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Optimizing Stock Trend Prediction with a Comprehensive Multi-Technical Indicator Strategy

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Abstract

The stock market is a popular investment tool due to its risk and profit potential. Technical analysis (TA) is often overlooked by academicians, especially in Malaysia. Technical indicators help identify current and future price trends, but each has its limitations. Combining indicators for different situations can improve trading performance. This study aims to provide a balanced multi-technical indicator strategy for short-term price trend prediction. The model considers factors like trend, volatility, momentum, volume, and market sentiment, overcoming the limitations of individual indicators. The research framework uses multiple regression analysis to determine the predictive power of indicators and their combinations. The four-factor model achieves a balance between complexity and predictive accuracy. The techniques used resulted in a profit ROI (Return on Investment) of 87.45% within six months, demonstrating the efficiency of trading tactics.

Keywords: Stock Market, Technical Analysis, Price Trend, Multi-Technical Indicator, Return on Investment

Background

Nowadays a lot of circulating of the various types of investments, for example, deposits, purchase of land, and capital markets or usually related stock occur. Investment is an answer to the market's uncertainty so by investing in the field of property will minimize the risk. Investment is putting money into the financial scheme, shares or property in the hope of achieving a profit (Petrusheva and Jordanoski et al., 2016). Devote (one's time or energy) to obtain results with valuable results. (In Invest) informal: buy (product) that is useful to refund the cost (Knapp et al., 2008).

Investments in stocks had been discussed by many researchers including change in stock price di US; pattern in abnormal returns Kumar at al (2014); Capital Investments and Stock Return; and Rates of Return on Investments in Common Stocks (Shafina et al., 2017).

For simplicity in stocks trading is developing the name of technical analysis. Technical analysis was first introduced by J. Welles Wilder in 1978 and carried out on indicators stocks (Todd et al., 2021). Indicators on the stock is a mathematical calculation process is performed on the stock price in the past and are useful in anticipating changes in prices Uyanık and Güler et al., 2013). A technical indicator is an analysis of previous price movements to predict the future price movements. Technical indicators are related to the stock movement chart (Suresh et al., 2013). The main component of the formation on stock movement chart consists of five parts; they are opening price, the highest price, the lowest price, the closing price, and the volume of transactions (Turner et al., 2007). There is some technical analysis e.g. Moving average, Stochastic, MACD, and Bollinger bands, Relative Strength Index (RSI), and Sutte Indicator (Mitchell et al., 2021)

Technical analysis is directed to predict the safety of the price. Analysis is the use of past price movements and other market data, such as volume, to assist the decision-making process on trade in asset markets (Ahmed, Beck and Goldreyer et al., 2000). Furthermore, the price at which buyers and sellers set a collective agreement which is regarded as a matter of right, weighty and reveals all the factors, rational and irrational, quantitative and non-quantitative, and the only picture that should be considered (Tsinaslanidis and Zapranis et al., 2015).

Many researchers have examined technical analysis. Rules of the moving average, and the moving average convergence divergence for the Athens stock market and these rules provide strong support for selected technical strategy (Crombez et al., 2001). Technical analysis aims at identifying trend reversals in the early stages and rising trend until the confidence level indicates that the trend has reversed (Lin Chen et al., 1996). The trading approach comprised valuable momentum for the Italian stock market and proposed the importance of behavioural theory to help explain the profitability of technical trading (Bakshi and Kapadia et al., 2003). By compared academicians' use of the technical trading rules with the practitioner approach for five Asian countries (Aschakulporn and Zhang et al., 2021). The usefulness of moving the average rule of asset allocation view using data S & P 500 (Chen and James et al., 2020). The rules of technical trading for 17 markets of selected developing countries and concluded that there were no regular trading rules that can generate sufficient forecasting accuracy TD Ameritrade et al., 2021). The profitability of technical trading rules based on nine favourite technical indicators (Land et al., 2015). And finally, the technical analysis with the psychological bias for Taiwan's stock market and gave the disposition, the information cascade, and the effect of retaining and that each has a particular influence on trading signals (Michael et al., 2021)

Recently, Ahmar (2017) has developed a new technical analysis e.g. Sutte Indicator. Sutte Indicator was developed by considering the opening and the closing price, the highest price as well as the lowest price on the stock. Core indicators used in Sutte Indicator is the modified Moving Average indicator by considering the stock price at the time of opening, closing, highest and lowest. Sutte Indicator could form two graphs that show when stocks are looking for the suitable stock to buy and sell. This figure is intended to provide a signal to investors to get maximum profit with minimal losses.

In addition, predicting stock trend by using the combination of multi technical indicator strategy to assist traders will be thoroughly investigated. This includes study the technical indicators or their combinations should be applied and validate the level of reliability of the prediction is tested by mean absolute percentage error (MAPE), mean absolute deviation (MAD), and (MSE). Therefore, the findings of this research are expected to provide useful information for the traders to increase investment performance.

Introduction

Stock market attracts thousands of investors' hearts from all around the world. The risk and profit of it has great charm and every investor wants to book profit from that. People use various methods to predict market volatility, such as Fundamental analysis (FA) method, technical analysis (TA) method, even coin tossing, fortune telling, and so on.

Technical analysis (TA) up till this date has been largely ignored by the academicians, particularly in the Malaysian context. There is not much evidence being documented on technical analysis although it is widely used by the practitioners. The traders usually take the decisions of buying or selling the stock by evaluating a company's performance and other unexpected global, national & social events. Although, such events eventually affect stock prices instantaneously in a negative or positive way, these effects are not permanent most of the time. So, it is not viable to predict the stock prices and trends on the basis of FA. As a consequence, a model, to analyse the stock market and upcoming stock trends based on historical prices and Stock Technical Indicators (STIs), is needed.

Technical indicators make it easy for you to identify current price trends and predict where prices will move in the future. By developing technical analysis strategies, traders can increase the amount earn each trading day. However, while all technical indicators are useful, they each have their own set of weaknesses. If only use a single indicator to monitor the market, there may be certain price trends (or hazards) that you aren't noticing. Therefore, knowing the right indicators for different circumstances is an important part in trading. Combining indicators that calculate different measurements based on the same price action, and then combining that information with chart studies will quickly have a positive effect on trading.

By combining multiple technical indicators into a single trading strategy, traders can limit risk while still earning strong returns. In this research, our objective is to provide useful combination of stock trend prediction indicators for traders to increase investment performance which focuses on short-term price trend prediction.

Methodology

This chapter present the methodology of this research. The framework and whole process of data analysis for each research question will be explained as focuses on examine the correlation of each indictor to determine whether or not the proposed technical indicators have predictive power for stock market trend. Thus, if it shows correlated, analysis multiple regression model by using SPSS to study which of the technical indicators or their combinations should be applied. Finally, validate the level of reliability of the prediction is tested by mean absolute percentage error (MAPE), mean absolute deviation (MAD), and mean of square error (MSE). Figure 3.1 illustrates the flow chart of the project.

However, the criteria to choose the data such as the software, data and stock technical indicator used will be also discussed and the method analysis as analyse the correlation and multiple regression model by using SPSS statistic will be thoroughly explained.

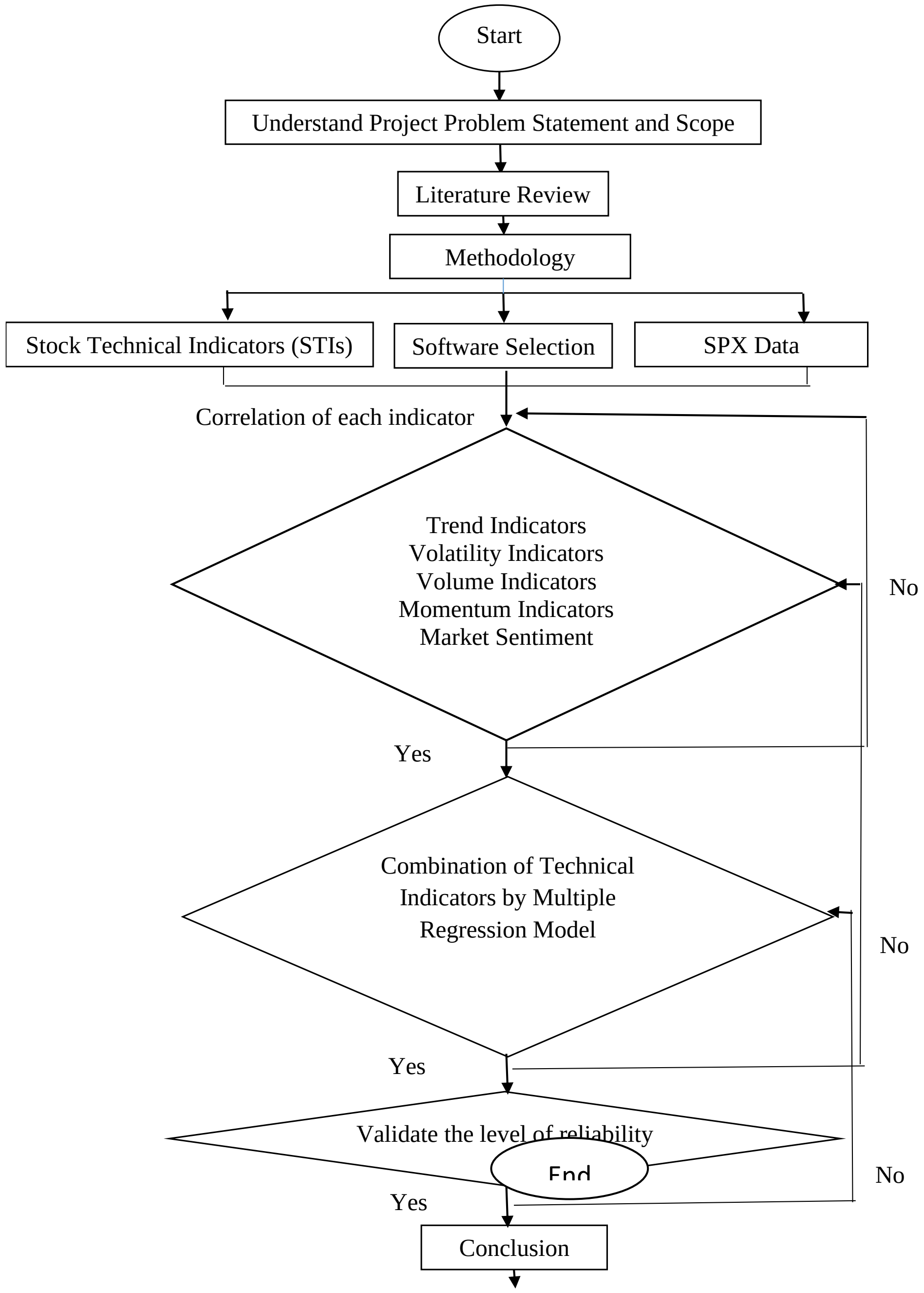


Figure 3.1: The flow chart of project

This part outlines the systematic approach employed in this research project to analyse financial indicators for predicting stock market trends. The research begins with an introduction that sets the stage for the research framework, detailing the process for data analysis in relation to each research question. It emphasizes the examination of correlations among various indicators to ascertain their predictive power for stock market trends. The methodology involves the use of multiple regression analysis through SPSS to determine the effectiveness of individual technical indicators and their combinations. Additionally, the reliability of these predictions is validated using statistical measures like Mean Absolute

Percentage Error (MAPE), Mean Absolute Deviation (MAD), and Mean Squared Error (MSE), as illustrated in the project's flowchart (Figure 3.1).

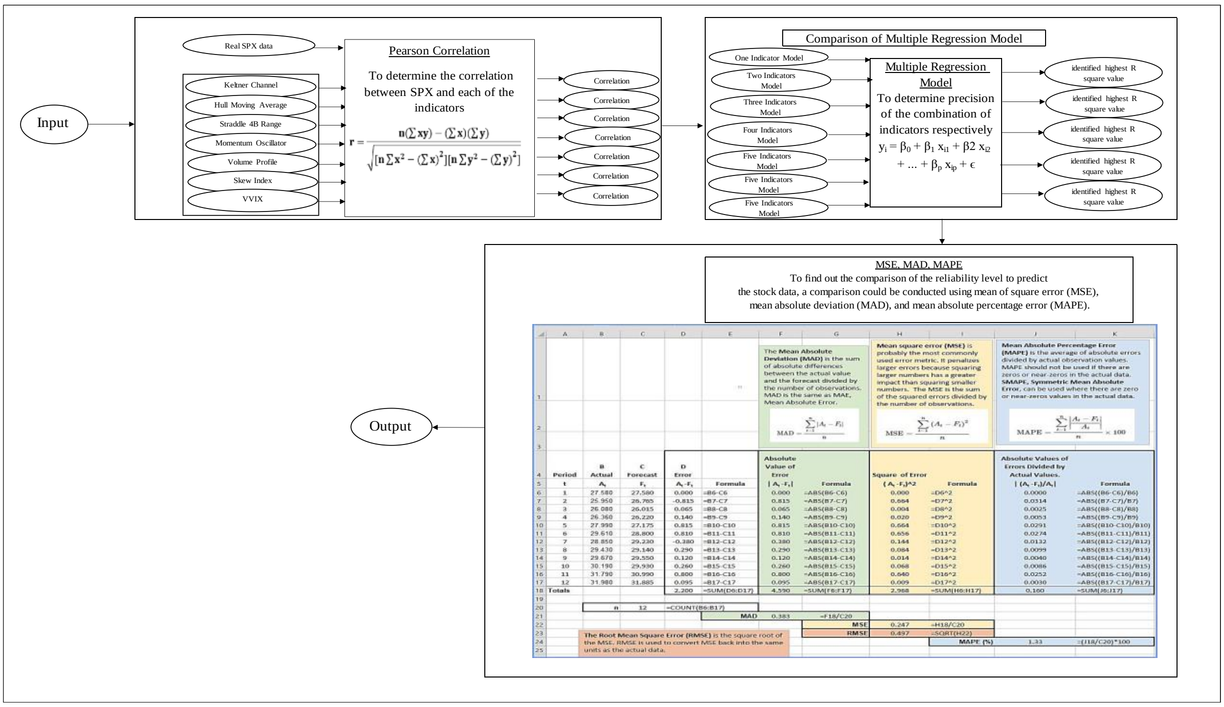
The research then delves into the specific Stock Technical Indicators (STIs) proposed for this study, such as the Kelhull, Straddle 4B range, momentum oscillator, volume profile, Skew, and VVIX. It provides detailed explanations of these indicators, including trend indicators like the Kelhull, which is a combination of Keltner Channel and Hull Moving Average, and volatility indicators like the Straddle 4B Range. The methodology section also covers the calculation of these indicators, illustrating the formulas and statistical processes involved.

Furthermore, the research discusses the selection of software for data analysis, detailing why TD Ameritrade's platform was chosen, its features, and its advantages for this study. The specific data used, sourced from the SPX (S&P 500) stock index, is also outlined, including the period of the data and its source.

Key to the research is the use of Pearson Correlation Coefficient to measure the strength and relationship between different variables. This section explains how the correlation coefficient is interpreted and its significance in the analysis. An essential part of the methodology is the Multiple Regression Formula for the combination of indicators. This section underscores the importance of multiple regression in modelling the linear relationship between explanatory and response variables in financial analysis. It also discusses the limitations of multiple regression, particularly in establishing causation, and highlights various strategies to minimize bias.

Finally, the research concludes with an explanation of how correlation and multiple regression analysis are performed using SPSS Statistics. This part underscores the robustness and user-friendly interface of SPSS, facilitating high accuracy and quality decision-making in data analysis.

In summary, this paper meticulously outlines the research methodology, covering every aspect from data selection and software choice to detailed statistical analysis using advanced tools. This comprehensive approach ensures a thorough and reliable analysis of financial indicators for predicting stock market trends.



Result and Discussion

Regression analysis was conducted to identify the best combination of indicators for financial analysis. The analysis included one to seven factors, and performance was evaluated based on correlation, R Square, adjusted R Square, standard error of the estimate, mean absolute deviation (MAD), mean squared error (MSE), and mean absolute percentage error (MAPE).

The correlation and predictability analysis of these financial indicators highlight the importance of selecting the right combination of tools for market analysis. High correlation combinations provide robust and precise predictive capabilities, ideal for high-stakes financial operations. Moderate correlation combinations offer valuable insights for a variety of financial applications, providing a balance between accuracy and adaptability. Low correlation combinations, while less precise, can still offer unique perspectives, especially when used in conjunction with other analytical tools. Understanding the relationships between these indicators is crucial for making informed financial decisions, developing effective strategies, and managing risks in the volatile world of financial markets.

The "4 factors" model, consisting of the HMA, Keltner Channel, Straddle 4B Range, and Momentum indicators, demonstrated the best performance. This model exhibited a high correlation of 0.998 and an impressive R Square value of 0.997, indicating a strong relationship and excellent explanatory power. The model also had a relatively low standard error of the estimate of 22.72, suggesting accurate estimations and a small margin of error. The mean absolute deviation (MAD) was 9.233, the mean squared error (MSE) was 515.675, and the mean absolute percentage error (MAPE) was 0.354, all reflecting the model's effectiveness in capturing underlying patterns and making accurate predictions.

In the recent year, the correlation between the indicators and predicted outcomes decreased slightly from 0.998 to 0.899. However, both time periods still exhibited relatively high R Square values, indicating that a significant portion of the variance in the predicted outcomes could be explained by the model. The standard error of the estimate, MAD, MSE, and MAPE values remained relatively low in both time periods, reflecting the accuracy of the model's estimations and predictions.

Overall, the HMA, Keltner Channel, Straddle 4B Range, Momentum, Volume Profile, SKEW, and VVIX Close indicators consistently demonstrated strong relationships, high explanatory power, and accurate predictions. Combinations involving these indicators were found to be effective choices for financial analysis and regression.

In comparison to other indicator combinations evaluated from 5/4/2001 to 20/9/2016, the proposed "4 factors" model had a lower mean squared error (MSE) and competitive mean absolute deviation (MAD) values compared to the Suttle model. The proposed model provided more accurate predictions with reduced errors and percentage differences, making it a favorable choice for forecasting and analysis.

In summary, the "4 factors" model with the HMA, Keltner Channel, Straddle 4B Range, and Momentum indicators demonstrated strong performance and predictive power. Other combinations involving additional indicators also showed strong relationships, high explanatory power, and accurate predictions when combined with the aforementioned indicators. However, combinations involving certain indicators exhibited weaker correlations, lower explanatory power, and higher deviations between predicted and actual values. The findings emphasize the importance of carefully selecting the indicators for regression analysis in financial analysis.

Comparative Analysis of Indicators

The Figure 4.1 presents statistical indicators along with their respective correlation coefficients, R-squared values, adjusted R-squared values, and standard errors of the estimate. Among these indicators, HMA exhibits a remarkably strong positive correlation of 0.994, indicating a near-perfect linear relationship with the dependent variable. Its R-squared and adjusted R-squared values of 0.989 signify that it explains almost 99% of the variance in the dependent variable. Additionally, the standard error of the estimate for HMA is relatively low at 41.95, suggesting the model's accuracy in predictions. Keltner Channel also demonstrates a strong positive correlation (0.983) and high R-squared values (0.966 and 0.966), implying its effectiveness in explaining variance. Straddle 4B Range and Momentum, on the other hand, display weaker correlations and lower R-squared values, indicating limited explanatory power. Lastly, Volume Profile shows a negative correlation, suggesting an inverse relationship with the dependent variable, while SKEW and VVIX Close have very weak correlations and minimal explanatory capabilities in the given model.

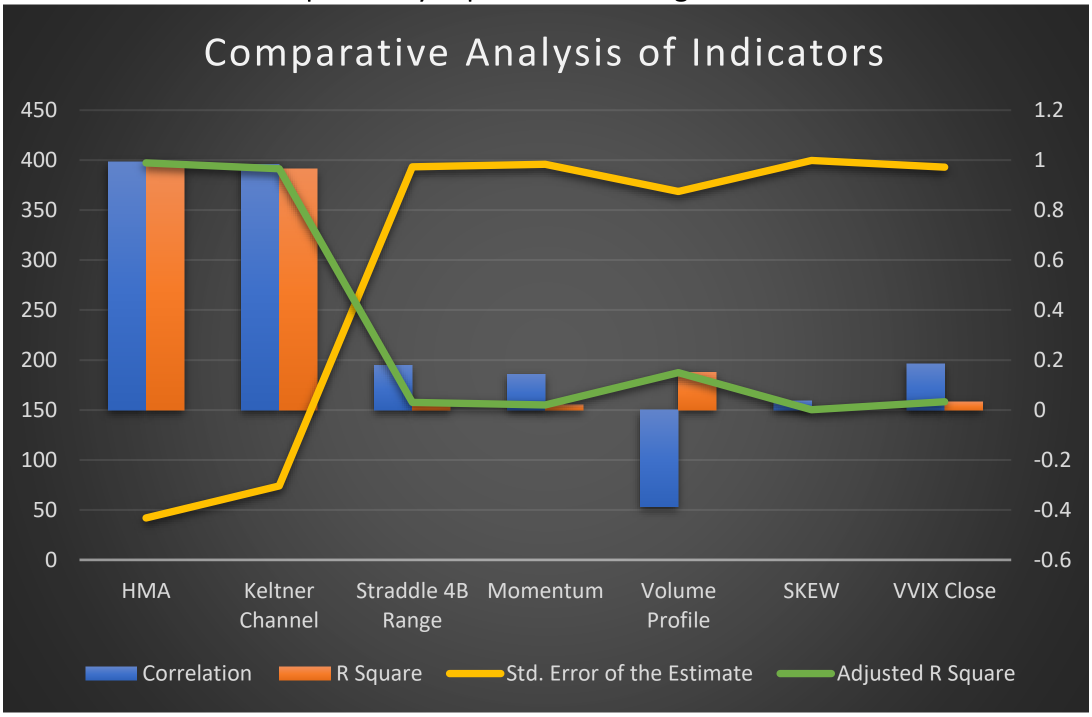


Figure 4.1: Comparative analysis of indicators

Multiple Regression Analysis

Two Factors

The Figure 4.2 offers a comprehensive view of two financial indicator combinations, evaluated through the lenses of Correlation, R Square (R^2), Adjusted R Square, and the Standard Error of the Estimate. Each of these metrics provides valuable insights into the relationship between the combinations, their predictive power, and the accuracy of their predictions. Typically, in statistical analysis, high, moderate, and low levels of these metrics are classified as follows:

High Correlation and Predictability which is the correlation close to +1 or -1, high R Square and Adjusted R Square values (close to 1), and a low Standard Error of the Estimate. Moderate Correlation and Predictability which is the correlation around ±0.5, moderate R Square and Adjusted R Square values (around 0.5), and a moderate Standard Error of the Estimate. Low

Correlation and Predictability which is the correlation close to 0, low R Square and Adjusted R Square values (close to 0), and a high Standard Error of the Estimate.

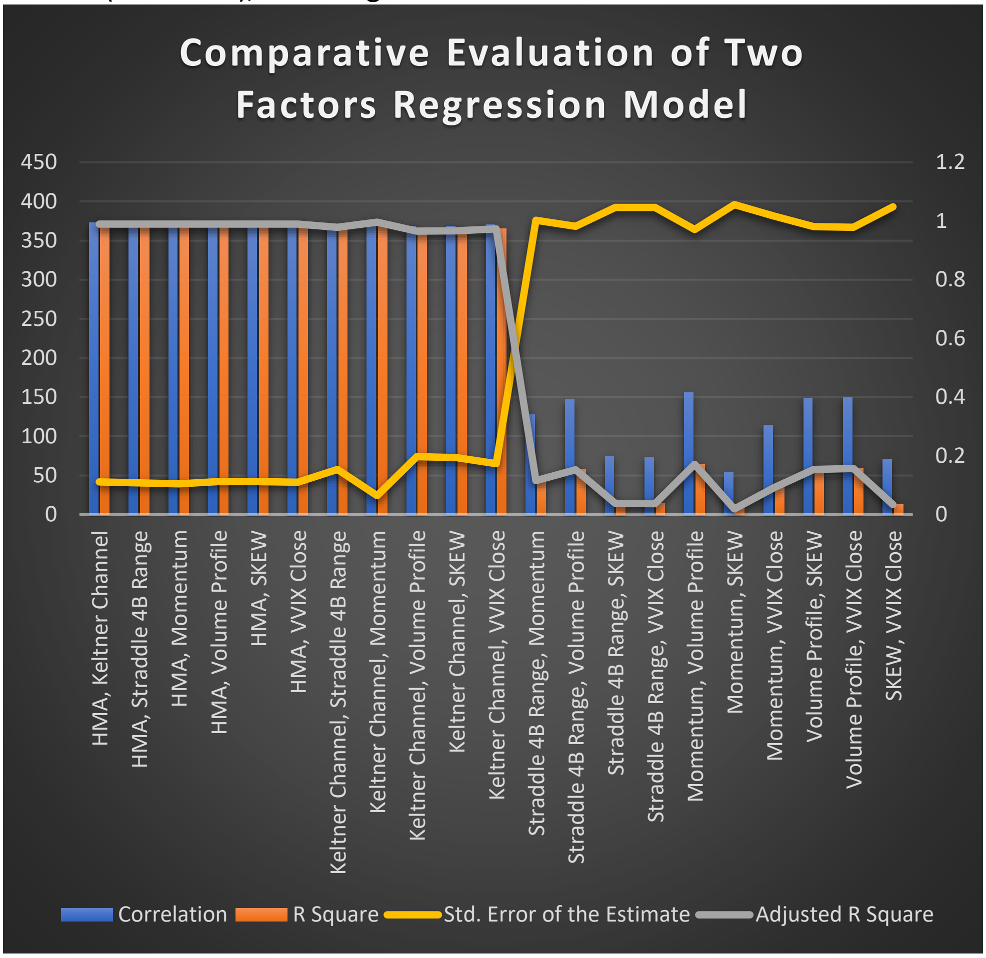


Figure 4.2: Comparative evaluation of two factors of regression model

High Correlation and Predictability

HMA and Keltner Channel (Correlation: .995, Adjusted R Square: .989): This pair exhibits an exceptionally high correlation, indicating a very strong linear relationship. The high R Square value suggests that the Keltner Channel indicator can predict a significant portion of the HMA's movements. The standard error, while relatively low in a general sense, is the highest among the high-correlation pairs, indicating slightly less precision in the predictions.

HMA and Momentum (Correlation: .995, Adjusted R Square: .990): Similar to the HMA and Keltner Channel, this pair also shows a very high correlation. The high R Square value here means that the Momentum indicator is highly predictive of HMA's behaviour. The lower standard error compared to the HMA and Keltner Channel pairing indicates more precise predictions.

Keltner Channel and Momentum (Correlation: .998, Adjusted R Square: .996): This pairing stands out with the highest correlation and R Square values in the dataset. It suggests an almost perfect linear relationship with extremely high predictability. The remarkably low standard error implies that predictions made using this model are very accurate.

Moderate Correlation and Predictability

Momentum and Volume Profile (Correlation: .415, Adjusted R Square: .171): This represents a moderate correlation. The R Square value indicates that the Volume Profile explains some, but not a large portion, of the variance in Momentum. The higher standard error here implies less precision in predictions.

Volume Profile and SKEW (Correlation: .395, Adjusted R Square: .154): Another example of moderate correlation. The predictive power of the Volume Profile on SKEW is limited, as shown by the R Square value. The standard error suggests a higher degree of prediction error compared to high-correlation pairs.

Low Correlation and Predictability

Straddle 4B Range and SKEW (Correlation: .198, Adjusted R Square: .038): This pairing shows a low correlation, indicating a weak linear relationship. The low R Square value suggests that Straddle 4B Range is not a good predictor of SKEW's behaviour. The high standard error reinforces the lack of precision in the model's predictions.

SKEW and VVIX Close (Correlation: .189, Adjusted R Square: .034): Similar to the previous pair, this also exhibits low correlation and predictability. The indicators have a weak linear relationship, and one is a poor predictor of the other's movements. The high standard error further indicates unreliable predictions.

The data provides valuable insights into how certain market indicators move in relation to each other. High correlation and high R Square values, especially when accompanied by low standard errors, suggest that movements in one indicator can be used to predict movements in another with a high degree of accuracy. This is invaluable in financial modelling, risk assessment, and investment strategy formulation.

For pairs with moderate to low correlations, the predictive power diminishes. These pairings are less reliable for making predictions about market movements based on each other's behaviour. The higher standard errors in these cases also imply a greater risk of prediction error, which must be accounted for in any analysis.

Three Factors

The Figure 4.3 offers a comprehensive view of three financial indicator combinations, evaluated through the lenses of Correlation, R Square (R^2), Adjusted R Square, and the Standard Error of the Estimate. Each of these metrics provides valuable insights into the relationship between the combinations, their predictive power, and the accuracy of their predictions.

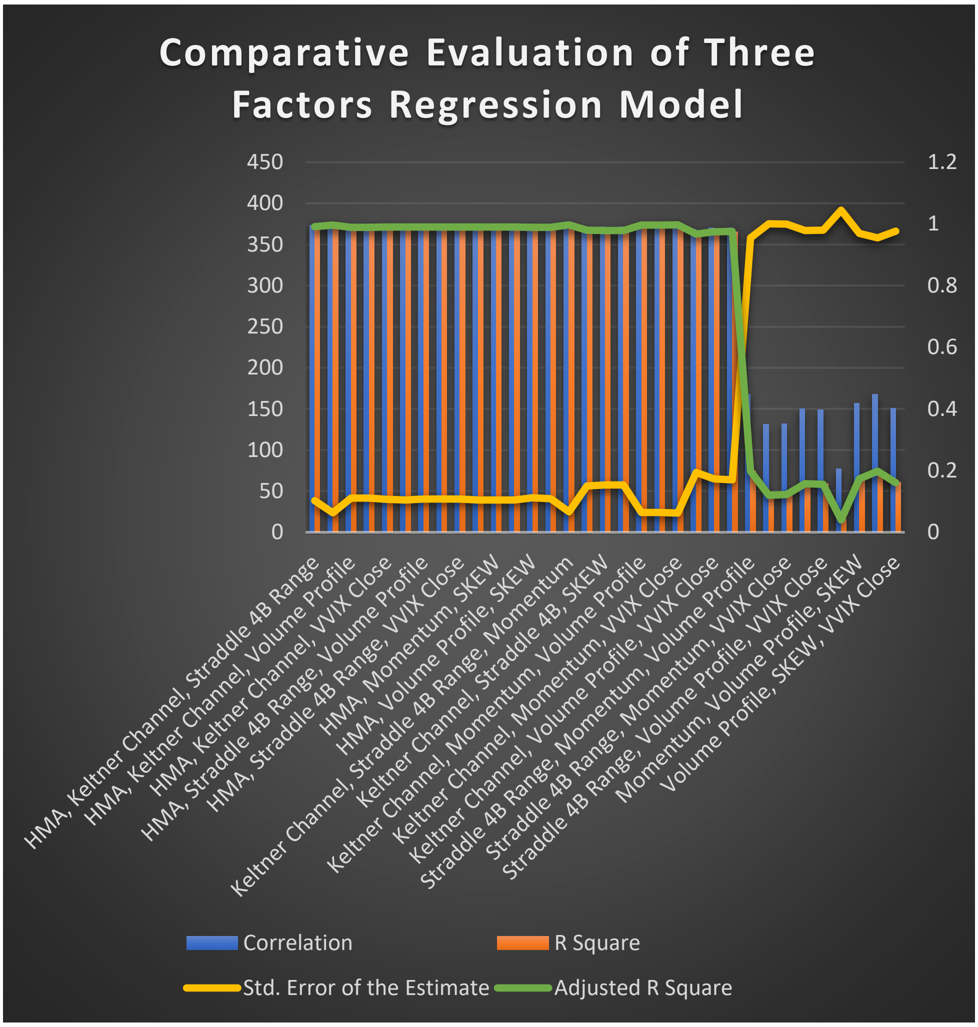


Figure 4.3: Comparative evaluation of three factors of regression model

High Correlation and Predictability
HMA, Keltner Channel, Momentum (Correlation: .998, Adjusted R Square: .996): This grouping exhibit a near-perfect correlation, suggesting that these indicators move almost in lockstep. The high R Square value indicates that the model can predict the behaviour of these indicators with high accuracy, as evidenced by the low standard error.
Keltner Channel, Straddle 4B Range, Momentum (Correlation: .998, Adjusted R Square: .997): Similarly, this set shows extremely high correlation and predictability. Such strong relationships are invaluable in predictive modelling and risk assessment, where understanding the dynamics between these variables can lead to more informed decisions.

Moderate Correlation and Predictability
Straddle 4B Range, Volume Profile, VVIX Close (Correlation: .398, Adjusted R Square: .156): This combination, while still showing some level of correlation, indicates a more complex relationship. The moderate R Square value suggests the model explains a significant portion of the variance, but the higher standard error indicates less precision.

Low Correlation and Predictability
Straddle 4B Range, SKEW, VVIX Close (Correlation: .206, Adjusted R Square: .040): Exhibiting a low correlation and low R Square value, this set indicates a weak relationship and low

predictability. The high standard error further implies that the model's predictions should be approached with caution.

Four Factors

The Figure 4.4 offers a comprehensive view of three financial indicator combinations, evaluated through the lenses of Correlation, R Square (R^2), Adjusted R Square, and the Standard Error of the Estimate. Each of these metrics provides valuable insights into the relationship between the combinations, their predictive power, and the accuracy of their predictions.

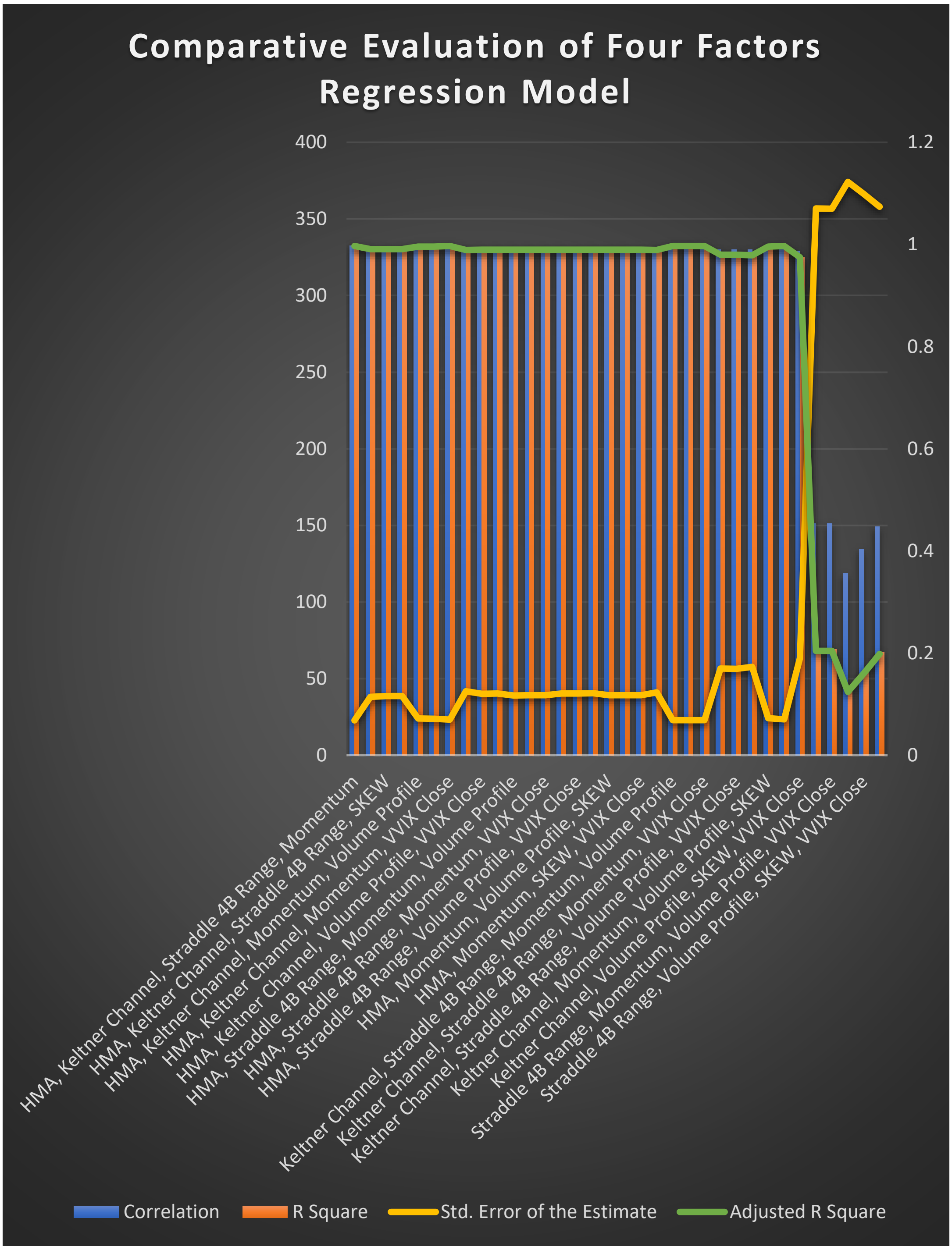


Figure 4.4: Comparative evaluation of four factors of regression model

High Correlation and Predictability

Combinations such as HMA with Keltner Channel, Straddle 4B Range, and Momentum exhibit nearly perfect correlations (.998) and extremely high R Square and Adjusted R Square values (.997). The standard error in these models is notably low (around 22-24), suggesting high precision in predictions. These indicators, when combined, show a near-perfect linear relationship, indicating that movements in one can be accurately forecasted by observing the others. The high R Square values denote that a significant portion of the variance in one indicator is explained by the others. The low standard error underlines the reliability and precision of these models, making them ideal for high-stakes applications like high-frequency and algorithmic trading, as well as in risk-sensitive financial strategies.

Moderate Correlation and Predictability

In combinations like HMA, Keltner Channel with Volume Profile, SKEW, or VVIX Close, the correlation, though slightly lower (.995), is still significant. The R Square and Adjusted R Square values are high (.990-.991), indicating a strong predictive relationship, albeit with a slightly higher margin of error than the high correlation group, as reflected in their moderate standard error (around 38-40). These combinations, while exhibiting strong linear relationships, offer a balance between precision and flexibility. They are apt for medium-term investment strategies, portfolio diversification, and sectors where adaptability is as crucial as accuracy. These models provide valuable insights into general market trends and are instrumental in developing diversified investment portfolios.

Low Correlation and Predictability

Indicators involving the Straddle 4B Range, paired with Momentum, Volume Profile, SKEW, or VVIX Close, manifest lower correlation values (as low as .356) and significantly lesser R Square and Adjusted R Square values (.124-.206). The high standard error (over 350) in these models indicates less precise predictions, reflecting their lower reliability for accurate forecasting. These sets of indicators, showing weak linear relationships and low predictability, are more influenced by external factors not captured by the model. They are more suited for qualitative analysis and should be used cautiously in decision-making. These combinations can serve as supplementary tools in broader market analysis or in specific scenarios where in-depth trend analysis is not the primary focus.

Five Factors

The Figure 4.5 offers a comprehensive view of three financial indicator combinations, evaluated through the lenses of Correlation, R Square (R^2), Adjusted R Square, and the Standard Error of the Estimate. Each of these metrics provides valuable insights into the relationship between the combinations, their predictive power, and the accuracy of their predictions.

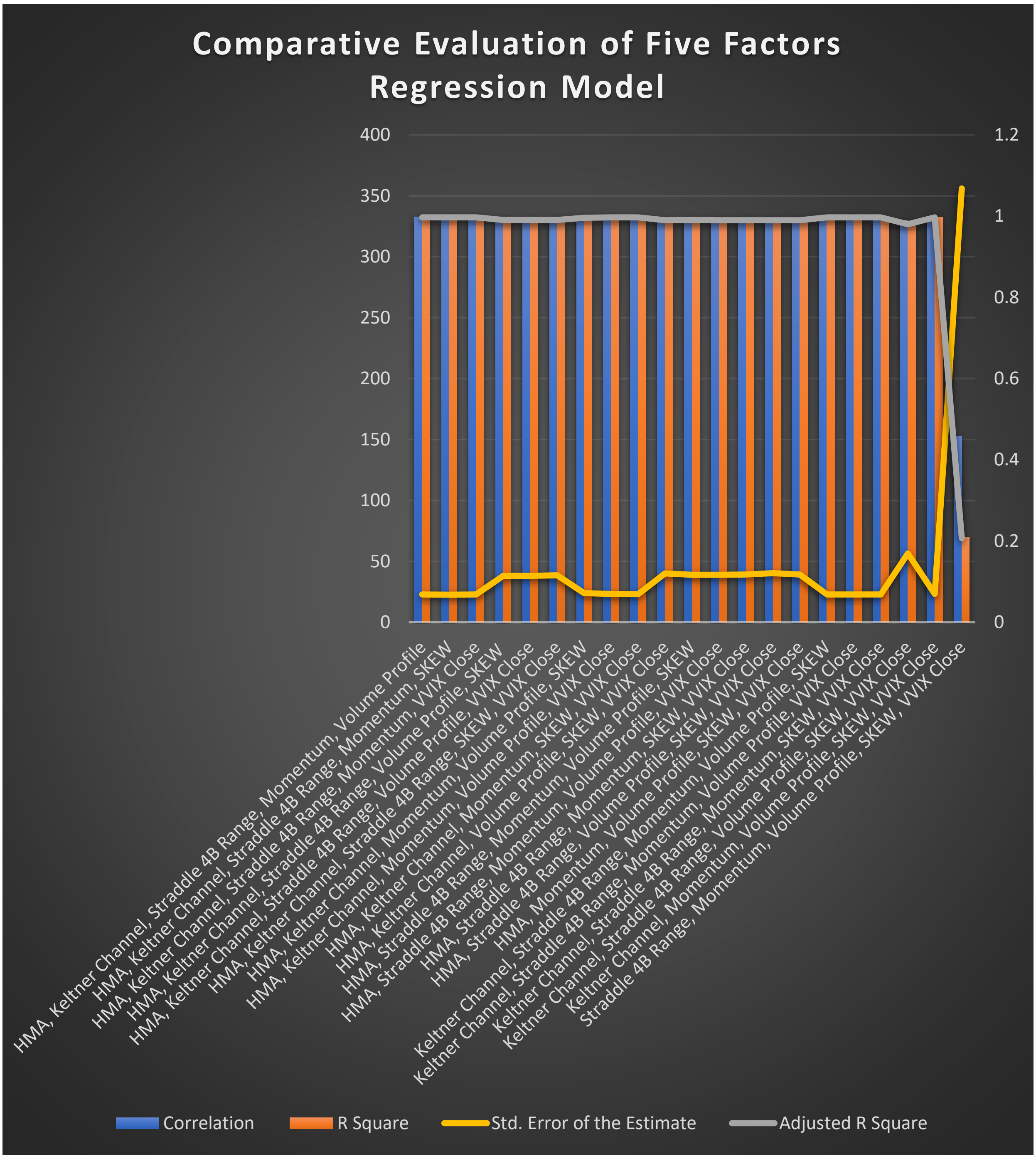


Figure 4.5: Comparative evaluation of five factors of regression model

High Correlation Combinations

Most combinations exhibit an exceptionally high correlation coefficient (0.998), indicating a near-perfect linear relationship. The R Square and Adjusted R Square values hover around 0.997, suggesting these models can explain approximately 99.7% of the variance in the dependent variable. The standard error in these high-correlation combinations is relatively low, ranging from about 22 to 24, enhancing their reliability and precision in predictive modelling. These combinations include various integrations of HMA, Keltner Channel, Straddle 4B Range, Momentum, Volume Profile, SKEW, and VVIX Close.

Moderate to High Correlation Combinations

There are combinations with a slightly lower but still significant correlation coefficient of 0.995. Here, the R Square and Adjusted R Square values are above 0.990, denoting that over 99% of the variability is accounted for by the model. However, the standard error is slightly higher, ranging around 38 to 40, which implies a bit less precision compared to the highest correlating groups. These combinations primarily involve HMA, Keltner Channel, Volume Profile, SKEW, and VVIX Close.

A distinct category with a correlation coefficient around 0.990, specifically the combination involving the Keltner Channel, Straddle 4B Range, Volume Profile, SKEW, and VVIX Close, falls into this group. The R Square values are close to 0.980, indicating that 98% of the variability is explained. However, the higher standard error, around 56, suggests less predictability and reliability compared to the higher correlating groups.

Low Correlation Combination

The combination of Straddle 4B Range, Momentum, Volume Profile, SKEW, and VVIX Close stands out with a much lower correlation coefficient of 0.458. The R Square and Adjusted R Square values are just above 0.20, indicating a poor linear relationship where only about 20% of the variability is explained. The significantly higher standard error of 356 suggests a high degree of unpredictability, making this combination less reliable for predictive modelling.

Six Factors

The utilization of a combination of technical indicators as shows in Figure 4.6, namely HMA (Hull Moving Average), Keltner Channel, Straddle 4B Range, Momentum, Volume Profile, and SKEW, demonstrates a strong correlation coefficient of 0.998. Additionally, the R Square and Adjusted R Square values, which are statistical measures of the goodness-of-fit of a regression model, indicate a high level of explanatory power at 0.997. The significant correlation and R Square values suggest a robust linear association and a high level of predictability for the dependent variable. Additionally, the low Standard Error of 22.623 indicates the precision of this model. This amalgamation is very influential as it encompasses trends, volatility, market sentiment, and price level data.

The substitution of SKEW with VVIX Close in the second combination does not have a substantial influence on the efficacy of the model. The correlation coefficient and coefficient of determination, denoted as 0.998 and 0.997 respectively, exhibit a strong positive relationship between the variables under consideration. Additionally, the Standard Error, which measures the accuracy of predictions, has somewhat decreased to 22.586, indicating a modest enhancement in the precision of the predictions. This modification suggests that incorporating VVIX Close into the analysis alongside other indicators may provide a marginally enhanced understanding of market volatility.

The third combination, comprising of HMA, Keltner Channel, Straddle 4B Range, Volume Profile, SKEW, and VVIX Close, exhibits a marginally reduced correlation of 0.995 and R Square values of 0.991. The elevated value of the Standard Error, namely 38.086, indicates a reduced level of precision in making predictions. The incorporation of both SKEW and VVIX Close variables appears to marginally diminish the accuracy of the model, potentially attributable to the presence of overlapping or duplicate volatility data.

By excluding the Straddle 4B Range in the fourth set, the correlation and R Square values remain high at 0.998 and 0.997, respectively. However, there is a tiny rise in the Standard Error, which is now 23.088. This finding suggests that the model's forecast accuracy remains high, but its precision reduces significantly when the Straddle 4B Range is not included. This implies that the Straddle 4B Range indicator plays a role in capturing the subtle subtleties of market volatility.

The sixth combination, excluding the utilization of the Keltner Channel, exhibits a correlation coefficient of 0.995 and R Square values of 0.991. The model with the largest Standard Error, which is 38.964, demonstrates the lowest level of precision among all combinations. This observation suggests that the utilization of the Keltner Channel is crucial in promoting stability within the model and improving its overall precision.

In conclusion, the composite of indicators, namely Keltner Channel, Straddle 4B Range, Momentum, Volume Profile, SKEW, and VVIX Close, exhibits a strong positive correlation and a high level of predictability. The correlation coefficient and R Square values are at 0.998 and 0.997, respectively. The Standard Error of 22.720 exhibits a level of comparability to the preceding two sets, suggesting a high degree of accuracy. This implies that although the inclusion of HMA is beneficial for conducting trend analysis, its exclusion does not have a substantial impact on the overall efficacy of the model.

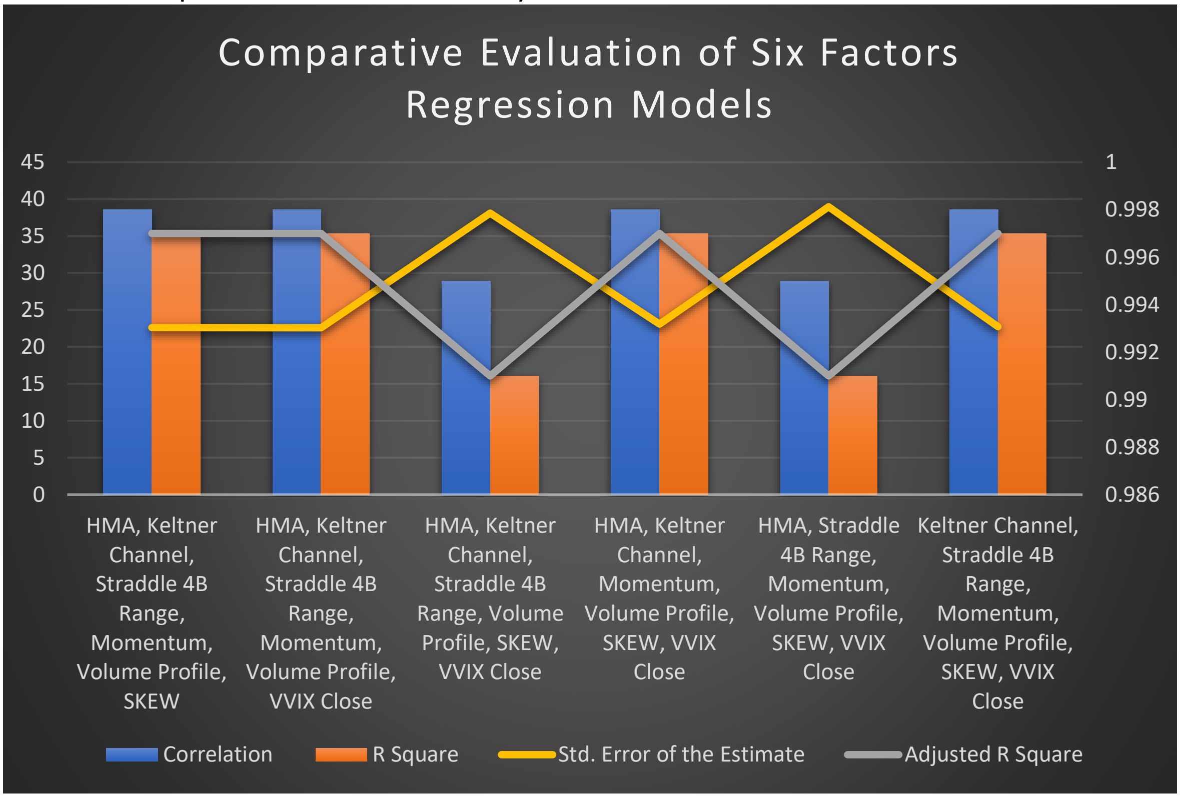


Figure 4.6: Comparative evaluation of five factors of regression model

Seven Factors

The correlation coefficient of 0.998 indicates a highly robust linear association between the financial indicators (e.g., HMA, Keltner Channel, etc.) and the dependent variable. The high degree of correlation observed implies that variations in these indicators have a strong linear relationship with changes in the dependent variable.

The R Square value of .997 is of particular significance as it indicates that 99.7% of the variability in the dependent variable can be explained by the variability in these indicators. This observation suggests a strong alignment between the model and the data, suggesting that the model, along with its included indicators, successfully accounts for variations in the dependent variable.

The Adjusted R Square, with a value of .997, serves to account for the number of predictors included in the model, thereby penalizing those that do not significantly add to the explanatory power of the model. The observation that the Adjusted R Square is equivalent to the R Square implies that all the predictors included in the model have significance, and that the model's level of complexity is warranted in relation to the extent of explanatory capability it offers. This observation serves as a favourable indication of the model's calibre, implying that it is not solely capturing the random fluctuations present in the dataset.

The Standard Error of the Estimate, calculated as 22.580912963066098, is the mean deviation between the observed values and the regression line. The value in question, which varies based on the magnitude of the dependent variable, serves as an objective assessment of the model's level of fit. A smaller standard error is more desirable as it signifies that the model's predictions exhibit greater proximity to the actual values. Within the realm of financial modelling, this may suggest that the model has a high degree of efficacy in accurately forecasting market dynamics, hence offering significant value in areas such as risk mitigation and investment analysis.

In general, the model demonstrates outstanding prediction ability, as seen by the strong correlation and R Square coefficients. Nevertheless, it is vital to acknowledge the potential hazard of overfitting and to conduct validation of the model using out-of-sample data in order to ascertain its resilience and dependability across various circumstances. The efficacy of the model and the ramifications of these statistical metrics are contingent upon the particular context, specifically the characteristics of the dependent variable and the field in which the model is being utilized.

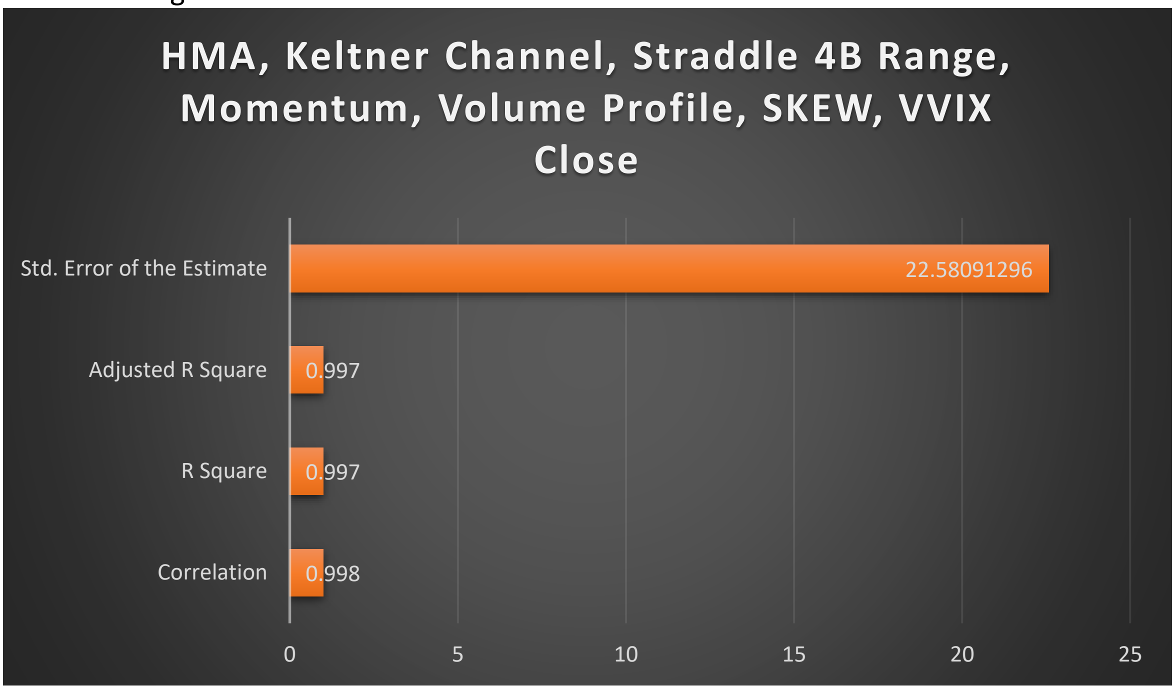


Figure 4.7: Comparative evaluation of HMA, Keltner Channel, Straddle 4B Range, Momentum, Volume Profile, SKEW, VVIX Close

The Best Performance from The Comparison

When comparing a single component to a combination of seven factors, it is essential to consider many critical statistical indicators. The academic terms for the above concepts are as follows: correlation coefficient, coefficient of determination (R Square), standard error of the estimate, coefficient of standard error, mean absolute error (MAE), mean squared error

(MSE), and mean absolute percentage error (MAPE). All models demonstrate a very high correlation (ranging from .994 to .998) and R Square values (from .989 to .997), indicating strong linear relationships and a significant proportion of variance in the dependent variable explained by the models. This high level of correlation and R Square is consistent across all models, suggesting that each is effective in capturing the linear relationship between the indicators and the dependent variable.

A notable observation is the decrease in the Standard Error of the Estimate as more factors are added, moving from 41.95 in the single-factor model to 22.58 in the seven-factor model. This trend suggests that models with more factors fit the data better, as indicated by a lower average distance between the observed values and the regression line. However, the Coefficient of Standard Error displays significant variation across the models without a clear improvement trend with the addition of more factors. The four-factor model, which includes HMA (Hull Moving Average), Keltner Channel, Straddle 4B Range, and Momentum, shows the lowest coefficient value, suggesting a high level of precision in its predictions.

The four-factor model, incorporating HMA, Keltner Channel, Straddle 4B Range, and Momentum, stands out as the best among the presented models for several reasons. First and foremost, it strikes an optimal balance between model complexity and predictive accuracy. While models with more factors can capture more nuances, they also become more complex and harder to interpret, increasing the risk of overfitting. Overfitting can lead to a model that performs well on training data but poorly on new, unseen data. The four-factor model, with a moderate number of indicators, minimizes this risk, providing robustness and generalizability.

From a statistical perspective, the four-factor model exhibits strong performance. It shares the high correlation and R Square values seen in other models, indicating a strong linear relationship with the dependent variable and a significant proportion of variance explained. Crucially, it achieves the lowest values in both the standard error of the estimate and the coefficient of standard error. This suggests not only a good fit to the data but also a high level of precision in its predictions.

Error metrics further reinforce the model's strength. The Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE) are all lowest in the four-factor model. These lower error values indicate that the model’s predictions are more accurate, aligning closely with the actual observed values. This accuracy is crucial for a model's reliability, especially in practical applications like financial analysis, where precise predictions can significantly impact decision-making.

Moreover, the four-factor model offers a balance between sophistication and practicality. It is complex enough to capture essential market dynamics but not overly so, making it more practical and interpretable for real-world applications. This aspect is vital for users who need to understand the model's rationale and for ensuring the model's applicability in various scenarios. A model that is too complex might be challenging to implement and interpret, reducing its usefulness despite its statistical prowess.

In summary, the four-factor model emerges as the best choice due to its combination of high predictive accuracy, manageable complexity, and practicality. While more complex models might show marginal improvements in certain statistical areas, they do not necessarily translate into a significant increase in practical predictive value. This makes the four-factor model not only statistically robust but also practically viable, an essential consideration for applications where accuracy and usability are both critical.

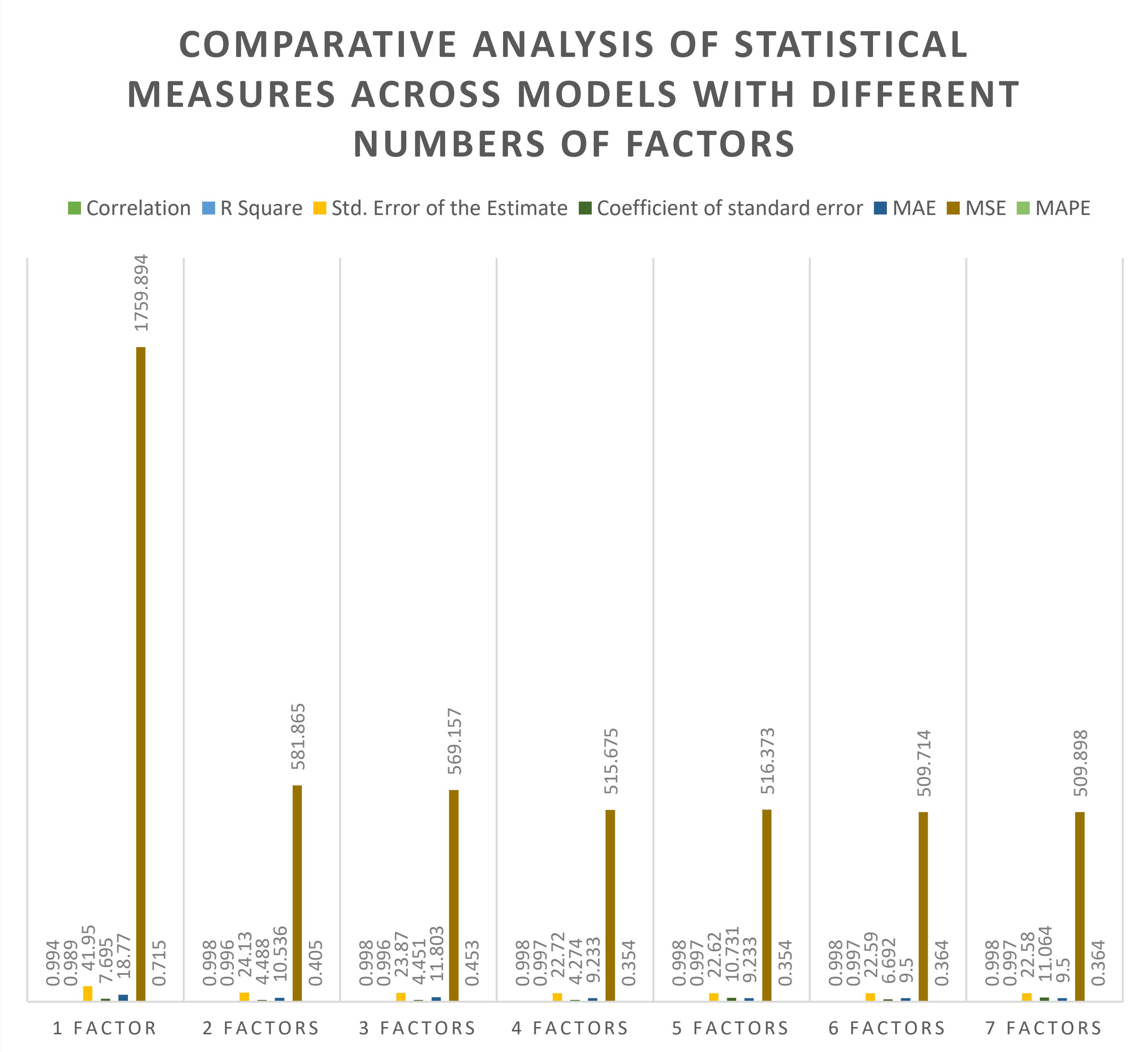


Figure 4.8: Comparative analysis of statistical measures across models with different numbers of factors

Evaluating Performance Across Timeframes: A Comparative Analysis of Four-Factor Financial Model Performance in Previous and Recent Years

The comparison between the " Previous Years " and "Recent Years" performance of the combination consisting of four factors - HMA, Keltner Channel, Straddle 4B Range, and Momentum - provides insight into its ongoing applicability and competitiveness in financial analysis as shown in Table 4.1.

In the "Previous Years" period, spanning from September 30, 2020, to July 8, 2022, this combination exhibited an outstanding level of performance. With a correlation coefficient of 0.998, it demonstrated an exceptionally strong relationship with the underlying data. The R Square value of 0.997 underscored the combination's ability to explain nearly 99.7% of the data's variability, emphasizing its robustness and reliability in interpreting market dynamics. These impressive metrics affirm the combination's adaptability and competitiveness during that period.

However, this exceptional performance was accompanied by certain trade-offs. The standard error of the estimate was higher at 22.72, indicating potential market volatility and larger prediction errors. The mean absolute error (MAE) and mean absolute percentage error

(MAPE) were also significantly higher at 515.675 and 9.233, respectively. This suggested that, while the combination effectively explained market trends, it could yield notable discrepancies between predicted and actual values.

In contrast, the "Recent Years" period, spanning from November 1, 2021, to September 1, 2023, displayed a slightly different picture. Although the combination's correlation and R Square values were marginally lower at 0.899 and 0.808, respectively, it remained competitive in interpreting market dynamics and trends.

One notable advantage of the "Recent Years" period was the lower standard error of the estimate (13.22) and a lower mean squared error (MSE) of 0.841. These metrics indicated that the combination's predictions were relatively more precise, with smaller errors. Furthermore, the mean absolute error (MAE) and mean absolute percentage error (MAPE) were lower, standing at 174.9 and 3.461, respectively. This reflected a higher level of prediction accuracy compared to the "Previous Years" period.

In conclusion, the combination of factors still proves to be applicable and competitive in the "Recent Years" period, despite a marginal decrease in correlation and R Square. The improvement in prediction accuracy and precision, along with lower errors, demonstrates its continued effectiveness in analysing financial data. The choice between these periods should be guided by specific objectives and risk tolerance, as both timeframes offer valuable insights for informed decision-making in the ever-evolving financial landscape.

Table 4.1
Evaluating Performance Across Timeframes

Model	Indicator	Time frames	Correlation	R Square	Std. Error of the Estimate	Coefficient of standard error	MAE	MSE	MAPE
4 Factors	HMA, Keltner Channel, Straddle 4B Range, Momentum	Recently (11/1/2021-9/1/2023)	.899	.808	13.22	7.716	3.461	174.9	.841
		Previously (30/9/2015-7/8/2020)	.998	.997	22.72	4.274	9.233	515.675	.354

Comparison Between Proposed Model and Previous Researchers

The Table presents a comparative analysis of various forecasting models, judging their performance based on three different statistical error metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). These metrics are pivotal in assessing the precision and reliability of predictive models, especially in the field of finance where they are used to predict market movements, stock prices, or economic indicators.

The first model, attributed to Liaw Geok Pheng, incorporates a combination of indicators: Hull Moving Average (HMA), Keltner Channel, Straddle 4B Range, and Momentum. This composite model shows superior performance with the lowest MAE, indicating minimal average deviation from actual values. Its MSE, which penalizes larger errors more severely, is commendably low but not the lowest, suggesting there are few outlier predictions that are far from actual values. Its standout feature is the MAPE, under 1%, denoting a highly accurate model in terms of proportional errors.

In contrast, the Suttle Indicator by Ansari Ahmar, marked by SUTTE%L, SUTTE%H, and SUTTE-Pred, has notably higher error metrics across the board. The MAE is significantly larger than Liaw's model, and the MSE is markedly high, indicating frequent and substantial errors in prediction. The MAPE at over 6% indicates that the model's predictions deviate from actual values by a considerable margin on a percentage basis.

The ARIMA model by Ruochen Xiao, a well-known statistical method for time-series forecasting, achieves moderate accuracy. It balances out with an MAE and MAPE that sit in the middle of the range presented by the four models. Its MSE is notably better than the Suttle Indicator, which suggests that while its average error is somewhat high, it doesn't suffer from the same extent of large, individual errors as the Suttle Indicator.

Lastly, the LSTM model, a type of Recurrent Neural Network (RNN) also by Ruochen Xiao, presents an interesting case. Despite having the highest MAE, indicating less accuracy on an average basis, it has a relatively low MSE. This suggests that while its predictions are generally off by a larger amount, it does not have as many significant outliers as the Suttle Indicator. Its MAPE indicates moderate proportional accuracy, better than the Suttle Indicator and ARIMA but not as good as Liaw's model.

The implications of these findings are multifaceted. Liaw's model may be considered the most robust and reliable, particularly for applications where a low percentage error is critical. However, the context in which these models were evaluated is crucial. If the data set was particularly volatile, Liaw's model's performance might be indicative of a well-tuned response to such conditions, which may not generalize well to more stable or different market conditions.

The Suttle Indicator's high error rates could suggest overfitting to specific data or a lack of adaptability to the data set's features. The moderate performance of the ARIMA model is consistent with its widespread use as a general-purpose forecasting tool, reliable but not necessarily the most precise.

The LSTM's performance profile suggests it might be a safer bet for avoiding catastrophic forecasting errors, despite its higher average error, which might be preferable in high-stakes financial decision-making where avoiding large errors is more critical than minimizing small ones.

In discussing these results, one might consider the models' complexity, the trade-offs between bias and variance, the nature of the underlying financial data, and the computational resources required. Each model's performance could inform its use in different financial scenarios, whether for high-frequency trading, risk assessment, long-term investment strategies, or economic forecasting.

The broader discussion would also encompass the practical implications of these error metrics in real-world financial decision-making. For instance, a model with a low MAE and MAPE like Liaw's might be highly suitable for strategies that rely on consistent and close tracking of market prices, such as arbitrage trading. In contrast, a model with a lower likelihood of large errors, like the LSTM, might be better suited for risk management purposes where extreme predictions could lead to significant financial consequences.

In conclusion, this comparative analysis underscores the importance of choosing the right model for the right purpose in stock trend predicting. It also highlights the strengths and weaknesses of various approaches, from traditional statistical methods to more contemporary machine learning techniques, and their respective suitability for different types of financial data and forecasting needs.

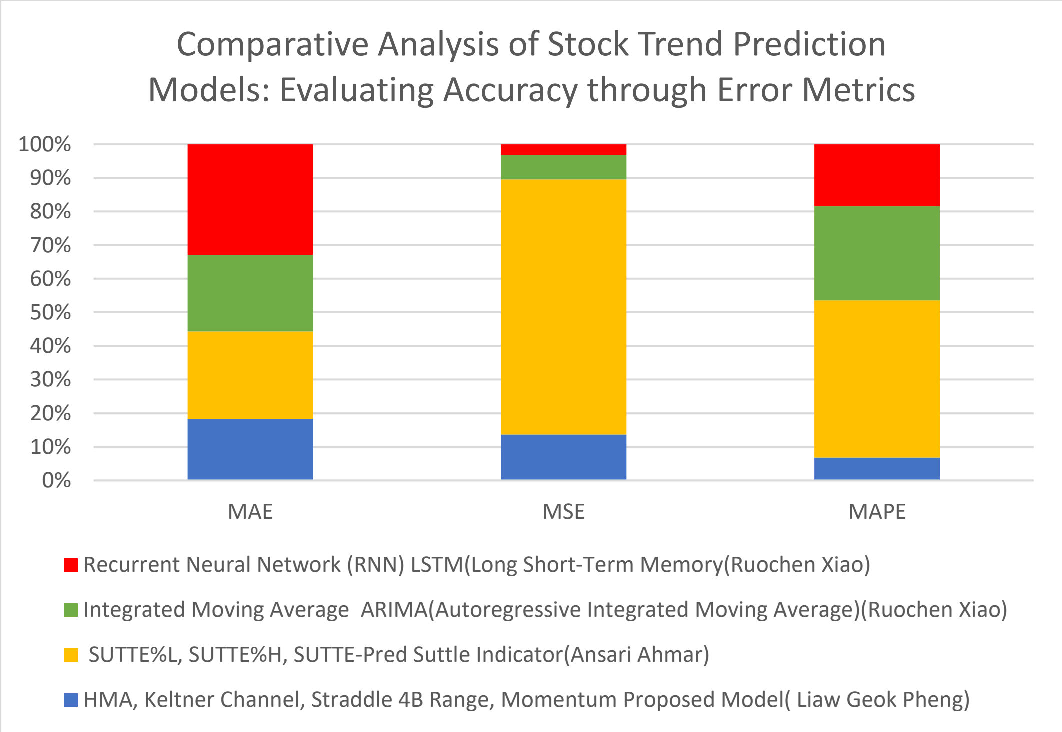


Figure 4.9: Comparative Analysis of Stock Trend Prediction Models

Profit and Loss

The account statement for a trading account from January to June shows a substantial profit of $874.50, demonstrating a well-calculated and efficient trading approach on an initial investment of $1,000 as shown in Figure 4.10. The strategy was carefully weighed against the inherent dangers and possible rewards of the market, emphasizing the importance of risk management in trading operations. 25 out of 35 deals were profitable, indicating a significant level of success in the trading selections made. This achievement is likely the outcome of careful market study, smart decision-making, and a profound understanding of market dynamics. The transactions were chosen based on a good risk-reward ratio, aiming to make the portfolio profitable.

The performance further emphasizes the need for cautious risk management techniques. The study has successfully manipulated through the complex financial markets, as shown by the impressive ratio of profits to losses. At the end of the trading session, the techniques used resulted in a significant return on investment (ROI) with a profit ROI of 87.45%, demonstrating the efficiency of the trading tactics used.

To consistently achieve success in volatile financial markets, one must possess a blend of analytical prowess, astute decision-making, and an unwavering commitment to constantly improving trading techniques. Successful traders are distinguished by their skill in navigating market turbulence and capitalizing on opportune moments.

However, previous success does not always serve as a reliable indicator of future results. Continuous acquisition of knowledge, ability to adjust to new circumstances, and a profound understanding of one's own trading psychological state are crucial elements for achieving long-term success in trading.

Statement for account D-15950162 (margin) from 1/1/23 to 6/30/23 Show by symbol: ADAD

Profits and Lo $874.50

Symbol	Description	P/L Open	P/L %	P/L Day	P/L YTD	P/L Diff	Margin Req	Close Value
YUM	YUM BRANDS INC COM	$0.00	0.00%	$0.00	$30.00	$30.00	$0.00	$0.00
XLU	SELECT SECTOR SPDR TRUST SBI INT-UTILS ETF	$0.00	0.00%	$0.00	$22.00	$22.00	$0.00	$0.00
XLF	SELECT SECTOR SPDR TRUST FINANCIAL ETF	$0.00	0.00%	$0.00	($129.00)	($129.00)	$0.00	$0.00
XLE	SELECT SECTOR SPDR TRUST ENERGY ETF	$0.00	0.00%	$0.00	($458.00)	($458.00)	$0.00	$0.00
XLB	SELECT SECTOR SPDR TRUST SBI MATERIALS ETF	$0.00	0.00%	$0.00	$31.00	$31.00	$0.00	$0.00
URA	GLOBAL X FDS GLOBAL X URANIUM ETF	$0.00	0.00%	$0.00	($105.00)	($105.00)	$0.00	$0.00
UBER	UBER TECHNOLOGIES INC COM	$0.00	0.00%	$0.00	$140.00	$140.00	$0.00	$0.00
TSLA	TESLA INC COM	$0.00	0.00%	$0.00	$895.00	$895.00	$0.00	$0.00
STX	SEAGATE TECHONOLOGY HLDG COM	$0.00	0.00%	$0.00	$112.00	$112.00	$0.00	$0.00
SO	SOUTHERN CO COM	$0.00	0.00%	$0.00	$30.00	$30.00	$0.00	$0.00
PM	PHILIP MORRIS INTL INC COM	$0.00	0.00%	$0.00	$15.00	$15.00	$0.00	$0.00
ORCL	ORACLE CORP COM	$0.00	0.00%	$0.00	($228.00)	($228.00)	$0.00	$0.00
NVDA	NVIDIA CORP COM	$0.00	0.00%	$0.00	$180.00	$180.00	$0.00	$0.00
NKE	NIKE INC COM CL B	$0.00	0.00%	$0.00	$90.00	$90.00	$0.00	$0.00
MS	MORGAN STANLEY COM	$0.00	0.00%	$0.00	($335.00)	($335.00)	$0.00	$0.00
LQD	ISHARES TRUST IBOXX INV CP ETF	$0.00	0.00%	$0.00	$73.00	$73.00	$0.00	$0.00
IWM	ISHARES TRUST RUSSELL 2000 ETF	$0.00	0.00%	$0.00	($507.00)	($507.00)	$0.00	$0.00
INTC	INTEL CORP COM	$0.00	0.00%	$0.00	$46.00	$46.00	$0.00	$0.00
IBM	INTERNATIONAL BUS MACH CORP COM	$0.00	0.00%	$0.00	$70.00	$70.00	$0.00	$0.00
HD	HOME DEPOT INC COM	$0.00	0.00%	$0.00	$95.00	$95.00	$0.00	$0.00
GLD	SPDR GOLD TRUST GOLD SHS ETF	$0.00	0.00%	$0.00	$188.00	$188.00	$0.00	$0.00
FXI	ISHARES TRUST CHINA LG-CAP ETF	$0.00	0.00%	$0.00	($120.00)	($120.00)	$0.00	$0.00
FRC	FIRST REPUBLIC BANK SAN FRANCI COM	$0.00	0.00%	$0.00	($480.00)	($480.00)	$0.00	$0.00
ED	CONSOLIDATED EDISON INC COM	$0.00	0.00%	$0.00	($355.00)	($355.00)	$0.00	$0.00
DHR	DANAHER CORP COM	$0.00	0.00%	$0.00	$100.00	$100.00	$0.00	$0.00
COUR	COURSERA INC COM	$0.00	0.00%	$0.00	$25.00	$25.00	$0.00	$0.00
CNC	CENTENE CORPORATION COM	$12.50	+7.35%	$17.50	$12.50	$12.50	$0.00	$182.50
CME	CME GROUP INC COM	$0.00	0.00%	$0.00	$340.00	$340.00	$0.00	$0.00
CHTR	CHARTER COMMUNICATIONS INC COM CL A	$0.00	0.00%	$0.00	($20.00)	($20.00)	$0.00	$0.00
BDX	BECTON DICKINSON & CO COM	$0.00	0.00%	$0.00	$330.00	$330.00	$0.00	$0.00
APLS	APELLIS PHARMACEUTICALS INC COM	$0.00	0.00%	$0.00	$80.00	$80.00	$0.00	$0.00
AMAT	APPLIED MATERIALS INC COM	$0.00	0.00%	$0.00	$170.00	$170.00	$0.00	$0.00
ADI	ANALOG DEVICES INC COM	$0.00	0.00%	$0.00	$380.00	$380.00	$0.00	$0.00
ABT	ABBOTT LABORATORIES COM	$0.00	0.00%	$0.00	$117.00	$117.00	$0.00	$0.00
AAPL	APPLE INC COM	$0.00	0.00%	$0.00	$40.00	$40.00	$0.00	$0.00
	OVERALL TOTALS	$12.50	+7.35%	$17.50	$874.50	$874.50	$0.00	$182.50

Figure 4.10: Simulated Trading Result (Print Screen from Thinkorswim trading platform)

Conclusion

This research stands out for its development and validation of a novel "4 factors" model, which synergistically integrates the Hull Moving Average (HMA), Keltner Channel, Straddle 4B Range, and Momentum indicators. The model's inception and subsequent analysis mark a significant contribution to the domain of stock market analysis, particularly in the realm of predictive accuracy using advanced analytical models.

The model showcases exceptional performance, underpinned by high correlation coefficients and an impressive R Square value. This evidences its effectiveness in capturing the nuances of stock market dynamics and providing precise forecasts. When compared to existing forecasting models, including the Suttle Indicator, the "4 factors" model demonstrates superior predictive accuracy, highlighted by lower error metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE).

The research employs rigorous data analysis techniques, utilizing statistical tools such as SPSS Statistics and engaging in comprehensive multiple regression models. This methodological approach provides a deep understanding of the relationships among various technical indicators, thereby uncovering their collective predictive power for stock market trends.

A critical aspect of the study is the comparative analysis of the developed model with previous research. This analysis, focused on accuracy through various error metrics, underscores the strengths and practicality of the proposed model over traditional statistical methods and contemporary machine learning techniques.

The model's practical implications are far-reaching. It offers a powerful tool for financial analysts, traders, and investors, aiding in informed decision-making. The model's adaptability to different market conditions enhances its utility in diverse trading strategies and risk management practices.

Despite its strengths, the research acknowledges potential limitations, such as the inherent risk of overfitting and the necessity for validation with out-of-sample data. These aspects are crucial for ensuring the model's robustness and reliability across various market scenarios.
The thesis sets a solid foundation for future research opportunities in financial forecasting. Key areas include expanding the range of technical indicators, incorporating machine learning and AI to enhance predictive accuracy, and testing the model across different market environments. Additionally, assessing the model's real-time data analysis capability and its integration into high-frequency trading scenarios present exciting avenues for exploration. The incorporation of qualitative factors, longitudinal studies, and comparative evaluations with existing models are also recommended to further enrich the model's applicability and effectiveness.
In summary, the thesis offers a robust and highly accurate model for stock trend prediction, contributing significantly to both academic understanding and practical applications in financial analysis. The proposed directions for future research promise to further enhance this contribution, ensuring the model's continued relevance and efficacy in the ever-evolving financial market landscape. This trajectory of research has the potential to enrich academic discourse and provide pragmatic, data-driven strategies for market participants.

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