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Predicting Turnover Rates for Short-Term Stock Index Investments Using Artificial Intelligence and Empirical Analysis

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Abstract

Short-term investments, particularly in stock index futures, have attracted significant interest among day traders seeking quick returns. However, consistently generating profits remains challenging due to suboptimal trading policies. To address this, our study explores the potential of artificial intelligence, specifically deep learning, in predicting optimal turnover rates for short-term stock index transactions. Through empirical methods and an extensive analysis of over 30,000 datasets, we examine the impact of turnover rates on prediction performance. Our findings highlight the substantial influence of higher turnover rates on day traders' profitability in short-term investments. Notably, our deep learning algorithm achieves an exceptional accuracy rate of 93.25% in predicting longer turnover rates. By elucidating the relationship between turnover rates and financial forecasting, this research offers a novel perspective to the existing literature. Traders can leverage these insights to make informed decisions, enhancing the potential for more consistent and profitable outcomes in their short-term investment strategies. Ultimately, this study empowers day traders with valuable knowledge, providing a pathway to navigate the challenges of achieving sustained success in short-term investments.

Keywords: Short-term Investments, Stock Index Futures, Artificial Intelligence Techniques, Turnover Rates, Financial Forecasting.

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1. Introduction

Forecasting stock price indices is a highly challenging task in financial technology (Atsalakis and Valavanis, 2009). Numerous short-term traders rely on basic analytical methods (e.g., foreign exchange rates) and closely monitor the Taiwan Stock Exchange Capital Weighted Stock Index (TAIEX) and other trading stock indices (Chou et al., 2019; Chou and Cho, 2020). Financial forecasting holds significant relevance in both academic research and financial institutions. Given the potential impact of day traders on daily market activities, it is crucial for them to stay updated with financial forecasts, stock index-related information, and exchange rates, which are readily available on various online platforms and newspapers. In the short term, day traders can benefit from considering financial time series, which are historical data generated rapidly in a series of economic activities and arranged in chronological order. Despite the potential for higher profits due to high turnover rates, day traders often struggle to maintain average monthly profitability compared to institutional traders. Additionally, the use of stock index futures for hedging purposes in short-term investments can be challenging due to the complexity of assessing the total impact of multiple time series on turnover. This complexity arises from the need to facilitate trading in the short-term futures market.

The turnover rate refers to the proportion of daily index stocks purchased by day traders during a given interval. However, due to transaction taxes, higher turnover rates can be costly for day traders. Short-term investments involve uncertain turnover rates, such as 5- or 10-minute intervals based on technical analysis. As a result, without empirical processes and technical support, day traders may lack an effective model for short-term investments, leading to high risks and preventing frequent investments (Cao and Wang, 2019). Furthermore, time constraints can make it challenging for traders to assess whether the results have changed within the previous round or two, especially with intervals as short as 5 minutes. Additionally, since day traders may have different preferences and views on short-term turnover, it can be challenging for them to identify the stock index that perfectly aligns with their requirements based on different needs. Therefore, the first research question is as follows:

RQ1: Do day traders adopt different investment strategies based on their turnover rates?

To address short-term variability, an effective approach could be to develop and personalize rules based on changing needs and preferences for different turnover rates (such as 5- or 10-minute intervals). However, dynamically adjusting and managing short-term turnover is a significant challenge. Individual preferences can vary, and even under the same conditions, they can influence the behavior of the short-term turnover rate, affecting investment effectiveness. Therefore, the second research question is as follows:

RQ2: What methodology can dynamically differentiate the predicted performance of machine learning models across different short-term turnover rates?

Effective forecasting methods should consider technological variability and leverage machine learning technologies, such as deep learning, to reduce the high risk associated with day trading. The main objective of this study is to develop a more accurate and personalized forecasting model suitable for short-term traders in making investment decisions. Additionally, this study aims to apply artificial intelligence (AI) to improve the empirical process of investments, making it more appropriate and reliable. The literature review is presented in the next section, followed by a description of the research methods. The experimental setup and results are described in Sections 4 and 5, respectively. Finally, the last section discusses the important contributions of this research, its limitations, and future prospects.

2. Literature Review

Existing studies frequently focus on stock prediction using technical applications like AI (Chou, 2023; Chou and Cho, 2023; Chou, 2024). However, despite identifying some forecasting-related factors, challenges such as lower accuracy and the exclusive suitability of patterns for medium- or long-term stock predictions remain unresolved. Experts commonly employ fundamental analysis of macroeconomic data, including exchange rates. With the rise of hedge funds, many variables have become harder to quantify, making dynamic market forecasts less suitable for decision-making solutions, such as foreign investments (Bebchuk et al., 2015). Certain characteristics are significantly different for short-term investments than for those of medium- and long-term investments, and adopting technical analysis methods may be more effective (Ince and Trafalis, 2008; Iqbal, 2013; Desai and Gandhi, 2014; Mozhaddam et al., 2016; Safi and White, 2017). In addition, different machine learning algorithms may have different effects on predictive models. Consequently, technical analysis methods based on different algorithms must be used for comparison. In recent years, an increasing number of traders have begun to pay attention to the concept of quantitative trading to determine the turnover rates (Chung and Shin, 2018). The key concept behind the turnover method in a financial time series is that high turnover results in high payments due to the frequent transaction taxes traders incur, leading to increased costs. Conversely, if effective concessions are implemented, high turnover may be more profitable than low turnover.

Regarding the turnover rates in Equation (1):

$$Turnover\ \ rates = \left(\frac{R}{A}\right) \times 100\% \tag{1}$$

Here, R means the actual amount of stock trading in a certain period, and A indicates the total stock index available for trading in a certain period. For day traders' investment strategies, frequent trading can negatively impact this time-consuming activity. Therefore, most day traders can attempt to save on transaction taxes by avoiding higher turnover.

Figure 1: An Example of Turnover Rates on 5-Minute Trading[2]

Since the impact of different turnover rates on short-term stock index trading is unclear, day traders should approach this strategy with caution. In Figure 1, our average transaction time from the first to the third stage is 5 minutes, and the results can vary significantly. Even with an effective predictive model for each transaction, the transaction taxes remain high. Therefore, this study attempts to address this issue by examining multiple turnover rates. Machine learning algorithms have proven effective in certain stock markets and are widely used in financial applications. These algorithms can also be used interactively for dynamic comparisons across different timelines, allowing for adjustments to various prediction targets and thereby improving the accuracy of stock predictions (Chou, 2022; Chou et al., 2022). This study determines the turnover rate of short-term index trading and uses deep learning to empirically address the second research question: how to dynamically distinguish forecast performance across different short-term turnover rates. To the best of our knowledge, this is the first empirical research to investigate the influence of different turnover rates on short-term stock indexes using deep learning

[2] https://histock.tw/futures/mainfutures.aspx

techniques. This study contributes new theoretical and practical perspectives on enhancing the effectiveness and precision of short-term investment predictions by adapting to different turnover rates.

3. Research Model and Hypotheses Development

Based on the limitations of existing research and novel ideas in classification algorithms, this section proposes a research model for building dynamic self-learning methods to address research questions in this field. While machine learning technology can automatically learn from large amounts of data, the challenge in classification methods lies in the numerous unclear attributes related to short-term stock indexes. Although existing research suggests that turnover rate may affect short-term stock indexes, the impact of different turnover rates remains unclear. Some classification algorithms, such as sequential minimum optimization, can handle multi-dimensional time series with high noise levels and make coordinated multi-resolution predictions (Huang et al., 2005; Bogle and Potter, 2015; Chou, 2020). The sequential minimum optimization (SMO) algorithm can be used instead of numerical quadratic programming (QP) to analyze the quadratic planning step (QP-Step), which can solve the optimization problem; therefore, it is suitable for use in stock prediction (Magaji, 2013).

If we use the perspective of an optimization problem to consider a binary classification by a dataset (x_1, y_1), ... (x_n, y_n), where x_i could be input vectors and $y_i \in \{-1, +1\}$ could be a binary dataset, but range from one to minus one, we can propose the formula as Equation (2) to solve the quadratic programming problems:

$$max_z \sum_{i=1}^{n} z_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i y_j K(x_i, x_j)\, z_i z_j \tag{2}$$

subject to:

$$0 \le z_i \le H, for \;\; i = 1, 2, \dots, n,$$

$$\sum_{i=1}^{n} y_i z_i = 0$$

In this equation, where H is a hyper-parameter and $k(x_i, x_j)$ is the kernel function, z_i variables are Lagrange multipliers, which could have the linear equality constraints as$0 \le z_1, z_2 \le H, y_1 z_1 + y_2 z_2 = k$ to allow the possible problems to be solved by such multipliers. Considering both the strengths and weaknesses of previous research, this study aims to 1) investigate the influence of various turnover rates on short-term stock indexes and 2) dynamically differentiate the predictive accuracy of stock indexes from different short-term turnover rates. To achieve these objectives, this study identifies relevant attributes, including different turnover rates, and integrates them into the classification algorithm to determine the forecast accuracy of stock indexes based on various turnover rates.

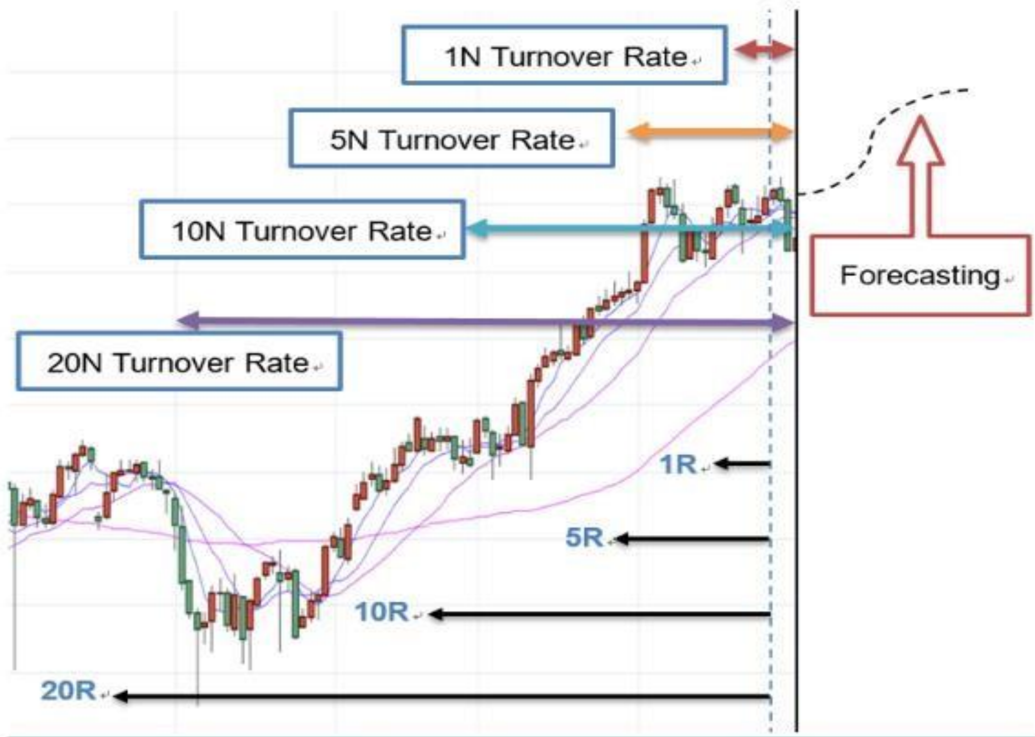

Figure 2: Predictive Methods on Different Turnover Rates

To better reflect the impact of different turnover rates on stock index trading within a day, the time interval for short-term investments can be limited to 1R (one round), 5R (five rounds), 10R (ten rounds), or 20R (twenty rounds), where one round represents 5 minutes. To distinguish between different turnover rates, the same condition time interval (i.e., 1R, 5R, 10R, or 20R) is used to predict 1N (next round), 5N (next five rounds), 10N (next ten rounds), or 20N (next twenty rounds), respectively (Figure 2). In the research model (Figure 3), short-term factors include 1R, 5R, 10R, and 20R to predict the accuracy of 1N, 5N, 10N, and 20N. Machine learning algorithms—such as Sequential Minimal Optimization (SMO), Deep Learning, Multi-Layer Perceptron (MLP), and Random Forest—are suitable for evaluating system performance. Since AI technology uses a significant amount of financial information for training, it can influence the overall system performance (Radner and Rothschild, 1975; Chou and Hung, 2021).

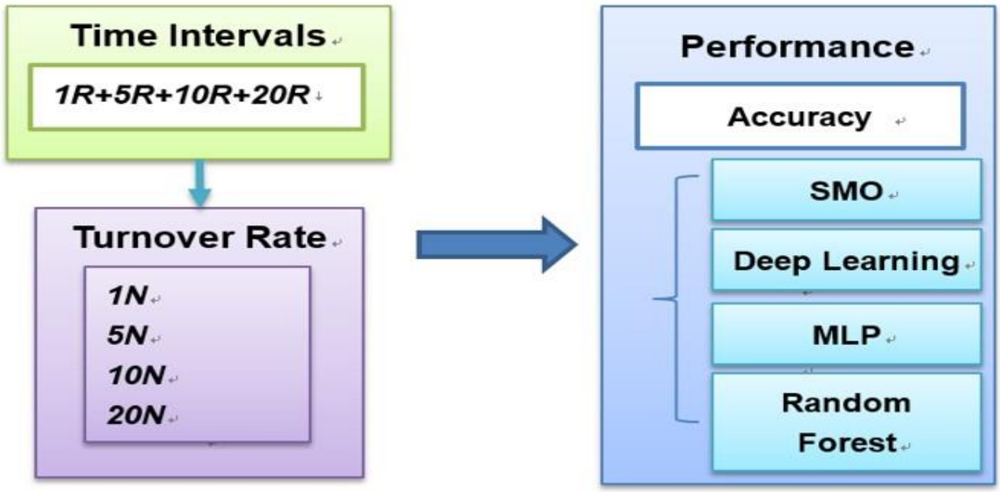

Figure 3: The Research Model

There has been no prior attempt to incorporate different turnover rates into deep learning for evaluation. As described below, these financial combinations may improve the accuracy of stock index forecasts. Therefore, this study aims to investigate the potential effects of different turnover rates on short-term stock indexes. The first hypothesis is as follows:

H1: To enhance the accuracy of short-term stock index investments, the combination of different conditional time intervals, such as 1R, 5R, 10R, and 20R, into distinct turnover rates, such as 1N, 5N, 10N, and 20N, may yield varying results.

Day traders may have varying preferences for 5- and 10-minute turnover rates to increase their profit margins. The turnover rate in the stock market refers to the total value of the stock index traded during a specific period, which can impact a trader's overall profit over a day or month. Therefore, dynamically distinguishing short-term investments based on different turnover rates is a crucial concern for traders. The second hypothesis is as follows:

H2: Compared to other short-term trading strategies, day trading can potentially yield significant profits.

The main objective of this study is to propose a novel approach for integrating various short-term turnover rates into stock index investments. Day traders need to adopt distinct investment tactics for daily trading when dealing with lucrative short-term investments.

4. Evaluation

To quantitatively measure hypotheses and predict the accuracy of stock index predictions, this study employs machine learning algorithms such as SMO, Deep Learning, MLP, and Random Forest. The training data sets are collected from the TAIEX stock index trading data between January 2, 2019, and August 31, 2019, comprising 35,952 data sets[3].

The study is divided into two parts: first, to evaluate the impact of different turnover rates on short-term stock index investments; and second, to determine profitable strategies for day traders compared to other turnover rates. The independent variables are different time intervals, including 1R, 5R, 10R, and 20R, while the dependent variable is the accuracy of the various turnover rates, including 1N, 5N, 10N, and 20N.

To test both hypotheses, 10% cross-validation will be used with machine learning algorithms—including SMO, Deep Learning, MLP, and Random Forest—to obtain the accuracy of the stock index predictions based on the financial factors used. In the dataset, the remaining sub-samples will serve as test validation data, ensuring that all data is used for training and validation. These algorithms were chosen because they are popular in machine learning and have been widely used in financial applications (Hung et al., 2020).

The performance of the SMO model is evaluated based on its accuracy, which is determined by calculating the true positive (TP), true negative (TN), false positive (FP), and false negative (FN) rates based on the observations of the classifier. The terms positive and negative refer to predictions made by the classifier in relation to the actual observations. The accuracy is calculated as the ratio of correct predictions to the total number of stock index predictions. This metric indicates the proportion of correct predictions and is calculated using Equation (3):

$$Accuracy\ Rate = \frac{TP + TN}{TP + TN + FP + FN} * 100\ \% \tag{3}$$

[3]https://drive.google.com/file/d/10S32fyzHUqbhn4xmCQgpAXTARaeQgucb/view?usp=sharing

5. Discussion

Table 1 provides the performance results for all the different turnover rates. For 1N, the average accuracy across SMO, Deep Learning, MLP, and Random Forest is 75.22%; for 5N, it is 85.65%; for 10N, it is 90.19%; and for 20N, it is 93.25%. The performance of the different turnover rates is also visually represented in Figures 4 to 11, which show the performance of SMO, Deep Learning, MLP, and Random Forest on 1N, 5N, 10N, and 20N, respectively.

Table 1: Accuracy of Different Turnover Rates

	SMO	Deep Learning	MLP	Random Forest
1N	75.22%	75.22%	75.22%	75.22%
5N	85.65%	85.65%	85.65%	85.65%
10N	90.19%	90.19%	90.19%	90.19%
20N	93.25%	93.25%	93.25%	93.25%

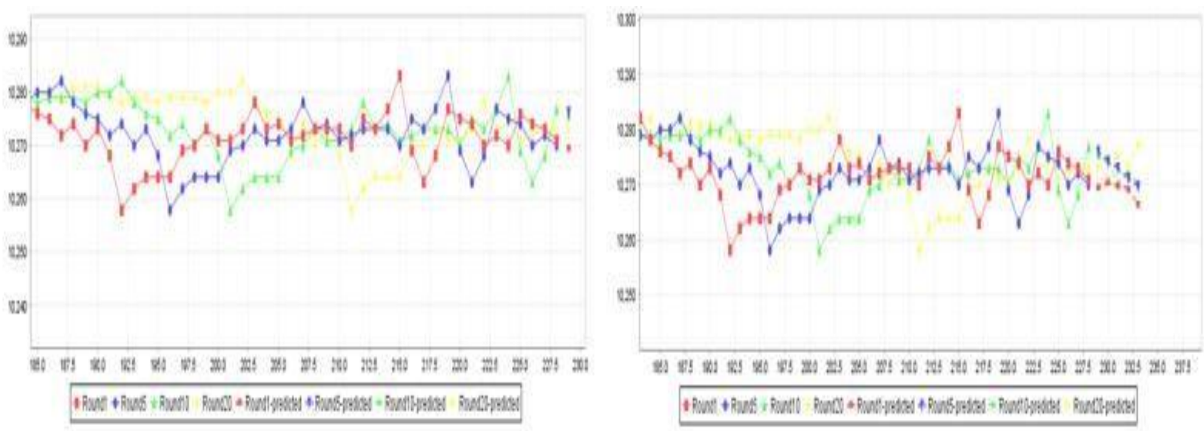

Figure 4: SMO Graphical Representation of 1N and 5N

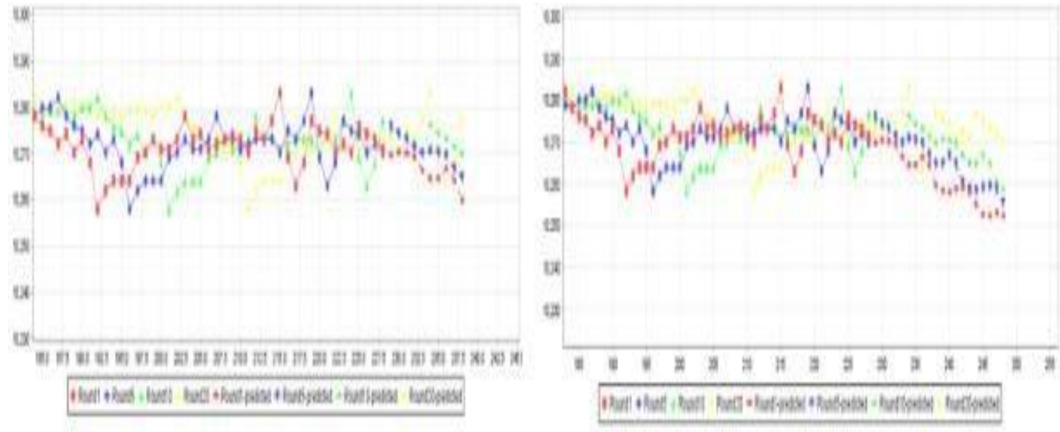

Figure 5: SMO Graphical Representation of 10N and 20N

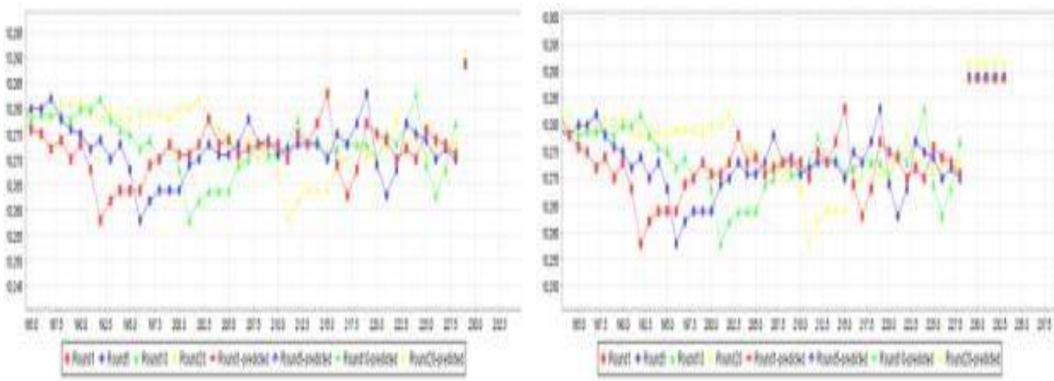

Figure 6: Deep Learning Graphical Representation of 1N and 5N.

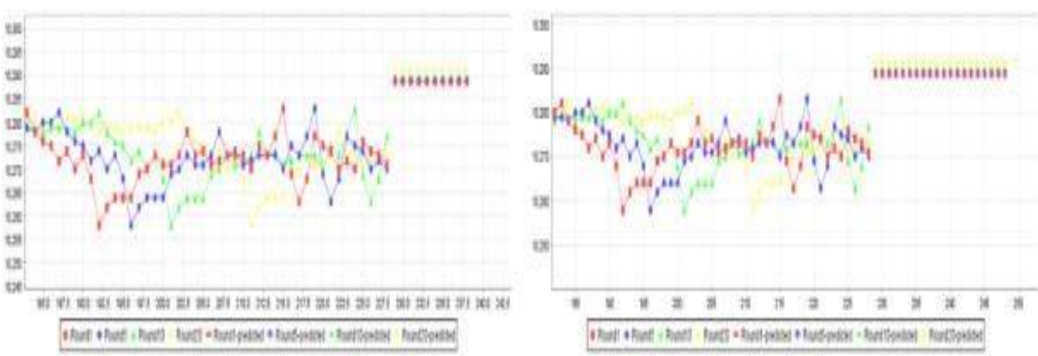

Figure 7: Deep Learning Graphical Representation of 10N and 20N

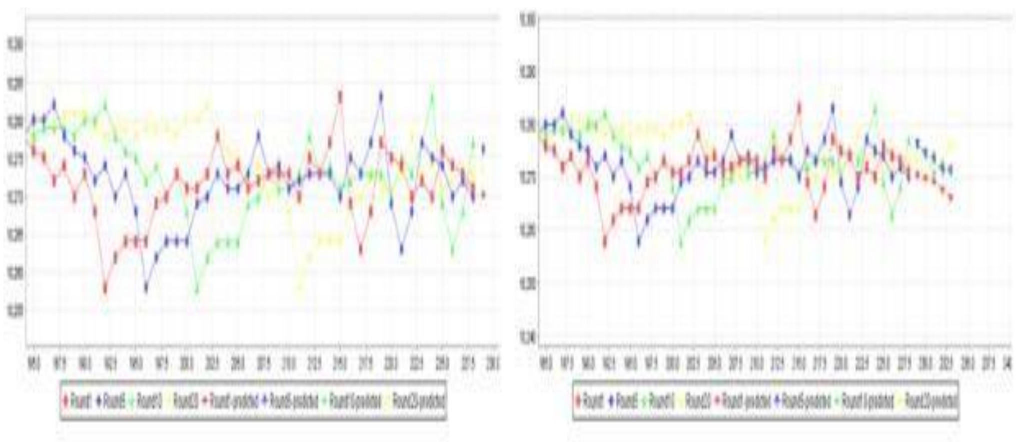

Figure 8: MLP Graphical Representation of 1N and 5N

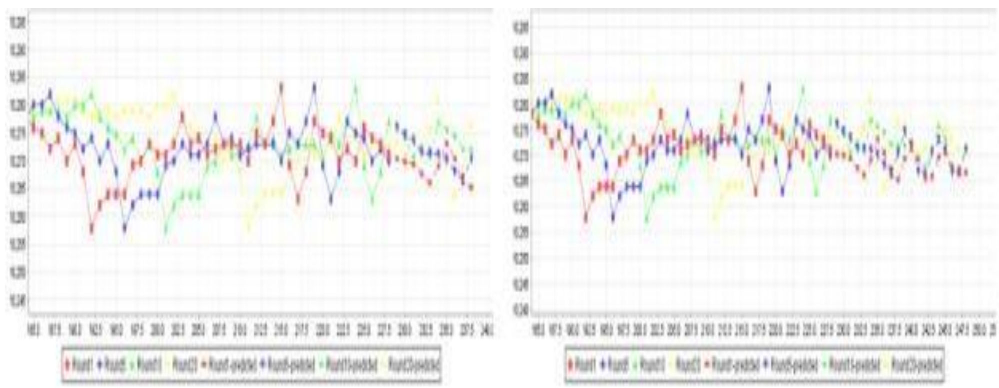

Figure 9: MLP Graphical Representation of 10N and 20N

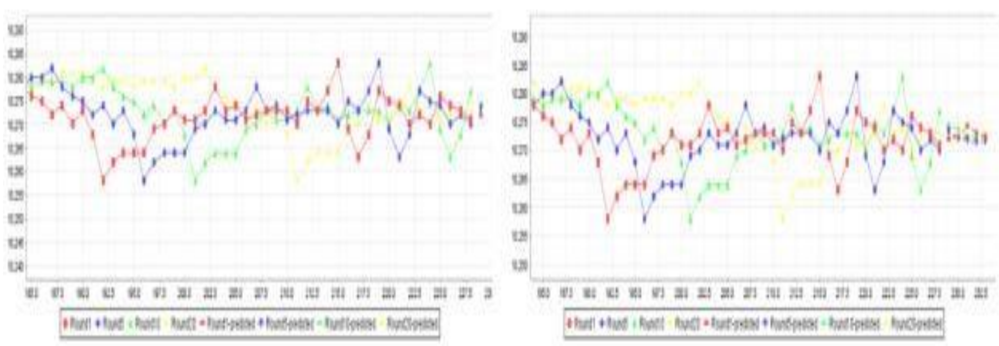

Figure 10: Random Forest Graphical Representation of 1N and 5N

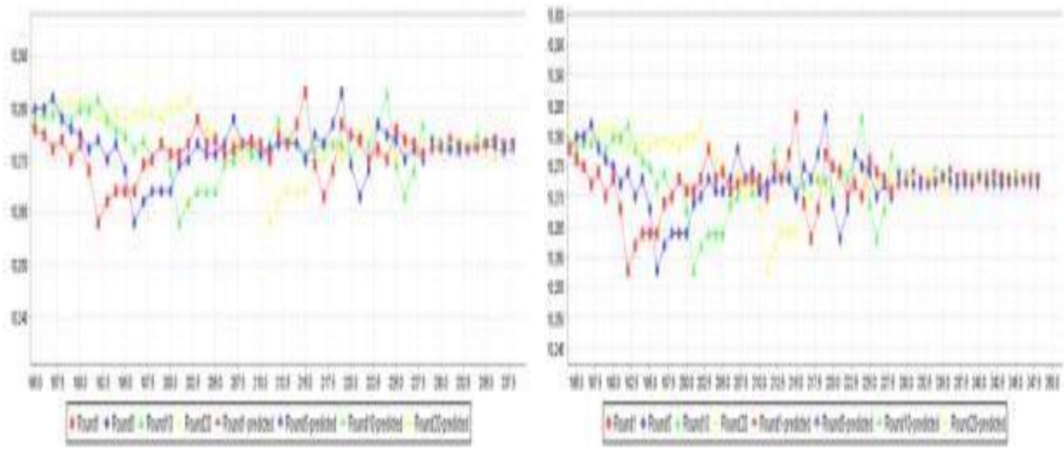

Figure 11: Random Forest Graphical Representation of 10N and 20N

When comparing all turnover rates, it was observed that 20N had significantly higher accuracy than the other turnover rates. To statistically analyze whether the turnover rate level has a positive effect on forecast accuracy, ANOVA was used. The analysis of variance table ($F(3,15) = 1.969E + 31$, $p < 0.01$) indicates significant differences. As a result, the first hypothesis is supported. Further comparisons of turnover rates at all levels were conducted using multiple Tukey HSD tests, revealing that 20N was significantly different from other levels ($p < 0.05$) (Table 2). Therefore, the second hypothesis is also supported.

Table 2: ANOVA of all *P* Values

	1R~20R+1N	1R~20R+5N	1R~20R+10N	1R~20R+20N
1R~20R+1N		0.000	0.000	0.000
1R~20R+5N	0.000		0.000	0.000
1R~20R+10N	0.000	0.000		0.000
1R~20R+20N	0.000	0.000	0.000	

p < 0.05 (The mean difference is significant at the 0.05 level.)

6. Conclusion

This investigation has made significant contributions to the existing literature. Firstly, it confirmed that different turnover rates are an important factor influencing futures index investment, with statistically significant differences. Secondly, the 20N turnover rate achieved an accuracy of approximately 93.25%, demonstrating a high prediction accuracy rate and significant differences compared to other methods tested in this study. Specifically, a 20N turnover rate can help day traders generate more short-term investment profits.

Based on the findings of this investigation, a better suggestion for day traders is to adopt a non-aggressive trading frequency strategy, which involves selecting an appropriate turnover rate to reduce trading frequency. However, the limitation of this study is that although the 20N turnover rate yielded higher accuracy than the others, it is necessary to record a real transaction process to calculate the actual investment profit. In some cases, a lower turnover rate, such as 5N, may increase the transaction time and lead to a higher total profit. Nevertheless, this study provides a valuable direction for future turnover rate prediction research.

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