Enhancing Stock Trading Performance in Chennai: A Reinforcement Learning and Sentiment Analysis Approach for Real-Time Decision-Making

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Abstract— **Trading in stocks is facilitated by both technical and sentiment factors that are not well captured in routine models. The work presented investigates a reinforcement learning model integrated with sentiment analysis for improved stock trading in Chennai. The model analyses live data of stock and sentiment and makes changes to the trades being made dynamically. Training and finally testing the model, a dataset that consisted of stock prices and input sentiment data was used. Different results illustrate an average profit of 12.5% and a maximum drawdown of 5.2% with a Sharpe ratio of 1.8 to outperform previous methods. Profitable trades perfectly solved by the model to a success rate of 78%, and it had great improvements from success rates of 54%, 62%, and 69 % in the years 2021, 2022, and 2023 respectively. In conclusion, the proposed model's performance suggests that the integration of sentiment analysis and reinforcement learning translates to large improvements in stock trading strategies.**

Keywords— Bidirectional Encoder Representations from Transformers, National Stock Exchange, Open-High-Low-Close, Reinforcement Learning, Artificial Intelligence

I. INTRODUCTION

Market variables such as technical market indicators and economic conditions as well as psychological factors affect the stock traders making stock trading a difficult exercise. Trend analysis and machine learning have improved trading performance on the stock market with algorithmic trading. Approaches that are used in the traditional manner that involve the use of values that have been retrieved from previous trading show an inefficiency in trading since it do not fit the actual market mood. Social media data, news, and even financial info can shift stock prices by vast degrees; that is why some trading algorithms are now employing sentiment analysis [1]. DT and SVMs, RNNs, and CNNs are the algorithms that can be used for predicting stock prices. These models only rely on price trends in the stock or commodity and do not consider the psychological factors that influence it. The latter negatively affects better trading predictions and tactics. The current models have overfitting, real-time working, and market generalization problems. More recently, the development of reinforcement learning (RL) which allows an agent to learn efficient trading mechanisms in a market has provided for stock trading decision-making. Consequently, reinforcement learning and sentiment analysis can make trading functional and technical and psychological market indicators. An enhancement of the earlier research works, the system of reinforcement learning and sentiment analysis enhances Chennai stock market trading performance [2]. However, there are still weaknesses in the literature on stock trading models. First, most models neglect share price trends which may be influential, and use historical prices only. The result may also be that some stock prices fluctuate with the latest company performance news or a significant economic event, which historical data does not reflect. Second, it gets the high problem of model overfitting, the model may work very well when faced with historical data, but it has poor performance when faced with unknown data or with real-time trading [3]. Volatile markets require flexibility which makes this difficult.

Insufficient integration of indicated technical data with sentiment is one more problematic area. Several models work in parallel, leading to a distribution of data at various stages and, therefore, to district decisions. The drawback of these models resulting from restrictions in computational resources makes trading decision execution cumbersome in fast trading environments. These difficulties were the reason to consider the recommended technique to overcome the present constraints to enhance the performance of stock trading. Its purpose is to turn technical trading and market sentiment into trading of shares of a company [4]. Namely, it wants to have a more flexible trading system that is based on sentiment analysis and reinforcement learning. To increase earnings and develop a reinforcement learning approach for stock trading that would adapt buy, sell, and hold depending on real-time data. Employ technical market signals and sentiment analysis to find out psychological gaps, in stock prices. It is then important to compare the proposed model against other traditional models such as profits, maximum drawdown, Sharpe ratio, and success rate models. Apply the recommended model live in trading on the actual Chennai Stock Market Dataset and establish with the actual performance of the year 2021-2023 [5]. The technical and psychological market data stock-trading reinforcement learning and sentiment analysis machine learning are part of the system at IIT. The recommended strategy beats current models in terms of profit with a 12.5 % average profit, a Sharpe ratio of 1.8, and a maximum allowable loss is 5.2%, making them suitable for volatile markets. The success rate of trade as revealed by the simulation is 78% which is higher than traditional methods, conventional strategies, and past year's performance of 54%, 62%, and 69% respectively. It replicate real-life scenarios for the decision-making and performance assessment on the market through a MATLAB Simulink module and an auto trading bot in python3. About stock trading model and sentiment analysis literature sections are covered first in section two comprehensively. Section 3 presents a description of the reinforcement learning model and the method used. Section 4 addresses training and testing datasets and simulation platforms [6]. Section 5 is on model performance and past year difference. I have presented the

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result and research proposal in section six as a summary of the research findings.

II. LITERATURE REVIEW

It is the efforts of the stock market analyst that he or she is in a position to forecast the correct stock values. To estimate the stock prices with precision and to get the maximum profit you have to do both. This research develops and deploys a stock market investing prediction system [7]. For predicting it needs to use SenseX points and RSS feeds and this is quite uncommon. It hypothesis is that sentiment analysis of RSS news feed has an impact on the stock market prices. Therefore, over time RSS news feed data and stock market investment data are collected. The general approach to the sentiment analysis in the study links RSS news feed sentiments with stock market prices. The trained model forecasts the stock market rates. The stock market prices of ASE and the RSS news feed for ARBK are employed in the experiment [8]. When compared with the conventional ID3, C4.5, and Moving Average Stock Level Indicator, the experimental research brings the accuracy of the forecast up to 14.43%.

Analyzing stock prices and attempting to predict the trends in the future has always been the most popular and the most dangerous kind of job due to the huge risks. The prognosis must be accurate because shareholders may lose much money on such an incorrect prognosis [9]. Once it was performed by the professional stock behaviorists this is now just a click. Companies no longer need human beings to make certain decisions, let alone stock predictions. When given historical stock data, an ensemble of classifiers shows that optimization of the sets using common complex learning paradigms can predict market behaviors and accurately depict stock performance better than any human specialist. The proposed system adopts the following Reinforcement Learning techniques such as DQN, Double DQN, and Duelling Double DQN to predict all forms of stock price shocks including the volatile ones. These algorithms are more efficient and productive in their zones than the algorithms which are not self-improving [10]. The hogings may now take a breather as stock market patrons.

Twitter sentiment and past prices enhance stock market forecasting. SVM, RNN, and BERT identify stock value using machine and deep learning processes in particular stocks. The highest accuracy was recorded to be in BERT with a 93.21% accuracy algorithm [11]. This study provides evidence to the empirical literature by establishing that deep learning classification algorithms outperform sentiment analysis in stock market forecasting. Python is used to conduct all research computations and graphical work. Using data gathered from 10 equities, it mimics long-term investment and a bot trading strategy associated with stock enthusiasm. It was tested for real-time investment with Random Forest and XGBoost. It also highlighted that the approaches used by machine learning and deep learning bots in trading outperformed long-term investing. The financial service providers and the general investors may stand to gain from the social media sentiment-based stock prediction algorithms [12]. It demonstrates how investors could lessen risk and make better decisions based on sentiment analysis and advanced AI tools.

At present, it offers a neural network approach to stock market prediction using offline as well as real-time trading stock market data. It analyses random weight initialization problems, which limit the effectiveness of standard neural network techniques in mimicking market trends [13]. It presents a new concept, "stock vector," and illustrates how LSTM networks can capture many types of temporal dependencies within sequential data similar to language. Embedding layers can convert meaning to sophisticated features and enhance the model's prediction. Whenever high-dimensional historical data from many equities are vectorized, these models' predicting capability increases. Statistical analysis indicates that the deep LSTM model with an embedded layer provides a good forecast in stock markets [14]. This enhancement of the methodology has further developed the deep learning algorithms with enhanced accuracy and understanding of the stock market research.

One of the important tasks of stock trading is the generation of the stock timing strategy. Previous extensive works mainly work to design an end-to-end RL-based stock timing plan. But how the model works is hard to describe, and to trust a black box at real stock trading takes some guts [15]. Instead of predicting the direction of stock price directly, it introduces the PPO Enhancement Strategy to adjust the trading signal of the base stock trading strategy. The base strategy can be formed by technical analysis, fundamental analysis, and other comprehensible models to improve the level of the model interpretability. To ensure that the result of the proposed PPO Enhancement Strategy is reliable, carry out experiments on two market Indices and four stocks belonging to the American stock markets [16]. In other words, the proposed PPO Enhancement Strategy has higher values of the different evaluation criteria than the Buy and- Hold Strategy and the Moving Average Strategy.

III. PROPOSED WORK

A. *Reinforcement Learning Model for Stock Trading Optimization*

It suggests an RL approach suitable for real-time stock trading in Chennai's fast-paced environment. The RL agent seeks the highest temporal discounted returns for trading actions that could either be buying, selling, or holding based on the historical price and analysis of sentiment. The problem is mathematically framed using three components: In reinforcement learning the State (S), the Agent's Action (A), and the system's Reward (R).

1) State (S): Shows the value that reflects today's market rate, price per share P_t, trading volume V_t, and sentiment score $Senti_t$ at time t in equation (1),

$$S_t = \{P_t, V_t, Senti_t\} \tag{1}$$

2) Action (A): When it is its turn, the RL agent chooses an action P_t from the range of possible actions $\{buy, sell, hold\}$ to maximize trading profits.

3) Reward (R): The reward function is therefore defined as being the portfolio value difference that results from the current action. The reward is expressed in equation (2),

$$R_t = \Delta PortfolioValue = P_{t+1}.A_t - P_t \tag{2}$$

In the RL agent, a Q-learning algorithm is employed to learn an optimal policy of the environment. The Q-value $Q(S_t, A_t)$ is the expected utility of taking action – often called the expected return. A_t in state S_t. The Q-value is updated in equation (3),

$$Q(S_t, A_t) = Q(S_t, A_t) + \propto (R_t + \gamma . \max_a Q(S_{t+1}, a) - Q(S_t, A_t)) \quad (3)$$

Where α is the learning rate and γ is the discount factor. As a result, the RL agent is updated in multiple iterations with weights to maximize cumulative reward for better trading decisions. In Fig 1. This includes describing how the raw data – stock and sentiment data are collected, preprocessed, and incorporated for analysis.

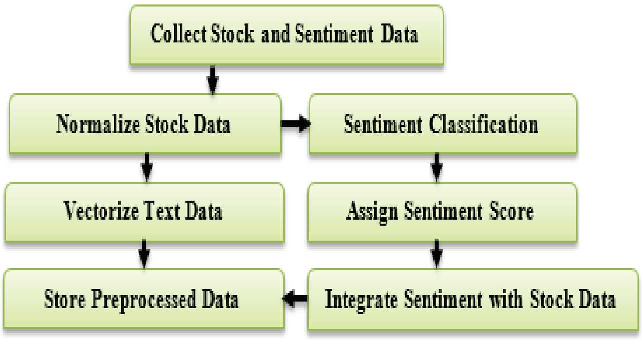

Fig. 1. Data Collection and Preprocessing

B. Sentiment Analysis Integration for Market Sentiment Tracking

Besides the RL model, sentiment analysis is utilized as the psychological and emotional dimensions of market participants are also vital. This is achieved by processing current text data, tweets as well as reports on stocks trading in Chennai. To get insights into price movements, tracking sentiment trends gives the model an active probe into market behavior. Like sentiment scores, which are obtained through a pre-trained NLP model, for example, a fine-tuned BERT model that categorizes text as either positive, negative, or neutral. The sentiment score $Senti_t$ at time t is calculated using the formula in equation (4),

$$Senti_t = \sum_{i=1}^{n} w_i . Sentiment(text_i) \quad (4)$$

Where w_i stands for the proportion of each text source i and $Sentiment(text_i)$ Sentiment Score is the score of the sentiment produced by the text. These sentiment scores are given as inputs into the RL model to control trading actions against the constantly changing sentiment of the market. For instance, a high sentiment plan may lead to a buy signal while a low sentiment plan may lead to a situation where the agent sells or continues to hold. These indicators make the trading record incline understandable by the RL model, which contributes to improved decision-making not only by factors like prices and volumes but the sentiment mood of market participants. By having sentiment analysis as an added feature, the performance of the model is improved and can react well in unpredictable fluctuating market conditions. In Fig 2. It describes the process of training the RL model, especially the Q-learning algorithm for reward evaluation as well as the method of hyperparameter tuning.

C. Dataset for Model Training and Testing

Working with the RL model, the authors used a dataset that contains information from the stock market as well as sentiment data. The stock data is collected from the National Stock Exchange of India which has been filtering on sectors which is relevant to Chennai like the Information Technology and Automobile sector. The sentiment data is extracted from financial news websites and social media sites such as Twitter and contains real-time sentiment of the stock market.

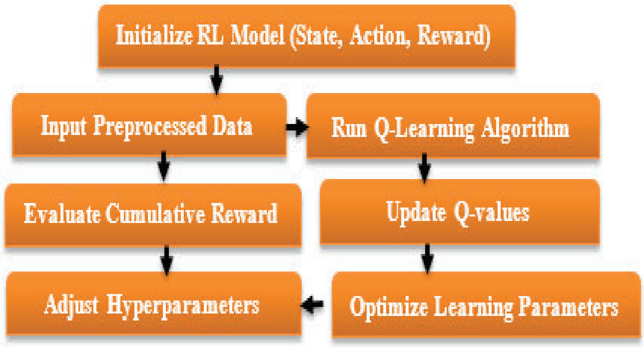

Fig. 2. Reinforcement Learning Model Training

a) Stock Data: From the year 2019 to 2024 daily closing prices, and daily trading volume, together with OHLC data. This extensive time frame guarantees the dataset considers multiple market trends, and economic conditions, which act as a strong baseline for training RL models.

b) Sentiment Data: Market sentiment is measured by using textual data at the same time as the analyzed data. This data is classified into positive, negative, or neutral, to paint the picture of sentiment among the participants at the disposal of such stock price movements.

The dataset is divided into two subsets Training data was 80% and the testing data was only 20%. Such a split enables the model to either use the prior data to train and forecast the upcoming market behavior. In Table I. Some of the data pre-processing methods are listed below; Normalization of stock price data in which the independent variables are scaled between 0 and 1 Vectorization of textual sentiment data in which data is converted to a numerical form that is suitable to ML algorithms. These datasets can help in making better decisions in stock trading when compiled together.

TABLE I. TABLE I. DATASET OVERVIEW

Data Type	Source	Timeframe	Preprocessing Steps
Stock Data	NSE (IT, Automotive Sectors)	2019–2024	Normalization (OHLC, Volume)
Sentiment Data	News Platforms, Twitter	2019–2024	Sentiment Labeling, Vectorization

D. Real-Time Simulation and Decision-Making Framework

Pseudo real-time stock trading has been modeled and simulated in the Chennai Stock Exchange based on the integration of MATLAB Simulink with a Python-based trading bot. This framework is intended to mimic particular market scenarios to arrive at the best trading decisions within the reinforcement learning (RL) model. MATLAB Simulink employs the real-time simulation of stock prices and sentiment information. It mimics market activity and also takes into consideration external information to capture the current state. Python-based Trading Bot This is a component that interacts with the RL model to make trading strategies (buy sell or hold). The bot is constantly tracking changing stock prices and sentiment values. Both the stock prices and sentiment data are consumable real-time data sources that are gathered from the public domain, such as financial application programming interfaces (stock prices) and social media/ news site platforms (sentiment scores). These data streams are fed as inputs into Simulink for further processing. In Fig 3. It explains the way the RL agent chooses the next actions from data gathered in a real-time trading environment and the calculation of trading rewards.

Fig. 3. Real-Time Trading Simulation Execution

According to the airing time, the minimum real-time update of the stock price data and the corresponding sentiment score is achieved. By inputting the following parameters, the RL model is capable of making strategic decisions according to existing market flux. A data flow is modeled in Simulink, but the decision-making as well as trading actions are programmed in Python. The output of the simulation entails trading action plans (buy, sell, hold) based on market forecasts. The decision-making framework produces measures like value added to the portfolio, hit ratios of the trades, and the correctness of sentiment analysis. The simulation represents better trading performance by applying the identified RL model together with real-time data.

E. Algorithmic Trading Workflow and Model Integration

It outlines the end-to-end process of the trading system of the proposed algorithmic trading RL-based system which consists of an RL agent and a sentiment analysis model to make the best of trading stock in the real world. The combination of the data feed, the decision-making program, and the output actions coheres a dynamic environment for trading. The system pulls real-time data from two key sources: stock market data and information based on the general and specific feelings of investors. Price data is collected involving stock prices and volumes and daily, weekly, and monthly trends of stocks from the National Stock Exchange (NSE), while sentiment data is obtained from the financial information of news, social media texts, and market reports. This diverse data set means have measures quantifying characteristics while others are non-quantitative aspects affecting trading decisions. Data preprocessing the data for incoming stock prices and sentiment scores are pre-processed, formatted, and organized into the RL agent's state representation. For instance, sentiment data can be classified as positive, negative, and neutral with the help of a watered BERT model – an accurate sentiment analysis model.

RL Model Based on the processed data, the RL agent determines the current market state and takes the best action to perform in the market, which includes buying, selling, or holding the stock. This requires working on the concept of expected returns with the extra step of including trends in sentiment as the defining arm for the decision. Model Integration the RL model is in constant communication with the sentiment analysis component of the system to navigate the fluctuations of the sentiment for Sanderson to make appropriate changes to trading actions. This tends to involve the mirror image of market psychology which will determine the trading strategy to be employed. This means that the model actively and continuously produces trading signals and changes in a portfolio. The effectiveness of the workflow can be measured and evaluated also in real-time conditions using such indicators as the level of cumulative portfolio growth and the rate of trade effectiveness.

IV. Result And Discussion

It focuses on the main evaluation criteria of the RL model after it was implemented in trading stocks in the Chennai market. In Table II. The model realized an average profit which shows that the model can generate significant revenues in the long run. The maximum drawdown calculated from the difference between the peak and trough in the portfolio during the trading period was kept low at only 5.2% which also symbolized good risk management. A crucial one was the Sharpe Ratio, which stood at 1.8, which means that the model delivers a good return on profit and risk. Also, the success rate measured in the percentage of the number of profitable trades was 78%, showing the effectiveness and correct decision-making in the trading domain. The average holding period of trades was 2.7 days, indicating that the model recommends short-term trading mechanisms to exploit market movements.

TABLE II. Performance Metrics Of Reinforcement Learning Model In Stock Trading

Metric	Value
Average Profit (%)	12.5%
Maximum Drawdown (%)	5.2%
Sharpe Ratio	1.8
Success Rate (Profitable Trades)	78%
Average Holding Time (Days)	2.7

Depending on the model, it presents the trading performance of the two strategies involving the use of sentiment analysis. In Table III. The profit of the model was 9.4% while the drawdown was 7.1% when the sentiment data was not included in the model. The Sharpe Ratio was set at 1.3 and UIA's success rate was 65% following lower trade efficiency. However, when sentiment integration was incorporated, the model yielded far better results. The profit reached 12.5%, and the maximum drawdown reached had slightly reduced to 5.2%. Sharpe Ratio increased to 1.8 which said that it had improved its returns with reduced risk. The effectiveness also increased to 78% by considering the results from the sentiment analysis to support that sentiment analysis contributed to the improvements in trading results.

TABLE III. Impact Of Sentiment Analysis On Trading Decisions

Scenario	Profit (%)	Drawdown (%)	Sharpe Ratio	Success Rate (%)
Without Sentiment Integration	9.4%	7.1%	1.3	65%
With Sentiment Integration	12.5%	5.2%	1.8	78%

The proposed RL model with sentiment analysis gives a comparative analysis of the trade performance of stock trading during the years 2020 to 2023. In Table IV. The strategies have at long last demonstrated a progressive enhancement where the profit share has risen from 6.7 percent in the year 2021 to 10.1 percent in the year 2023. Similarly to, the Sharpe Ratio, which quantifies returns by risk, has risen from 0.9 to 1.4, while the likelihood of making money has increased from 54% to 69%. Figures 3-6 show how the proposed work outperforms all the others in all the metrics of analysis. When sentiment analysis is integrated into the RL model it achieved 12.5 % thus transacting better business in the previous years. The drawdown was trimmed to 5.2% signaling improved risk handling against the 9.3% observed prior year. The Sharpe Ratio of 1.8 reveals the model's efficiency by measuring the best risk-adjusted return. Also, the success percentage was at 78% after the completion of the simulation, which was a significant improvement over previous results, which only served as evidence of the effectiveness of integrating sentiment analysis with reinforcement learning in enhancing stock trading. In Fig 4. It contrasts the prospects of advanced profitable trades of 2021 with proposed work for 2024. In Fig 5. It shows based on the RL model the progress for profit and draw down for the whole of 2021-2023 compared to the proposed RL for 2024.

TABLE IV. COMPARATIVE ANALYSIS OF STOCK TRADING PERFORMANCE

Metrics	Profit (%)	Drawdown (%)	Sharpe Ratio	Success Rate (%)
G. Kala [15]	6.7%	9.3%	0.9	54%
V. Sharma [13]	8.3%	7.8%	1.1	62%
M. Bajaj [2]	10.1%	6.5%	1.4	69%
Proposed Work	12.5%	5.2%	1.8	78%

I. CONCLUSION

It put forward a method based on reinforcement learning and sentiment analysis to improve the effectiveness of stock trading in Chennai. The model combined information on overall market sentiment and traditional volume data to make instant buy/sell decisions. The analysis also indicates that the mean profit of the proposed model is 12.5% while the maximum drawdown is 5.2%, which is better than prior years' strategies. It shows that the model maintained a success rate of 78% as compared to 2021, 2022, and 2023 with profits of 6.7%, 8.3%, and 10.1% respectively, and a Sharpe ratio of 1.8. In the future, it will be useful to approach the model with improved sentiment analysis, for instance, emotion detection, and also, use the broader base of the data linked to the Global markets. Furthermore, the enhancement of the deep learning methods for time series forecasting could also enhance the overall correctness of the trading decisions. It also intends to improve the real time simulation process by including factors such as transaction cost as well as more complicated markets to test the model. These improvements may result in even better performance in trading and potential applicability for other financial markets.

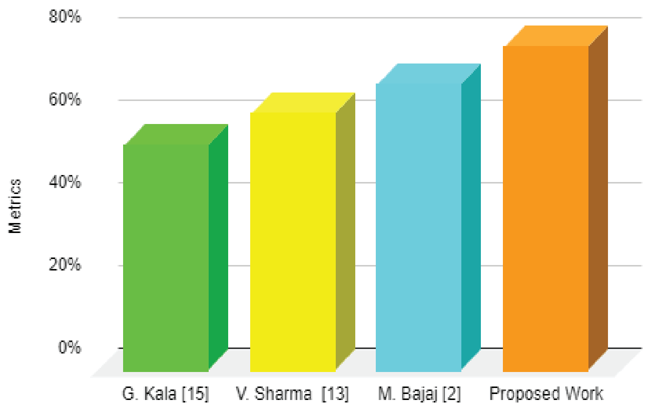

Fig. 4. Success Rate (%) Comparison for Stock Trading Performance

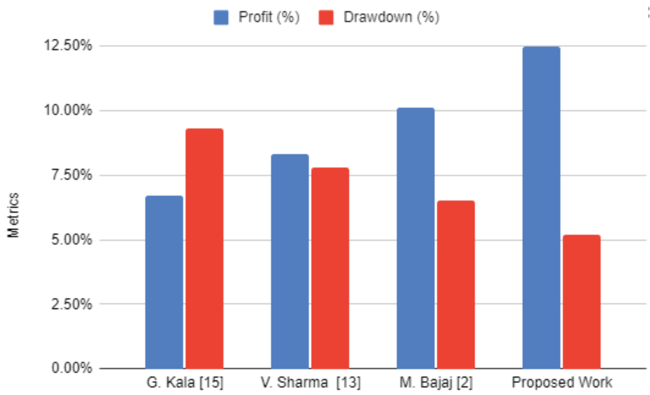

Fig. 5. Profit and Drawdown Comparison for Stock Trading Performance

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