Data Science

Capstone Report - Fall 2023

The Pitfall and Opportunity of Deep Learning in Stock Return Prediction

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Preface

This report embarks on a rigorous exploration of deep learning-based financial forecasting techniques within the realm of the Shanghai Composite Index (SHCI) returns. Our involvement in financial analysis and machine learning forms the foundation for this project, fostering an interest in harnessing advanced technologies to enhance predictive modeling in finance.

Targeted towards finance professionals, academics, and data analysts, this report elucidates the intersection of deep learning methodologies and stock return prediction. Its significance lies in the empirical investigation of the viability of deep learning models in capturing the complexities inherent in stock market dynamics. By addressing this intersection, this work aims to provide a pragmatic understanding of machine learning applications in finance, fostering informed decision-making processes in the financial domain.

This report serves as a scholarly exploration into the potential of advanced machine learning models in financial forecasting, seeking to elucidate both their efficacy and limitations in predicting the intricate behavior of the SHCI returns. It aims to present a comprehensive analysis, offering insights valuable to researchers, practitioners, and academics operating at the intersection of finance and machine learning.

Acknowledgements

We extend our heartfelt gratitude to NYU Shanghai professors, for their invaluable guidance and unwavering support throughout this project. Their expertise and encouragement have been instrumental in shaping the direction of this research. Our deepest thanks go to our family and friends for their patience, understanding, and continuous encouragement during this endeavor. Lastly, we are grateful to the academic community for providing resources and knowledge that have been instrumental in shaping this research.

Abstract

This project centers on the deployment and evaluation of deep learning models, specifically Long Short-Term Memory (LSTM) and Transformers, in the context of predicting the Shanghai Composite Index (SHCI) returns, a crucial undertaking within the volatile Chinese stock market landscape. The distinctive attributes of these models, including LSTM's memory cells for temporal pattern discernment and Transformers' attention mechanisms for sequential data processing, underscore their efficacy in handling time series analysis and sequential data prediction, prompting our exploration. Our initiative investigates the predictive capabilities of LSTM and Transformers in capturing intricate temporal dependencies within SHCI returns, leveraging American market factor data, evaluating sensitivity to market fluctuations, and examining the impact of varying time intervals. By comparing these deep learning models against a traditional Autoregressive (AR) model, this study illuminates the effectiveness of LSTM and Transformers in handling complexities inherent in financial forecasting, offering insights into their potentials and limitations within this domain.

Keywords

Deep Learning Models; Stock Return Prediction; NYU Shanghai

Contents

1 Introduction

Deep learning models, such as Long Short-Term Memory (LSTM) and Transformers, have proven to be exceptionally effective in handling sequential data. They exhibit distinctive features that make them particularly effective in handling sequential data. Unlike traditional models, LSTM models possess memory cells that can capture and retain information over time, allowing them to discern patterns and dependencies in sequences [1]. This makes them highly effective in applications such as time series analysis, where understanding temporal relationships is paramount. For Transformers models, attention mechanisms have emerged as powerful tools for sequential data processing, providing the ability to focus on specific parts of a sequence, contributing to the success of Transformers in time series data prediction [2]. The inherent depth and adaptability of deep learning models make them invaluable for unlocking insights and making predictions from sequential data in various domains [3, 4]. Consequently, we have undertaken an initiative to investigate and explore the viability of deploying this model to address challenges and opportunities pertinent to financial applications.

In this project, we choose the Shanghai Composite Index(SHCI) as our target variable, as it is a representative of the China's stock market and its future performance is a formidable undertaking due to the intricate dynamics and multifaceted factors that shape its fluctuations. As a composite index, the SHCI consolidates the performance of numerous stocks listed on the Shanghai Stock Exchange, amplifying its complexity and volatility, thereby posing significant challenges in achieving precise and reliable predictions.

This project aims to explore the pitfall and opportunity of deep learning models. It will take the traditional Autoregressive (AR) model, which uses time series data and lagged values(previous values) to make predictions, as our baseline model. Specifically, we aim to investigate from the following four aspects:

1. Whether deep learning models, specifically LSTM and Transformers, have strong predictive capabilities in capturing complex temporal dependencies and patterns in SHCI returns;

2. Whether deep learning models can utilize high-dimensional American market factor data, even if these factors may not be statistically significant, to predict the SHCI returns;

3. Whether deep learning models are sensitive to market fluctuations and are in need of the integration of filtering techniques, such as the Kalman Filter, to mitigate noise in the data and improve the predictive performance;

4. Whether deep learning models would be affected by the varying time interval lengths, such as 20-year data and 10-year data, in the SHCI return prediction.

By addressing these research questions, this project aims to explore SHCI return prediction, uncover new insights regarding the deep learning models under the impact of American market factors, filtering techniques such as Kalman Filter, and time interval selection.

2 Related Work

The prediction of financial market performance has been a subject of extensive interest in the field of finance. Numerous studies have explored various factors and modeling techniques to enhance the accuracy and reliability of stock return predictions. In this related work section, we will examine relevant studies that have investigated the prediction of the SHCI return and the incorporation of American market factors, filtering techniques, and time interval selection in deep learning models for stock return prediction.

2.1 Prediction of the Shanghai Composite Index under American Market Factors

The Shanghai Composite Index (SHCI), China's earliest composite index, contains all stocks traded on the Shanghai Stock Exchange, including all A-shares and B-shares. This makes it a representative of the overall performance of the Chinese financial market. However, predicting its movements is a challenging task due to the multitude of factors that must be taken into account. One traditional way is to use the historical data of the stock return as a predictor, given that its future returns can be closely linked to the past performance. In addition, the American market also has a great impact on the performance of the Chinese stock return. A research done by Liu et al. employed ADCC-GARCH(1,1) and DCC-GARCH(1,1) models to investigate the relationship between the SHCI return and the American financial markets [5]. This results suggested that the correlations have the tendency to amplify during financial crises, thus highlighting the necessity of considering American market factors when forecasting the SHCI return. Despite the mention of the necessity to take American market factors into account, there are few research papers take those factors as predictors when predicting the SHCI future return, whatever the model they use. Acknowledging the influence that American market factors can exert on the SHCI return, we intend to employ American market factors as predictive variables for forecasting the future returns of the SHCI.

2.2 Traditional Models in Stock Return Prediction

The field of stock return forecasting is indeed rooted in econometric models, with Autoregressive (AR) models and multi-linear regression models being commonly employed for this purpose.

For AR models, they use time series data and lagged values to make predictions. Numerous studies in financial research have utilized AR models to predict stock returns, highlighting their effectiveness in capturing the dynamics of the financial market. For example, a study by Campbell et al. compared the performance of various forecasting models and found that AR models outperformed other approaches in capturing short-term stock return predictability [6]. The authors emphasized the importance of incorporating lagged values and time series data, which are key features of AR models, in capturing the persistence and autocorrelation often observed in stock returns. Moreover, the simplicity and interpretability of AR models make them appealing for stock return forecasting. The estimated coefficients in AR models represent the impact of past values on future returns, allowing researchers and practitioners to assess the significance and direction of these relationships. This transparency aids in understanding the underlying factors influencing financial market dynamics and can provide valuable insights for decision-making. Overall, the extensive usage of AR models in financial research, their ability to incorporate historical data, and their interpretability contribute to their suitability for conducting stock return regression forecasting. These characteristics have established AR models as a fundamental tool in the field and continue to make them relevant and valuable for predicting stock returns.

However, AR models do have notable disadvantages. One primary limitation is their reliance on historical data alone. AR models assume that future values depend solely on past observations, neglecting external factors and market dynamics that can significantly influence stock returns. This lack of consideration for exogenous variables makes AR models susceptible to unexpected events, such as economic shifts, geopolitical developments, or market sentiment changes, which can have a substantial impact on stock movements. Specifically, they face challenges during periods of heightened market volatility, characterized by frequent unexpected events and rapid shifts in the data. These models tend to overlook the potential influence of those sudden market shocks, which can significantly impact the stock returns, and struggle to capture these dynamic changes effectively, hindering their reliability as predictive tools in such circumstances. In addition to the aforementioned limitations, another challenge faced by AR models is their inability to effectively handle situations involving multiple variables. AR models are primarily designed to analyze the relationship between a single variable and its past values. When dealing with complex financial markets where multiple variables play significant roles and exhibit intricate interdependencies, AR models fall short in capturing their inner complexities, leading to inaccurate forecasts in predicting stock returns. As a result, we have become interested in more advanced models, such as deep learning algorithms, to navigate the challenges posed by volatile markets as well as multiple interconnected variables.

Capital Asset Pricing Model (CAPM) and Fama-French Three Factor Model (FFTFM) fall under the purview of traditional methodologies in stock return prediction, particularly within the framework of multi-linear regression models. The CAPM is a foundational model that attempts to delineate the relationship between expected stock returns on an investment and its risk. It postulates that the expected return on an asset should be commensurate with the stock's systematic risk and the expected market return [7]. The model assumes a linear relationship between the excess return of a stock and the market excess return, with a variable called beta to quantify the sensitivity of a stock's return to market fluctuations. On the other hand, the FFTFM expands upon CAPM by introducing additional factors that capture more nuances influencing stock returns. This model considers not only market risk but also two additional factors: the size effect (small-capital stocks outperforming large-capital stocks) and the value effect (value stocks outperforming growth stocks) [8]. By integrating these factors into a multi-linear regression framework, the FFTFM aims to explain the variability in stock returns beyond what the CAPM alone can account for. It enhances the predictive power of stock returns by incorporating these additional dimensions of risk and return.

Both CAPM and the Fama-French Three Factor Model serve as cornerstones in traditional stock return prediction, using multilinear regression techniques to estimate expected returns based on market risk and additional factors that encompass size and value effects. Despite their widespread use, their limitations lie in their assumptions. These models often rely on the efficient market hypothesis and linear relationships between risk factors and stock returns, overlooking factors like market anomalies and non-linear dynamics prevalent in real-world financial markets. Their simplicity may not capture the full spectrum of factors affecting stock returns, especially in volatile or unconventional market conditions, which has led to the exploration of more sophisticated models like deep learning to address these shortcomings.

2.3 Deep Learning Models in Stock Return Prediction

Deep learning models possess several advantages over AR models in the realm of stock return prediction, allowing for more accurate predictions in dynamic and volatile market conditions. A significant advantage is the ability of deep learning models, such as multi-layer neural networks, to capture nonlinear relationships between various market variables. This capability enables them to model complex patterns and dependencies that may be difficult to capture with traditional models. Moreover, deep learning models have the capability to automatically extract relevant features from the input data, reducing the need for manual feature engineering. This feature learning process can uncover hidden patterns, potentially enhancing their predictive power. Besides, deep learning models excel at processing and analyzing high-dimensional data. They can effectively handle large amounts of data with many input variables, making them suitable for forecasting where numerous market factors need to be considered simultaneously. They can capture temporal dependencies and long-term patterns in the data, making them valuable for forecasting financial returns that involve sequences and time-dependent variables.

Two prominent deep learning architectures, Long Short-Term Memory (LSTM) networks and Transformers, have gained prominence in financial time series prediction. LSTM networks, a type of Recurrent Neural Network (RNN) architecture, consist of interconnected memory cells, each having an input gate, a forget gate, and an output gate. The input gate controls how much new information should be stored in the memory cell, while the forget gate determines how much of the existing information in the memory cell should be discarded. The output gate regulates the amount of information to be passed onto the next step in the sequence [1]. LSTMs were designed to address the limitations of traditional RNNs in capturing and retaining long-term dependencies in sequential data. They can selectively learn and forget information over time, allowing them to retain relevant information for longer periods and discard irrelevant or redundant information. One study conducted by Siami-Namini et al. found that LSTM networks are able to achieve an average reduction in error rates of 84% - 87% in various stock return predictions, compared with the Autoregressive Integrated Moving Average (ARIMA) model [3]. Moghar and Hamiche also reported that LSTM models demonstrated success in predicting the performance of GOOGL and NKE assets with a significantly low loss [9]. However, it is noteworthy that these papers do not thoroughly examine the challenges that LSTM encounter in the context of financial predictions, and this lack of thorough examination leaves ample room for further exploration in our research.

Similarly, the Transformers model is another popular deep learning model. It is known for its ability to capture long-range dependencies in sequential data, and given this characteristic, it has also been applied to stock return prediction. It uses a self-attention mechanism to weigh the importance of different elements in a sequence, enabling it to capture complex patterns in historical stock return data [2]. This has been demonstrated in the research of Wang et al. that, by using the encoder-decoder architecture and multi-head attention mechanism, the Transformers model effectively captures the underlying rules of stock market dynamics, showcasing significant outperformance compared to traditional methods and the potential for generating excess earnings for investors [4]. Nevertheless, there is still a noticeable dearth of comprehensive discussions regarding the potential challenges confronted by this model.

Overall, deep learning models inherently possess the capability to adapt and learn from evolving financial data. In the scenario of stock return prediction, where market conditions can change rapidly, deep learning models can dynamically adjust their predictions to account for shifts in market trends and other factors affecting returns. This adaptability makes them well-suited for handling time-varying financial data. As mentioned above, both LSTM models and Transformers models perform better than simple regression models when doing prediction, but relevant research papers do not reveal the possible disadvantages deep learning models may have in the field of financial prediction. Therefore, in our research, we aim to find what factor may influence the prediction accuracy of deep learning models on financial data.

2.4 Filtering Techniques for Noise Reduction

The Kalman Filter is first proposed by American scholars R. E. Kalman and R. S. Bucy, who introduced the state variables and state space concept of systems into Wiener filtering theory, resulting in the development of Kalman filtering theory. It is a recursive mathematical algorithm used to estimate and predict the future state of a dynamic system based on noisy measurements and a model of the system's behavior [10]. Given its effectiveness in handling complex systems with multiple variables, dynamic temporal changes, and non-stationary random processes, the Kalman Filter holds significant potential in the financial domain. A study conducted by Xu and Zhang demonstrated the effectiveness of the Kalman Filter in predicting stock prices [11]. In other words, by real-time tracking highly volatile and time-varying stock returns, the Kalman Filter can successfully incorporate noise, identify underlying trends, and recognize patterns in financial data, thereby enhancing the accuracy of stock return predictions. In Xu and Zhang's paper, they use Kalman predictor and MATLAB computer simulation to do prediction. This is different from our research approach. We will use the Kalman Filter to process the data and then input these data into deep learning models to see whether the use of Kalman Filter can improve the prediction accuracy of these deep learning models.

2.5 Dataset Size Selection

The choice of different dataset sizes can have a notable influence on the ultimate accuracy of the prediction model. A larger dataset with longer time length offers a broader historical view as it captures long-term trends, but it may require more complex models. It tends to be more stable, generalizable to various market conditions, and less sensitive to noise. In contrast, a smaller dataset with shorter time length focuses on recent market conditions, which can result in higher sensitivity to short-term fluctuations. In the context of the Toronto Stock Exchange, Alzaman explored the consequences of varying dataset size. It is discovered that this approach is essential for discovering and excluding the influence of irrelevant market shocks, thus underscoring the importance of selecting suitable time length for prediction [12]. However, the longest time length selected by Alzaman is still quite short, which is less than one year. We will use datasets with 20-year time length and 10-year time length, as such large data set has not been tested in that research and explore how longer time length may affect the prediction accuracy.

3 Solution

3.1 Data

1. SHCI Returns:

The Shanghai Composite Index (SHCI) returns serve as the target variable in our analysis, representing the aggregated performance of constituent stocks listed on the Shanghai Stock Exchange. Comprised of a diverse array of stocks across various sectors including finance, technology, manufacturing, and more, the SHCI holds significance as a key indicator of China's economic health and market sentiment. The SHCI returns encapsulate the fluctuations and movements in stock prices, enabling assessments of market trends, volatility, and overall performance within the Chinese financial market.

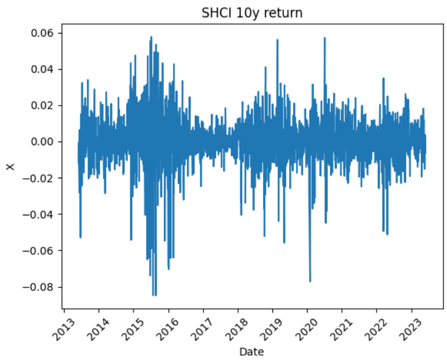

Figure 1: SHCI 10-year Return.

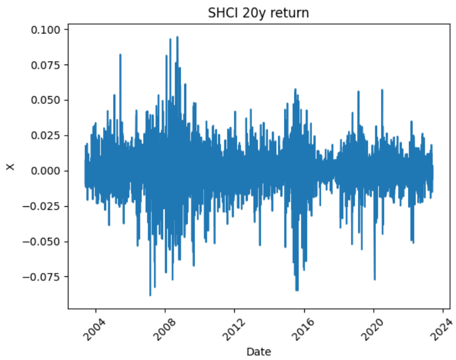

Figure 2: SHCI 20-year Return.

2. S&P 500 Returns:

The S&P 500 returns stand as a critical explanatory variable within our analysis, representing the movements and fluctuations of the stock returns of 500 leading publicly-traded companies in the United States. Renowned as a benchmark index for the U.S. stock market, the S&P 500 captures a diverse spectrum of industries, encompassing major sectors such as technology, healthcare, finance, and consumer goods. Its significance extends beyond the boundaries of the U.S. financial market, serving as a global barometer influencing market trends worldwide. The inclusion of S&P 500 returns as an explanatory variable in our study aims to explore the interplay and potential correlations between the movements of the U.S. market and the SHCI returns. By analyzing the impact of S&P 500 returns on SHCI returns, our research endeavors to unravel the interconnectedness between these two influential indices, providing valuable insights into the dynamics of global markets and its implications for Chinese financial landscape.

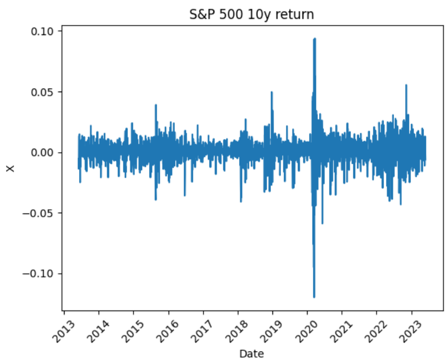

Figure 3: S&P 500 10-year Return.

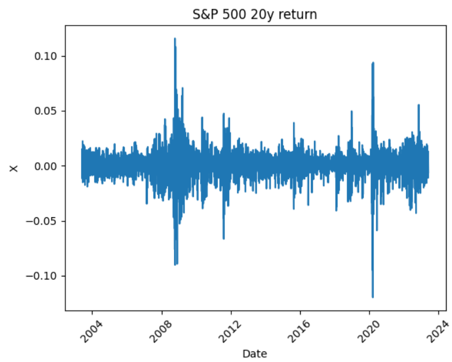

Figure 4: S&P 500 20-year Return.

3. NASDAQ Returns:

NASDAQ returns represent a pivotal variable within our project, delineating the performance of technology and growth-oriented stocks listed on the NASDAQ stock exchange. Comprising a wide array of innovative companies spanning sectors such as technology, biotechnology, and telecommunications, the NASDAQ index holds distinction as a beacon for high-growth industries and technological innovation. As a premier indicator for the performance of tech-heavy stocks, NASDAQ returns serve as a crucial metric influencing market trends. In our analysis, the inclusion of NASDAQ returns as a key variable aims to investigate the potential impact of foreign technology-driven market movements on the SHCI returns. Understanding the relationship between NASDAQ returns and SHCI returns is integral to unraveling the interconnectedness between the tech-centric U.S. market and the broader Chinese financial landscape.

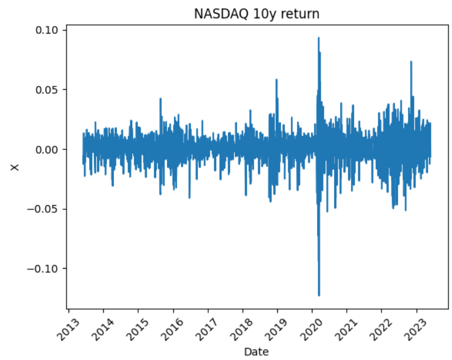

Figure 5: NASDAQ 10-year Return.

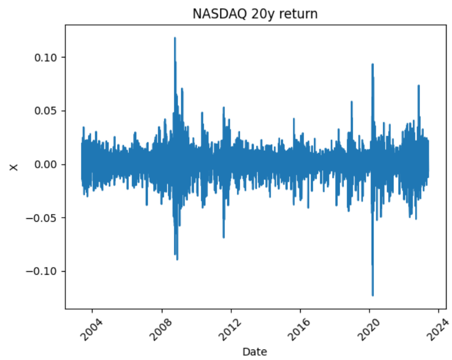

Figure 6: NASDAQ 20-year Return.

4. VIX Returns:

VIX returns, rooted in the CBOE Volatility Index, serve as a important variable in our project, reflecting market volatility and investor sentiment within the U.S. financial landscape. The VIX measures expected volatility in the market, particularly pertaining to the S&P 500 Index options. Elevated VIX levels often coincide with increased market uncertainty and risk aversion, while lower levels typically indicate relative stability and confidence. In our analysis, VIX returns assume significance as a measure of risk perception, offering insights into potential fluctuations influencing both the U.S. market and, potentially, the SHCI returns. By exploring the relationship between VIX returns and SHCI returns, our research aims to uncover how shifts in market volatility in the U.S. might impact Chinese financial market dynamics.

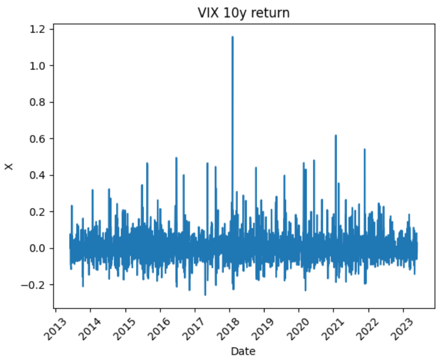

Figure 7: VIX 10-year Return.

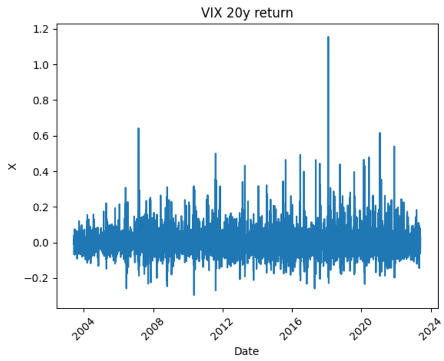

Figure 8: VIX 20-year Return.

5. U.S. Risk-free (RF) Returns:

The U.S. RF returns stands as a cornerstone metric within financial analysis, representing the hypothetical return on investment devoid of risk, typically anchored in U.S. Treasury securities. This metric serves as a pivotal benchmark for assessing the performance of riskier investments. As a fundamental gauge of the baseline return available without assuming any risk, the U.S. RF returns serves as a pivotal reference point for evaluating the relative performance and risk-adjusted returns of other assets and indices, such as the SHCI. In our analysis, incorporating U.S. RF returns provides a vital perspective for understanding the interplay between U.S.market and the SHCI.

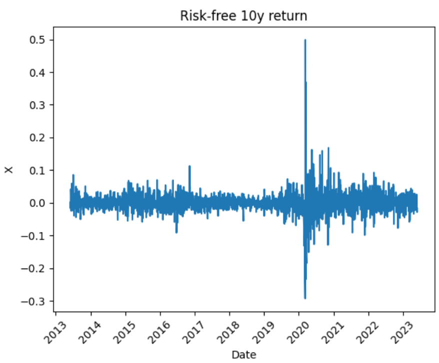

Figure 9: RF 10-year Return.

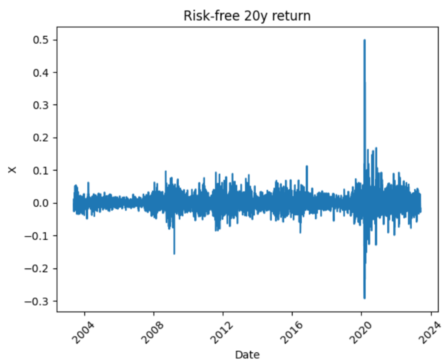

Figure 10: RF 20-year Return.

3.2 Solution

Our project focuses on exploring factors influencing the efficacy of deep learning models in predicting SHCI returns, culminating in a systematic approach comprised of four key steps.

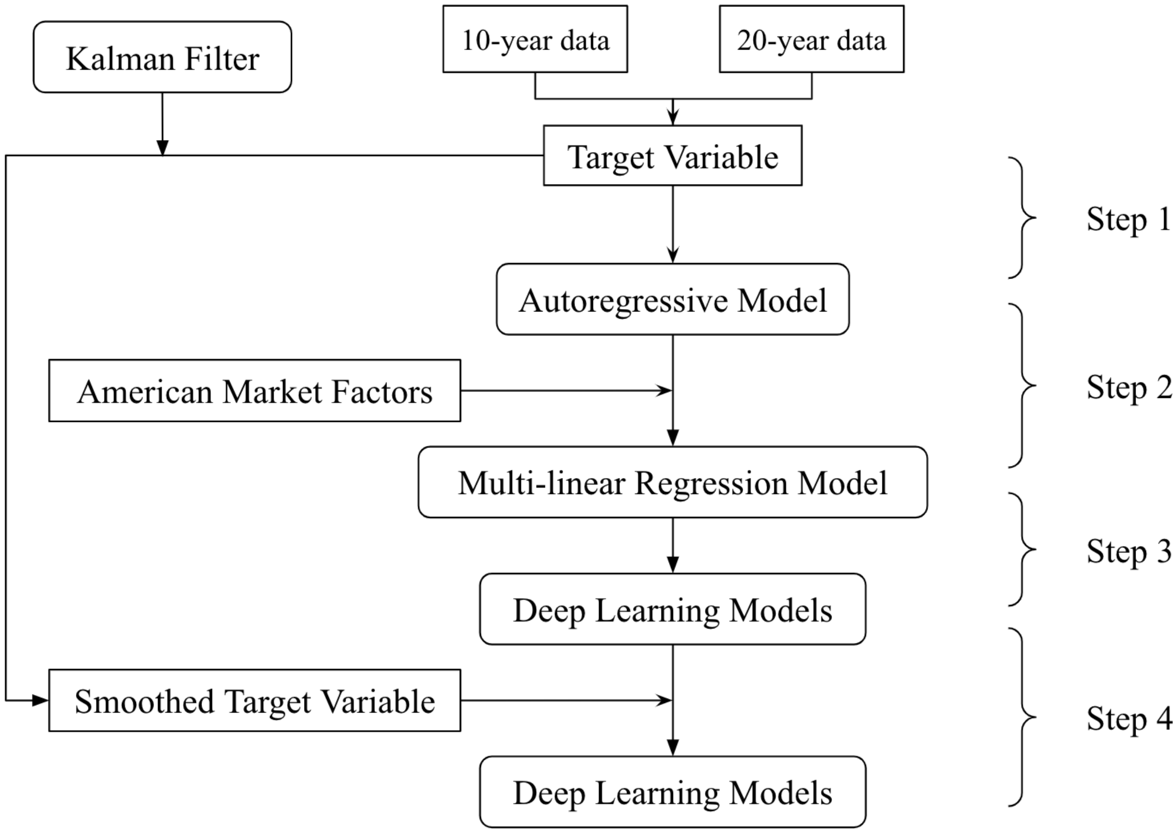

Figure 11: Flow chart of our solution.

As shown in Figure 11:

1. Baseline Model Establishment: Our initial step involves establishing a baseline model for stock return prediction using an AR model. We begin by checking the stationarity of the data, and then employing lagged SHCI returns. This creates a foundation for subsequent model enhancements.

2. Incorporation of American market factors: Building upon the baseline model, our exploration expands to assess the significance of additional factors, particularly American market factors, in predicting stock returns and implement a multi-linear regression model. This rigorous analysis aims to discern the impact and relevance of these supplementary factors in the SHCI returns.

3. Model Evaluation: Our project progresses to evaluate the performance of different deep learning models such as LSTM and Transformers. We systematically compare their predictive capabilities against the baseline AR model and the multi-linear regression model. This stage aims to discern the strengths and weaknesses of each model in forecasting SHCI returns.

4. Integration of Kalman Filter: Addressing the inherent noise and volatility in stock return

data, we introduce the Kalman Filter as a filtering technique. Our objective is to refine the predictive accuracy of the deep learning models. The Kalman Filter's ability to minimize mean squared error and estimate latent states amidst noisy observations is anticipated to enhance the robustness and precision of our predictive models.

Additionally, we will analyze the impact of dataset size variation. We will explore the influence of dataset size by employing different time lengths. By varying the temporal intervals of the dataset—ranging from shorter spans to longer durations—we aim to investigate how dataset size impacts the predictive performance of our deep learning models. This step seeks to provide insights into the optimal dataset length for accurate stock return predictions.

Each stage of our methodology represents a distinct contribution to the refinement and enhancement of deep learning models for SHCI returns. Through meticulous analysis and iterative refinement, our project endeavors to offer a comprehensive and effective framework for leveraging deep learning models in stock return prediction.

4 Results and Discussion

4.1 Result

4.1.1 Result of Baseline Model

The analysis commenced with the establishment of a baseline model for SHCI return prediction, initially employing lagged returns. The preliminary findings from this baseline model lay the groundwork for subsequent enhancements and provide crucial insights into the initial predictive capabilities.

Table 1 illustrates the Root Mean Square Error (RMSE) metrics obtained from employing AR models across varying time lengths, specifically 10 years and 20 years. Notably, the RMSE for the 10-year time length stands at 0.0125, while the 20-year time length yields a slightly higher RMSE of 0.0149. This discrepancy suggests that the AR model exhibits marginally better predictive accuracy with the 10-year dataset as opposed to the 20-year dataset. The lower RMSE value for the 10-year interval signifies a relatively closer alignment between the predicted values and the actual stock returns within this shorter timeframe. Conversely, the higher RMSE for the 20-year duration indicates a marginally larger deviation between predicted and actual returns, implying a slightly reduced predictive accuracy over a longer historical dataset.

This baseline model serves as a fundamental benchmark for evaluating the predictive per-

Time Length	AR Model (RMSE)
10-year	0.0125
20-year	0.0149

Table 1: Results of AR Model.

formance of more sophisticated models in subsequent stages. The initial results obtained from this foundational model serve as a reference point against which the incremental improvements achieved by incorporating additional factors, advanced algorithms, and filtering techniques will be measured. Besides, the outcomes derived from the baseline model underscore the importance of elucidating the significance and impact of supplementary factors, particularly American market factors, in augmenting the predictive accuracy beyond the rudimentary lagged SHCI returns. These findings form the basis for subsequent stages in our analysis, facilitating a comparative evaluation of model performances and highlighting the significance of advancements made in refining stock return prediction models.

4.1.2 Result of Multi-linear Regression Model

The multi-linear regression model employed in this project constitutes a fundamental predictive tool utilized to forecast the SHCI returns with American market factors. This regression framework incorporates a collection of explanatory variables, including lagged SHCI returns, S&P 500 returns, NASDAQ returns, VIX returns, and RF returns. The model operates on the premise of assessing the linear relationship between the SHCI returns and these selected predictor variables. By leveraging historical data and incorporating a diverse set of influential factors, this regression model forms a cornerstone in financial modeling, providing a quantitative understanding of the interplay between SHCI returns and U.S. market indices.

Time Length	Multi-linear Regression Model (RMSE)
10-year	0.0128
20-year	0.0148

Table 2: Results of Multi-linear Regression Model.

Table 2 summarizes the RMSE values obtained from the multi-linear regression model. At the 10-year time length, the model yields an RMSE of 0.0128, indicating a relatively lower deviation between the predicted and actual SHCI returns within this temporal interval. Conversely, the 20-year duration exhibits a slightly higher RMSE of 0.0148, signifying a marginally increased deviation between predicted and actual returns. These RMSE outcomes underscore the multi-linear regression model's competence in capturing and forecasting the SHCI returns, demonstrating its relatively higher predictive accuracy within the shorter 10-year timeframe compared to the 20-year duration.

4.1.3 Result of Deep Learning Models

The deep learning models, LSTM and Transformers, constitute sophisticated architectures employed to forecast the SHCI returns. These models are distinguished by their capacity to capture temporal dependencies and intricate patterns within sequential data, offering robust predictive capabilities. The LSTM model, characterized by its ability to retain long-term dependencies, and the Transformers model, known for its self-attention mechanism, were both trained using historical SHCI data along with American market factors including S&P 500 returns, NASDAQ returns, VIX returns, and RF returns.

Time Length	LSTM (Test RMSE)	Transformers (Test RMSE)
10-year	0.0090	0.0091
20-year	0.0098	0.0097

Table 3: Results of Deep Learning Models.

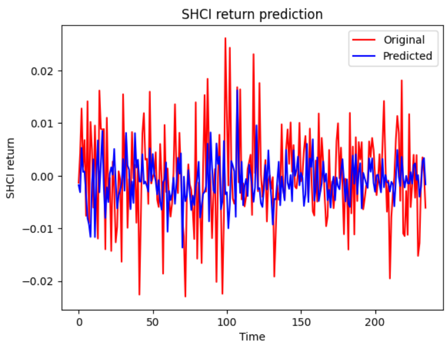

Figure 12: LSTM for 10-year.

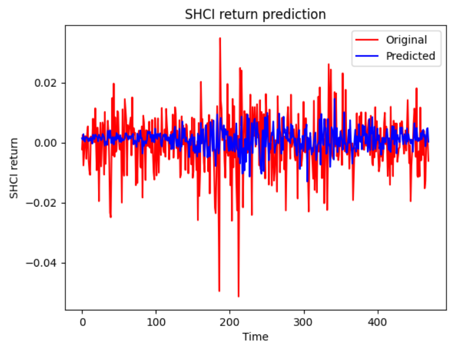

Figure 13: LSTM for 20-year.

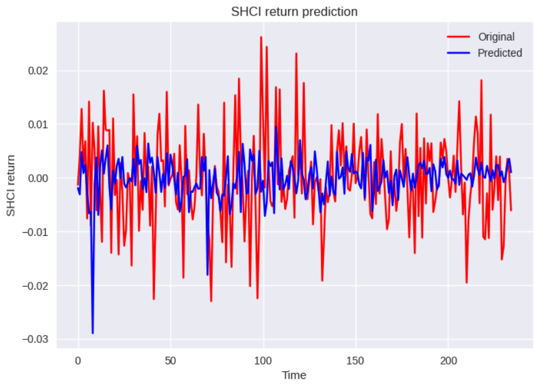

Figure 14: Transformers for 10-year.

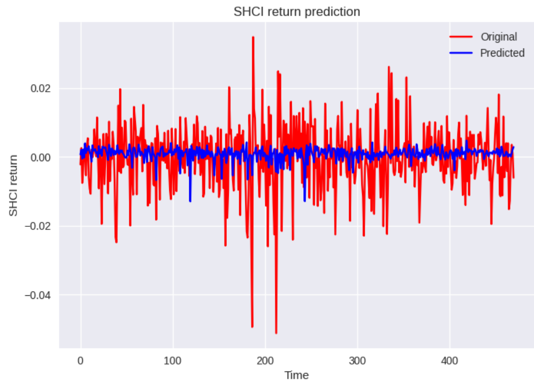

Figure 15: Transformers for 20-year.

The results showcased in Table 3 display the Test RMSE values obtained from both the LSTM and Transformers models across different time lengths. Notably, both models exhibit relatively low RMSE values across the 10-year and 20-year time intervals, suggesting their adeptness in forecasting SHCI returns. The LSTM model achieves a Test RMSE of 0.0090 for the 10-year duration and 0.0098 for the 20-year duration. Similarly, the Transformers model demonstrates a Test RMSE of 0.0091 for the 10-year period and 0.0097 for the 20-year period.

Notably, the LSTM model showcases slightly superior performance in shorter-term forecasting, as evidenced by its lower Test RMSE values of 0.0090 for the 10-year duration compared to the 0.0091 of Transformers. Conversely, as the forecasting horizon extends to the 20-year interval, the Transformers model exhibits marginally improved performance with a Test RMSE of 0.0097, slightly lower than the LSTM's 0.0098. This nuanced performance variation implies that while the LSTM model excels in capturing shorter-term dependencies and patterns within the SHCI returns, the Transformers model demonstrates enhanced adaptability in handling longer-term forecasting, leveraging its self-attention mechanism to discern and comprehend complex temporal relationships present in lengthier data sequences.

These RMSE values portray the models' predictive accuracy, signifying their proficiency in capturing and forecasting SHCI returns. Despite minor variations in RMSE between the LSTM and Transformers models, both exhibit commendable performance, showcasing their capacity to comprehend the intricate patterns within the SHCI returns and American market factors, contributing to accurate predictions of SHCI returns across varying temporal intervals.

4.1.4 Result of Deep Learning Models with Kalman Filter

In this section, we introduce the outcomes derived from integrating the Kalman Filter (KF) into the LSTM and Transformers models utilized for forecasting the SHCI returns. The models now incorporate a refined set of explanatory variables consisting of S&P 500 returns, NASDAQ returns, VIX returns, U.S. RF returns, and Kalman-filtered SHCI returns. This augmented dataset aims to enhance the predictive capacity of the models by reducing noise and volatility inherent in the historical SHCI returns.

Time Length	LSTM + KF (Test RMSE)	Transformers + KF (Test RMSE)
10-year	0.0022	0.0021
20-year	0.0019	0.0018

Table 4: Results of Deep Learning Models with Kalman Filter.

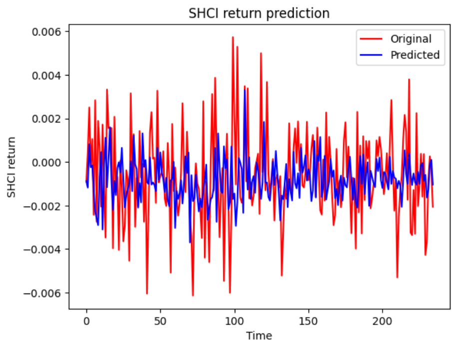

Figure 16: LSTM+KF for 10-year.

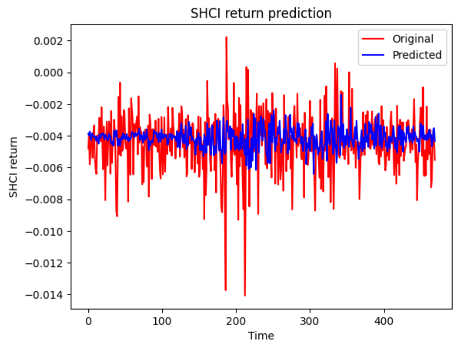

Figure 17: LSTM+KF for 20-year.

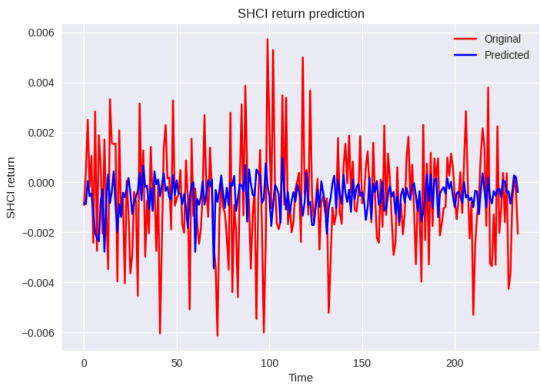

Figure 18: Transformers+KF for 10-year.

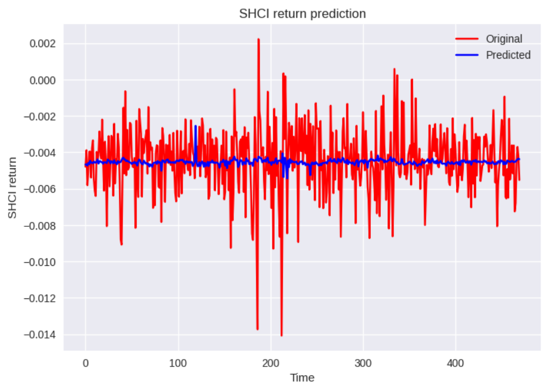

Figure 19: Transformers+KF for 20-year.

The incorporation of the Kalman Filter into the LSTM and Transformers models has notably refined their predictive accuracy in forecasting the SHCI returns.

Table 4 presents the Test RMSE values, showcasing the enhanced performance of both models across different time intervals. Surprisingly, with the integration of the Kalman Filter into both the LSTM and Transformers models, a notable shift in performance dynamics across varying time intervals has emerged. Upon incorporating the Kalman Filter, the LSTM model showcases an impressive reversal in its predictive capabilities. For the 10-year interval, the Test RMSE stands at a significantly reduced 0.0022. Strikingly, as the forecasting horizon extends to the 20-year duration, the Test RMSE drops even further to an impressive 0.0019, surpassing the 10-year interval in predictive accuracy. Similarly, the Transformers model, post-Kalman Filter integration, demonstrates a similar trend. While achieving a respectable Test RMSE of 0.0021 for the 10-year duration, the model exhibits a noteworthy improvement in forecasting performance with a reduced Test RMSE of 0.0018 for the 20-year period.

This trend is contrasting as it shifts the trend of shorter time length and smaller dataset size having better results. This indicates that contrary to the previous observations without the Kalman Filter, this integration has remarkably bolstered the models' capacity to effectively capture and forecast the SHCI returns over longer time intervals. The Kalman Filter's ability to mitigate long-term noises and enhance the quality of the historical SHCI returns has notably contributed to the models' heightened accuracy, particularly for extended temporal forecasts.

4.2 Discussion

4.2.1 Factor Assessment

In this section, we present the outcomes derived from employing a multi-linear regression model to predict the SHCI returns. The model incorporates lagged SHCI returns along with a selection of explanatory variables, including S&P 500 returns, NASDAQ returns, VIX returns, and U.S. RF returns. The objective is to discern the influence of these variables on forecasting SHCI returns.

1. For 10-year Data:

Variables (10-year)	Coefficient	Significance Level
Lagged SHCI Return	0.0194	0.344
S&P 500 Return	-0.0564	0.472
NASDAQ Return	0.1240	0.051
VIX Return	-0.0210	0.000
RF Return	-0.0233	0.009

Table 5: Coefficients and Significance Level (10-year).

- Lagged SHCI Return (0.0194, $p = 0.344$): The coefficient for Lagged SHCI Return, though positive, lacks statistical significance ($p > 0.05$). This indicates a weak association between past SHCI returns and predicting future SHCI returns within a 10-year period.

- S&P 500 Return (-0.0564, $p = 0.472$): The coefficient for S&P 500 Return exhibits a negative impact on future SHCI returns, but it fails to achieve statistical significance ($p > 0.05$). This suggests that changes in the S&P 500 returns do not significantly influence SHCI returns within the specified timeframe.

- NASDAQ Return (0.1240, $p = 0.051$): The coefficient for NASDAQ Return is positive and shows a nearly significant impact ($p = 0.051$) on predicting future SHCI returns over the 10-year interval. Although not statistically conclusive, it suggests a potential association between NASDAQ performance and SHCI returns.

- VIX Return (-0.0210, $p = 0.000$): The VIX Return coefficient exhibits a statistically significant negative impact ($p < 0.05$) on future SHCI returns within the 10-year horizon. This suggests that higher volatility, as indicated by the VIX, tends to coincide with lower SHCI returns.

- RF Return (-0.0233, $p = 0.009$): The coefficient for RF Return shows statistical significance ($p < 0.05$), indicating that changes in the U.S. RF returns exert a negative impact on SHCI returns within the 10-year timeframe.

2. For 20-year Data:

Variables (20-year)	Coefficient	Significance Level
Lagged SHCI Return	-0.0079	0.587
S&P 500 Return	0.0078	0.894
NASDAQ Return	0.1238	0.014
VIX Return	-0.0128	0.002
RF Return	-0.0113	0.192

Table 6: Coefficients and Significance Level (20-year).

- Lagged SHCI Return (-0.0079, $p = 0.587$): The coefficient for Lagged SHCI Return indicates a negative impact but lacks statistical significance ($p > 0.05$). This implies a weak relationship between past SHCI returns and predicting future SHCI returns within the specified 20-year duration.

- S&P 500 Return (0.0078, $p = 0.894$): The coefficient for S&P 500 Return exhibits a negligible positive impact, and it is statistically insignificant ($p > 0.05$). Changes in the S&P 500 returns do not significantly influence SHCI returns over the 20-year horizon.

- NASDAQ Return (0.1238, $p = 0.014$): The coefficient for NASDAQ Return is positive and statistically significant ($p < 0.05$) in predicting future SHCI returns over the 20-year interval. This suggests a substantial association between NASDAQ performance and SHCI returns within this timeframe.

- VIX Return (-0.0128, $p = 0.002$): The VIX Return coefficient displays a statistically significant negative impact ($p < 0.05$) on future SHCI returns within the 20-year horizon. Higher volatility, as indicated by the VIX, aligns with lower SHCI returns over this extended period.

- RF Return (-0.0113, $p = 0.192$): The coefficient for RF Return lacks statistical significance ($p > 0.05$), indicating that changes in the U.S. RF returns do not significantly influence SHCI returns over the 20-year timeframe.

3. Conclusion:

The examination of the variables' impact on predicting the SHCI returns over different time spans reveals nuanced insights into their significance and influence. Notably, while examining the impact of American market factors, it becomes evident that their influence on SHCI returns is limited. Specifically:

- Lagged SHCI Return: Across both the 10-year and 20-year intervals, the Lagged SHCI Return demonstrates a lack of statistical significance in predicting future SHCI returns. This indicates a weak association between past SHCI performance and its subsequent returns within these timeframes.

- S&P 500 Return: The S&P 500 Return exhibits statistically insignificant impacts on SHCI returns over both periods, suggesting that changes in the S&P 500 Index do not significantly influence SHCI returns within either a 10-year or 20-year timeframe.

- NASDAQ Return: While statistically insignificant in the 10-year model, NASDAQ Return emerges as a significant predictor of SHCI returns within the 20-year horizon. This suggests an association between NASDAQ performance and SHCI returns over an extended timeframe.

- VIX Return: The VIX Return consistently demonstrates a significant negative impact on SHCI returns over both the 10-year and 20-year periods. Higher volatility, as indicated by the VIX, correlates with lower SHCI returns within these timeframes.

- RF Return: The U.S. RF Return, while statistically significant in the 10-year model, lacks significance in the 20-year model. This implies that changes in the risk-free rate may influence SHCI returns in the shorter term but exhibit less influence over an extended 20-year duration.

These findings underscore that, apart from volatility captured by the VIX, American market factors demonstrate limited influence on SHCI returns over varying horizons. This shows that the Chinese financial market is highly influenced by the external global risks. This emphasizes the nuanced nature of factors influencing SHCI returns and the importance of considering specific market dynamics when predicting returns within the Chinese financial market.

4.2.2 Deep Learning Model Effects

In this section, we undertake a comparative analysis between the multi-linear regression model and two deep learning models, namely LSTM and Transformers, in the context of forecasting the SHCI returns. The comparison focuses on evaluating the predictive performance of these models across different time spans—10 years and 20 years. It aims to discern the efficacy of traditional regression-based approaches against sophisticated deep learning architectures in handling and forecasting financial time series data. The assessment delves into the models' abilities to leverage shared factors, revealing insights into how deep learning models handle and utilize information that might be deemed insignificant by conventional regression models, ultimately impacting their predictive accuracy for SHCI returns.

Time Length	Multi-linear Regression (RMSE)	LSTM (Test RMSE)
10-year	0.0128	0.0090
20-year	0.0148	0.0098

Table 7: Comparison of Multi-linear Regression Model and LSTM.

Time Length	Multi-linear Regression (RMSE)	Transformers (Test RMSE)
10-year	0.0128	0.0091
20-year	0.0148	0.0097

Table 8: Comparison of Multi-linear Regression Model and Transformers.

The results in Table 7 and Table 8 reveal a stark difference in predictive performance between the multi-linear regression model and the deep learning models across both 10-year and 20-year time spans.

Across the evaluated time intervals, the multi-linear regression model showcases RMSE values of 0.0128 and 0.0148, respectively. In stark contrast, both LSTM and Transformers demonstrate substantial outperformance. The LSTM model displays notably lower RMSE values of 0.0090 and 0.0098 for the 10-year and 20-year spans, respectively. Similarly, the Transformers model delivers improved predictive accuracy, showcasing reduced RMSE values of 0.0091 and 0.0097 across the corresponding time intervals. This underscores the Transformers' proficiency in leveraging the identical set of factors featured in the multi-linear regression model, despite the lack of significance in certain variables within the regression model. It accentuates the deep learning models' autonomous capacity to process and extract valuable insights from data elements that the multi-linear regression model might overlook, thereby contributing to an amplified predictive capacity in forecasting SHCI returns.

However, it's noteworthy that across both multi-linear regression models and deep learning models, there's a discernible trend showcasing relatively higher Test RMSE values for longer time intervals compared to shorter durations. This trend indicates a reduced predictive accuracy for both types of models when forecasting SHCI returns over longer time horizons. Those models appear to face challenges in effectively capturing and extrapolating complex temporal dependencies and patterns inherent in lengthier historical datasets, leading to slightly higher prediction errors compared to shorter intervals. Specifically, While deep learning models exhibit strong predictive capabilities for shorter-term forecasting, they encounter increased difficulty in maintaining the same level of accuracy when forecasting over more extended periods. This highlights the importance of considering temporal dynamics in the financial market that may influence models' capacities in effectively capturing long-term trends within the volatile financial data.

4.2.3 Impact of Volatile Finarncial Market

contrary to expectations, the inclusion of more data over longer durations doesn't yield better results than shorter intervals with fewer data points. Additionally, an intriguing observation within our deep learning models lies in the peculiar phenomenon where the training RMSE surpasses the test RMSE—a deviation from the conventional model behavior. To investigate this anomaly, an exploration was conducted, focusing on the impact of historical financial crises on the predictive capability of models. We first change the 20-year data to the period starting in 2009, taking into account the 2008 global financial crisis.

Models	Training RMSE	Test RMSE
LSTM (20-year)	0.0158	0.0098
LSTM (after 08 crisis)	0.0140	0.0103

Table 9: LSTM Results under the Impact of 08 Crisis.

Models	Training RMSE	Test RMSE
Transformers (20-year)	0.0154	0.0097
Transformers (after 08 crisis)	0.0135	0.0101

Table 10: Transformers Results under the Impact of 08 Crisis.

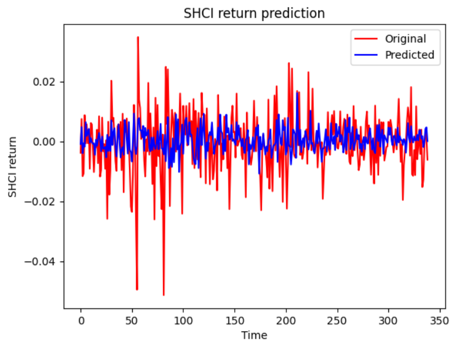

Figure 20: LSTM Results (after 08).

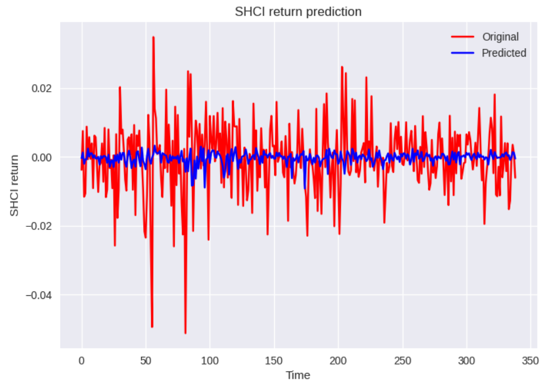

Figure 21: Transformers Results (after 08).

As shown in Tables 9 and 10, it's noteworthy that the training RMSE notably decreases after the crisis period, indicating an improvement in the model's performance in fitting the training data. However, the test RMSE sees a slight increase, albeit not significantly, suggesting that the predictive accuracy on unseen data isn't considerably affected. This discrepancy in performance before and after the crisis strongly suggests that the higher training RMSE is, to a certain extent, influenced by the turbulent market conditions of 2008. The substantial change observed in the training RMSE after the 2008 financial downturn vividly demonstrates its disruptive effect on the learning process of our deep learning models. This reinforces the idea that although the models have effectively adapted to post-crisis data, there might still be effects from other financial crises, causing this relatively high RMSE values. This highlights the intricate and enduring influence of such market disruptions on the learning dynamics of financial forecasting models.

This sets the stage for further exploration into the 2015 Chinese stock market crash.

Models	Training RMSE	Test RMSE
LSTM (10-year)	0.0137	0.0090
LSTM (20-year)	0.0158	0.0098
LSTM (after 08 crisis)	0.0140	0.0103
LSTM (after 15 crisis)	0.0115	0.0086

Table 11: LSTM Results under the Impact of 15 Crisis.

Models	Training RMSE	Test RMSE
Transformers (10-year)	0.0133	0.0091
Transformers (20-year)	0.0154	0.0097
Transformers (after 08 crisis)	0.0135	0.0101
Transformers (after 15 crisis)	0.0112	0.0086

Table 12: Transformers Results under the Impact of 15 Crisis.

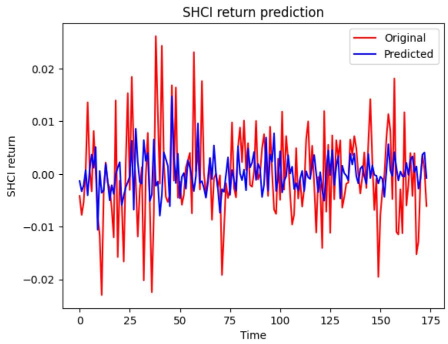

Figure 22: LSTM Results (after 15).

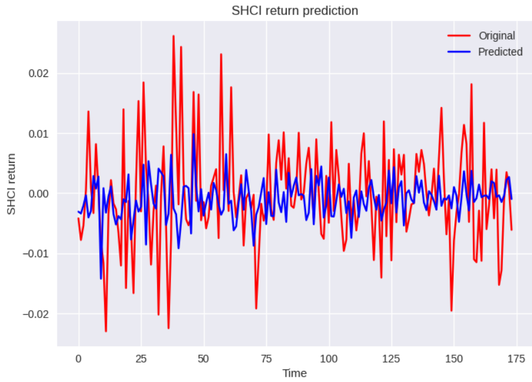

Figure 23: Transformers Results (after 15).

In Table 11 and Table 12, the training and test RMSE values provide insights into how these models are affected by the 2015 crisis. In both the LSTM and Transformers models, the training RMSE decreases noticeably after the 2015 crisis compared to the previous periods (post-2008 crisis). Specifically, the LSTM model exhibits a drop in training RMSE from 0.0140 to 0.0115 after the 2015 crisis, indicating improved performance in capturing the trends in the training data following this event. Similarly, the Transformers model showcases a decline in training RMSE from 0.0135 to 0.0112, emphasizing its enhanced ability to learn from the dataset after the 2015 crisis. Moreover, examining the test RMSE, both the LSTM and Transformers models demonstrate reduced error rates after the 2015 crisis. The test RMSE for the LSTM model decreases from 0.0103 to 0.0086, while the Transformers model also displays a decline in test RMSE from 0.0101 to 0.0086. These diminished error rates signify the models' improved predictive accuracy on unseen data post the 2015 crisis, suggesting their enhanced adaptability to the evolving market conditions.

Comparing the models' performance after the 2015 crisis with their performance using a 10-year dataset, both the LSTM and Transformers models display notable improvements. In terms of training RMSE, the models trained after the 2015 crisis exhibit lower errors compared to those trained on a 10-year dataset. Specifically, the training RMSE for the LSTM model decreases from 0.0137 (10-year dataset) to 0.0115 (after the 2015 crisis). Similarly, the Transformers model shows a drop in training RMSE from 0.0133 (10-year dataset) to 0.0112 (after the 2015 crisis). This is because the 10-year dataset includes the 2015 crisis. These reductions in RMSE after 2015 crisis signify enhanced model learning and adaptation to the newer data patterns. Analyzing the test RMSE, the models trained after the 2015 crisis also showcase improved predictive accuracy compared to their performance based on a 10-year dataset. The LSTM model's test RMSE decreases from 0.0090 (10-year dataset) to 0.0086 (after the 2015 crisis), while the Transformers model exhibits a similar decline in test RMSE from 0.0091 (10-year dataset) to 0.0086 (after the 2015 crisis). These reductions in test RMSE indicate better generalization and predictive capabilities of the models trained after the 2015 crisis when evaluated on unseen data.

In summary, the LSTM and Transformers models trained after the 2015 Chinese stock market crisis display improved performance in both training and test RMSE compared to models trained on all other datasets. This suggests deep learning models' ability to capture and utilize the information increases after the 2015 and 2008 crises, highlighting their heightened susceptibility to market fluctuations and disruptions. However, due to significant upheavals in the financial markets, such as the impact of the COVID-19, the training RMSE of the models trained after 2015 crisis still surpasses the test RMSE. This shows that volatility, particularly during extreme events such as the pandemic, continues to pose challenges in completely mitigating its influence, resulting in lingering discrepancies between training and test RMSE of our deep learning models.

4.2.4 Kalman Filter Effects

In the field of financial forecasting models, the integration of advanced filtering techniques, such as the Kalman Filter (KF), stands as a critical component aimed at enhancing predictive accuracy and refining models' robustness against market noises and fluctuations. In this section, the effects of incorporating the Kalman Filter into LSTM and Transformers models for SHCI returns prediction are explored across varying time intervals.

Time Length	LSTM (Test RMSE)	LSTM + KF (Test RMSE)
10-year	0.0090	0.0022
20-year	0.0098	0.0019

Table 13: Comparison of LSTM Results.

Time Length	Transformers (Test RMSE)	Transformers + KF (Test RMSE)
10-year	0.0091	0.0021
20-year	0.0097	0.0018

Table 14: Comparison of Transformers Results.

As shown in Table 13 and Table 14, at the 10-year duration, the LSTM model, augmented by the Kalman Filter, achieves a significantly reduced Test RMSE of 0.0022 compared to its non-filtered counterpart, highlighting a remarkable improvement from the previous Test RMSE of 0.0090. Similarly, the Transformers model, integrated with the Kalman Filter, exhibits enhanced predictive capability with a Test RMSE of 0.0021, substantially lower than the non-filtered model's 0.0091. The same enhancement in predictive performance also applies to the 20-year interval. The LSTM model with the Kalman Filter showcases a notably reduced Test RMSE of 0.0019, a substantial improvement from its non-filtered RMSE of 0.0098. Likewise, the Transformers model, augmented by the Kalman Filter, demonstrates enhanced accuracy with a Test RMSE of 0.0018 compared to the non-filtered model's 0.0097.

These significantly decreased RMSE values emphasize the Kalman Filter's profound impact on improving the models' resilience to market noises and refining models' predictive capabilities. Applying the Kalman Filter to mitigate fluctuations and uncover underlying trends in the forecast SHCI returns significantly aids in enhancing the predictability of SHCI returns. These findings highlight the practical utility of advanced filtering techniques in bolstering the accuracy and reliability of deep learning-based financial forecasting models.

5 Discussion

Our approach successfully unveiled the limited impact of American market factors on the SHCI returns. This revelation stemmed from our novel approach of combining S&P 500 returns, NASDAQ returns, VIX returns, and RF returns with the SHCI returns. Additionally, our project identified the key drawback of deep learning models: heightened sensitivity to market volatility. While these models exhibit predictive prowess, their vulnerability to market fluctuations became evident through our analysis.

However, our project faces certain limitations. The inherent volatility of financial markets poses a significant challenge as it's impossible to entirely eliminate all exceptional fluctuations. The outbreak of the COVID-19 pandemic in 2019 introduced an unprecedented level of disruption, which, when excluded, led to a reduction in available data, thereby impacting the robustness of our models. Moreover, our analysis did not include emotionally-driven market fluctuations, a factor that could noticeably influence stock returns but was not incorporated in our project.

To mitigate these limitations, future research could explore advanced sentiment analysis techniques, incorporating emotional and sentiment-driven data into the models. Additionally, devising mechanisms to handle extreme market volatility, especially during exceptional circumstances like pandemics, could further enhance the accuracy and reliability of financial forecasting models. Given the insights gained from this project, avenues for future exploration could include exploring hybrid models that combine deep learning models' capabilities with sentiment analysis or other methods to better capture the intricacies of financial markets and further improve prediction accuracy.

6 Personal Contribution

Throughout this capstone project, my primary responsibilities included the development of the baseline model, the implementation of the multi-linear regression model and LSTM models, and the integration of the Kalman Filter technique. Additionally, I actively participated in fine-tuning the Transformers models. I took a significant role in drafting various sections of the report, including the related works, solutions, results and discussions, as well as the reflective conclusions. I was involved in data collection, contributing to the comprehensive groundwork essential for our research.

7 Conclusion

Through this project, we examined the performance of deep learning models—specifically LSTM and Transformers—in predicting SHCI returns. We examined their aptitude in capturing complex temporal patterns, leveraging American market factors, and handling market fluctuations. Additionally, our exploration involved evaluating these models across varying time intervals. Several key findings have emerged:

1. American Influence on SHCI: Our project revealed varying impacts of different American market factors on the performance of SHCI returns. While VIX returns demonstrated significance in predicting stock returns, others exhibited limited relevance and effectiveness, showcasing that Chinese financial market is influenced by external global risks.

2. Deep Learning Model Efficiency: Notably, our investigation highlighted the contrasting strengths of deep learning models. LSTM models displayed slightly superior performance in shorter time spans, while Transformer models showcased enhanced predictive capabilities over longer durations, aligning well with their respective characteristics.

3. Sensitivity to Market Volatility: A critical insight gleaned from our analysis is the remarkable sensitivity of both deep learning models to market volatility, showcasing that the stock return prediction is highly influenced by both global and domestic financial crises and market noises. Hence, preprocessing and mitigating the impact of market fluctuations are pivotal for refining

the accuracy of financial predictions.

Moving forward, one notable limitation remains the need for further refinement in mitigating the influence of market volatility. Future research could delve deeper into developing mechanisms to better exclude and manage market volatility, thereby refining the robustness of deep learning models.

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