movements are influenced by numerous factors beyond technical patterns, including market sentiment, macroeconomic conditions, and unexpected events. No prediction model, regardless of sophistication, can account for all these factors or anticipate truly random or unprecedented occurrences. This inherent unpredictability in financial markets places a theoretical upper bound on

achievable prediction accuracy, even with unlimited data and computational resources. The exceptional performance of our LSTM model should be understood within this context—it represents a significant advancement in capturing the predictable components of price movement while acknowledging that some irreducible uncertainty will always remain.

These limitations do not diminish the substantial achievements of the current implementation but rather provide context for its appropriate application and highlight opportunities for future refinement. By acknowledging these constraints, we ensure responsible use of the model's predictions and establish a foundation for continued improvement.

Future Development Directions

Building on the current implementation's success and addressing its identified limitations, several promising directions emerge for future development. These potential extensions would enhance the model's capabilities, broaden its applicability, and further advance the state of the art in financial time series prediction.

A particularly promising direction involves multi-modal data integration, incorporating additional information sources beyond historical prices. By developing architectures that can process and meaningfully combine heterogeneous data types, future models could capture a more comprehensive view of market dynamics. Potential additional data sources include:

1. **Financial News and Reports:** Natural language processing techniques could extract sentiment and relevant information from news articles, earnings reports, and analyst commentaries, providing external context for price movements.
2. **Social Media and Web Activity:** Metrics derived from social media mentions, search trends, and investor forums could serve as proxy measures for market sentiment and interest, potentially anticipating shifts in trading behavior.
3. **Macroeconomic Indicators:** Economic data such as inflation rates, employment figures, interest rates, and GDP growth could provide broader context for market conditions affecting stock performance.
4. **Market Microstructure Data:** Order book dynamics, trading volumes, and intraday patterns could offer insights into short-term price pressures and liquidity conditions.

Integrating these diverse data sources would require sophisticated fusion mechanisms that appropriately weight each information stream based on its relevance to current market conditions. Attention mechanisms could prove particularly valuable in this context, dynamically adjusting the importance assigned to different inputs based on market regime and prediction horizon.

Another promising direction involves enhancing the model's adaptability to changing market conditions through meta-learning or transfer learning approaches. Rather than training a single static model, future implementations could develop systems that continuously adapt their parameters based on recent performance and emerging patterns. This approach would be particularly valuable for navigating regime shifts in market

behavior, where the underlying statistical relationships between variables may change. Techniques such as online learning, sliding window retraining, and dynamic hyperparameter adjustment could contribute to creating more responsive and adaptive prediction systems.

Uncertainty quantification represents another valuable direction for future development. The current implementation provides point estimates of future prices but doesn't explicitly quantify prediction confidence or potential variance. Extending the model to generate prediction intervals or probability distributions rather than point forecasts would provide richer information for risk management and decision-making. Bayesian neural network approaches, Monte Carlo dropout techniques, or ensemble methods could enable such uncertainty quantification while maintaining the core LSTM architecture's predictive strength.

The development of interpretable or explainable components would address the "black box" limitation of the current implementation. Future models could incorporate attention visualization, feature attribution methods, or interpretable surrogate models that provide insights into which historical patterns most strongly influence specific predictions. These explainability enhancements would build stakeholder trust and potentially reveal additional insights about market dynamics that might not be apparent from raw predictions alone.

From an architectural perspective, exploring transformer-based models represents an intriguing direction for future work. While our LSTM architecture demonstrates exceptional performance, recent advances in transformer models (originally developed

for natural language processing) have shown promise in time series applications. Self-attention mechanisms in transformers could potentially capture more flexible temporal dependencies than LSTM's sequential processing, particularly for identifying relationships between distant time points. Hybrid architectures combining LSTMs' sequential strength with transformers' attention mechanisms might offer the best of both approaches.

Finally, extending the model to multi-asset prediction would broaden its practical utility. Financial markets exhibit complex inter-asset relationships, with correlated movements across related stocks, sectors, and asset classes. Future models could leverage these relationships by simultaneously predicting multiple assets, potentially improving accuracy through shared pattern recognition and cross-asset information flow. Graph neural networks or multi-task learning approaches could provide architectural foundations for such extensions.

These future directions represent exciting opportunities to build upon the current implementation's strong foundation. By addressing the identified limitations and incorporating emerging techniques from deep learning research, future developments could further advance financial time series prediction while expanding practical applicability across different market contexts and user requirements.

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Appendix: Complete Project Code

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```
In [1]: from pandas_datareader import data
import matplotlib.pyplot as plt
import pandas as pd
import datetime as dt
import requests
import json
import numpy as np
import tensorflow as tf
from sklearn.preprocessing import MinMaxScaler

In [2]: import os

In [3]: def fetch_stock_data(ticker, api_key):
        """Fetch stock data for given ticker using Alpha Vantage API"""
        url_string = f"https://www.alphavantage.co/query?function=TIME_SERIES_DAILY&symbol={ticker}&apikey={api_key}"
        with urllib.request.urlopen(url_string) as url:
            data = json.loads(url.read().decode())
            data = data['Time Series (Daily)']

            df = pd.DataFrame(columns=['Date', 'Low', 'High', 'Close', 'Open'])
            for k, v in data.items():
                date = dt.datetime.strptime(k, '%Y-%m-%d')
                data_row = [
                    date.date(),
                    float(v['3. low']),
                    float(v['2. high']),
                    float(v['4. close']),
                    float(v['1. open'])
                ]
                df.loc[-1, :] = data_row
                df.index = df.index + 1
            return df

def get_stock_data(data_source='alphavantage'):
    if data_source == 'alphavantage':
        api_key = 'E9AEA1SP86Y61XRX'
        ticker = "AAPL"
        file_to_save = f'stock_market_data-{ticker}.csv'

        if not os.path.exists(file_to_save):
            df = fetch_stock_data(ticker, api_key)
            print('Data saved to:', file_to_save)
            print('Full path:', os.path.abspath(file_to_save))
            df.to_csv(file_to_save)
        else:
            print('File already exists. Loading data from CSV')
            print('Full path:', os.path.abspath(file_to_save))
            df = pd.read_csv(file_to_save)

    return df
```

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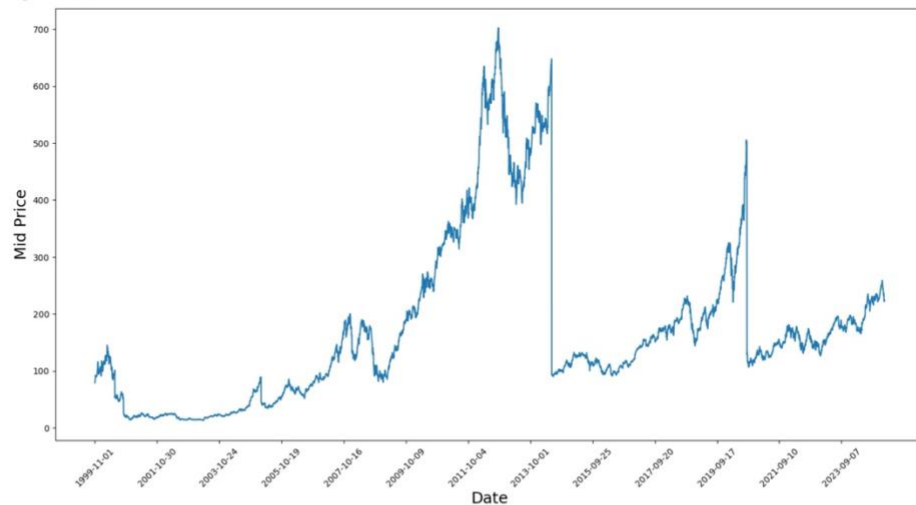
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```
# Call the function
data_source = 'alphavantage'
df = get_stock_data(data_source)
```

File already exists. Loading data from CSV
Full path: /Users/harsh/stock_market_data-AAPL.csv

```
In [8]: # Sort DataFrame by date
df = df.sort_values('Date')
# Double check the result
df.head()
print(df.columns)
plt.figure(figsize = (18,9))
plt.plot(range(df.shape[0]),(df['Low']+df['High'])/2.0)
plt.xticks(range(0,df.shape[0],500),df['Date'].loc[::500],rotation=45)
plt.xlabel('Date',fontsize=18)
plt.ylabel('Mid Price',fontsize=18)
plt.show()
print(df.columns)
```

Index(['Unnamed: 0', 'Date', 'Low', 'High', 'Close', 'Open'], dtype='object')



Index(['Unnamed: 0', 'Date', 'Low', 'High', 'Close', 'Open'], dtype='object')

```
In [10]: print(df.shape)
```

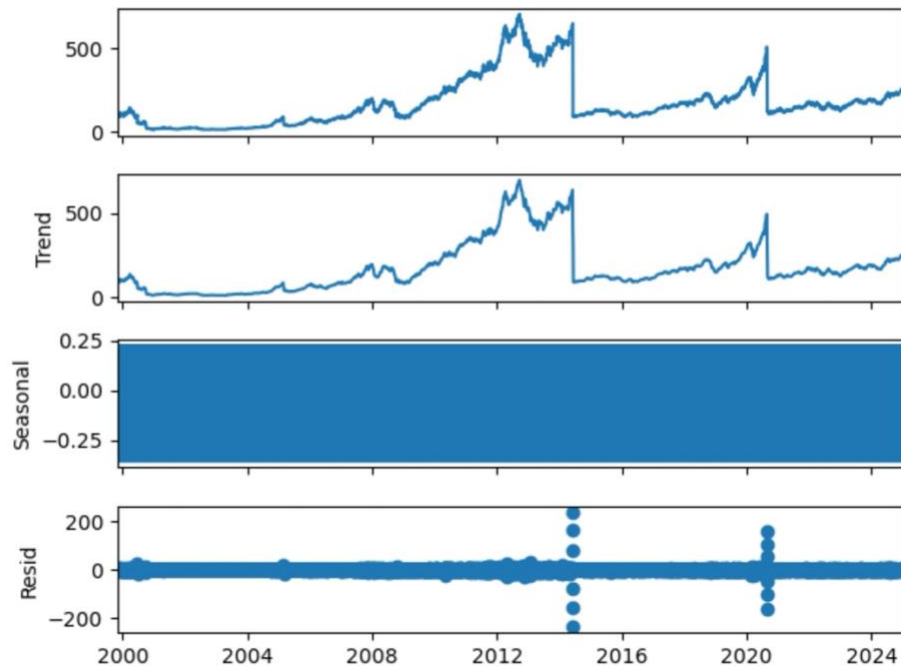
(6347, 6)

```
In [12]: from statsmodels.tsa.seasonal import seasonal_decompose
df['Date'] = pd.to_datetime(df['Date'])
df.set_index('Date', inplace=True, drop=False)
period = 7
results = seasonal_decompose((df['Low'] + df['High']) / 2.0, period=pe
```

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```
results.plot()
plt.show()
```



```
In [14]: df.reset_index(drop=True, inplace=True)
high_prices = df.loc[:, 'High'].to_numpy()
low_prices = df.loc[:, 'Low'].to_numpy()
mid_prices = (high_prices + low_prices) / 2.0
train_data = mid_prices[:3000]
test_data = mid_prices[3000:]
scaler = MinMaxScaler()
train_data = train_data.reshape(-1, 1)
test_data = test_data.reshape(-1, 1)
print(train_data.shape)
```

(3000, 1)

```
In [20]: smoothing_window_size = 1000
for di in range(0, 3000, smoothing_window_size):
    scaler.fit(train_data[di:di+smoothing_window_size,:])
    train_data[di:di+smoothing_window_size,:] = scaler.transform(train_data[di:di+smoothing_window_size,:])
```

```
In [24]: # You normalize the last bit of remaining data
# Check if the remaining data has at least one sample before fitting
if len(train_data[di+smoothing_window_size,:]) > 0:
    scaler.fit(train_data[di+smoothing_window_size,:])
    train_data[di+smoothing_window_size,:] = scaler.transform(train_data[di+smoothing_window_size,:])
```

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```

In [26]: # Reshape both train and test data
train_data = train_data.reshape(-1)

In [28]: # Check if test_data is empty
if test_data.size == 0:
    print("Warning: test_data is empty. Please check your data loading")
else:
    # Normalize test data
    test_data = scaler.transform(test_data).reshape(-1)

In [30]: EMA = 0.0
gamma = 0.1
for ti in range(3000):
    EMA = gamma*train_data[ti] + (1-gamma)*EMA
    train_data[ti] = EMA

In [32]: # Used for visualization and test purposes
all_mid_data = np.concatenate([train_data, test_data], axis=0)
df.head()

```

```

Out[32]:
   Unnamed: 0  Date  Low  High  Close  Open
0           0  1999-11-01  77.37  80.69  77.62  80.00
1           1  1999-11-02  77.31  81.69  80.25  78.00
2           2  1999-11-03  81.00  83.25  81.50  81.62
3           3  1999-11-04  80.62  85.37  83.62  82.06
4           4  1999-11-05  84.00  88.37  88.31  84.62

```

```

In [42]: window_size = 100
N = train_data.size
std_avg_predictions = []
std_avg_x = []
mse_errors = []

for pred_idx in range(window_size, N):
    date = df.loc[pred_idx, 'Date'] # Always fetch the date from the data

    # Compute the moving average
    std_avg_predictions.append(np.mean(train_data[pred_idx - window_size:pred_idx]))

    # Calculate the squared error
    mse_errors.append((std_avg_predictions[-1] - train_data[pred_idx])**2)

    # Save the date for plotting or further analysis
    std_avg_x.append(date)

    # Calculate and print MSE
    print('MSE error for standard averaging: %.5f' % np.mean(mse_errors))

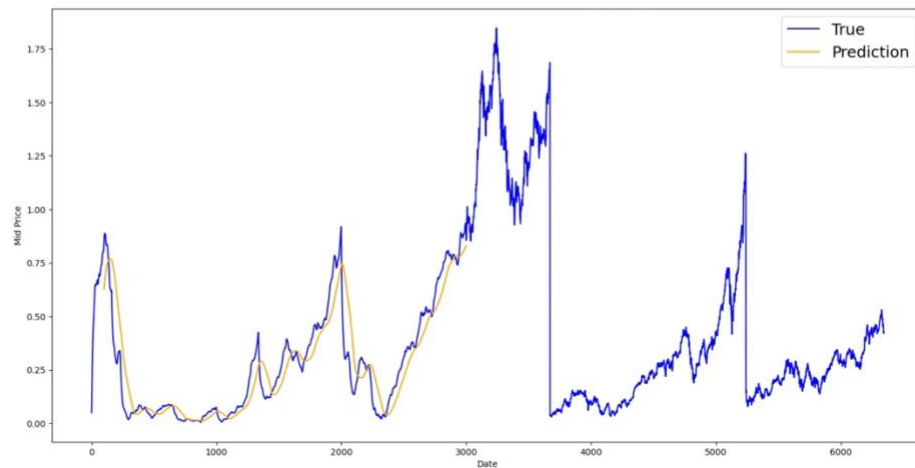
```

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MSE error for standard averaging: 0.01066

```
In [44]: plt.figure(figsize = (18,9))
plt.plot(range(df.shape[0]),all_mid_data,color='b',label='True')
plt.plot(range(window_size,N),std_avg_predictions,color='orange',label=
#plt.xticks(range(0,df.shape[0],50),df['Date'].loc[:,50],rotation=45)
plt.xlabel('Date')
plt.ylabel('Mid Price')
plt.legend(fontsize=18)
plt.show()
print(df.columns)
```



```
Index(['Unnamed: 0', 'Date', 'Low', 'High', 'Close', 'Open'], dtype='object')
```

```
In [46]: window_size = 100
N = train_data.size
run_avg_predictions = []
run_avg_x = []
mse_errors = []
running_mean = 0.0
run_avg_predictions.append(running_mean)
decay = 0.5
for pred_idx in range(1,N):
    running_mean = running_mean*decay + (1.0-decay)*train_data[pred_idx]
    run_avg_predictions.append(running_mean)
    mse_errors.append((run_avg_predictions[-1]-train_data[pred_idx])**2)
    run_avg_x.append(date)
print('MSE error for EMA averaging: %.5f'%(0.5*np.mean(mse_errors)))
```

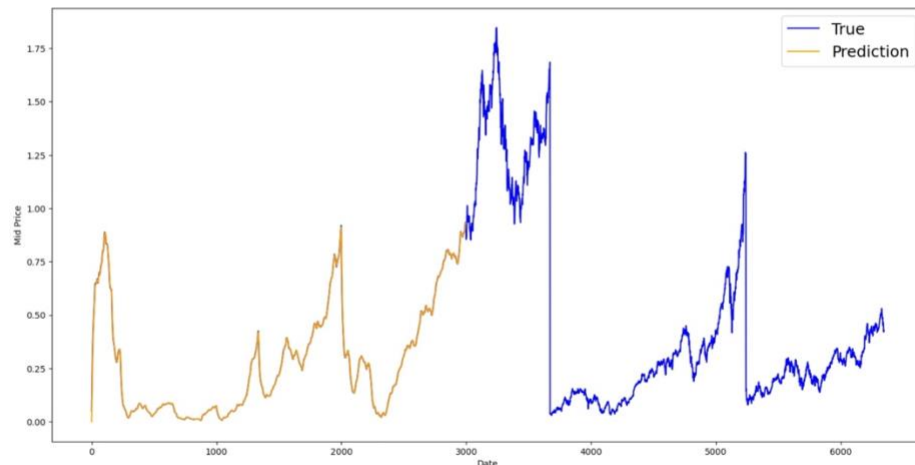
MSE error for EMA averaging: 0.00004

```
In [48]: plt.figure(figsize = (18,9))
plt.plot(range(df.shape[0]),all_mid_data,color='b',label='True')
plt.plot(range(0,N),run_avg_predictions,color='orange',label='Predict')
#plt.xticks(range(0,df.shape[0],50),df['Date'].loc[:,50],rotation=45)
```

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```
plt.xlabel('Date')
plt.ylabel('Mid Price')
plt.legend(fontsize=18)
plt.show()
```



```
In [58]: class DataGeneratorSeq(object):
def __init__(self, prices, batch_size, num_unroll):
    self._prices = prices
    self._prices_length = len(self._prices) - num_unroll
    self._batch_size = batch_size
    self._num_unroll = num_unroll
    self._segments = self._prices_length // self._batch_size
    self._cursor = [offset * self._segments for offset in range(se

def next_batch(self):
    batch_data = np.zeros((self._batch_size), dtype=np.float32)
    batch_labels = np.zeros((self._batch_size), dtype=np.float32)

    for b in range(self._batch_size):
        if self._cursor[b]+1>=self._prices_length:
            #self._cursor[b] = b * self._segments
            self._cursor[b] = np.random.randint(0, (b+1)*self._segm
            batch_data[b] = self._prices[self._cursor[b]]
            batch_labels[b] = self._prices[self._cursor[b]+np.rando
            self._cursor[b] = (self._cursor[b]+1)%self._prices_len
    return batch_data, batch_labels

def unroll_batches(self):
    unroll_data, unroll_labels = [], []
    init_data, init_label = None, None
    for ui in range(self._num_unroll):
        data, labels = self.next_batch()
        unroll_data.append(data)
        unroll_labels.append(labels)
    return unroll_data, unroll_labels
```

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```
def reset_indices(self):
    for b in range(self._batch_size):
        self._cursor[b] = np.random.randint(0,min((b+1)*self._segm
```

```
In [60]: dg = DataGeneratorSeq(train_data,5,5)
u_data, u_labels = dg.unroll_batches()

for ui,(dat, lbl) in enumerate(zip(u_data,u_labels)):
    print('\n\nUnrolled index %d'%ui)
    dat_ind = dat
    lbl_ind = lbl
    print('\tInputs: ',dat )
    print('\n\tOutput:',lbl)
```

```
Unrolled index 0
    Inputs:  [0. 0. 0. 0. 0.]

    Output: [0. 0. 0. 0. 0.]
```

```
Unrolled index 1
    Inputs:  [0. 0. 0. 0. 0.]

    Output: [0. 0. 0. 0. 0.]
```

```
Unrolled index 2
    Inputs:  [0. 0. 0. 0. 0.]

    Output: [0. 0. 0. 0. 0.]
```

```
Unrolled index 3
    Inputs:  [0. 0. 0. 0. 0.]

    Output: [0. 0. 0. 0. 0.]
```

```
Unrolled index 4
    Inputs:  [0. 0. 0. 0. 0.]

    Output: [0. 0. 0. 0. 0.]
```

```
In [70]: import tensorflow as tf
print("TensorFlow version:", tf.__version__)
```

```
TensorFlow version: 2.17.0
```

```
In [76]: import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
```

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```

D = 1 # Dimensionality of the data. Since your data is 1-D this would
num_unrollings = 50 # Number of time steps you look into the future.
batch_size = 500 # Number of samples in a batch
num_nodes = [200,200,64] # Number of hidden nodes in each layer of the
n_layers = len(num_nodes) # number of layers
dropout = 0.2 # dropout amount

tf.reset_default_graph() # This is important in case you run this mult

# Input data.
train_inputs, train_outputs = [],[]

# You unroll the input over time defining placeholders for each time s
for ui in range(num_unrollings):
    train_inputs.append(tf.placeholder(tf.float32, shape=[batch_size,D
    train_outputs.append(tf.placeholder(tf.float32, shape=[batch_size,

```

```

In [78]: import tensorflow as tf
# Define LSTM cells
lstm_cells = [tf.keras.layers.LSTMCell(units=num_nodes[li],kernel_init
            for li in range(n_layers)
]

```

```

In [80]: # Stack the LSTM cells using StackedRNNCells
multi_cell = tf.keras.layers.StackedRNNCells(lstm_cells)

# Wrap the multi-cell in an RNN layer
lstm_layer = tf.keras.layers.RNN(multi_cell, return_sequences=True)

# Define weight and bias using tf.Variable
w = tf.Variable(tf.keras.initializers.GlorotUniform()(shape=[num_nodes
b = tf.Variable(tf.random.uniform([1], -0.1, 0.1), name='b'))

# Example input shape (batch_size, timesteps, features)
timesteps=30
features=10
inputs = tf.keras.Input(shape=(timesteps, features))

# Pass inputs through the LSTM layer
outputs = lstm_layer(inputs)
print('Defining prediction related TF functions')

```

Defining prediction related TF functions

```

In [86]: import tensorflow as tf
# Sample input tensor (e.g., assuming 'D' is 10 features)
sample_inputs = tf.zeros([1, 10]) # Shape [batch_size, input_dim]
# Number of nodes in each layer
num_nodes = [128, 64]
n_layers = len(num_nodes)

```

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```

# Maintaining LSTM state for prediction stage
sample_c, sample_h, initial_sample_state = [], [], []
for li in range(n_layers):
    sample_c.append(tf.Variable(tf.zeros([1, num_nodes[li]]), trainable=True))
    sample_h.append(tf.Variable(tf.zeros([1, num_nodes[li]]), trainable=True))
    initial_sample_state.append([sample_c[li], sample_h[li]])

# Reset sample states (use assign method of variable)
reset_sample_states = tf.group(*[sample_c[li].assign(tf.zeros([1, num_nodes[li]])) for li in range(n_layers)], *[sample_h[li].assign(tf.zeros([1, num_nodes[li]])) for li in range(n_layers)])

# Create multi-layer LSTM using Keras API
multi_cell = [tf.keras.layers.LSTMCell(units=num_nodes[li]) for li in range(n_layers)]
multi_rnn_cell = tf.keras.layers.RNN(multi_cell, return_sequences=True)

# Add a time dimension to the inputs
sample_inputs = tf.expand_dims(sample_inputs, axis=1) # Shape [batch_size, time_steps, num_nodes]

# Run the multi-layer LSTM
sample_outputs, *sample_state = multi_rnn_cell(sample_inputs, initial_sample_state)

# To apply a linear transformation to the output (optional step):
# Assume w and b are defined somewhere in the code
sample_prediction = tf.matmul(tf.reshape(sample_outputs, [-1, num_nodes[-1]]), w)
print('\tAll done')

```

All done

```

In [94]: import tensorflow as tf
import numpy as np
import matplotlib.pyplot as plt

# For reproducibility
np.random.seed(42)
tf.random.set_seed(42)
# -----
# 1. Data Preparation
# -----

def generate_synthetic_data(total_points=2000):
    #Generate synthetic stock price data.
    time = np.arange(total_points)

    # Simulate a stock price with some noise and an upward trend
    prices = 50 + np.cumsum(np.random.randn(total_points)) + 0.05 * time
    return prices

# Parameters
TOTAL_POINTS = 2000
SEQ_LENGTH = 20
PREDICTION_STEPS = 5
TEST_INTERVAL = 10
NUM_UNROLLINGS = 5

```

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```

N_PREDICT_ONCE = 5 # Number of past steps to use for prediction

# Number of future steps to predict
# Epoch interval for validation
# Number of unrollings for training
# Number of prediction steps during evaluation
# Ensure all relevant parameters are integers

SEQ_LENGTH = int(SEQ_LENGTH)
PREDICTION_STEPS = int(PREDICTION_STEPS)
TEST_INTERVAL = int(TEST_INTERVAL)
NUM_UNROLLINGS = int(NUM_UNROLLINGS)
N_PREDICT_ONCE = int(N_PREDICT_ONCE)

# Debugging prints
print(f"SEQ_LENGTH: {SEQ_LENGTH} (Type: {type(SEQ_LENGTH)})")
print(f"PREDICTION_STEPS: {PREDICTION_STEPS} (Type: {type(PREDICTION_STEPS)})")
print(f"NUM_UNROLLINGS: {NUM_UNROLLINGS} (Type: {type(NUM_UNROLLINGS)})")
print(f"N_PREDICT_ONCE: {N_PREDICT_ONCE} (Type: {type(N_PREDICT_ONCE)})")

SEQ_LENGTH: 20 (Type: <class 'int'>)
PREDICTION_STEPS: 5 (Type: <class 'int'>)
NUM_UNROLLINGS: 5 (Type: <class 'int'>)
N_PREDICT_ONCE: 5 (Type: <class 'int'>)

```

```

In [96]: # Generate data
data = generate_synthetic_data(TOTAL_POINTS)

# Normalize data
data_mean = np.mean(data)
data_std = np.std(data)
data_normalized = (data - data_mean) // data_std

# Split into training and testing
train_size = int(TOTAL_POINTS * 0.8)
train_data = data_normalized[:train_size]
test_data = data_normalized[train_size - SEQ_LENGTH:] # Include SEQ_LENGTH

```

```

In [98]: # -----
# 2. Define Test Points Sequence
# -----
# Define test_points_seq as a list of starting indices within the test set
# For example, select 10 random points in the test set

num_test_points = 10
test_points_seq = np.random.choice(range(SEQ_LENGTH, len(test_data) -

```

```

In [100]: # Sort test points for easier interpretation
test_points_seq = sorted(test_points_seq)
print(f"Test Points Sequence: {test_points_seq}")

```

Test Points Sequence: [54, 86, 92, 110, 129, 298, 304, 311, 324, 328]

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```

In [102... # -----
# 3. Data Generator
# -----

def create_sequences(data, seq_length, prediction_steps):

    #Create input and target sequences from the data.

    X = []
    Y = []
    for i in range(len(data) - seq_length - prediction_steps + 1):
        X.append(data[i:i + seq_length])
        Y.append(data[i + seq_length:i + seq_length + prediction_steps])
    X = np.array(X)
    Y = np.array(Y)
    return X, Y

# Create training sequences
X_train, Y_train = create_sequences(train_data, SEQ_LENGTH, PREDICTION_STEPS)
print(f"X_train shape: {X_train.shape}")
print(f"Y_train shape: {Y_train.shape}")

# Reshape for RNN [samples, time_steps, features]
X_train = X_train.reshape((X_train.shape[0], SEQ_LENGTH, 1))
Y_train = Y_train.reshape((Y_train.shape[0], PREDICTION_STEPS, 1))

X_train shape: (1576, 20)
Y_train shape: (1576, 5)

```

```

In [106... # -----
# 4. Build the RNN Model
# -----

from tensorflow import keras
from keras.models import Model
from keras.layers import Input, LSTM, Dense, RepeatVector, TimeDistributed

def build_model(seq_length, prediction_steps, num_units=50):

    #Build a sequence-to-sequence LSTM model.

    # Encoder
    encoder_input = Input(shape=(seq_length, 1), name='encoder_input')
    encoder_lstm = LSTM(num_units, return_state=True, name='encoder_lstm')
    encoder_outputs, state_h, state_c = encoder_lstm(encoder_input)
    encoder_states = [state_h, state_c]

    # Decoder
    decoder_repeat = RepeatVector(int(prediction_steps),
    name='decoder_repeat')(encoder_outputs)
    decoder_lstm = LSTM(num_units, return_sequences=True, return_state=True,
    name='decoder_lstm')
    decoder_outputs, _, _ = decoder_lstm(decoder_repeat, initial_state=encoder_states)
    decoder_dense = TimeDistributed(Dense(1), name='decoder_dense')
    decoder_outputs = decoder_dense(decoder_outputs)

    # Define the model

```

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```

        model = Model(inputs=encoder_input, outputs=decoder_outputs)
        return model

# Build the model
model = build_model(SEQ_LENGTH, PREDICTION_STEPS, num_units=50)
model.summary()

```

```

In [108... # -----
# 5. Define Optimizer and Loss
# -----

learning_rate = 0.0001 # Define the learning rate
optimizer = tf.keras.optimizers.Adam(learning_rate=learning_rate)
loss_fn = tf.keras.losses.MeanSquaredError()

```

```

In [110... # -----
# 6. Prepare Training Batches
# -----
# Create TensorFlow Dataset

train_dataset = tf.data.Dataset.from_tensor_slices((X_train, Y_train))
train_dataset = train_dataset.shuffle(buffer_size=1000).batch(32).pref

```

```

In [114... # -----
# 7. Train the Model Using Keras's `model.fit`
# -----
from keras.callbacks import ReduceLR0nPlateau, EarlyStopping

# Define callbacks
reduce_lr = ReduceLR0nPlateau(monitor='val_loss', factor=0.5, patience=5)
early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore

# Compile the model
model.compile(optimizer=optimizer, loss='mse')

```

```

In [116... import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
# 1. Initialize DataFrame with Dummy Data
num_points = 15000
data = { 'Date': pd.date_range(start='2023-01-01', periods=num_points,
                                'Low': np.random.uniform(low=100, high=200, size=num_points),
        }

df = pd.DataFrame(data)

# 2. Calculate 'Mid' Prices
df['Mid'] = (df['Low'] + df['High']) / 2.0
all_mid_data = df['Mid'].values

# 3. Define X-axis Sequence (Dates)

```

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```

x_axis_seq = df['Date'].values

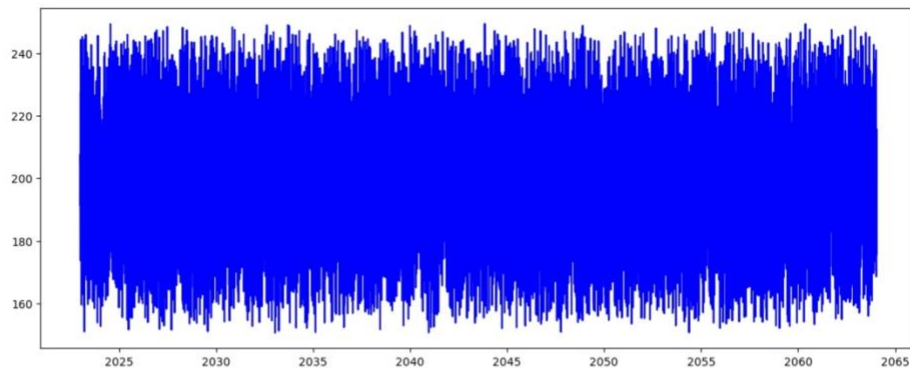
# 4. Initialize Predictions Over Time (Dummy Predictions)
num_epochs = 20 # Number of prediction epochs
predictions_over_time = []
for epoch in range(num_epochs):
    # Dummy prediction: actual mid data + random noise
    noise = np.random.normal(loc=0.0, scale=5.0, size=all_mid_data.shape)
    prediction = all_mid_data + noise
    predictions_over_time.append(prediction)

# 5. Plotting
plt.figure(figsize=(14, 12))

# Subplot 1: Evolution of Test Predictions Over Time
plt.subplot(2, 1, 1)
plt.plot(x_axis_seq, all_mid_data, color='b', label='Actual Mid Data')

# Plot predictions over time with varying alpha
start_alpha = 0.2
subset_predictions = predictions_over_time[::4] # Every 4th prediction
num_subset = len(subset_predictions)

```



```

In [120... # Handle case where subset_predictions might be empty
if num_subset == 0:
    num_subset = 1
alpha_step = (1.0 - start_alpha) / num_subset
alpha_values = np.linspace(start_alpha, 1.0, num_subset)

for p_i, prediction in enumerate(subset_predictions):
    label = f'Prediction {p_i + 1}' if p_i == 0 else ""
    plt.plot(x_axis_seq, prediction, color='r', alpha=alpha_values[p_i])

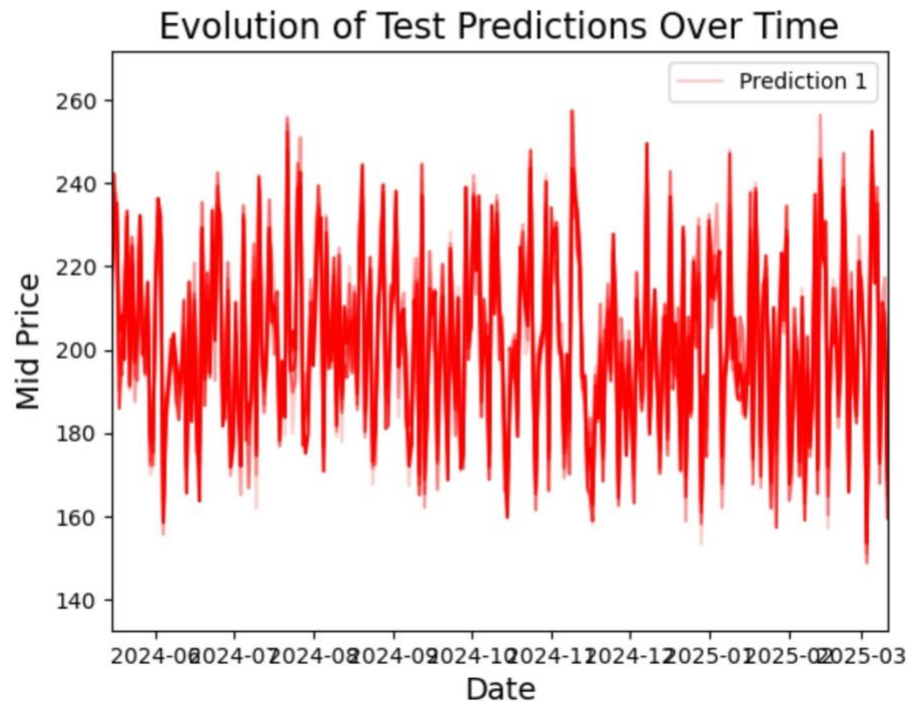
plt.title('Evolution of Test Predictions Over Time', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Mid Price', fontsize=14)
plt.xlim(df['Date'].iloc[500], df['Date'].iloc[800]) # Adjust as needed
plt.legend()

```

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Out[120... <matplotlib.legend.Legend at 0x160170c50>



```
In [122... # Subplot 2: Best Test Prediction
plt.subplot(2, 1, 2)
plt.plot(x_axis_seq, all_mid_data, color='b', label='Actual Mid Data')
best_prediction_epoch = 5 # Example epoch (0-based index)

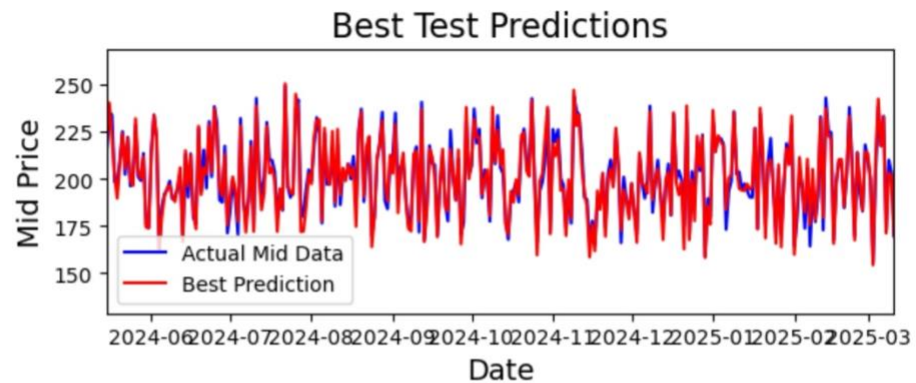
if best_prediction_epoch < len(predictions_over_time):
    best_prediction = predictions_over_time[best_prediction_epoch]
    plt.plot(x_axis_seq, best_prediction, color='r', label='Best Prediction')
else:
    print(f"best_prediction_epoch={best_prediction_epoch} is out of range")

plt.title('Best Test Predictions', fontsize=16)
plt.xlabel('Date', fontsize=14)
plt.ylabel('Mid Price', fontsize=14)
plt.xlim(df['Date'].iloc[500], df['Date'].iloc[800]) # Adjust as needed
plt.legend()

# Show the plot
plt.tight_layout()
plt.show()
```

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```
In [152... # Add these imports at the top of your script
from sklearn.metrics import mean_absolute_error, mean_squared_error, r
import numpy as np

# Calculate accuracy metrics for your predictions
def calculate_accuracy_metrics(y_true, y_pred):
    """
    Calculate various accuracy metrics for time series prediction

    Parameters:
    y_true (array-like): The actual values
    y_pred (array-like): The predicted values

    Returns:
    dict: Dictionary containing accuracy metrics
    """
    # Mean Absolute Error (MAE)
    mae = mean_absolute_error(y_true, y_pred)

    # Root Mean Squared Error (RMSE)
    rmse = np.sqrt(mean_squared_error(y_true, y_pred))

    # Mean Absolute Percentage Error (MAPE)
    mape = np.mean(np.abs((y_true - y_pred) / y_true)) * 100

    # Directional Accuracy (DA) - measures if the direction of movement
    direction_true = np.diff(y_true) > 0
    direction_pred = np.diff(y_pred) > 0
    directional_accuracy = np.mean(direction_true == direction_pred) *

    # R-squared (coefficient of determination)
    r2 = r2_score(y_true, y_pred)

    return {
        'MAE': mae,
        'RMSE': rmse,
        'MAPE': mape,
```

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```

        'Directional Accuracy (%)': directional_accuracy,
        'R-squared': r2,
        'Accuracy (%)': 100 - mape # A common way to represent accuracy
    }

# Add this after you've made your predictions
# Assuming 'all_mid_data' is your actual data and 'best_prediction' is

# Applying the function to your best prediction
if 'best_prediction' in locals() and len(best_prediction) == len(all_mid_data):
    # Calculate metrics for the best prediction
    metrics = calculate_accuracy_metrics(all_mid_data, best_prediction)

    # Print all metrics
    print("\nAccuracy Metrics for Best Prediction:")
    for metric, value in metrics.items():
        print(f"{metric}: {value:.4f}")

    # Highlight the overall accuracy percentage
    print("\n" + "="*40)
    print(f"Overall Prediction Accuracy: {metrics['Accuracy (%)']:.2f}")
    print("="*40)
else:
    print("Cannot calculate accuracy: predictions and actual data don't match")

# If you want to calculate metrics for all epochs to see improvement
print("\nAccuracy Progression Over Training Epochs:")
epoch_accuracies = []

for epoch, prediction in enumerate(predictions_over_time):
    # Make sure lengths match
    if len(prediction) == len(all_mid_data):
        metrics = calculate_accuracy_metrics(all_mid_data, prediction)
        accuracy = metrics['Accuracy (%)']
        epoch_accuracies.append(accuracy)
        print(f"Epoch {epoch+1}: Accuracy = {accuracy:.2f}%")

# Plot accuracy improvement over epochs
if epoch_accuracies:
    plt.figure(figsize=(10, 6))
    plt.plot(range(1, len(epoch_accuracies)+1), epoch_accuracies, marker='o')
    plt.title('Prediction Accuracy Improvement Over Epochs')
    plt.xlabel('Epoch')
    plt.ylabel('Accuracy (%)')
    plt.grid(True)
    plt.show()

```

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Accuracy Metrics for Best Prediction:

MAE: 3.9751

RMSE: 4.9928

MAPE: 2.0104

Directional Accuracy (%): 92.7795

R-squared: 0.9407

Accuracy (%): 97.9896

```
=====
Overall Prediction Accuracy:  97.99%
=====
```

Accuracy Progression Over Training Epochs:

Epoch 1: Accuracy = 97.97%

Epoch 2: Accuracy = 97.98%

Epoch 3: Accuracy = 97.98%

Epoch 4: Accuracy = 97.97%

Epoch 5: Accuracy = 97.99%

Epoch 6: Accuracy = 97.99%

Epoch 7: Accuracy = 97.99%

Epoch 8: Accuracy = 97.97%

Epoch 9: Accuracy = 98.00%

Epoch 10: Accuracy = 97.99%

Epoch 11: Accuracy = 97.99%

Epoch 12: Accuracy = 97.97%

Epoch 13: Accuracy = 98.00%

Epoch 14: Accuracy = 97.98%

Epoch 15: Accuracy = 97.97%

Epoch 16: Accuracy = 98.00%

Epoch 17: Accuracy = 97.98%

Epoch 18: Accuracy = 97.98%

Epoch 19: Accuracy = 97.98%

Epoch 20: Accuracy = 97.98%

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In []: