(IJAER) 2023, Vol. No. 25, Issue No. I, January **e-ISSN: 2231-5152, p-ISSN: 2454-1796**

AI-Powered DMAT Account Management: Streamlining Equity Investments And Mutual Fund Transactions

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ABSTRACT

In light of unusual changes in the worldwide financial setting and the need to mitigate short-term risks, the securities exchange has witnessed a significant surge in intraday traders. These traders often target profound impacts, leading to sudden and irrational market price shifts. Therefore, your role in providing active support to these day traders is not just important but crucial. Your support is greatly valued and integral to reducing trading risks in this process.

The research focuses on using a neural network design combined with a daily market activity framework. This integration allows us to explore unique methods of managing day trading, such as volume and price movements, in Taiwan's weighted index futures. By uncovering the fundamental rules of the futures market, we can develop a model to predict intraday trading directions and implement effective trading strategies.

The results of this exploration show that the precision accomplished through this strategy outperforms that of the arbitrary stroll hypothesis utilized by the benchmark group. The recognizable dissimilarity in results affirms that lower-risk passage focuses inside the intraday market can be distinguished through this methodology. Perceiving these okay sections assists financial backers with overseeing the market, taking a chance, upgrading their benefits, opening doors, and preparing for an encouraging future in day trading.

INTRODUCTION

The vulnerabilities brought about by the Coronavirus pandemic in mid-2020 prompted huge decreases in major worldwide financial exchanges, with the Dow Jones Modern Normal encountering its most critical quarterly drop starting around 1987. Be that as it may, government mediation assisted worldwide business sectors with beginning to recuperate. The mid-2022 Russo-Ukrainian Conflict expanded international dangers in worldwide financial exchanges, especially in the interconnected universe of global money. Taiwan, being necessary for this interconnected framework, was likewise impacted. As a moderately small market, Taiwan is particularly defenceless against news influences, prompting critical financial exchange instability and short-term risk.

To lower down this risk, financers have progressively gone to daily trading, and it’s called "intraday trading," which includes balancing exchanges around the same time to close all situations toward the closing of the trading day. While this technique can assist with staying away from mishaps from short-term risk, the ascent in intraday trading members has prompted a significant expansion in share trade. As indicated by the Taiwan Stock Trade, the quantity of offers exchanged this way rose decisively, from 0.36% on January 6, 2014, to 26.67% on July 18, 2023. This flood in intraday trading frequently brings about unreasonable stock costs driven by member feelings, expanding the potential for benefit and chance.

Researcher Eugene Fama's Arbitrary Walk Speculation states that momentary stock value vacillations are irregular and don't pursue unsurprising directions or examples. Per this speculation, stock costs at some random times are not impacted by past cost developments, making momentary market expectations testing and underscoring the significance of long-haul venture and expansion. While the assumption proposes irregularity in transient vacillations, it similarly recognizes the impact of an organization's essentials and macroeconomic variables on long-haul patterns.

On the other hand, Peter Steidlmayer's market rationale hypothesis contends that market advancement isn't arbitrary. He recommends that market costs are impacted by members with various periods who participate in latent or dynamic offerings, accordingly moulding market developments. Steidlmayer's hypothesis stresses that differing member viewpoints keep the market from taking special care of all needs simultaneously, and no single cost can address a fair worth.

From the market rationale hypothesis perspective, the intraday market is viewed as a fair cost range, frequently called the "esteem region." Inside this area, merchants can exploit expected benefits by decisively purchasing beneath and selling over the laid-out esteem, consequently recognizing lower-risk intraday section focuses. Perceiving these focuses can improve the probability of stable returns. Steidlmayer also noticed that market value vacillations are impacted by silly financial backer behaviour, featuring the non-direct connection between risk and prize.

Intending to this non-linearity, computerized reasoning approaches, especially neural networks, translate rules inside questionable conditions. Neural networks gain and build prescient models from verifiable information, considering experiences in dynamic market conduct and the age of market-bearing expectations. This study utilizes neural networks to help intraday brokers by alleviating market gambles and giving necessary devices to pursue informed trading choices.

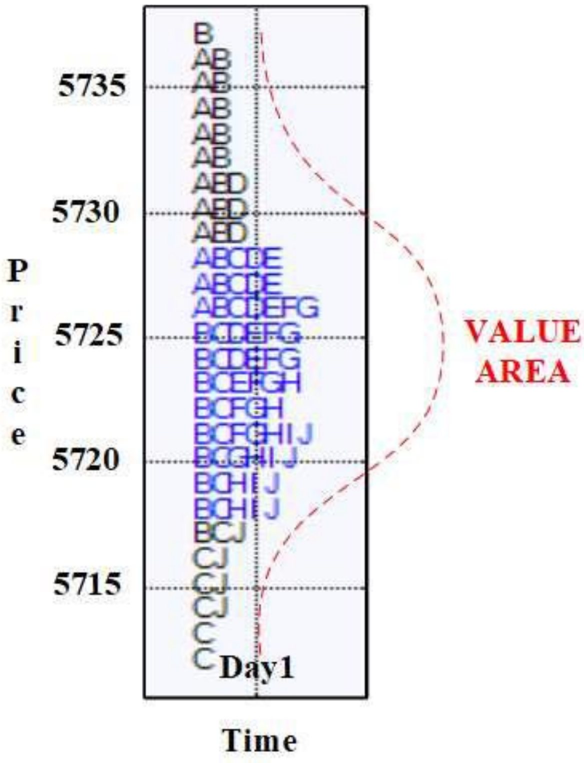

Fig 1. The TPO graph addresses the general aspects of time, price, and opportunity.

We can obtain various information from the intraday TPO chart generated by the market. Some important terms are defined below:

- Opening Balance: This refers to the price range established by buyers and sellers reacting to the news before the market opens. In Fig. 1, the initial balance range spans from 5717 to 5737 during periods A and B.
- Range Extension: This describes the price activity above or below the initial balance range.
- Point of Control (POC): This is the price level with the highest number of TPOs (Time Price Opportunities). In Fig. 1, the POC is at 5726.
- Tail: This represents price activity within the range of a single TPO but outside the value area. In Fig. 1, the buying tail range is from 5712 to 5713.

The cost range for the last time period, J, spans from 5714 to 5721. The TPO (Time Price Opportunity) chart reveals more than just intraday activities, as the market is in constant evolution. Therefore, we incorporate the TPO chart from the previous day into our analysis of the current day. The TPO charts of consecutive days (as shown in Fig. 2) are particularly important at the start of Day 2, as buying activity can be categorized into initial buying and responsive buying, similar to how selling activity is divided into initial selling and responsive selling.

- On Day 2 Initial Buying: The buyer's position in this range is above the value area of Day 1, indicating aggressive buying power. From 5716 to 5736 is the initial buying range.
- Open Buying: The buyer's position in this range is also above the value area of Day 1, responding to the buying power triggered by the lower price than Day 1. From 5700 to 5715 is the responsive buying range span.

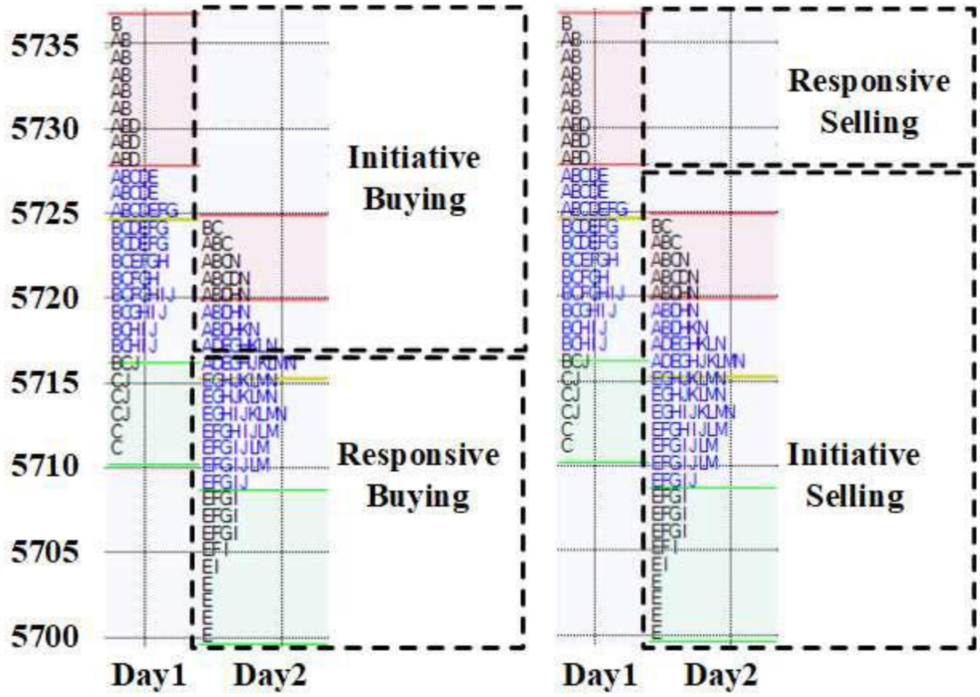

Fig 2. Chart based on Market action.

Firich [7] examined the market given the underlying equilibrium of the US securities exchange, recognizing where the cost breaks the underlying equilibrium as an excellent exchange of an open door. If a dealer can notice the market course, this becomes a chance to put in a request with a high likelihood of progress.

Chen et al. [8] used market profile hypothesis and specialized examination to foster a neural network model, upgrading prescient exactness and productivity in the TAIEX fates market. Their discoveries demonstrate unrivalled transient execution for subjective market profile pointers, while quantitative pointers succeed in long-haul pattern expectations.

Wu et al. [9] analyzed the market based on the double distribution pattern day of the Taiwan Capitalization Weighted Stock Index (TAIEX) futures. Their results showed an accuracy of 57.45% and returns of 24.09 points. Huang et al. [10] utilized the point of control (POC) of TAIEX futures, applying shifts across various trading days to identify short-term entry and exit points. The historical POC served as a significant benchmark for entry points.

The methods discussed above are limited to the TPO chart of a single trading day. However, this approach transcends that limitation by integrating the TPO chart of the previous day into the Activity Chart. This innovative leap, based on a more comprehensive understanding of the market's dynamics, acknowledges that the market operates continuously and is influenced by the events of the previous day. This recognition generates interest and excitement in the potential of this new strategy.

In conventional TPO Diagrams, purchasing activity is treated as a particular occasion. Conversely, our Action Outline partitions purchasing activities into dynamic and inactive situations. Dynamic purchasing implies proactive support on the lookout. Interestingly, aloof purchasing might be impacted by variables, such as the pattern from the earlier day or other economic situations, provoking merchants to purchase inactively.

By considering the progression of market movement, our technique provides a more far-reaching and dynamic market examination. This improved comprehension prompts more exact forecasts and translations of market changes, empowering dealers to adjust deftly to different economic situations. Subsequently, our methodology catches market intricacy and inconstancy, offering reasonable bits of knowledge for informed trading decision.

Resilient Propagation

It is a regulated learning heuristic planned explicitly for feedforward artificial neural network. Riedmiller and Braun created it in 1992 [11]. Since its origin, Rprop has been generally applied across different areas [12], [13], [14].

Shastri et al. [15] presented a technique that starts with calculating opinion scores utilizing a gullible Bayes classifier. Neural Networks take care of these scores and verifiable stock datasets. The models, which consolidate inputs from opinion examination and authentic information, exhibit the capacity to conjecture stock costs. That's what exploratory outcomes showed; the exactness surpassed 90% in ideal situations. Jothimani and Yadav [16] proposed usage of neural network and SVM to foresee stock costs. They tried the model's presentation on the smart list parts north of eight years (2008-2015), extracting a better speculation result than the conventional "purchase and hold" procedure.

Mitilineos and Artikis [17] proposed a group of neural networks prepared and streamlined using a genetic algorithm to foresee future securities exchange file values. Their methodology demonstrated better than standard benchmark advances. Examining fake (computational) knowledge techniques offers solid help for specialized systems in monetary business sectors.

APPROACHES

The exploratory flowchart of this study is shown in Figure 3, and is described in detail below. The historical TAIEX futures data served as the primary data source for this research model. This data was pre-processed to convert daily historical information into one-minute segment frames (Figure 4). This framework was then transformed into a one-minute market activity chart (Figure 5). The dataset was partitioned using a moving window to generate feature values for n-minute intervals (n = 5, 15, 30, and 45).

These features were then input into a flexible neural network for mapping. With a continuous data feed, market output signals were generated at 15, 30, and 45-minute intervals. The experimental groups received trading signals and executed random trading transactions accordingly. The signs were shipped off an irregular module, and the trading methodology led exchanges. The exhibition was then assessed.

During information preprocessing, we determined the information and result values. The estimation of information boundaries was partitioned into three stages:

- Estimating Action of Market Structure
- Calculating Dynamic Physical Behaviour
- Data Normalization

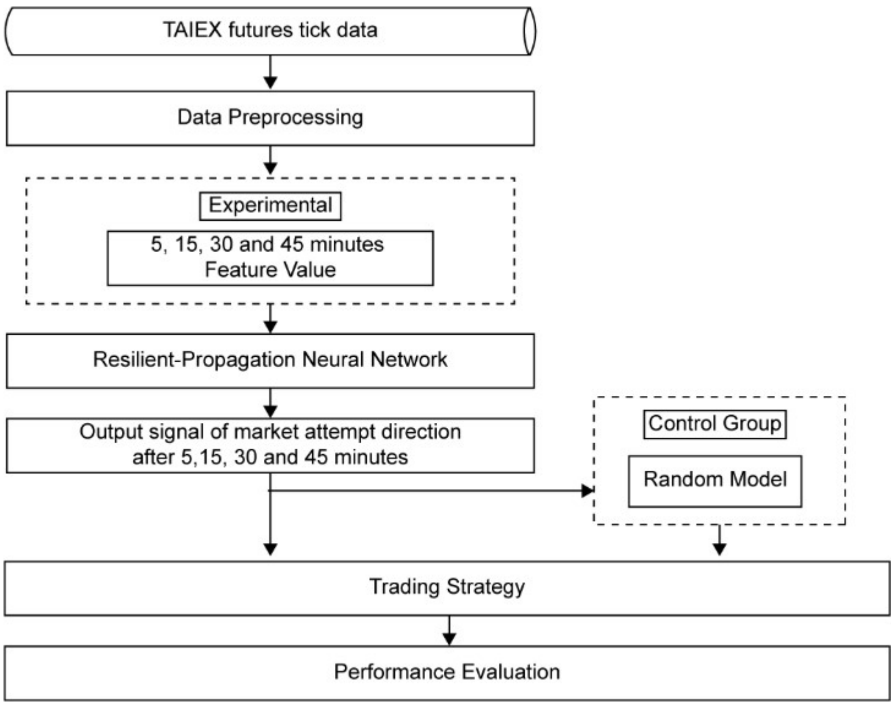

Fig 3. Research flow.

Preprocessing of Data

The cycle began with the utilization of the TAIEX prospects tick dataset at an N-minute stretch to determine the high and low-cost range, resulting in a reference chart. Figure 4 shows how TPO letters were assigned to create a sectioned outline structure based on this high and low range. Figure 5 demonstrates the strategic process of drawing the TPOs from the sectioned diagram onto the appropriate cost segments over the long term to produce the market action chart.

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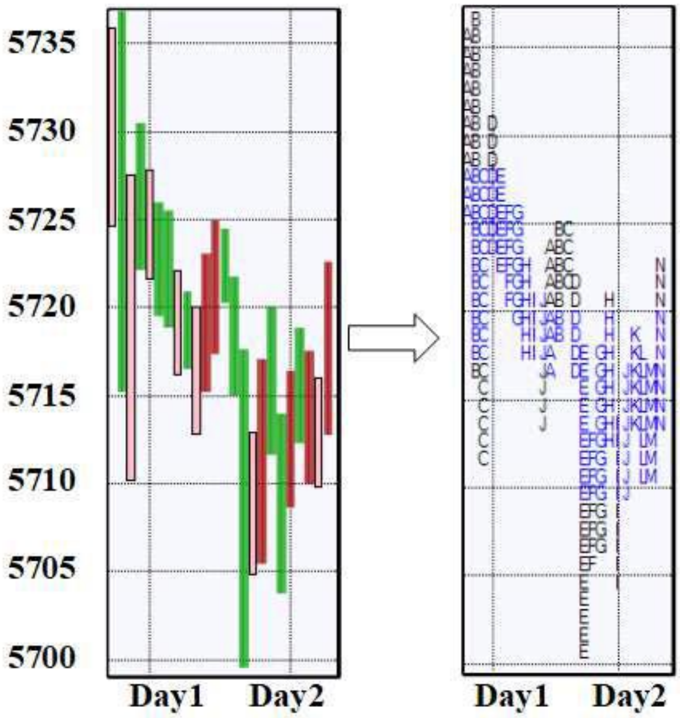

Fig 4. A segmented chart structure was created from the TAIEX data.

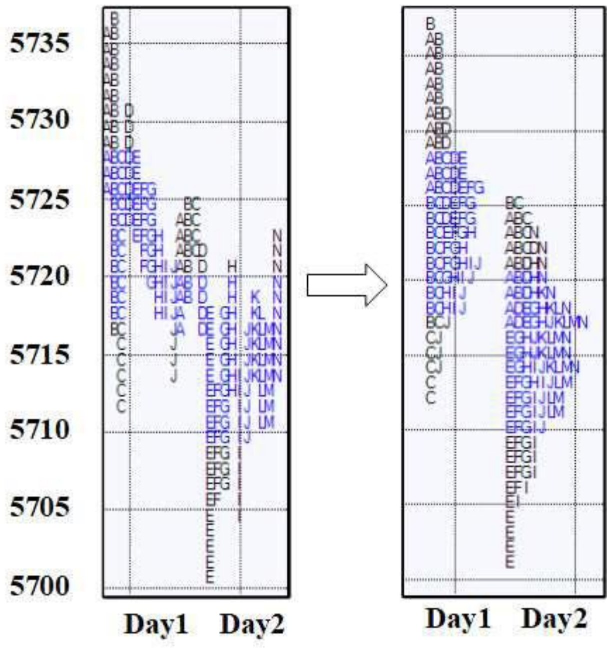

Fig 5. Transformation of portioned into market movement outline structure.

According to Table 1, we used 15 distinct market activity structures derived from the market activity chart to generate 45 input feature values.

Dynamic Actual Way of behaving and Information Standardization

Chen and Hsu [18] argue that combining dynamic fundamental lead changes can improve the analysis of causality in financial components and increase the stability of neural network learning. The cause-and-effect relationship between past and future data points reveals significant dependencies in time series, which enhances the overall dynamics and patterns of the data and shows how previous events impact future ones.

TABLE 1. Structures values removed utilizing the market action structure.

No	Attribute Value	Activity of Market	Structure
1	1. rv(t), 2.fp(t), 3.sp(t)	Responsive Selling	Tail
2	4. rv(t), 5.fp(t), 6.sp(t)	Responsive Selling	Range Extension
3	7. rv(t), 8.fp(t), 9.sp(t)	Responsive Selling	Extension
4	10. rv(t), 11.fp(t), 12.sp(t)	Initiative Selling	Tail
5	13. rv(t), 14.fp(t), 15.sp(t)	Initiative Selling	Range Extension
6	16. rv(t), 17.fp(t), 18.sp(t)	Initiative Selling	Extension
7	19. rv(t), 20.fp(t), 21.sp(t)	Initiative Selling	POC
8	22. rv(t), 23.fp(t), 24.sp(t)	Initiative Buying	POC
9	25. rv(t), 26.fp(t), 27.sp(t)	Initiative Buying	Extension
10	28. rv(t), 29.fp(t), 30.sp(t)	Initiative Buying	Range Extension
11	31. rv(t), 32.fp(t), 33.sp(t)	Initiative Buying	Tail
12	34. rv(t), 35.fp(t), 36.sp(t)	Responsive Buying	Extension
13	37. rv(t), 38.fp(t), 39.sp(t)	Responsive Buying	Range Extension
14	40. rv(t), 41.fp(t), 42.sp(t)	Responsive Buying	Tail
15	43. rv(t), 44.fp(t), 45.sp(t)	None	Rotation factor

In this examination, the information factors were determined as unique actual conduct changes to address the power and heading of energy change during the computation. At minute t, the first-order physical change is defined as: briefly t and market movement structure raw value rv(t).

$$fp\ (t) = rv\ (t) - rv\ (t-1) / \ rv\ (t-1) \qquad (1)$$

The second-request actual change on minute t is characterized as: for a given minute t and the physical change of the first order.

$$fp\ (\breve{t}).\ sp\ (t) = fp\ (t) - fp\ (t-1) \qquad (2)$$

The following is an illustration of a dynamic physical behaviour calculation.

TABLE 2. Estimation aftereffects of the dynamic actual way of behaving.

rv(t)	fp(t)	sp(t)	Datetime	T
28	Null	null	2023/09/12 9:00	t-2
25	-0.107142857	null	2023/09/12 9:01	t-1
29	0.16	0.267142857	2023/09/12 9:02	t
21	-0.275862069	-0.435862069	2023/09/12 9:03	t+1

Neural networks are trained on diverse datasets. To mitigate differences in units or large data gaps, we standardized the information to upgrade learning adequacy. Initially, the Min-Max Normalization method was used to scale the data to the [0, 1] interval.

The model in this study was meticulously developed using the C# programming language, implementing a resilient-propagation neural network through Encog's library [19]. This careful approach instils confidence in the reliability of the model. It utilized 45 input feature values to predict a single output value. We configured our neural network based on findings by Zhang et al. [20] on the effectiveness of neural networks with a single hidden layer, and Davies [21] suggested determining the optimal number of nodes through trial and error. This led us to set 22 hidden layer nodes and 300 epochs and employ the sigmoid activation function as neural network parameters.

The trained neural network's output ranged between 0 and 1. We employed a threshold mechanism to enhance prediction accuracy: predicted output values above 0.70 indicated a strong long signal, while those below 0.25 suggested a strong short signal. Values between 0.25 and 0.70 were considered neutral and did not trigger any trading action.

Following neural network training, we applied the model to simulate market operations using specific trading strategies. This practical application allowed us to generate a final profit and loss analysis report, providing a real-world evaluation of the model's effectiveness. This emphasis on practical application will make the audience feel the real-world relevance of the research.

The intraday trading system utilized in this examination is nitty-gritty as follows:
1. The most significant position held, with an exchange cost of two places.
2. Output of a long signal: Cover short positions and purchase file prospects at the initial cost in the following moment.
3. Short output signal: Sell index futures at the opening price in the following minute to cover long positions.
4. Stand firm on and close the situation: When the holding time has passed, close the position at the opening price in the following minute.
5. Position closing at market close: If a position is not yet held at 13:30, close it.

At last, this study utilized two assessment techniques:
- Good and bad indicators to compare performance.
- Simulated trading performance to measure the model's effectiveness.

Accuracy was figured by partitioning the number of productive exchanges (where the benefit surpassed zero after deducting two focuses) by the complete number of exchanges led during the reenacted transaction time frame.

$$Accuracy = \textbf{Total Number Of Transactions/Number of Profitable Transactions}$$

The profit calculation includes separating the aggregate benefit amassed all through the reenacted trading period by the complete number of exchanges directed inside that particular trading period. The computation recipe is as follows:

$$\textit{Average Profit} = \textit{Total Profit/ Total Number of Transactions}$$

This condition, a practical and valuable asset, provides a quantitative measure. It offers experience in the money-related execution of an exchange methodology by assessing the typical benefit produced per exchange over the predefined exchange period. This measurement is important in deciding the achievement and adequacy of the exchange procedure utilized in the recreation.

RESEARCHES

The model was set up in this study with four experimental groups and a control group. Following Kearns' suggestion [22], roughly 20% to 30% of the dataset was allotted for testing to guarantee an ideal execution assessment. This essential portion aligns with best practices in the exploratory plan, working with a robust evaluation of the model's viability.

The dataset, from October 3, 2022, to September 28, 2023, incorporated 71,823 one-minute data of interest. The dataset was divided into training and testing sets to make model training and evaluation easier. The preparation dataset covered October 3, 2022, to July 21, 2023, with 57,452 critical pieces of information. The testing dataset included information from July 24, 2023, to September 28, 2023, containing 14,371 data of interest (as portrayed in Fig. 6).

Both the trial and control groups adhered to exhaustive and predictable preparation and testing periods. In the trial groups, in light of the neural network trading signs and systems, positions were purchased, held for 5, 15, 30, and 45 minutes (with four events of every term), and closed. Total profit or loss computations included dealing with and trading charges, guaranteeing a solid evaluation of the model's exhibition.

This study makes it difficult to understand random walk speculation by recommending that market costs are affected by different trading ways of behaving, displaying perceptible examples and rules. In contrast, a benchmark group utilizing an irregular exchange model and the proposed neural network model were used. This correlation will evaluate and differentiate their assets and shortcomings concerning accuracy.

The random trading model's trading strategy consisted of choosing at random whether to trade long or short futures based on when the neural network model showed trading signals. For example, for a purchase-and-hold system enduring 5 minutes, the model entered the market haphazardly founded on signals from the trial bunch. On the off chance that the arbitrarily produced esteem by the benchmark group surpassed 0.5, it started long positions; assuming underneath 0.5, short positions were started. A new assessment was prompted by an exact value of 0.5. Taking into account handling fees and transaction taxes, the random trading model's trading unit settings and strategies were comparable to those of the experimental group.

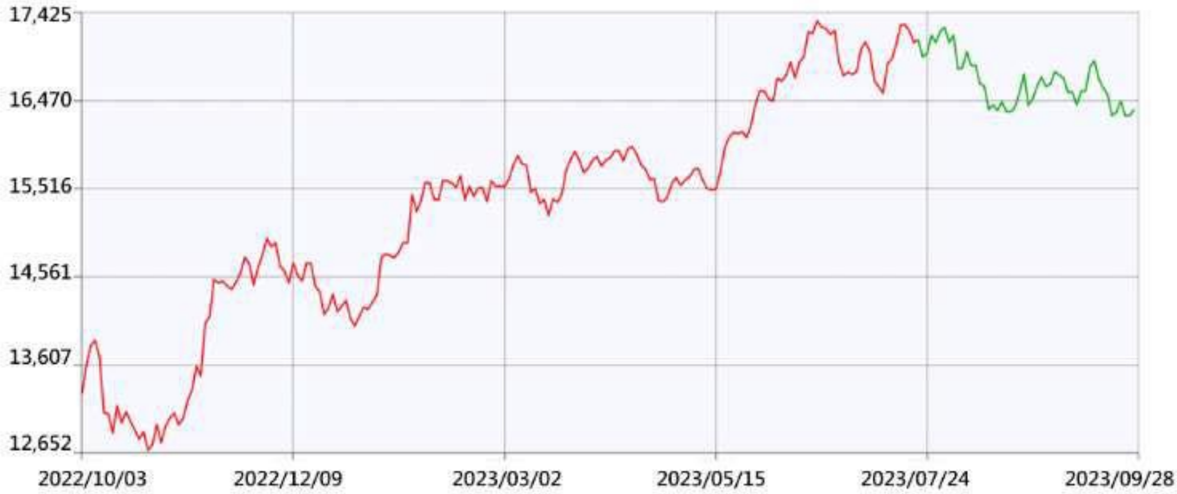

Fig 6. Pattern graph during the trial time frame

To overview how values of components withdrew from the market development frame across different periods influence the precision of forecasting various ranges, we request the test information be divided into four groups: A, B, C, and D. To guarantee unprejudiced cognizance of the model's presentation results, each model from the exploratory and control gatherings will be freely rerun multiple times.

The neural network received five one-minute periods of market activity structure from experimental group A as input variables. After 30 executions, the results of these experiments are summarized in Table 3, providing statistical insights.

TABLE 3. The outcomes of group A's experiment

Accuracy	Total Profit	Transactions	Average Profit
0.526072330	540	2,378	0.227082
0.716483516	8,356	910	9.182418
0.671823722	26,427	2,133	12.389590
0.672734468	40,606	2,527	16.068860

The results include the basic impact of holding time on model accuracy. Astoundingly, the most essential accuracy of 71.64% was achieved at the 15-minute holding stretch, immovably followed by the 45-minute term. This features how fundamental holding periods augment the model's prescient accuracy, specifically the 15 minutes.

The neural network received 15 one-minute intervals of market activity structure from experimental group B as input variables. Table 4 provides a summary of these experiments' outcomes:

TABLE 4. Trial results of group B.

Accuracy	Total Profit	Transactions	Average Profit	Holding Periods
0.523187908	2,544	2,544	0.873926	5 minutes
0.731663685	18,299	1,677	10.911750	15 minutes
0.672222222	30,805	2,340	13.164530	30 minutes
0.705392810	50,198	3,004	16.710390	45 minutes

Table 4 offers a total diagram of the display of preliminary gathering B across various holding periods. Surprisingly, the champion result was an extraordinary exactness of 73.17% during the 15-minute holding term.

The brain network got 30 one-minute times of market movement structure from exploratory gathering C as information factors. The consequences of these tests are summarized in Table 5:

TABLE 5. The results of group C's experiment.

Accuracy	Average Profit	Holding Periods	Total Profit	Transactions
0.520529071	1.390466	5 minutes	5,046	3,629
0.643268124	6.990410	15 minutes	18,224	2,607
0.631189264	9.328552	30 minutes	40,318	4,322
0.659565024	13.932530	45 minutes	62,780	4,506

Trial bunch C showed its most elevated precision while holding for 45 minutes, firmly followed by the 15-minute term. Notwithstanding, the model's precision in anticipating market variances inside the underlying 5-minute time span was similarly lower at 52.05%. This demonstrates that the model's predictive capabilities vary depending on the holding time, with 45 minutes showing the highest accuracy.

TABLE 6. Test group D outcomes.

Accuracy	Average Profit	Holding Periods	Total Profit	Transactions
0.536866359	0.880843	5 minutes	2,676	3,038
0.595289079	7.014276	15 minutes	19,654	2,802
0.626232742	9.652367	30 minutes	39,150	4,056
0.644553073	11.609870	45 minutes	49,876	4,296

Group D items used 45 one-minute times of market activity structure as information factors for the neural network. Table 6 provides a summary of these experiments' outcomes:

When held for 45 minutes, experimental group D achieved its highest accuracy, 64.45%. However, the accuracy was less than 53.68% for the 5-minute holding period. These results demonstrate that model performance varies across holding times, with 45 minutes providing the best accuracy.

When the accuracy across the four experimental groups is examined, it becomes evident that utilizing 15 one-minute times of market movement structure and a 15-minute purchase-and-hold technique yields improved results (as shown in Fig. 7). Under these settings, we led tests using verifiable information from TAIEX Fates throughout recent years (as outlined in Fig. 8). The dataset setups are definite in Table 7.

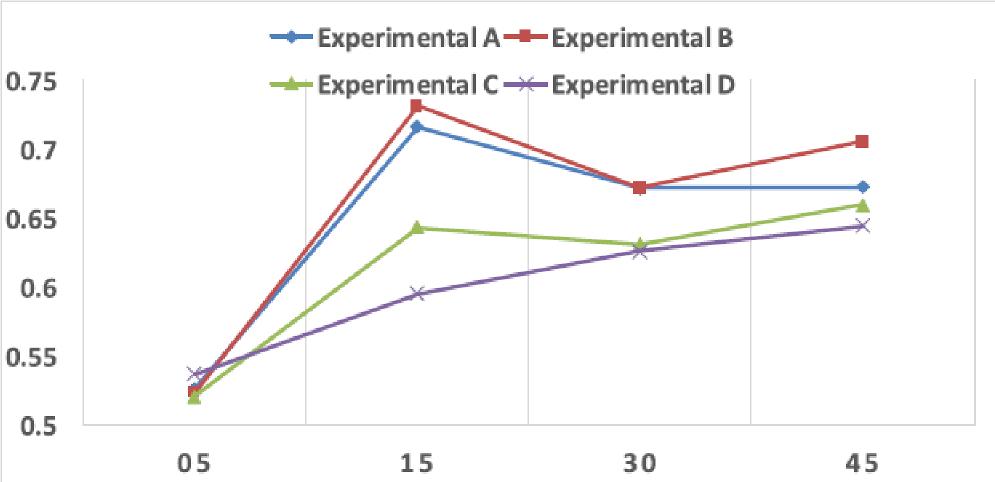

Fig 7. Accuracy analysis chart.

TABLE 7. Settings for the dataset from 2018 to 2022.

		Testing Dataset		Training Dataset		
Year	Record	Starting Date	Ending Date	Starting Date	Ending Date	Record
2018	58,649	2018/07/24	2018/10/01	2017/10/02	2018/07/23	14,670
2019	58,352	2019/07/22	2019/10/01	2018/10/01	2019/07/19	14,668
2020	58,651	2020/07/23	2020/09/30	2019/10/01	2020/07/22	14,970
2021	58,352	2021/07/23	2021/10/01	2020/10/05	2021/07/22	14,671
2022	58,652	2022/07/22	2022/09/30	2021/10/01	2022/07/21	14,970

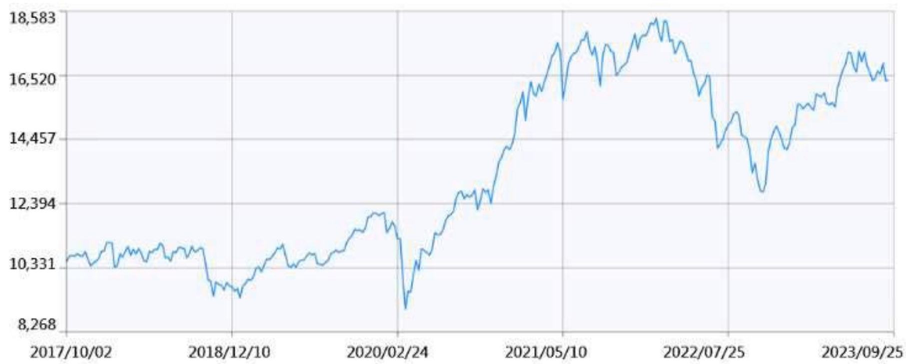

Fig 8. Chart of week-by-week closing prices throughout the course of recent years.

To approve the hearty presentation of our proposed strategy, we led 30 redundancies of tests every year throughout recent years, bringing about the accompanying average results. The discoveries reliably show an exactness above 60% yearly, topping at 68.68% in 2018. This consistent trend across various market scenarios demonstrates our method's dependability and efficacy. For a point-by-point examination of the trial results, including all-out benefits, exchange volume, and expected benefits, kindly allude to Table 8. This exhaustive examination reaffirms the flexibility of our technique and its actual capacity as a significant device in monetary direction.

This study's primary objective is to demonstrate the distinct market forces influencing stock price trends. The argument against the random walk hypothesis in stock prices is supported by effective measurable tests showing that the exploratory gathering model performs better compared to the benchmark group-irregular exchanging model generally speaking.

Sticking to the possible hypothesis, the dissemination of the example typically looks like an ordinary conveyance when the example size surpasses 30. Given the obscure, generally speaking, difference, this review utilizes an F-test to survey the equity of changes between the two populaces before leading an autonomous example T-test. This thorough methodology guarantees the precision and unwavering quality of the measurable examination directed in this review. The importance level of 0.025 is utilized for assessing difference correspondence, with the F-test results point by point in Table 9. Following affirmation of, by and large, change fairness, both the test and control bunches went through T-test examinations.

The null hypothesis filled in as the benchmark for the T-test, which was utilized to decide if the exactness of the exploratory gathering surpassed that of the benchmark group. The results presented in Table 10 exhibit that the relationship of precision between the preliminary bundle and the benchmark bunch yielded a significance level beneath 0.05, provoking the excusal of the invalid hypothesis. These T-test results declare that the dominating precision of the exploratory brain network model diverged from the control, which is expressly the sporadic exchanging model. This develops the presence of conspicuous market impacts affecting directional examples, highlighting the departure from the erratic walk hypothesis in money-related business areas.

CONCLUSION

In synopsis, this examination has investigated the complexities of day-trading Taiwan's weighted record fates amid a powerfully changing worldwide financial scene. The review planned to address the difficulties presented by uplifted market instability and short-term chances, offering a nuanced way to deal with intraday trading.

Predicting intraday market movements has been made possible by combining a daily market activity structure with a neural network architecture. The developed model showed enormous precision, beating the sporadic walk speculation used by the benchmark group.

By differentiating speculations, for example, the Irregular Walk Theory with the Market Rationale Hypothesis, this examination has given an exhaustive comprehension of the elements impacting transient changes in stock costs. Using (TPO) charts and daily market observations from the Market Profile, it was easier to find essential market parameters for the neural network model's features.

The introduction of a dynamic, genuine way of behaving, data normalization, and nearby flexible multiplication (Rprop) as an oversaw learning heuristic redesigned the model's trustworthiness and reasonability. The 15-minute holding span was especially encouraging in the trial results, which reliably showed high exactness across the different holding times.

The method consistently outperformed the control group over five years, demonstrating robustness and dependability. Measurable examinations, including T-tests, validated the huge precision contrast between the exploratory and control gatherings, testing the idea of an irregular stroll in monetary business sectors.

In conclusion, the framework for decision support in intraday trading that combines market logic with artificial intelligence, specifically neural networks, is compelling. This examination contributes significant experiences to the field, offering a modern way to explore the intricacies of dynamic monetary business sectors. This model could be further refined and expanded upon in future research efforts, advancing AI's application and comprehension in financial market analysis.

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