SENTIMENT DRIVEN REINFORCEMENT LEARNING TRADING STRATEGIES TO ENHANCE MARKET PERFORMANCE

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***Abstract*—This research paper seeks to present a comprehensive examination of algorithmic trading algorithms, encompassing a range of techniques that extend from supervised learning to sentiment-aware reinforcement-based trading algorithms. The study further investigates the transformative potential of artificial intelligence (AI) in the field of stock trading, emphasizing the advantages of leveraging AI within this domain. Furthermore, the paper explores the incorporation of natural language processing (NLP) algorithms to account for the influence of news on algorithmic predictions. Subsequently, a comparative analysis of the algorithms' performance is carried out based on the profits generated by each. Lastly, the paper outlines the future implications of the subject matter and concludes by summarizing the obtained results.**

Keywords—Stock analysis, Reinforcement Learning, Algorithms, Sentiment,Model,Natural Language Processing, Long Short-Term Memory, Neural Network

I. Introduction

Algorithmic trading, commonly known as automated trading, involves the utilization of computer programs to execute trades based on predetermined instructions. The primary objective is to generate profits at a speed and frequency that would be arduous for a human trader to achieve. The prediction of stock market movements is a crucial factor that influences trading decisions. However, this is a complex task due to the intricate and volatile nature of the stock market, which is influenced by various stochastic factors, such as political events and financial reports.

In recent times, there has been a substantial upsurge in the level of interest in the field of artificial intelligence (AI), as indicated by the annual proliferation of research papers. This surge in enthusiasm can be attributed, in large part, to the remarkable successes attained by deep learning modus operandi, which rely on deep neural networks structured to emulate the intricate organization of the human brain.These Advanced methods are currently leading the way in various practical applications, such as NLP, speech articulation, and image categorization. In addition to deep learning (DL), the research community has also demonstrated significant interest in deep reinforcement learning (DRL). This field focuses on studying the training mechanism of an astute agent.

(i) Partaking a consecutive chain of activities within an unfamiliar context

(ii) Trying to attain the utmost advantages that can be obtained cumulatively

(iii) Employing DL approaches to extrapolate insights from the knowledge acquired through the engagements with the surroundings.

II. Literature Survey

To initiate this concise literature review, it is imperative to underline two fundamental points.It is imperative to understand that a significant number of scientifically rigorous works pertaining to algorithmic trading are not available to the general populace. According to Li (2017), this is pertaining to the substantial amount of capital involved, which dissuades private FinTech firms from divulging their latest research findings to the general public. Moreover, it is essential to recognize that objectively assessing the efficacy of trading procedures gives a formidable undertaking, owing to the absence of a standardized and deep rooted framework for properly evaluating their performance.The authors often devise their own evaluation criteria/framework, which can introduce personal biases into their work. Additionally, a crucial challenge is the inconsistency in the definition of trading price, which are often either vaguely. It's worth noting that the majority of the current algorithmic trading strategies were created by mathematicians, economists, and traders without utilizing AI techniques. Many of these traditional methods, such as trend following methods and mean reversion methods, have been studied in depth in works by authors like Chan and Narang. However, there hasn't been much exploration into how AI can improve these strategies.

Most research using machine learning in algorithmic trading has focused on predicting future market trends. In the event that the evolution of the financial market is accurately anticipated It is possible to make optimal trading decisions with a significant level of certainty using appropriate techniques.The use of deep learning techniques has shown promising results in tackling algorithmic trading problems. In particular, studies such as Ar´evalo et al. (2016) and Bao et al. (2017) have shown successful outcomes in applying deep neural networks and recurrent models such as long short-term memory to develop profitable trading strategies. Moreover, various researchers have explored reinforcement

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learning (RL) techniques to address this challenge, including the works of Moody and Saffell (2001) and Dempster and Leemans (2006), which employ recurrent RL algorithms and adaptive RL techniques for investment and foreign exchange trading. In recent times, a handful of studies have delved into the deep reinforcement learning techniques to tackle algorithmic trading problems in a methodologically robust way. Previous research on algorithmic trading primarily centered around the creation of trading strategies and algorithms, yet significant gaps existed in addressing vital considerations. For instance, limited attention was devoted to market microstructure, encompassing aspects like order book dynamics and liquidity provision and financial indicators. Furthermore, an area that has been frequently disregarded is the criticality of risk management. While the pursuit of maximizing returns and generating profits remains paramount, the implementation of effective risk management strategies is equally imperative. These encompass multifaceted dimensions, such as position sizing, stop-loss mechanisms, portfolio diversification, and stress testing, which collectively contribute to fortifying the stability and sustainability of algorithmic trading systems. By analyzing the past problems we have come up with a way to integrate a novel LSTM model with an NLP model with input of gold price, and other factors in the analysis for better price prediction.

III. LSTM

Long Short-Term Memory is a neural network architecture that has been processed to address the deficiencies of traditional semantic networks when rectifying successional data.Traditional neural networks are limited in their ability to process long sequences of data as they tend to face the problem of vanishing gradients during the training process. This occurs when the gradients of the error function become very small, causing the network to learn slowly or not at all.

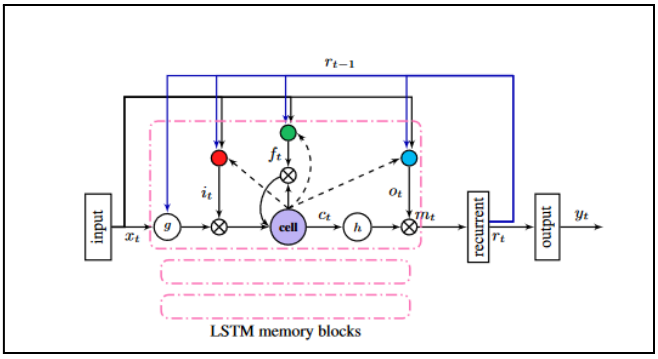

Fig.1. LSTM RNN Architecture

The LSTM architecture has found a lot of versatile applications across diverse fields, including NLP, speech articulation, and image characterization. In natural language processing, LSTMs have been used to model language, determine sentiment in text, and facilitate translation between languages. In speech recognition, LSTMs have been leveraged to identify individual speech sounds, known as phonemes, and transcribe spoken words into text. In image captioning, LSTMs have been employed to generate descriptions of visual content.The versatility of LSTM architecture has made it a valuable tool in advancing research and innovation in various fields.

The implementation of the actor-critic algorithm with multiple asynchronous flows has yielded remarkable enhancements in operational quality. In order to conduct research on this topic, a software system has been developed for training and testing, utilizing the Python programming language and the TensorFlow framework. The system encompasses two global processes, i.e., training and testing, whereby the model is stored in the hard disk, and the architecture and trained parameters are loaded into the testing system for association. The selection of architecture plays a pivotal role in the training and testing processes. The model is trained every Nsteps = 200 steps, and the number of parallel processes (Nworker) is fixed at 10 for the current study. The training of each epoch comprises 50,000 one-minute steps of data spanning over three months. The convergence of the algorithm necessitates approximately 1000 epochs for a step size of around 10–3. To accelerate the testing process, we have implemented a testing subsystem that omits training and writing to the history. In the testing, we have replaced the probabilistic approach with the arg max function, and the dropout function has been disabled to expedite the process.

IV. WORKING

Algorithmic trading, or quantitative trading, refers to the use of automated trading decisions based on mathematical rules calculated by a machine. Although there may be different interpretations of this term, this research paper follows the commonly recognized definition

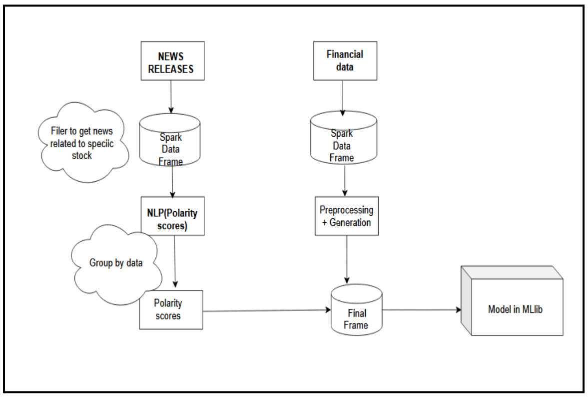

Fig.2. Flowchart diagram of the proposed method

The exchange trading process pertains to the trading of a specific financial instrument, futures on the RTS index. At regular intervals of one minute, the agent is required to make a decision amongst three possible actions: long, neutral, or short. In the long position, the agent owns the futures, while in the neutral position, all assets are converted to cash. In the short position, the agent borrows a fixed volume and is obligated to purchase it later at the future price.

The system is modeled as a Markov decision-making process, with the environment described by the tuple M =

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{S, A, P, γ, R}. The space of observed states is denoted as S ∈ Rm and is composed of current bids or an internal state of the LSTM memory cell. The space of actions is represented by the set A = {–1, 0, 1}, with the action selected from the developed policy π(a|s), which determines the probability of choosing action in state s. The transition probability of the Markov process is represented by P(s'|s, a).

The reward function R(s, a) plays a crucial role in determining the agent's success at each step. The reward that the agent receives not only depends on its current action but also on its previous actions. This is denoted as rt = R(st, at). The decay multiplier γ ∈ [0, 1] determines the weightage given to the next reward in the total reward received for an action. A smaller value of γ reduces the impact of future rewards on the agent's current actions, while a larger value gives greater importance to future rewards.

A) Q Learning Agent

The initial function, named Agent class, serves to define several important variables such as state size, window size, batch size, and inventory list. Additionally, this function includes various static variables like decay, gamma, and epsilon. Two neural network layers are defined to execute the buy, hold, and sell commands. The Gradient Descent Optimizer is also utilized in this function.

The Agent class has been implemented with functions designed to facilitate buying and selling of options. The get_state and act functions of the class utilize the Neural network for producing the next state of the system. The reward function calculates the profits obtained by buying or selling the call option. The choice of action at the next state is influenced by the previous action. The buy call is represented by 1 while the sell call is represented by 2. The state at each iteration is determined, and an appropriate action, either buying or selling some stocks, is executed. The cumulative rewards are stored in the total profit variable.

B) Data Preprocessing

Data preprocessing is an essential process in developing a reliable machine learning model. It involves several steps, including identifying and addressing missing data and performing feature engineering to convert the data into an ideal form for modeling is crucial to ensure its effective utilization in machine learning algorithms. This stage is essential in preparing the data for accurate analysis and interpretation.

[251 rows x 7 columns],			Open	High	Low	Close
Date						
2022-04-07	136.617996	137.701508	134.857254	136.464996	136.464996	
2022-04-08	136.250000	136.250000	133.752502	134.010498	134.010498	
2022-04-11	132.899994	132.939194	129.617493	129.796494	129.796494	
2022-04-12	132.423492	132.423492	127.575996	128.374496	128.374496	
2022-04-13	128.626495	130.655746	128.438599	130.285995	130.285995	
...	...	...	...	...	...	
2023-03-31	101.709999	104.190002	101.440002	104.000000	104.000000	
2023-04-03	102.669998	104.949997	102.379997	104.910004	104.910004	
2023-04-04	104.839996	106.099998	104.599998	105.120003	105.120003	
2023-04-05	106.120003	106.540001	104.101997	104.949997	104.949997	
2023-04-06	105.769997	109.629997	104.815002	108.900002	108.900002	

Fig.3. Dataset used for the model

Technical indicators : In the context of actual trading, multiple sources of information must be considered, such as classical stock values, equity., and technical indicators. This paper highlights two technical indicators - MACD and RSI. The turbulence index is a metric that considers an investor's inclination to avoid risk, a characteristic that can significantly influence their trading approach and capacity to safeguard their invested capital, particularly in the face of fluctuating market volatility.

C) Performance

In the context of algorithmic trading, the use of machine learning techniques is of great importance for developing successful trading strategies. One such technique is the use of deep reinforcement learning (DRL) which has shown promising results in maximizing investment performance. To this end, this research aims to explore the effectiveness of DRL in trading stocks by developing a novel trading strategy that can achieve high Sharpe ratios on a diverse set of markets, regardless of market conditions such as bull and bear markets and varying levels of volatility. The objective is to maximize the overall performance of the strategy by achieving a high Sharpe ratio across all currently existing stock markets. This refers to the anticipated total value of rewards, in the form of daily returns, that will be earned over an indefinite period when subjected to a discounting process, even though the ultimate goal is to maximize the Sharpe ratio. This optimisation criterion, while not precisely identical to maximizing profits, is a near approximation. It can be considered as a relaxation of the Sharpe ratio criterion. Future research could potentially focus on reducing the discrepancy between these two objectives, which may be of significant interest.

V. NEED OF SENTIMENT ANALYSIS IN ALGORITHMIC TRADING

Traders utilize sentiment analysis as a method to comprehend the emotional inclination of the market, which involves analyzing substantial amounts of data sourced from outlets such as social media and news articles. By scrutinizing the sentiment of the market, traders can attain valuable understanding regarding emerging trends and probable investment prospects.

In the event that sentiment analysis reveals an upward trend of positive sentiment directed towards a specific company or product, traders may consider investing in said entity, anticipating future growth. Conversely, if the sentiment analysis indicates a negative sentiment towards a company or product, traders may opt to refrain from investing in it.By leveraging the power of sentiment analysis, traders can stay ahead of the curve and capitalize on booming trends in the market.

VI. SENTIMENT ANALYSIS USING NLP

The utilization of sentiment analysis using NLP can be a highly advantageous tool for organizations seeking to comprehend customer perception of their products, services, or brand. This method entails the analysis of vast quantities of text-based data, including social media posts, customer

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reviews, and news articles, to determine the overall sentiment conveyed as positive, negative, or neutral.

The initial step to conduct sentiment analysis is to preprocess the textual data by eliminating any redundant characters and transforming the text into a machine-readable format. This involves segmenting the text into individual words, eliminating stop words (common words such as "the" and "and" that contribute minimal significance to the text), and converting the remaining words into numerical features.

To commence the study, we made use of an existing pre-trained Word2Vec Model that was specifically trained on the Reuters News Corpus. The Word2Vec framework comprises a group of models designed to generate word embeddings. These models are structured as two-layer neural networks that have the capability to learn and recognize the linguistic context of words. In order to generate these word embeddings, a vast collection of textual data is fed as input to the Word2Vec algorithm. Subsequently, the textual data is transformed into a vector space of several hundred dimensions and each unique word is allocated a corresponding vector in this vector space. The spatial location of each word within this vector space is determined based on its contextual relationship with other words in the textual data. For this investigation, we leveraged the pre-existing Word2Vec model to obtain 100-dimensional vectors for each headline concerning Amazon and IBM (spanning the period between 2006 and 2016) that were obtained from the Reuters Key Development Corpus.

VII. INNOVATION

After conducting a thorough literature review, we came across several research studies centered on LSTM-based algorithmic trading. However, we wanted to refrain from producing another paper that simply trains an LSTM Algorithmic Trading Model. Instead, we opted to employ recursive feature elimination and principal component analysis techniques in our model. We also introduced several hyperparameters, such as Spread Cost, Market Impact Cost, and Timing Cost, to assign variable weights to each input and yield more favorable outcomes. Upon training our LSTM-based model, we discovered that it solely considered technical indicators, and there are other factors beyond these that influence the stock market. Notably, several financial indicators such as balance sheets, financial news, and current political news hold sway over the market. To incorporate these factors, we analyzed news to take all these parameters into account. Furthermore, we aimed to automate this process by utilizing an NLP model for news sentiment analysis. We incorporated the data into the model alongside other parameters to generate superior outcomes. Additionally, we included political news in our analysis, as it exerts a significant impact on market conditions. We leveraged news data and market sentiment from the largest stock trading subreddits to introduce these factors into our model.

VIII. RESULTS

The following sections involve the results we achieved from our Model. The images listed below include charts and statistical data achieved from our results. All the results are being explained properly with the paragraph below.

DATE	CLOSE	PREDICTION
2023-03-17	155.00	154.291397
2023-03-20	157.399994	155.100
2023-03-21	159.279999	156.141479
2023-03-22	157.83002	157.394135
2023-03-23	158.929993	158.236725
2023-03-24	160.250000	158.965805
2023-03-27	158.279999	159.733597
2023-03-28	157.649994	160.023682
2023-03-29	160.770004	159.980316
2023-03-30	162.360001	160.361603
2023-03-31	164.899994	161.101624
2023-03-03	166.169998	162.296310
2023-03-04	165.630005	163.666458

Fig.4 Prediction table of the model

The table shows the predictive data that the model generated.

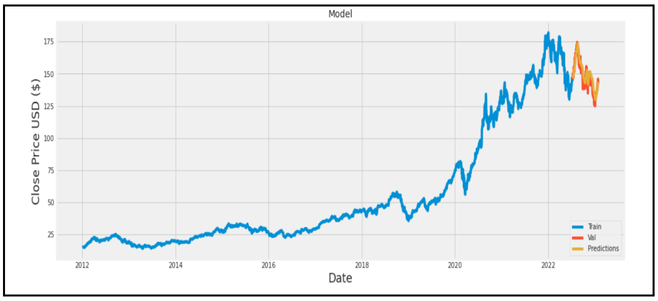

Fig.5 Prediction of Model

This graph shows the relationship between the closing price of a stock and its corresponding date.The blue line represents the dataset that was used to train the model,while the yellow line represents the predictions made by the model based on the provided data.The red indicator describes the actual closing price of the stock on the particular day.

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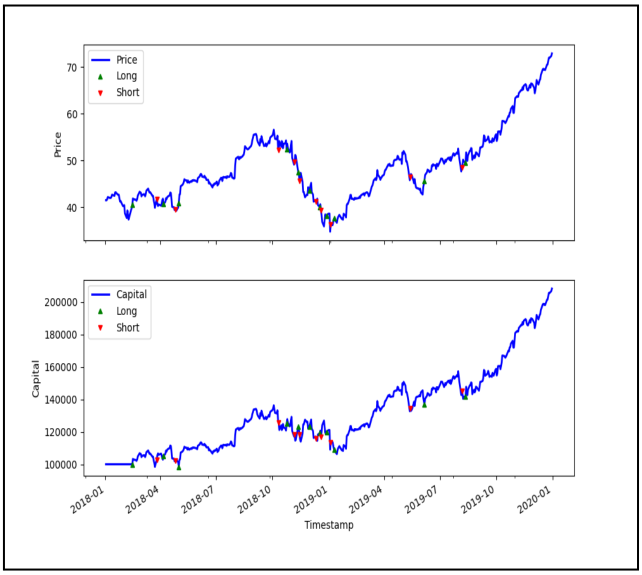

Fig.7 Long-Short Prediction Graph

The blue line on the chart indicates the stock prices. A green marker has been placed to indicate the optimal point at which a trader should consider purchasing the stock, while a red marker has been placed to indicate the point at which it is advisable to sell the stock.

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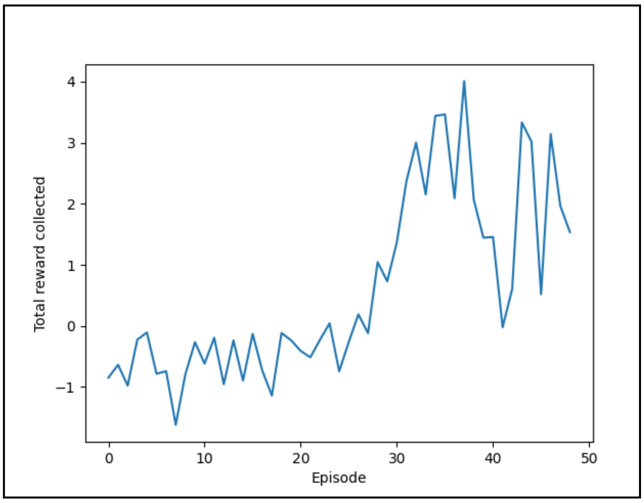

Fig.9 RL Agent Reward Vs Episode

This graph shows the total rewards earned by a reinforcement learning agent in each episode. It illustrates the relationship between the rewards obtained and the number of episodes completed. Each episode corresponds to a set of actions taken by the agent in response to the environment. The graph provides a visual representation of the agent's performance over time.

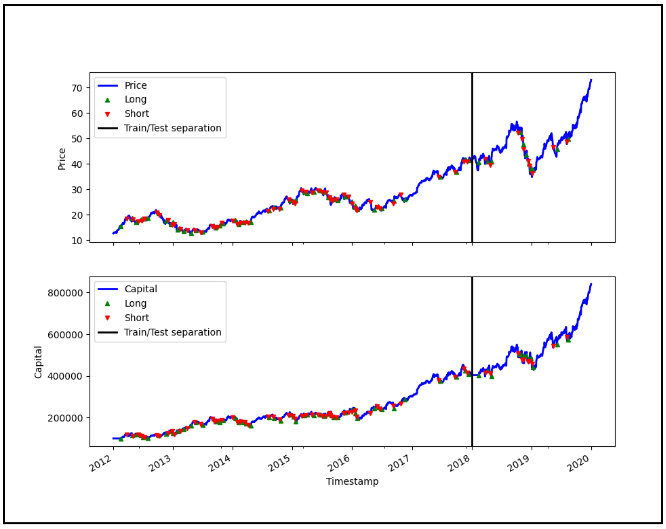

Fig.10 Long-Short Prediction Graph

The graphs illustrate how the value of the initial investment changes over time by following the buy and sell algorithmic trading strategies. The plots show the increment in the capital value at different time intervals. The trading strategies are based on determining when to purchase and sell assets to maximize profits. The graphs provide a visual representation of the investment's performance over time.

compound	neg	neu	pos
0.011591	0.06976	0.84745	0.08281
0.071903	0.064	0.83722	0.0986
0.056758	0.03972	0.88354	0.07673
0.11526	0.031	0.8591	0.10954
0.093016	0.05966	0.82578	0.11460
0.164733	0.038	0.81431	0.14739

Fig.11 Sentiment Analysis Table

The above table depicts the analysis of the news and tweets for the 6 different chosen stocks. Based on the data scraped, The model predicts the positive score, neutral score and the negative score of the news, it not only measures the counts but also the intensity of news and based on its deduced scores. The three scores are then used to form a compound score which tells us the overall sentiment of the stock in the current market.

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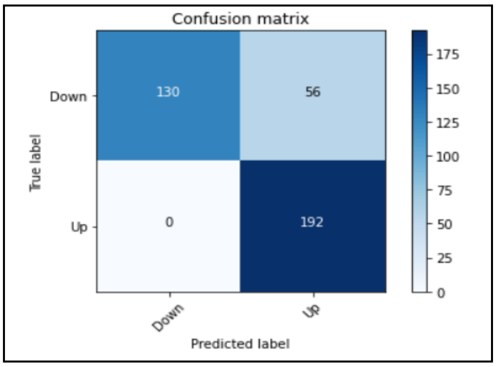

Fig.12 Confusion Matrix

The accuracy score came out to be “85.17” for our model. The above confusion matrix tells the model prediction on the price movement and the accuracy of the model. ‘1’ for uptrend and ‘0’ for downtrend. The confusion matrix helps us visualize the accuracy of the model. How many predictions of the model were correct and how many of them were incorrect.

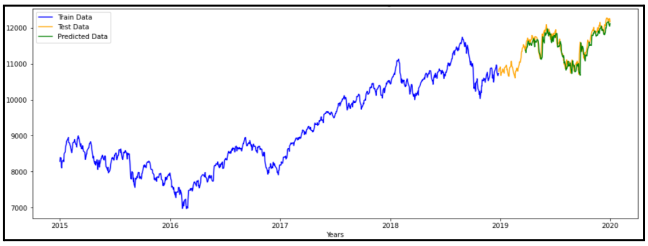

Fig.13 Model Prediction with Sentiment Analysis

The above image shows the working of our model in predicting the closing price of a stock rather than just predicting 1/uptrend or 0/downtrend of the stock. As we can see the stock price is very close to the real values. The model incorporating sentiment analysis performs better than the model without sentiment analysis.

VIII. CONCLUSION

Sentiment-aware RL trading strategies have shown promising results in enhancing market performance by analyzing sentiment data to inform trading decisions.We recognized the limitations of the LSTM model and decided to improve our algorithmic trading approach by introducing reinforcement learning. This approach allowed us to adapt and optimize our trading strategies in real-time, taking into account the constantly changing market conditions and feedback from previous trades. In contrast, the LSTM model relied on a fixed set of inputs and struggled to adapt to dynamic market conditions. Additionally, we used sentiment analysis to gain insights into the market sentiment. By combining sentiment analysis with reinforcement learning, we were able to make more informed trading decisions and further improve our trading strategies. The current research still has a lot of scope for improvement by including twitter and reddit to get the exact sentiment of the market. We can build a system which cumulatively analyzes the news, twitter and reddit sentiment for a more accurate prediction of the stock price. In the nutshell I would like to say, we have a long way in the field of algorithmic trading but there are several milestones to achieve in the path ahead.

REFERENCES

[1] Shavandi, A. and Khedmati, M., 2022. A multi-agent deep reinforcement learning framework for algorithmic trading in financial markets. Expert Systems with Applications, 208, p.118124.

[2] Tudor, C. and Sova, R., 2022. Flexible decision support system for algorithmic trading: Empirical application on crude oil markets. *IEEE Access*, *10*, pp.9628-9644.

[3] Chen, X., & Chen, S. (2021). Deep reinforcement learning with sentiment analysis for stock trading. IEEE Transactions on Cybernetics, 51(1), 216-228.

[4] Felizardo, L.K., Paiva, F.C.L., de Vita Graves, C., Matsumoto, E.Y., Costa, A.H.R., Del-Moral-Hernandez, E. and Brandimarte, P., 2022. Outperforming algorithmic trading reinforcement learning systems: A supervised approach to the cryptocurrency market. Expert Systems with Applications, 202, p.117259.

[5]Jin, B., 2023. A Mean-VaR Based Deep Reinforcement Learning Framework for Practical Algorithmic Trading. IEEE Access, 11, pp.28920-28933.

[6]Joiner, D., Vezeau, A., Wong, A., Hains, G. and Khmelevsky, Y., 2022, November. Algorithmic Trading and Short-term Forecast for Financial Time Series with Machine Learning Models; State of the Art and Perspectives. In 2022 IEEE International Conference on Recent Advances in Systems Science and Engineering (RASSE) (pp. 1-9). IEEE.

[7] Prudencio, R.F., Maximo, M.R. and Colombini, E.L., 2023.A survey on offline reinforcement learning: Taxonomy, review, and open problems. IEEE Transactions on Neural Networks and Learning Systems

[8]Tang, C., & Chen, Y. (2021). Sentiment-aware deep reinforcement learning for stock trading with feature engineering. IEEE Transactions on Emerging Topics in Computational Intelligence, 5(5), 890-901.

[9]Pabuçcu, H., Ongan, S. and Ongan, A., 2023. Forecasting the movements of Bitcoin prices: an application of machine learning algorithms. arXiv preprint arXiv:2303.04642.

[10]Kong, M. and So, J., 2023. Empirical Analysis of Automated Stock Trading Using Deep Reinforcement Learning. Applied Sciences, 13(1), p.633.

[11]Rahwan, I., Cebrian, M., Obradovich, N., Bongard, J., Bonnefon, J.F., Breazeal, C., Crandall, J.W., Christakis, N.A., Couzin, I.D., Jackson, M.O. and Jennings, N.R., 2022. Machine behaviour. Machine Learning and the City: Applications in Architecture and Urban Design, pp.143-166.

[12]Cao, Y., Ren, X., Qiu, C. and Wang, X., 2022. Hierarchical reinforcement learning for blockchain-assisted software defined industrial energy market. IEEE Transactions on Industrial Informatics, 18(9), pp.6100-6108.

[13]Yan, Y., Guo, S., & Hu, Y. (2021). Sentiment-aware deep reinforcement learning for high-frequency stock trading. IEEE Access, 9, 22796-22806.

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