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Analyzing the Impact of COVID-19 on Short-Term Investment Behavior through Stochastic Oscillator Indicators

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Abstract

This research examines how the COVID-19 pandemic affects short-term investments, particularly focusing on the reliability of Stochastic Oscillator Indicators (SOI) used by investors. Utilizing an artificial intelligence learning prediction model, the study investigates the pandemic's impact on short-term investment strategies guided by SOI, comparing data from pre-pandemic and pandemic periods. The findings suggest that during the COVID-19 period, employing KD analysis with a nine-round turnover rate leads to higher forecast accuracy. Short-term investors tend to adopt a conservative approach, with higher turnover rates resulting in lower winning rates. Overall, the study challenges the notion that COVID-19 only affects medium and long-term investment habits, shedding light on its influence on daily investment profits and potentially increasing short-term profits for larger, conservative investors. Further research is warranted to explore the investor profile of conservative hedgers in more depth.

Keywords: COVID-19, Stochastic Oscillator Indicators, Artificial Intelligence, Short-term Investors, Conservative Approach

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1. Introduction

Short-term trading faces ongoing challenges, particularly in forecasting models that utilize statistical or machine learning techniques such as linear regression, unsupervised learning, and supervised learning, to predict stock market trends (Chou and Hung, 2021; Chung et al., 2021). Given the market impact of COVID-19, short-term trading requires a reassessment of investment strategies to adjust to the evolving landscape (Ienca and Vayena, 2020; Wang et al., 2020). Day traders depend heavily on technical indicators like Bollinger Bands (BB) and Stochastic Oscillator Indicators (SOI) to improve their trading forecasts. The frequent transactions in day trading pose a challenge for human judgment alone to keep pace with market dynamics (Chou and Cho, 2020; Pedirappagari and Babu, 2019; Chen et al., 2018; Zhou et al., 2018; Leung and Chong, 2003; Yan et al., 2017; Lai et al., 2016). Using SOI for stock market prediction inherently presents challenges and involves high risks (Pedirappagari and Babu, 2019; Dang et al., 2018). Nevertheless, despite the challenges and risks, technical indicators like SOI can be effective for short-term predictions, especially in transactions with a frequency of 5 minutes or less (Cao and Wang, 2019).

The aim of this research is to investigate the usefulness of SOI for day traders in identifying turning points, specifically focusing on the K value 9/14 or the D value 9/14 indicator. By utilizing the SOI indicator, our goal is to develop effective prediction models that compare various index numbers and evaluate the impact of different turning points on short-term trades. Additionally, we aim to enhance the stability of our prediction model by integrating machine learning techniques to address high-risk unforeseen events, such as COVID-19. Empirical experiments will be conducted, focusing on day traders operating in the Taiwan Stock Exchange Capitalized Weighted Stock Index (TAIEX).

2. Literature Review

Historically, significant diseases have often impacted medium- and long-term investments, including foreign exchange rates (Valsecchi, 2020). From a macroeconomic standpoint, when the consumer market undergoes a recession, it can create a ripple effect on the operational performance of diverse industries. Consequently, this may affect the stock market, resulting in medium- and long-term price fluctuations (Chou et al., 2019) . Day traders have the opportunity to capitalize on both upward and downward price movements in the stock market. However, distinguishing significant differences between regular and irregular periods can pose challenges. The complexities and uncertainties inherent in short-term market dynamics contribute to a relatively scarce amount of research specifically dedicated to short-term investment investigations. Consequently, this research area remains relatively unexplored, presenting opportunities for further exploration (Valsecchi, 2020).

Day traders, who prioritize rapid short-term gains, frequently lean towards technical indicators over fundamental macroeconomic analysis. This preference stems from the ability of technical indicators to offer swift responses within short timeframes, enabling day traders to execute immediate profit-taking transactions. Technical analysis furnishes them with insights into price patterns, trends, and market sentiment, facilitating prompt trading decisions. Consequently, day traders commonly emphasize technical analysis as a pivotal tool in their quest for short-term profits (Chou et al., 2019; Ince and Trafalis, 2008; Iqbal, 2013; Desai and Gandhi, 2014; Mozhaddam et al., 2016; Safi and White, 2017). Applying artificial intelligence methods to stock index prediction could prove beneficial for regular periods (Chou et al., 2019; Safi and White, 2017; Bebchuk et al., 2015). Moreover, technical indicators like moving averages could be incorporated into artificial intelligence methods as significant factors by analyzing historical data (Jabbarzadeh et al., 2016). While technical indicators are widely utilized by day traders for swift decision-making, it's crucial to recognize the ongoing potential for enhancing their predictive accuracy and ease of use. Among these indicators is SOI, which holds promise in assisting day traders in reducing the risk of losses and potentially attaining high returns within very short timeframes. SOI, developed by Dr. George Lane and J. Welles Wilder, is a momentum indicator that operates on a scale of 0 to 100. However, it's important to note that the effectiveness of any indicator, including SOI, can vary depending on market conditions and individual trading strategies. Therefore, while SOI may offer advantages, it's essential for day traders to consider multiple indicators and factors in their decision-making process to improve their overall trading performance (Chakrabarty and Majundar, 2020; Faraz et al., 2020; Kouatli and Yunis, 2021; Ni et al., 2020).

SOI, rooted in statistical probability, serves as a measure of the average gain or loss over a specific look-back period. It quantifies the average percentage gain or loss, with the formula incorporating a positive value for the average loss. Day traders often rely on SOI and its 70 zone to identify turning points, but it's important to note that alternative thresholds, such as 80, can sometimes provide more accurate signals, warranting patience for the stock index to reach that level. When the upper track reaches the lower or equal to SOI or 20 zone, it indicates an oversold condition in the near term, creating an opportunity for day traders to buy the stock index within that range. Conversely, if SOI exceeds 70 or 80, it may be prudent to consider selling (Pedirappagari and Babu, 2019). By leveraging the strengths and unique characteristics of different algorithms, a combined approach can enhance the overall predictive capabilities of the model. This allows for a more comprehensive analysis of the data and increases the potential for accurate predictions across various scenarios and data patterns (Pedirappagari and Babu, 2019; Dang et al., 2018; Cao and Wang, 2019; Chung and Shin, 2018; Bai et al., 2019; Bhargavi et al., 2017).

SOI is utilized in financial predictions for very short-term investments, where a higher SOI value can indicate potential turning points towards a downward movement. While day traders may find success in trading stock index futures within short timeframes without solely relying on SOI, the accuracy of identifying turning points solely based on 30/70 or 20/80 thresholds remains unclear. Additionally, even if effective SOI models exist for decision support, it is essential to consider the impact of unforeseen events like COVID-19 as empirical tests and exceptions. Therefore, it is prudent to carefully incorporate SOI options in different scenarios to mitigate losses and navigate very short-term investments more effectively.

3. Research Model and Hypotheses Development

Day traders frequently employ the five-minute moving average line of the stock index to pinpoint critical turning points, often set at the 70 threshold (refer to Figure 1). When utilizing the Stock Oscillator Indicator (SOI), traders typically base their decisions on five-minute intervals. A SOI reading surpassing 70 or 80 often signals entry into a high-risk zone, indicating a potential downward trend. Conversely, reaching the lower range associated with 20 may foreshadow an upward turning point. Our research endeavors to leverage the short-term trend line of SOI to evaluate the impact of these turning points.

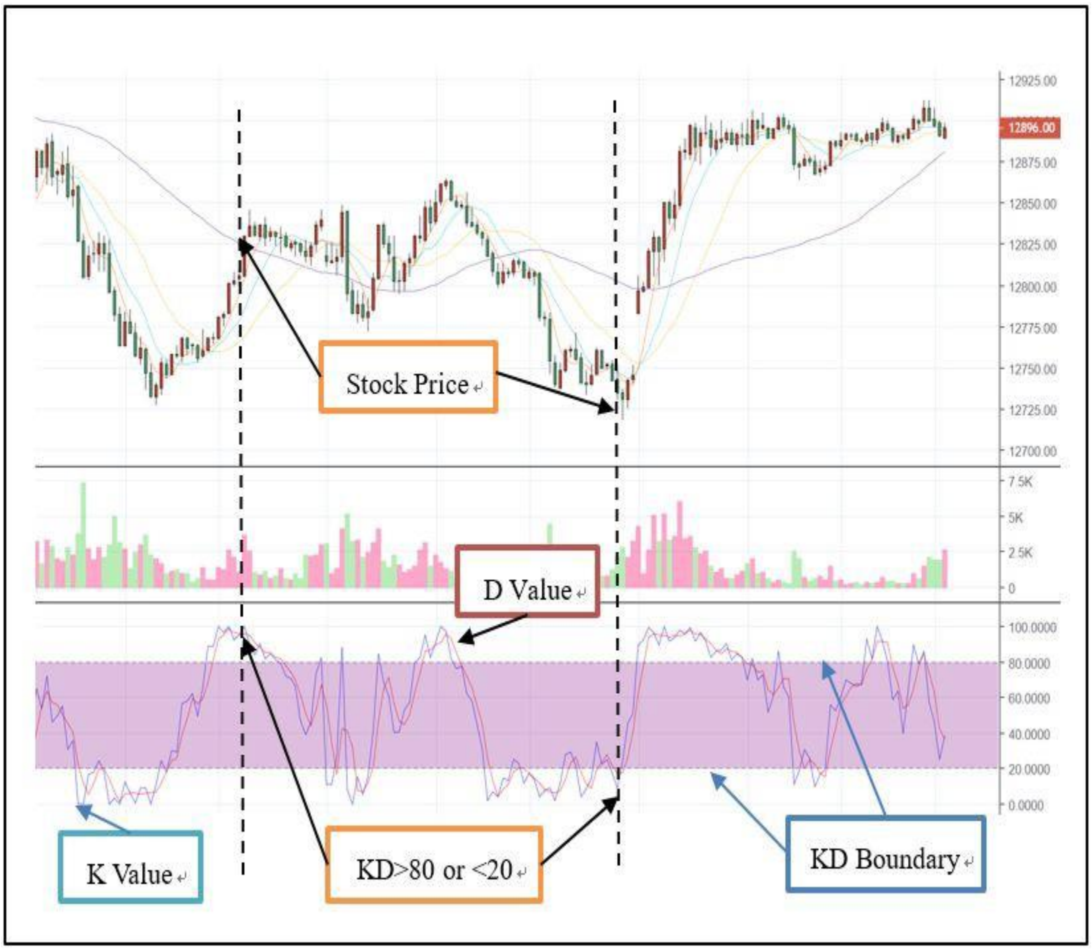

Figure 1: Short-term turning points in SOI approach

Turning points manifest when the SOI indicator, gauging relative lows within a specific five-minute moving average line of the stock index, descends to 20. Day traders perceive this decline as a cue to acquire stock index futures. Nonetheless, a prevailing challenge resides in the broad range of SOI readings, prompting exploration into enhancing accuracy by diminishing transaction times linked with the indicator.

The subsequent algorithm delineates the implementation of our COVID-19 SOI approach. It commences by initializing requisite parameters and establishing logical functions. Subsequently, it calculates dynamic turning points to extract the desired value. Traders can then leverage this value to dynamically refine their transactions, adhering to the prescribed algorithm.

Algorithm : COVID-19 for SOI Approach

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Initialization of parameters:
  RSV9 = (Now-Min(9 Rounds))/(Max(9 Rounds)-Min(9 Rounds))*100
  RSV14 = (Now-Min(14 Rounds))/(Max(14 Rounds)-Min(14 Rounds))*100
  K9 = ((K9-1)*(2/3))+RSV9*(1/3)
  D9 = ((D9-1)*(2/3))+K9*(1/3)
  K14 = ((K14-1)*(2/3))+RSV14*(1/3)
  D14 = ((D14-1)*(2/3))+K14*(1/3)
  R1 = Now (close price) – Now-1(close price)
  R9 = Now (close price) – Now-9(close price)
  R14 = Now (close price) – Now-14(close price)
Set up logic functions:
  If K9 >=80 or <=20 then R1 Turnover
  If K9 >=80 or <=20 then R9 Turnover
  If K9 >=80 or <=20 then R14 Turnover
  If K14 >=80 or <=20 then R1 Turnover
  If K14 >=80 or <=20 then R9 Turnover
  If K14 >=80 or <=20 then R14 Turnover
Compute the accuracy rate :
  COVID_R1 (K9) vs. Non COVID_R1 (K9)
  COVID_R9 (K9) vs. Non COVID_R9 (K9)
  COVID_R14 (K9) vs. Non COVID_R14 (K9)
  COVID_R1 (K14) vs. Non COVID_R1 (K14)
  COVID_R9 (K14) vs. Non COVID_R9 (K14)
  COVID_R14 (K14) vs. Non COVID_R14 (K14)
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Previous research in the field has primarily focused on a single turning point within the SOI approach. In contrast, our innovative algorithm introduces the concept of multiple turning points, distinguishing it from prior methodologies. However, despite incorporating multiple SOIs into our algorithm, we encounter the ongoing challenge of addressing the second research question regarding the efficacy of artificial intelligence methods in prediction and dynamic self-learning. While machine learning algorithms have demonstrated utility in stock market predictions, caution is warranted before relying solely on them. In this study, we utilized machine learning algorithms to dynamically discern the optimal performance of various turning point predictions in the short term. Our research represents pioneering empirical inquiry into examining the impact of multiple turning points on short-term stock index futures prediction and trading using machine learning techniques (Chou and Cho, 2020; Chou et al., 2019; Das and Sudersan, 2012; Lin et al., 2012; Chou, 2020). Our primary aim was to develop a self-learning approach to mitigate the existing uncertainty surrounding the predictive capacity of the SOI approach regarding turning points. Through this endeavor, we sought to bridge the knowledge gap and offer clarity on this subject.

Certain classification algorithms, like the sequential minimal optimization (SMO), demonstrate the ability to adeptly manage multi-dimensional time-series data marked by substantial noise levels. Simultaneously, they offer coordinated multi-resolution predictions. This positions the SMO algorithm as a promising substitute for numerical quadratic programming in addressing optimization challenges in stock forecasting. Notably, its capacity for accurate predictions further enhances its appeal in this domain (Huang et al., 2005; Bogle and Potter, 2015).

To effectively capture various turning points in stock index day trading, we have defined multiple turning points for short-term investment. These include: the nine-period SOI with COVID-19 (Treatment 1), the fourteen-period SOI with COVID-19 (Treatment 2), the nine-period SOI without COVID-19 (Treatment 3), and the fourteen-period SOI without COVID-19 (Treatment 4). In our research model, depicted in Figure 2, Treatments 1 and 2 represent conventional SOI turning points commonly utilized by day traders, while Treatments 3 and 4 are devised to address unforeseen circumstances, aiming to mitigate potential significant losses or even yield gains. Treatments 1 and 2 involve assessing the difference in SOI with thresholds set at 20 and 30, respectively, while Treatments 3 and 4 are handled similarly.

To assess investment performance, machine learning algorithms such as SMO, deep learning, multilayer perceptron (MLP), and random forest are considered suitable and employed in our study. These machine learning techniques rely on the analysis of extensive financial data during the training phase. Consequently, the predictive performance of these techniques may vary based on the specific training data utilized and the algorithm employed. The quality and representativeness of the training data, along with the appropriateness of the chosen algorithm for the given problem, are pivotal factors influencing the predictive accuracy of machine learning models in the financial domain.

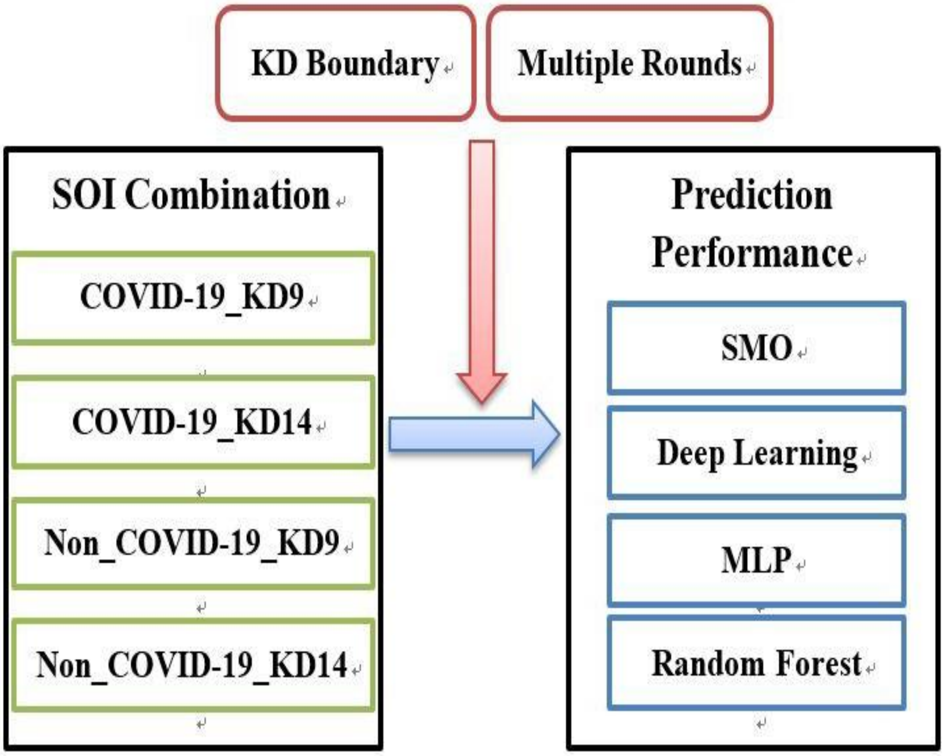

Figure 2: The research model

To the best of our knowledge, our research marks the inaugural endeavor to differentiate among SOI for assessing turning points and employ a machine learning system to predict stock index futures. Prior studies have indicated that distinct turning points may yield varying levels of accuracy in short-term stock index futures predictions. Consequently, our study endeavors to address two hypotheses, with the first hypothesis articulated as follows:

H1. Incorporating different boundaries for SOI yields varied impacts on the turning points of short-term stock index predictions.

Given the potential variations in efficacy among day traders across various time intervals and unforeseen crisis scenarios, the net gain or loss during specific periods, such as the COVID-19 pandemic, can significantly influence traders' overall profit over the long term. Hence, it becomes imperative to distinguish between regular and non-regular time periods for short-term investments and dynamically adjust strategies to make informed decisions. Building upon this premise, our second hypothesis is as follows:

H2. A notable discrepancy exists in the investment effectiveness of day traders between COVID-19 and regular non-COVID-19 periods.

4. Evaluation

In our assessment, we evaluated the accuracy rates of stock index predictions utilizing several machine learning algorithms, namely SMO, deep learning, MLP, and random forest. The training dataset encompassed TAIEX stock index trading data spanning from January 2, 2019, to May 31, 2019, and from January 2, 2020, to May 31, 2020, comprising a total of 11,464 datasets[2] (as outlined in Table 1).

Table 1: COVID-19 periods.

Date	Open	High	Low	Close	Volume	RSV9	RSV14	K9	D9	K14	D14	C1	C9	C14
2020/1/2	12062	12064	12054	12058	1422	87.5	71.79	58.28	34.75	23.93	7.977	-4	2	-5
2020/1/2	12059	12061	12052	12060	1236	93.75	76.92	70.1	46.53	41.6	19.18	2	26	3
2020/1/2	12060	12079	12059	12075	4799	100	100	80.07	57.71	61.06	33.14	15	45	20
2020/1/2	12075	12081	12072	12073	3005	95.12	95.56	85.09	66.84	72.56	46.28	-2	39	10
2020/1/2	12074	12078	12073	12076	1354	100	100	90.06	74.58	81.71	58.09	3	42	7
2020/1/2	12075	12078	12073	12078	948	100	100	93.37	80.84	87.8	68	2	35	22
2020/1/2	12078	12088	12077	12083	2938	100	100	95.58	85.75	91.87	75.95	5	36	49
2020/1/2	12082	12093	12081	12089	2572	100	100	97.05	89.52	94.58	82.16	6	27	59
2020/1/2	12090	12095	12088	12092	1467	100	100	98.04	92.36	96.39	86.9	3	34	58
2020/1/2	12092	12103	12092	12101	2440	100	100	98.69	94.47	97.59	90.47	9	41	67
2020/1/2	12103	12104	12092	12095	1936	78.57	89.66	91.98	93.64	94.95	91.96	-6	20	52
2020/1/2	12095	12099	12089	12092	1374	67.86	83.33	83.94	90.41	91.07	91.66	-3	19	45
2020/1/2	12092	12101	12092	12100	1015	96	97.67	87.96	89.59	93.27	92.2	8	24	38
2020/1/2	12100	12104	12095	12103	923	100	100	91.97	90.39	95.52	93.31	3	25	45
2020/1/2	12103	12106	12098	12102	1116	95	97.67	92.98	91.25	96.24	94.28	-1	19	42
2020/1/2	12101	12107	12099	12105	775	100	100	95.32	92.61	97.49	95.35	3	16	30
2020/1/2	12105	12110	12104	12107	989	100	100	96.88	94.03	98.33	96.34	2	15	34

This study was conducted in two phases to gauge the effectiveness of various SOI methodologies concerning different turning points in short-term stock index trading. The initial phase centered on assessing the performance of Treatments 1, 2, 3, and 4 as independent variables, each representing distinct SOI-related approaches. The dependent variable in this analysis was the accuracy of these treatments in predicting stock index movements. Subsequently, the second phase of the study aimed to investigate whether superior SOI techniques led to increased profits for day traders during the COVID-19 period, serving as an independent variable.

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[2] https://drive.google.com/file/d/1gO_N7boCPcgKnjm7-Q2M3drY_uS3LWyw/view?usp=sharing
https://drive.google.com/file/d/1Wpzthe9Ntxkj0LLNreeT4MvIZVEvtabP/view?usp=sharing

To test the two hypotheses, we utilized the four machine learning algorithms (SMO, deep learning, MLP, and random forest) employing a 10-fold cross-validation approach (refer to Figures 3 and 4). A subsample of the dataset was set aside for validation purposes. These algorithms were selected for their widespread popularity and extensive usage across various domains, including stock market prediction (Jahangiri and Rakha, 2015; Kremic and Subasi, 2016; Chou et al., 2017).

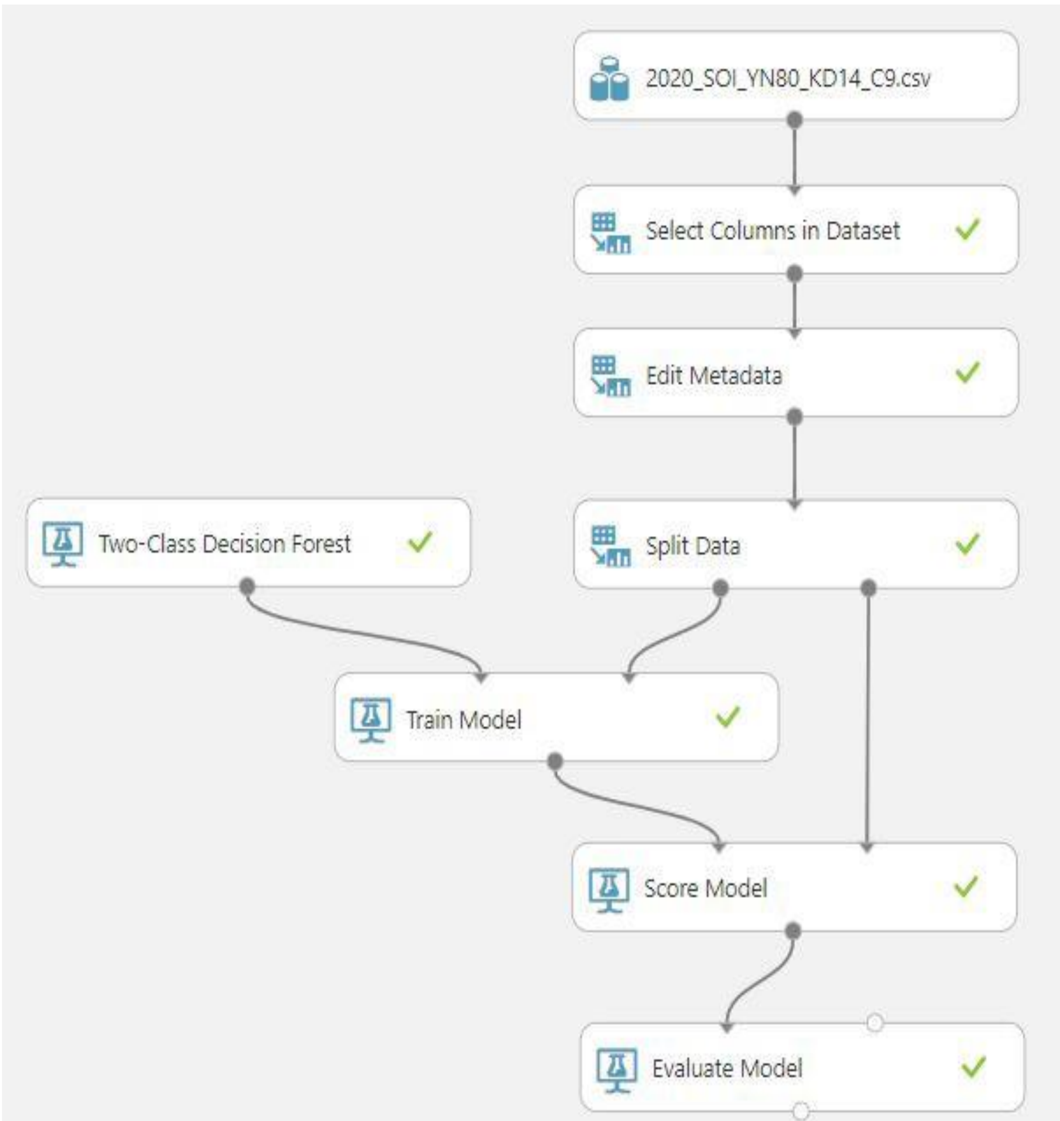

Figure 3: The train model

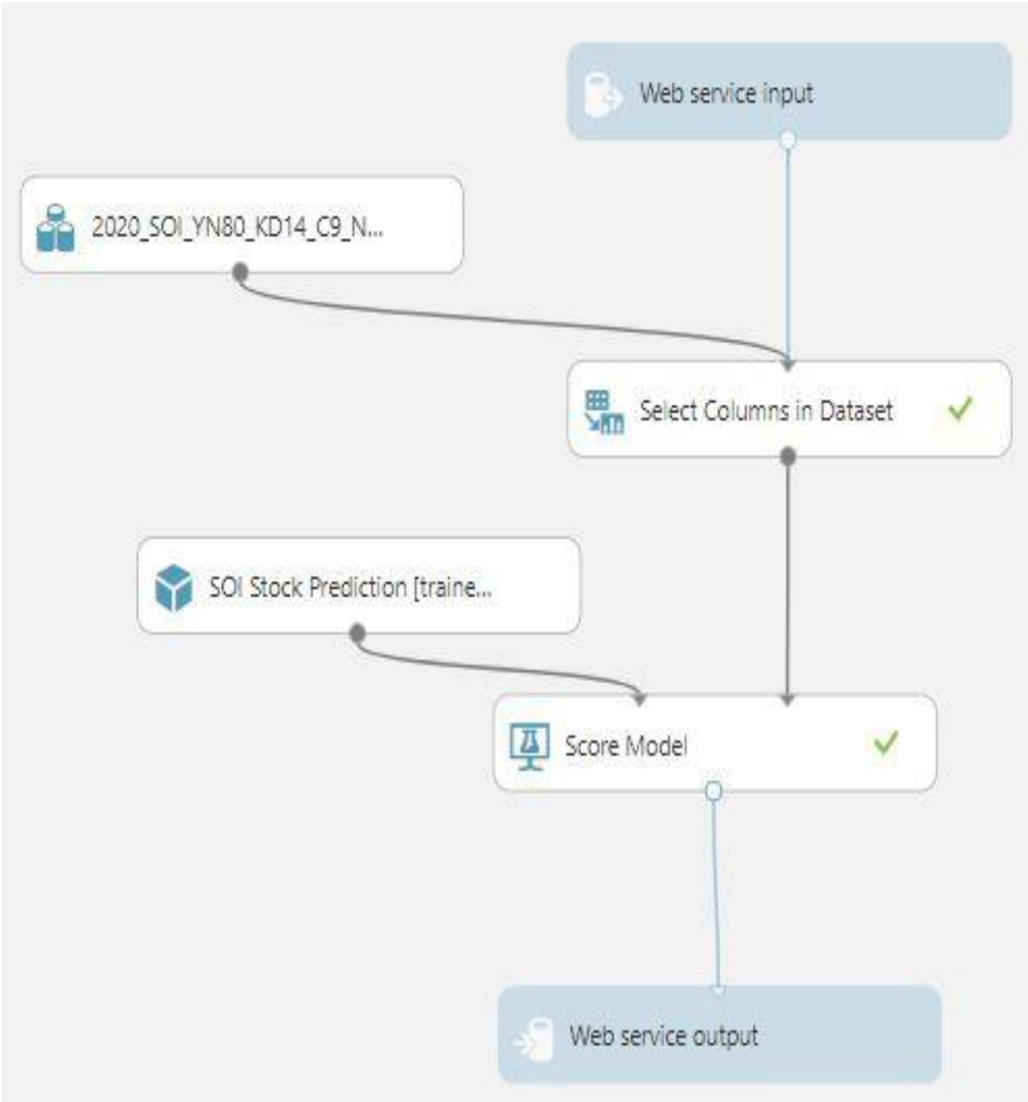

Figure 4: The real-time prediction

Model performance was evaluated by computing their accuracy, a metric assessing the correctness of predictions. This assessment included determining true positive (TP), true negative (TN), false positive (FP), and false negative (FN) rates. The accuracy rate was subsequently derived by dividing the total number of correct predictions by the total number of stock index predictions made (Chou et al., 2019).

5. Discussion

The tables (2, 3, 4, and 5) present the performance of the turning points. Calculating the average accuracy of the algorithms during the COVID-19 period involves excluding the upper and lower limits of KD (set at 80, 70, 30, and 20) and assessing the overall performance of the algorithm across these varying limits. To facilitate a precise response, kindly provide the specific accuracy values for each time period (1, 9, and 14) along with the corresponding limits of KD. With this information, I can compute the average accuracy for each time period and furnish a summarized table of the results.

Table 2: COVID-19 periods and not consider KD boundary

	R1	R9	R14	Average
KD9	64.62%	84.26%	81.46%	76.78%
KD14	63.28%	85.97%	83.08%	77.44%
Average	63.95%	85.12%	82.27%	77.11%

Table 3: COVID-19 periods and consider KD boundary

	R1	R9	R14	Average
KD9	64.62%	78.86%	75.09%	72.85%
KD14	63.28%	83.78%	72.14%	73.06%
Average	63.95%	81.32%	73.61%	72.96%

During the COVID-19 period, utilizing a 14-cycle KD and a trading frequency of 9 rounds yielded the highest profit expectation, reaching 85.97%. Conversely, employing the same 14-cycle KD but with a trading frequency of only 1 round resulted in the lowest profit expectation of 63.28%, which also corresponded to the lowest correct rate. Notably, both the highest and lowest profit expectations occurred within the KD 14 period. The variation in time frequency notably impacts the application of technical analysis using KD 14. The choice of trading frequency significantly influences profit expectation, with a higher frequency of 9 rounds yielding the highest profit expectation, whereas a reduced frequency of only 1 round yields the lowest profit expectation. This emphasizes the critical role of timing and frequency in optimizing the performance of the algorithm under KD 14's technical analysis during the COVID-19 period.

Table 4: All periods and not consider KD boundary.

	R1	R9	R14
COVID-19_KD9	64.62%	84.26%	81.46%
COVID-19_KD14	63.28%	85.97%	83.08%
Non_COVID-19_KD9	64.06%	83.15%	80.27%
Non_COVID-19_KD14	62.46%	84.77%	83.23%

Table 5: All periods and consider KD boundary

	R1	R9	R14
COVID-19_KD9	64.62%	78.86%	75.09%
COVID-19_KD14	63.28%	83.78%	72.14%
Non_COVID-19_KD9	64.06%	77.86%	73.66%
Non_COVID-19_KD14	62.46%	82.82%	75.05%

Considering the upper and lower limits of KD, specifically the stringent limits of 80 and 20, and focusing on the KD 14 cycles, a trading frequency of 9 rounds results in a profit expectation of 83.78%. This is slightly lower than the profit expectation of 85.97% observed in the KD 70/30 scenario. Similarly, when employing KD 14 cycles but restricting the trading frequency to one round, the profit expectation remains at 63.28%, consistent with the profit expectation in the KD 70/30 scenario. In both instances, the profit expectations are inferior compared to when the KD 70/30 scenario is considered.

In the comparative analysis of rounds during the COVID-19 period in 2020, notable disparities were observed in R1, R9, and R14 when considering or omitting the KD boundary. The ANOVA table revealed significant differences ($F(2, 11) = 7.201E+31$, $p < 0.01$) when the KD boundary was taken into account, and even higher significance ($F(2, 11) = 1.255E+32$, $p < 0.01$) when the KD boundary was not considered. LSD analysis further substantiated these significant differences, as all pairwise comparisons yielded a value of 0. However, in 2019, both considering and disregarding the KD boundary did not exhibit significant differences in R1, R9, and R14.

6. Conclusion

In comparing the effects of COVID-19 and non-COVID-19 periods, it's evident that while COVID-19 notably impacts medium and long-term investments, its influence on short-term and very short-term hedging strategies appears relatively minor. This implies that COVID-19 does not significantly alter very short-term investment tactics. However, some discrepancies in the results are apparent. Specifically, forecasts conducted using KD analysis during COVID-19 with a trading frequency of 9 rounds seem to exhibit higher accuracy compared to other scenarios. The heightened accuracy of the forecasts during the COVID-19 period, particularly with a nine-round turnover rate and a transaction frequency as high as 86%, can be attributed to several factors. Firstly, the data suggests that even for short-term investors, a conservative approach tends to yield better results. Higher turnover rates, such as one round, are associated with lower winning rates, indicating investor preference for a cautious, wait-and-see approach and extending the number of rounds, likely due to concerns about the index not returning to favorable buying or selling points.

Secondly, the analysis indicates that investors remain cautious even when considering common boundary settings like the 80/20 threshold. The correct rate does not increase, and in some cases, even decreases, suggesting a conservative trading mentality among investors. Despite this conservative approach, the nine-round trading strategy still yields higher winning rates compared to the 14-round strategy, indicating investor concerns about the ineffectiveness of low trading frequency for hedging and their willingness to bear associated costs. Another noteworthy finding is the decrease in the trading frequency of investors, coupled with an increase in trading volume. This suggests a shift towards larger investors, potentially indicating changes in the investor composition with a greater presence of institutional or large-scale investors. This challenges the assumption that COVID-19 solely impacts medium and long-term investment habits, highlighting its influence on daily investment profits of retail investors while also potentially boosting short-term profits for larger, conservative investors. However, further research is essential to delve into the nature of these conservative hedgers and ascertain whether they predominantly belong to large investors or if a significant portion represents medium-sized and retail households. Such research can provide insights into the broader impact of COVID-19 on different investor segments.

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