Predicting Price Trends Combining Kinetic Energy and Deep Reinforcement Learning

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Abstract

Investing in the stock market and Forex can be lucrative, but it is important to approach it with caution and a clear understanding of the risks involved. Predicting the direction of prices in financial markets is a complex task, and there is no guaranteed way to do it. One innovative approach that has been proposed involves using a combination of the kinetic energy formula and indicator signals to predict prices, besides another predictions using deep reinforcement learning (DRL). This approach has led to the development of the TDQN method, which incorporates the kinetic energy of stocks/currencies as a condition rule in the Trading Deep Q-Network algorithm. The proposed approach, TKDQN method, has shown promising results in terms of accuracy and profitability, outperforming previous versions based on several metrics.

Keywords: Prediction; Price movement; Forex; Deep Reinforcement learning; Artificial intelligence; Algorithmic trading, Stock market

1 Introduction

Since the introduction of artificial intelligence (AI), its worldwide applications have been expanding due to its accurate algorithms. The stock market has the potential to utilize AI models to achieve better predictions for two main reasons. Firstly, the accuracy of AI models is supported by evidence. Secondly, AI can effectively process vast amounts of data, further enhancing its predictive capabilities (Gülmez, 2023; Milana and Ashta, 2021).

Using AI in financial markets has the potential to change the behavior of market participants as they are increasingly compelled to become more open and collaborative. This shift is driven by the need to effectively integrate AI models into trading strategies, which in turn requires a more collaborative and transparent approach to market participation. (Ashta and Herrmann, 2021).

Stocks and cryptocurrencies have gained popularity among millions of investors worldwide, who strive to earn higher profits regardless of what they trade and where. In this context, accurate predictions play a vital role in making informed investment decisions. Predictive analysis can help answer key questions such as which stocks to choose, when to invest, and how much to invest. A higher accuracy rate in predictions can lead to a greater return on investment (ROI), making it a critical factor for investors looking to maximize their profits (Théate and Ernst, 2021).

Prediction is one of the most challenging activities, and when it is related to financial markets, it becomes even more difficult due to the added complexities and risks involved (Chou and Truong, 2019). Making accurate predictions in financial markets is a challenging task, as the prices of stocks and currencies can be influenced by a wide range of factors such as news, economics, politics, and more (Nassirtoussi et al., 2015).Accurately predicting financial market prices is a complex task, as prices of stocks and currencies are influenced by a wide range of factors, including news, economics, politics, and more (xian Wang et al., 2022). These factors are often intricate and difficult to analyze. Furthermore, financial market prices are constantly changing, and the fluctuations can occur at any moment, often related to significant wealth. As such, predicting market movements requires a nuanced understanding of these complex and ever-changing factors (Wang et al., 2022; Anagnostidis et al., 2016). On the other hand, the trades might be influenced by the feelings such as fear and greed (Lin et al., 2018a,b). Besides, they cannot monitor markets all the time, in effect, 24 hours per weekday by themselves (Yang et al., 2018). Furthermore, there are a vast amount of data as input that is required to be analyzed for making a decision. Because data production is related to time, it is totally dynamic and the changes are rather fast. Therefore the investors must adapt themselves to it, or use automated traders or agents, as we strongly recommend. In addition to enabling more accurate predictions, the use of automated traders or agents can lead to higher profits for investors, making it a recommended solution for navigating the challenges of financial markets (Gülmez, 2023; Théate and Ernst, 2021; Park and Lee, 2021; Li et al., 2019).

The challenge in this concept is basically prediction which is well deserved to solve in terms of profitability(Hu et al., 2021). Because it is infuenced by a number of factors which can be economic, political, or psychological. In other words, price prediction or even the trend of it would be so challenging (Maneejuk and Srichaikul, 2021; Erturul and Taluk, 2018; Qin et al., 2016; Zhang, 2016; Wang et al., 2012). Additionally, The direct relationship between accurate predictions and profitability in financial markets is widely recognized, highlighting the importance of making informed investment decisions (Hu et al., 2021). In general, the financial markets embody utter chaos deeply inside (Speth et al., 2010). Dynamic and rather constant changes are among the feature of the markets, which means they are changing all the time (Lei et al., 2020). Moreover, the human trader could involve their emotional perspective in dealing. Among them, fear and greed can stand out (Lin et al., 2018a).

The growing body of literature reveals that this research area has remained an open problem. It is such a challenging problem that even one algorithm cannot solve the prediction on all indexes even in one financial market (Wang et al., 2021). Numerous researchers are interested in spending time on it because no one can claim they guarantee a one hundred percent accurate strategy. Inevitably, some mistakes exist in the case of prediction, while the researchers are trying to minimize them.

Automated trading is one of the most noticeable methods in the related growing body of literature. Based on the fact that they include some algorithms from Artificial intelligence science (Gülmez, 2023). Although, at first machine learning models were trendy, nowadays Reinforcement learning and its deep version are showing more promising results (Théate and Ernst, 2021). Besides, deep learning methods are wildly used in this area. Among them, LSTM is the most popular one. Its basic structure can be considered a suitable model for time series. Besides, CNN, DNN, RNN, and the rest algorithms in DL are used (in terms of usage frequency, they are respectively ordered.) (Hu et al., 2021). There is a trend for using DL methods, which the experimental comparison between them and other prediction methods is required (Jiang, 2021).

On the other hand, Physics in this concept can be used for providing some information about the behavior of traders on the markets (Lin et al., 2018a). The most intriguing fact about it is related to stock shares. It is accepted that each participle in the financial market has its kinetic energy. To be more precise, classic formulas of Physics are used for modeling the financial market based on basic information. An open question here is the way of determining the sign of the kinetic energy (Khrennikov, 2010), which is tried to answer in the current paper. Understanding the behavior of traders in financial markets through the use of physics-based models can provide valuable insights for making informed investment decisions (Lin et al., 2018a; Chen and Hsu, 2010). The kinetic energy of market participants, for example, can be modeled using classic formulas from physics, with the sign of the kinetic energy being an open question (Khrennikov, 2010). By leveraging physics concepts in financial markets, investors can gain a deeper understanding of market behavior and make more relevant investment decisions (Chen and Hsu, 2010).

2 Literature review

In recent decades, the field of stock market prediction has seen rapid growth, with a multifaceted body of research emerging. However, prior to the application of artificial intelligence (AI) to trading markets, researchers primarily focused on mathematical models, economics, and trader experiences, which often lacked a suitable scientific approach (Bailey et al., 2014). With the advent of AI, new opportunities for making accurate predictions in financial markets emerged, and approaches such as the random walk method were utilized in trading. AI methods have since been employed to maximize prediction accuracy, with their beneficial strategies leading to more precise results. These methods have been used extensively in market prediction to date (Chen et al., 2021; Pongsena et al., 2021; Qi et al., 2020).

AI models and machine learning (ML) methods, such as neural networks and long short-term memory (LSTM), have been increasingly applied in stock market prediction (Hochreiter and Schmidhuber, 1997; Gers and Cummins, 1990). LSTM, which is matched based on time with the time-based activities in the market, is often used alone or in combination with other methods (Bao et al., 2017). However, the limitations of ML techniques point to the need for a fitted model of financial market evolution, which is not always straightforward to obtain (Théate and Ernst, 2021; Huang et al., 2018). This has led to the introduction of newer strategies, such as deep neural networks and deep reinforcement learning, which have shown considerable promise in some studies (Théate and Ernst, 2021; Boukas et al., 2021). Recent experiments have shown that the relative strength index (RSI) and moving average convergence divergence (MACD) indicators can be effective in predicting price direction in the stock markets. In a study of 26 stocks across 7 distinct markets, RSI and MACD achieved correct prediction percentages of 81% and 56%, respectively, for markets including the Bombay Stock Exchange, Tokyo Stock Exchange, Hongkong Stock Exchange, and more localized stock exchanges like Dhaka Stock Exchange, Indonesia, Malaysia, and Thailand (Sami et al., 2022). Based on these findings, a combination of MACD and RSI may be a promising candidate for stock market prediction.

Hybrid methods, such as combining individually successful prediction methods, have been an attractive area of research for improving prediction accuracy (Sami et al., 2022). In this paper, we aim to explore the use of a hybrid approach that includes kinetic energy, deep reinforcement learning, and TDQN methods. Our goal is to improve the accuracy of stock market predictions and contribute to the ongoing development of effective prediction strategies.

Through our exploration of a hybrid approach, we aim to gain a deeper understanding of the strengths and limitations of different prediction methods and identify new opportunities for improving prediction accuracy in the dynamic and complex environment of the stock markets. By leveraging the unique advantages of each method, we hope to develop a more robust and accurate prediction model that can provide valuable insights for traders, investors, and other stakeholders in the financial industry.

3 Background

In the following subsections, we provide a short history of baseline methods, which are used in our proposed method reviews.

3.1 Financial concept

This section provides a detailed description of the Forex market. Forex, also known as foreign exchange, is a global market for trading currencies and is one of the most actively traded markets in the world (Hu et al., 2021). In the Forex market, traders buy or sell one currency in exchange for another currency, effectively trading currencies "against" each other in a pair category. This means that when a trader buys one currency in a pair, they are simultaneously selling the other currency in the pair. For instance, in the EUR/USD currency pair, if a trader buys euros, they are at the same time selling US dollars. (Gallo, 2014).

The prices of currency pairs in the Forex market are continuously fluctuating, and traders need to closely monitor these changes to make informed decisions (Bebarta et al., 2021). Forex traders typically use various time frames to analyze price movements, including 5 minutes, 15 minutes, 30 minutes, one hour, four hours, one day, and one week. Of these time frames, daily data is the most commonly used for research purposes and is more popular than other time frames (Gallo, 2014). Understanding the different time frames and their implications is crucial for developing accurate prediction models, especially in the context of our proposed method.

n the Forex market, the use of candlesticks is a popular method for analyzing price movements. By considering different time frames, several candlesticks can be formed, and each candlestick indicates the highest, lowest, opening, and closing prices for a given period. These are basic information in financial markets and are crucial for understanding market movements (Tsantekidis et al., 2021). In this section, we outline the main idea of our research and present the structure of our system, which consists of two phases. In phase I, we aim to calculate the Kinetic energy for stocks. Our proposed model involves comparing the Kinetic energy of each stock per determined time frame to the average Kinetic energies of all stocks, which allows us to identify the stocks that are performing better or worse than the market average in terms of their Kinetic energy.

In phase II, we have the option to incorporate either indicators or advanced machine learning techniques to further refine our predictions. Indicators are widely used in financial markets to identify trends and patterns in price movements, and we use them to complement the momentum-based approach of phase I. Advanced machine learning techniques, such as deep reinforcement learning and trading deep Q-network algorithm, can learn from experience and improve their predictions over time. By incorporating either indicators or advanced machine learning techniques in phase II, we aim to develop a more effective and accurate prediction model that can provide valuable insights for traders and investors in the financial industry.

Our proposed method is based on the concept of Kinetic energy, which is a fundamental concept in physics. By applying this concept to stocks, we can calculate the Kinetic energy of each stock and use it to predict future trends in the market. The Kinetic energy concept allows us to measure the momentum or velocity of a stock's price movement, which is a critical factor in understanding market trends. By incorporating the Kinetic energy concept into our prediction model and using either indicators or advanced machine learning techniques in phase II, we aim to develop a more effective and accurate method for predicting stock prices and market trends that can provide valuable insights for traders and investors in the financial industry.

3.2 Kinetic energy

Undoubtedly, physics rules exist everywhere, and financial markets are no exception. In our proposed method, we apply the concept of Kinetic energy, which is a fundamental concept in physics, to stocks. The equation 1 for calculating Kinetic energy is considered:

$$k = \frac{1}{2} * mv^2 \tag{1}$$

The concept of Kinetic energy can be adapted to any system, where 'k' corresponds to the Kinetic energy of the system, 'm' represents the mass of the ith particle of the system, and 'v' corresponds to the velocity of the particle.

To be more detailed, the volume of a stock represents the number of shares that are being traded in a given period of time. Higher trading volume indicates higher market participation and liquidity, which can have an impact on the stock's price movement.

(Khrennikov, 2010) suggested a novel interpretation of the Kinetic energy equation in the context of financial markets by considering 'm' as the financial mass, and 'v' as the dynamics of the prices, according to equation 2. It has been shown that using Kinetic energy can model the features of the financial market (Fakult, 2017).

In our proposed method, we incorporate the volume of the stock as a proxy for the mass 'm' in the Kinetic energy equation. By using the volume of the stock, we aim to capture the trading activity and liquidity of the stock, which can have an impact on its price movement.

$$v_j(t) = \lim_{\Delta t \to 0} \frac{q_j(t + \Delta t) - q_j(t)}{\Delta t} \quad (2)$$

Where $v_j(t)$ is dynamics of price, q_j is price, and Δt is the period of time.

In reality, time is not considered a continuous element in financial markets, and changes in prices might be regarded as discrete values in certain time frames.

Using a Kinetic energy-based model can generate better descriptions of features in financial markets (Fakult, 2017). By incorporating Kinetic energy into our prediction model, we aim to provide more accurate and effective predictions of stock prices and market trends, which can offer valuable insights for traders and investors in the financial industry.

3.3 TDQN

Reinforcement learning algorithms, such as Deep Q-Network (DQN), are effective in handling trading problems and operate as sequential decision makers, without the need for a complete environment. As a model-free algorithm, DQN can produce promising results in trading environments, including partially observable ones (Mnih et al., 2013). Another reinforcement learning algorithm, TDQN, is a variant of DQN that uses a double deep reinforcement learning (DRL) approach. The TDQN algorithm involves initializing the memory of experiences, updating it as new actions are taken, and initializing the weights of the deep neural network (DNN) for both the main and target networks. The algorithm repeatedly acquires observations from the environment, preprocesses the data (including normalizing the relevant data), and randomly chooses an action until a specific point. While similar to standard Q-learning, TDQN uses a double DRL approach that involves cloning the experience in the memory and storing the opposite version in the cloned environment. In the context of trading, selling and buying would be opposite actions that are stored in the memory as cloned experiences (Théate and Ernst, 2021).

3.4 DL Based Method

AI is widely used in various fields, including financial markets, but it has both benefits and limitations when it comes to making accurate predictions.

Popular methods for making accurate predictions are those that use strategies. For economic predictions, particularly for predicting the trend of price movements, a sequence of time series can be considered as input. Therefore, deep learning models like LSTM and CNN are suitable for addressing this challenge (Yang et al., 2020). In our study, we evaluate our methods by comparing them with a CNN-LSTM-based model.

For this method, several layers are determined for the CNN, including Convolutional and Dense ones. As it was introduced in (Yang et al., 2020), the output of the CNN model is used as input for the LSTM model. This model includes an LSTM layer with 50 neurons, followed by a dense layer.

4 Proposed approaches

The proposed hybrid method combines two significant steps to improve trading accuracy. Firstly, it calculates the Kinetic energy based on the information provided in the dataset. The same dataset is then fed into the baseline model. Finally, the hybrid proposed model controls trading activity, particularly under special circumstances.

This section details the three strategies investigated. The first strategy is a hybrid method that uses Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) indicators with Kinetic energy. The second strategy combines the Deep Reinforcement Learning (DRL) method with Kinetic energy. The last strategy is the TKDQN, which uses the Kinetic formula in the TDQN algorithm. These strategies aim to improve trading models by incorporating the Kinetic energy concept into the model and are explained in further detail in this section.

Here's a revised version of the pseudocode in LaTeX format:

This pseudocode describes the TKDQN algorithm, which is a variant of the DQN algorithm that uses a double deep reinforcement learning (DRL) approach and incorporates the Kinetic energy concept. The algorithm initializes the experience replay memory M and the weights

Algorithm 1 TKDQN

Require: Initializing the experience replay memory M of capacity C, the main DNN weights Θ (Xavier initialization), and the target DNN weights $\Theta^- = \Theta$.

while *episode* $\neq 0$ **do**
  Obtain an observation o_1
  Preprocess o_1
  for $t = 1$ to T **do**
    $s \Leftarrow$ Uniform random number between 0 and 1
    if $s < \epsilon$ **then**
      Select a random action a_t from A
    else
      $a_t = \text{argmax}_{a \in A} Q(o_t, a;\ \Theta)$
    end if
    if $K \geq \Delta K$ **then**
      Reverse(a_t)
    end if
    $E^- \Leftarrow E$
    Take $E(a_t)$ $(E^-(o_t^-))$ and get o_{t+1} (o_{t+1}^-) and r_t (r_t^-)
    Preprocess o_{t+1} and o_{t+1}^-
    Store $e_t = (o_t, a_t, r_t, o_{t+1})$ and $e_t^- = (o_t, a_t^-, r_t^-, o_{t+1}^-)$ in M
    if $t \% T = 0$ **then**
      Randomly sample from M a minibatch of N_e experiences $e_i = (o_i, a_i, r_i, o_{i+1})$
      if state s_{i+1} is terminal **then**
        $y_j \Leftarrow r_i$
      else
        $r_i + \gamma Q(o_{i+1}, \text{argmax}_{a \in A} Q(o_{i+1}, a;\ \Theta);\ \Theta^-)$
      end if
      Compute and clip the gradients based on the Huber loss $H(y_i, Q(o_i, a_i;\ \Theta))$
      Optimize the main DNN parameters Θ based on these clipped gradients
      Update the target DNN parameters $\Theta^- = \Theta$ every N^- steps
    end if
    Anneal the ϵ-Greedy exploration parameter ϵ
  end for
end while

of the deep neural network (DNN) for both the main network (Θ) and the target network (Θ^-). It then repeatedly obtains observations from the environment and preprocesses the data. The algorithm randomly chooses an action until a specific point and reverses the action if the Kinetic energy exceeds a certain threshold. The experience is stored in the memory, and a minibatch of experiences is randomly sampled from the memory to update the DNN parameters. The target DNN parameters are also updated every N^- steps. Finally, the algorithm anneals the ϵ-Greedy exploration parameter ϵ over time.

Algorithm 2 Reverse

Require: an action a_t as its input.

if $a_t < 0$ **then**
  $a_t > 0$
else if $a_t > 0$ **then**
  $a_t < 0$
end if

4.1 General description

Our model has a unique feature that utilizes Kinetic energy. Specifically, when it's time to consider the actions suggested by our model, certain conditions are checked. If the Kinetic energy level is high, it necessitates making several different decisions. This is because of the logic of changing rates, which we discussed earlier.

The use of Physics formulas is widespread in different fields, especially in energy-related ones. In financial markets, stocks also possess Kinetic energy, but determining its sign has been a challenge (Khrennikov, 2010). However, our paper proposes a way to determine it.

Referring to Equation 1, we specialize and customize the formula by setting m to financial close prices and v to the Volume of the stock in the market. After calculating the Kinetic energy, it's necessary to calculate its average. According to our proposed method, if the value of Kinetic energy is higher than its average, it indicates a high probability of price change. This is an alarming situation, and two approaches could be applied: using indicator signals or using the labels of the days (or special time frame). In our proposed method, we choose the former. If the MACD/RSI/DRL/TDQN signal shows an uptrend and the Kinetic energy-based formula indicates a high level of change, we anticipate an opposite trend, and vice versa. On the other hand, when the current Kinetic energy is lower than its average, the market is predicted to remain stable without any unexpected changes.

4.2 RSIK

Studies have shown that using indicators can lead to better predictions compared to not using them (Lui, Kim; Chong, 2013; Chong et al., 2014). As mentioned in section 4.1, the indicator part of our proposed method would be replaced by the RSI method. Therefore, signals based on the RSI method would be used to determine the sign of Kinetic energy. If the signals indicate a buy or -1 and the Kinetic energy is higher than our suggested threshold, then the prediction would be a sell signal because the high Kinetic energy indicates an upcoming change.

4.3 DRLK

Our second proposed approach, called DRLK, is based on a DRL method and incorporates the use of kinetic energy. As explained in section 4.1, the signals generated by the DRL model serve as a basic signal in our method. By analyzing the market situation, we identify cases based on a predetermined threshold where our proposed method, which uses kinetic energy, can be applied. We then operate an anti-signal action on the environment. The promising results of our approach are shown in section 5.3.

4.4 TDQNK

This proposed method is based on TDQN (Théate and Ernst, 2021), which is a trading algorithm that utilizes deep reinforcement learning. The goal of this section is to combine TDQN with a physics formula to make decisions on financial markets, as discussed in Section 3.

The main difference between TDQN and TKDQN can be observed in line 11 of Algorithm 1, where we check if k is greater than the threshold, which is the average kinetic energy. If this condition is met, the Reverse function introduced in the pseudocode of Algorithm 2 is called to determine the current reverse action. Then, in line 14, the environment is copied, and the agent interacts with it using both the original and the reverse actions, receiving a reward in line 15 and generating a new observation. The observations are preprocessed in line 16, and both experiences are stored in the memory M in line 17. Finally, the Huber loss function is used to achieve a more stable training process for the model.

5 Results and discussion

In this section, the performance of our proposed method is going to be evaluated. To accomplish this goal, considering the dataset and the performance measure is significant as well as providing results. Therefore, we separately introduce all of them in the parts 5.1 to 5.3.

5.1 Dataset

The three distinct datasets which are used in this paper would be introduced in this section.

The first one is downloaded from the Yahoo finance website. In effect, the data was related to Apple company, APPL. Although, there are several features in that dataset, what attracted our attention was OHLCV of "close" and "high" amounts.

Besides, the experiments were repeated on another dataset called GPBUSD, which is Great Britain Pound-United Stated Dollar. Again, one time on "close" and another time on "high" values of data, experiments were carried out. Besides, the other dataset, AUDUSD, which is stands for Gold-United States Dollar used. It can be interpreted as the exchange rate of the US dollar to the gold price. The related data can be downloaded from the Forex market using well-known software such as RoboForex or Alpari.

In detail, for the first approach, the Forex data, for two indexes, namely, XAUUSD and GBPUSD, related to 3 months of 2022 (from January to the end of March), on 5 minutes time frames, is used. This data is downloaded from the "MetaQuoted software crop" history center, using the RoboForex account. Again, the dataset is split into two distinct parts, training 80 % and testing 20%.

5.2 Evaluation criteria

For evaluating a strategy a huge number of metrics could be used. In our case, some of the most well-known ones would be applied (Théate and Ernst, 2021).

Generally, Accuracy, Precision, Recall, and F-measure are somehow more widely applied in several distinct concepts. Therefore, in this paper, for the first approach, these are used as well (Berkovsky and Freyne, 2010; POWERS, 2011).

In the scenario of the current paper, recall refers to all the time frames in which the predicted tag is the same as the real one. In this case, its tag can embody the sign of the market trend, which may represent upward, or downward movement, or remain unchanged.

According to recent research, the strategy for determining the class labels for stock can be determined by Equation 3, which divides the prediction of price movement into two classes, 1 for upward, and 0 for downward (Yang et al., 2020) based on close price. However, in our study, we considered 3 distinct classes 1 for upward, -1 for downward, and 0 for unchangeable situations. These labels would be used for metrics 4 to 7.

$$Label_t = \begin{cases} 1, & \text{if } Close_{t+1} > Close_t \\ -1, & \text{if } Close_{t+1} < Close_t \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In this concept, TP can be referred to all the predictions with the correct positive or upward label which actually was positive. Using this representation is so common in many majors (Alhoori and Furuta, 2017; Harman, 1995). Similarly, TN represents the number of negative labels for truly negative ones. Moreover, FP and FN shows the number of positive and negative labels which are wrongly taken, respectively. To be more detailed, Equations 4 to 7, reveals Recall, Accuracy, Precision, and F-measure which are popular performance measures.

$$\text{Recall} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{5}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{6}$$

$$\text{F} - \text{measure} = 2 \times \frac{Recall \times Precision}{Recall + Precision} \tag{7}$$

5.2.1 Profit & Loss

Profit and loss (P&L) is a measure of the financial performance of a trading strategy. It represents the difference between the total revenue generated by the strategy and the total expenses incurred during a specific trading period.

If the total revenue generated by the strategy is greater than the total expenses incurred, the P&L is positive, indicating a profit. Conversely, if the total expenses incurred exceed the total revenue generated, the P&L is negative, indicating a loss.

P&L is an important metric for investors and traders as it provides a measure of the profitability of a trading strategy over a specific period. It can be used to evaluate the effectiveness of a strategy and to make informed decisions about future investments. However, it's important to keep in mind that P&L is just one measure of performance and should be considered in conjunction with other metrics such as risk, volatility, and fees when evaluating the overall performance of a trading strategy.

5.2.2 Annualized Return

Annualized return is a metric used to measure the performance of an investment or trading strategy over a specific time period, usually one year. It represents the average percentage return earned by the investment per year, assuming that the returns are compounded.

To calculate the annualized return, we typically take the total return generated by the investment over the period and divide it by the number of years in the period. This gives us the average return per year. However, if the returns are not compounded, we need to adjust for this by using a compound interest formula.

Annualized return is an important metric for investors and traders as it provides a standardized way of comparing the performance of different investments and trading strategies over the same time period. However, like with any metric, it's important to consider other factors such as volatility, risk, and fees when evaluating the performance of an investment or trading strategy.

5.2.3 Annualized Volatility

Annualized volatility is a commonly used metric to estimate the risk associated with a trading strategy over a specific time period. To calculate it, we take the standard deviation of the daily returns and multiply it by the square root of 252, which is the approximate number of trading days in a year. This provides an estimate of how much the returns of the strategy are likely to vary over a year.

By comparing the annualized volatility of different trading strategies, investors and traders can assess which strategies carry more or less risk and make more informed decisions about their investments. However, it's important to keep in mind that past performance is not always indicative of future performance, and other factors beyond volatility should also be considered when evaluating a trading strategy.

5.2.4 Sharp Ratio

Profitability is a crucial factor in evaluating the effectiveness of a trading strategy because the ultimate goal of investors is to maximize their profits. Therefore, in this research, we also considered the total profit generated by our proposed technique as an evaluation metric (Li, 2020).

A trading strategy that generates higher profits is generally considered to be more efficient and useful in practice. Therefore, the total profit generated by our proposed technique serves as an important indicator of its effectiveness.

By considering profitability as an evaluation metric, we can gain insights into the effectiveness of our proposed technique in generating profits and compare it with other trading strategies. This information can be useful in making informed decisions about the practical applicability of our proposed technique.

5.2.5 Sortino Ratio

the Sortino ratio and the Sharpe ratio are both measures of risk-adjusted performance, but they differ in the way they account for downside risk.

The Sharpe ratio was introduced by William F. Sharpe in 1966 and is calculated as the excess return of an investment over the risk-free rate divided by the standard deviation of the investment's returns. The Sharpe ratio takes both the positive and negative deviations from the mean into account when measuring risk, which means that it penalizes both upside and downside risk equally.

In contrast, the Sortino ratio was introduced by Frank A. Sortino and Robert van der Meer in 1988 and is calculated as the excess return of an investment over the risk-free rate divided by the downside deviation of the investment's returns. The downside deviation is a measure of the volatility of the investment's returns that only considers returns that fall below a certain threshold, which is typically the minimum acceptable return or the risk-free rate. By focusing only on downside risk, the Sortino ratio provides a more targeted measure of risk-adjusted performance that is particularly useful for investments with high downside risk.

Therefore, while both the Sharpe ratio and the Sortino ratio are measures of risk-adjusted performance, they differ in the way they account for downside risk. The Sharpe ratio penalizes both upside and downside risk equally, while the Sortino ratio only penalizes downside risk (Sortino and Van der Meer, 1988).

5.2.6 Maximum Drawdown

The metric you are referring to is the Maximum Drawdown (MDD), which measures the maximum loss incurred by a trading strategy during a specific period. The MDD is calculated by determining the maximum percentage drop in the value of an investment from its peak to its trough over a specified period.

The MDD is an important performance metric because it provides a measure of the downside risk associated with a trading strategy. A higher MDD indicates that the trading strategy is associated with a greater risk of incurring significant losses.

By considering the MDD as a performance metric, we can gain insights into the risk associated with a trading strategy and make informed decisions about its potential for practical applications.

5.2.7 Maximum Drawdown Duration

The Maximum Drawdown (MDD) is a measure of the largest loss that an investment or trading strategy has experienced from its peak value to its trough value over a particular period. It represents the maximum percentage decline from the investment's highest point to its lowest point.

On the other hand, Drawdown Duration is the length of time between the peak and trough of an investment's or trading strategy's value during a specific period. It reflects the length of time an investor or trader would have had to wait to recover from the maximum drawdown.

Drawdown Duration is an important metric for investors and traders as it provides insight into the time it takes for the investment or strategy to recover from a significant loss. By analyzing the Drawdown Duration, investors can better understand the risks and potential rewards associated with a particular investment or trading strategy.

5.3 Results

5.3.1 Result of the first approach

The study's findings suggest that the proposed methods outperform classic ones when evaluated on the same dataset using the evaluation criteria mentioned in subsection 5.2. Both methods showed better performance compared to traditional methods in terms of the metrics mentioned. Additionally, the RSIK method demonstrated even better accuracy than RSI, particularly in analyzing the GBPUSD.

The DL approach outperformed both the MACDK and RSIK methods. Based on these findings, the authors decided to combine the proposed DL methods with traditional kinetic energy methods to further improve the accuracy of the trading strategy.

The study highlights the potential benefits of using advanced machine learning methods in trading strategies and demonstrates that combining these methods with traditional ones can lead to even better performance. However, it's important to note that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods.

The results are visualized in Figure 2. The figure shows that the proposed method outperforms the RSI Indicator, with a reported accuracy of 47 percent compared to 41 percent for RSI. This improvement is also observed for MACDKI and MACD, with almost 44 percent and 13 percent gains, respectively, when using the proposed method.

These results demonstrate the potential benefits of using advanced machine learning methods in trading strategies. By combining these methods with traditional ones, investors and traders can potentially improve the accuracy of their trading strategies and make more informed decisions about their investments. However, it's important to keep in mind that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods.

To further confirm the effectiveness of the proposed method, its performance was compared to another index in the Forex market, namely GBPUSD. This index is well-known in the Forex market, and the same dataset and resources used in section 5.1 were used for the second series of experiments. The results, illustrated in Figure 1, show that the proposed methods outperform traditional ones and, in some cases, even outperform DL.

These findings provide further evidence of the potential benefits of using advanced machine learning methods in trading strategies and demonstrate the effectiveness of the proposed method in analyzing different datasets. However, it's important to note that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods.

5.3.2 Results of the second approach

The average profit generated by the proposed DRLK approach and its corresponding approach, DRL, is shown in Figure 3. The figure demonstrates that the proposed DRLK approach outperforms its corresponding approach. For example, on the APPL dataset, the profitability of DRLK is 22.16, compared to 0 for DRL. Similarly, on XAUUSD, DRLK generated an average profit of 7.35.

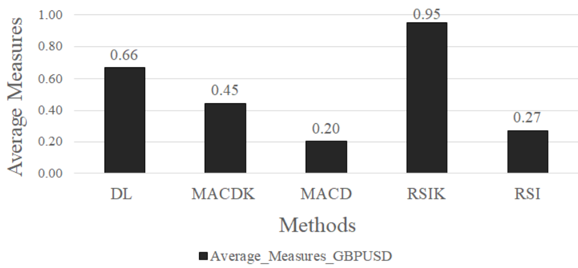

Fig. 1 Average Results on GBPUSD

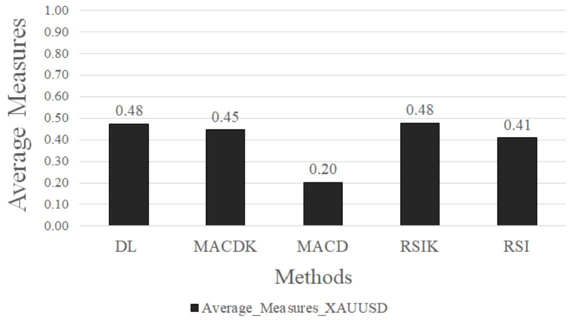

Fig. 2 Average Results on XAUUSD

These findings highlight the potential benefits of using advanced machine learning methods, such as DRLK, in trading strategies. The improved profitability of DRLK compared to DRL suggests that the proposed method may be more effective in identifying profitable trades and maximizing returns. However, it's important to keep in mind that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods.

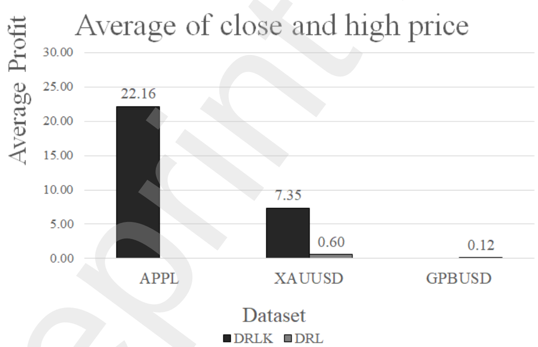

Fig. 3 Average Results on APPL, XAUUSD, and GBPUSD using DRLK and DRL

5.3.3 Results of the third approach

Based on the results presented in Table 1, our proposed trading strategy appears to be a reliable approach as its performance is better than its corresponding method in most metrics. For instance, the profit and loss generated by the proposed method is 116,126, while for TDQN, it is only 91,098. Additionally, the proposed method exhibits higher annualized return, Sharpe ratio, Sortino ratio, and profitability compared to TDQN.

Furthermore, the maximum drawdown of TDQNK is slightly worse than TDQN, with a difference of less than one percent. Overall, these results suggest that the proposed trading strategy may be a more effective approach for trading compared to TDQN, and can potentially lead to higher profitability and better risk-adjusted returns. However, it's important to keep in mind that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods. Figure 5.3.3 illustrates the expected performance

Table 1 Result on close values of datasets

Performance Indicator	TDQNK	TDQN
Profit & Loss (P&L)	116126	91098
Annualized Return	35.75%	31.14%
Annualized Volatility	26.10%	26.27%
Sharpe Ratio	1.612	1.368
Sortino Ratio	1.943	1.714
Maximum Drawdown	24.41%	23.53%
Maximum Drawdown Duration	69 days	69 days
Profitability	57.89%	54.55%

of the TKDQN and TDQN algorithms for both the training and test sets as a function of the number of training episodes (up to 50 iterations). The expected performance of TKDQN, shown in Figure 4, is significantly better than the performance achieved by TDQN, especially after the 30th episode.

These results suggest that the TKDQN algorithm may be a more effective approach for trading when compared to TDQN. As the number of training episodes increases, the performance of TKDQN improves considerably, outperforming TDQN in terms of expected performance. However, it's important to note that these results are specific to the dataset and time period used in the study and may not necessarily generalize to other datasets or time periods.

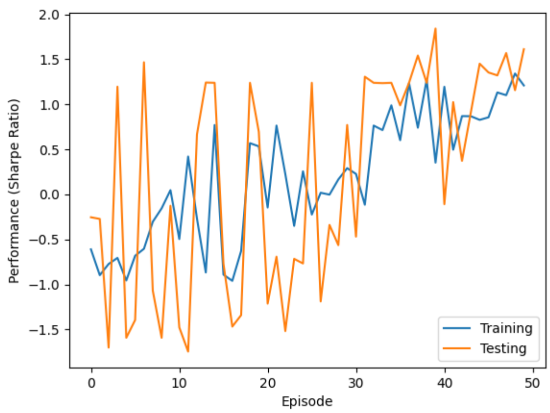

Fig. 4 TKDQN sharp ratio

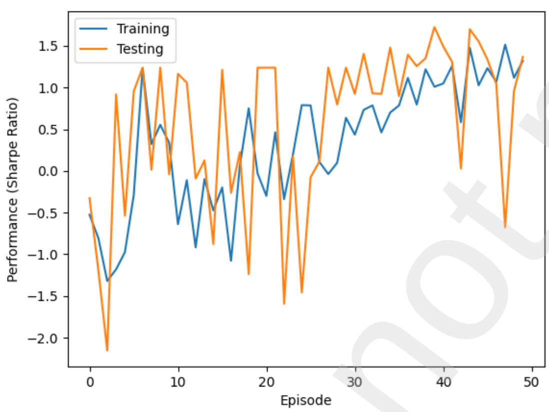

Fig. 5 TDQN sharp ratio

6 Discussion and conclusion

In this study, a new hybrid model for price trend prediction is introduced, which combines Kinetic energy, MACD, RSI, and deep reinforcement learning model. The proposed model is evaluated on three different datasets, including APPL, GBPUSD, and AUDUSD, and compared with the DRL model, TDQN, and DL model in three different approaches, with experiments conducted on 5-minute and daily data.

The findings of the study demonstrate the effectiveness of the proposed method in terms of generating profits compared to its corresponding methods. Additionally, the proposed method is able to identify situations where classic methods might not be efficient enough and provide its own decision to make better decisions under such circumstances.

The results of the experiments show that using the proposed method leads to better performance in terms of total profit gained compared to the corresponding method. This highlights the potential benefits of using the proposed method in trading strategies and suggests that it may be an effective approach for generating profits in the market.

It's important to note that the results of the study are specific to the datasets and time periods used in the experiments and may not necessarily generalize to other datasets or time periods. However, the findings of the study provide valuable insights into the potential benefits of using advanced machine learning methods in trading strategies and suggest that further research in this area may lead to improved trading strategies and better investment decisions.

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