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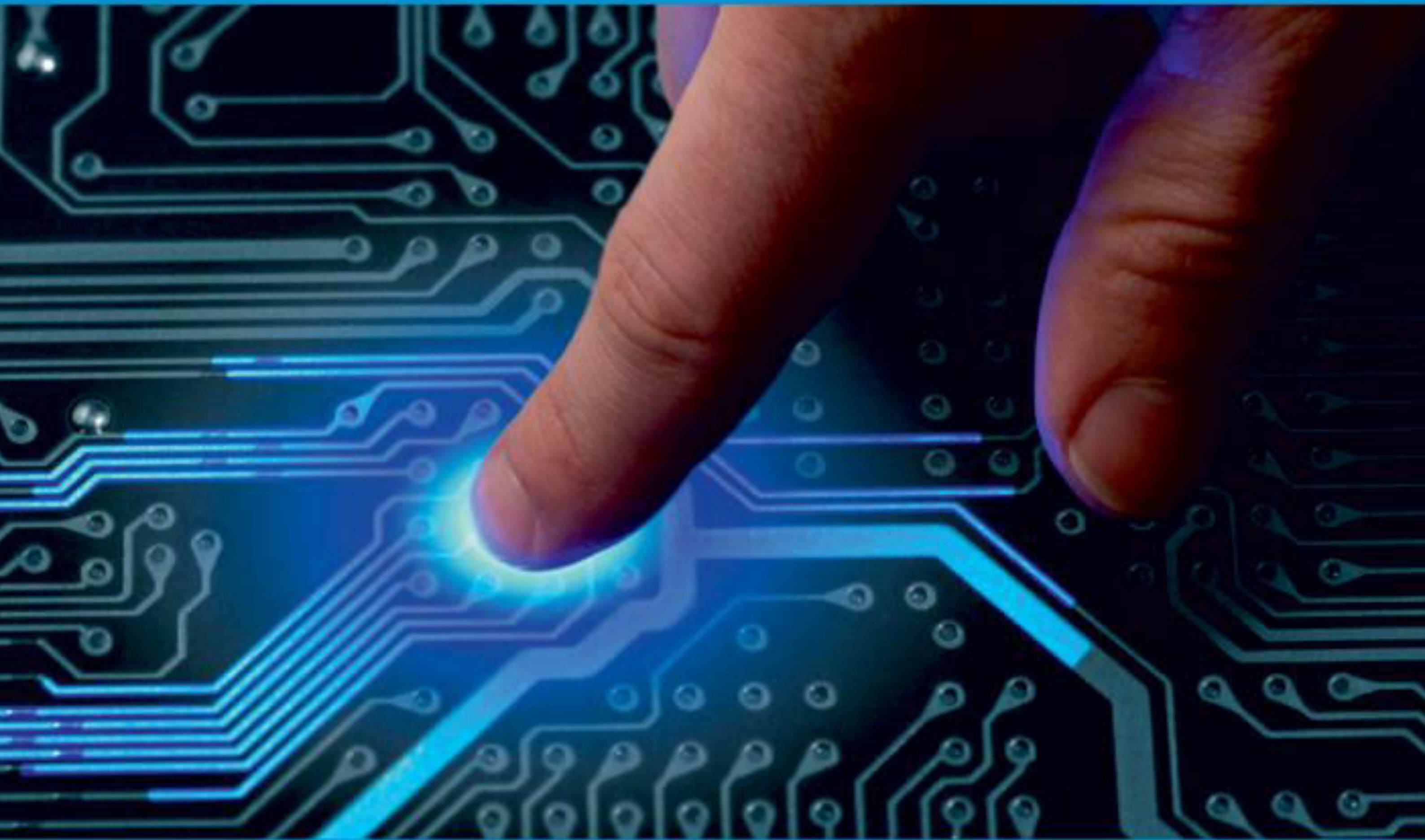

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Real-Time Stock Market Forecasting Using Deep Learning

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ABSTRACT-There is no one approach that appears to anticipate stock price both precisely and long-term at the same time, despite years of research on the subject by academics and financial experts. This is brought on by the unpredictable pattern of stock movement and numerous factors that affect market performance. The real-time stock market prediction uses real-time market data to forecast stock price movements and provide buy/sell signals to investors, lowering risk of loss while boosting profit. To anticipate the stock price, the proposed paper employs an ensemble of approaches, including the Rainbow Deep Q Network, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Moving Average Convergence Divergence (MACD).

KEYWORDS: Real-time stock, LSTM, GRU, MACD

I. INTRODUCTION

The stock market can be described as unpredictable, non-linear, and dynamic. It is difficult to predict stock values since they depend on several variables, such as the state of the world's politics, the performance of the company's finances, and more. By examining the pattern over the last few years, strategies to estimate stock values in advance could therefore prove to be very helpful for making stock market movements, maximizing profit and minimizing losses. For estimating an organization's stock price, there have historically been two basic approaches put forth. The closing and opening prices of stocks, volume traded, adjacent close values, and other historical stock price data are all used by technical analysis methods to forecast future stock prices.

The second sort of analysis is qualitative, and it is carried out based on outside variables such as the firm profile, the market environment, political and economic issues, textual data in the form of financial news stories, social media, and even blogs written by economic analysts. Modern predictive methods involve sophisticated intelligence procedures based on technical or fundamental analyses. An effective model that can find the hidden patterns and intricate relationships in this vast data collection is required to handle this diversity of data. Compared to previous methodologies, machine learning techniques in this field have been shown to increase efficiencyby 60–86%. However, with the aid of the ensemble, AI has enabled us to analyze both technical and fundamental data.

For the purpose of predicting stock prices, a number of machine learning and deep learning algorithms have been separately implemented. They only appear to function effectively for a brief period of time, and the crucial aspect of generalization—the ability to function well on previously unknown data—is lost. A martingale impact on the stock price is to blame for this. This has made these methods ideal for achieving quick results. Better models with state-of-the-art performance are the product of recent advancements and concepts in the field of artificial intelligence, and they have the potential to provide outcomes that have never been seen before.

One of those concepts that has been floating around for a while is ensemble techniques, commonly known as bagging and stacking. Data scientists use this method since it has been demonstrated to produce superior results to using individual models. The idea behind this is that while different aspects of the data may be discovered during training, individual models may correct each other's errors after an ensemble. The same is true for stock market forecasting. Higher compute requirements have also been prompted by better performance. Recent advancements in computation handling and community initiatives have given us methods that have become standards in their respective industries. These methods are assemblages of intra- and inter-domain approaches.

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II. LITERATURE REVIEW

Technical and fundamental analyses. Both were employed in the stock market analysis.

Prediction Methods

[Wavelet analysis and the ARIMA SVR model are used in the stock forecasting process. 3rd International Conference on Information Management (ICIM), 2021 Tian Ye used ARIMA-SVR and wavelet analysis to forecast stock market prices. Wavelet decomposition and wavelet reconstruction were used to separate the stock price into a reconstructed portion and an error portion. Then, the reconstructed component and the incorrect part are anticipated using the ARIMA model and the SVR model, respectively. The models were developed and evaluated using a 90%–10% train–test–split on the Shanghai Pudong Development Bank's closing price from January 5, 2019, to January 29, 2021. The MSE of 0.57 was deemed satisfactory for the results. technical and theoretical evaluations. In the stock market study, both were used. Restrictive Boltzmann machines for forecasting trends in financial time series [B]. International Joint Conference on Neural Networks (IJCNN) in 2021 Rafael Ramos, Wenderson Dias, Eduardo G. Carrano, Wenderson Assis, and Carlos A. S. Assis proposed using the Restricted Boltzmann machine to predict stock price. The method was applied to five real time series from BM&F BOVESPA and involved five steps: extraction of historical data, transformation, dimensionality reduction and feature extraction, classification, and result analysis. The combined accuracy for RBM and SVM was found to be between 54% and 66%.

Multi-Financial Market Prediction Using Cross-Domain Deep Learning. International Joint Conference on Neural Networks (IJCNN) 2020.
For various financial market prediction, Xinxin Jiang, Shirui Pan, Jing Jiang, and Guodong Long used a cross domain deep learning approach. On many models, attention processes were deployed in the stock and currency domains. The strategy was tested both before and after the financial crisis on the currency and stock markets of the USA, China, and India. F1 Score and Area Under Curve (AUC) were used to evaluate performance.
[D] An evaluation of the use of neural network models in predicting individual stock prices.
International Conference on Computer Engineering and Artificial Intelligence (ICCEAI), 2021 On the basis of data from the Chinese Stock Market, Chen, Zhou, and Dan (2021) make predictions. The training data was sampled from intervals that offered a range of results. This significantly changes how well the model performs. This research closes that gap. By centering noise from trend reversal signals and preventing skewed model weights, standardization on the data improves the performance of the models. In addition to enhancing the performance of LSTM models, this study introduces the usage of GRU models and ICA for price predictions.

Foundational Skills

Making stock market investing predictions using emotive analysis Printed in: 2016 ICRITO 5th International Conference on Reliability, Infocom Technologies and Optimization The study highlighted SM actions that, as a result of domestic and international factors, have a significant impact on the market value of specific enterprises. Three aspects of Brazilian social media activity on Twitter were examined in the study: (A) the total quantity of Tweet emotions; (B) Tweet sentiments with likes; and (C) Balanced feelings should be acknowledged. They used the Multilayer Perceptron approach directly in their attempt to produce SA in Portuguese. [B] Analysis of text sentiment of trending social events on Weibo. 10th International Symposium on Chinese Spoken Language Processing in 2020 J. Lin, A. Yang, and Y. Yong looked examined how public comments on a trending social event on Weibo were classified based on their emotional content. First, the author proposed a categorization system based on sentiment dictionaries, with a close to 50% accuracy rate. They also suggested a sentiment classification method based on Naive Bayesian that employed TF as the feature weight and chi-square test to extract features for each class in order to increase accuracy. It has fixed the lack of sentiment analysis aimed at common occurrences on Weibo and is superior to the current method that targets the entire unified text on Weibo.

III. PROPOSED WORK

The proposed technique predicts market prices using ensemble approaches, a combination of deep learning and machine learning methods including the LSTM (Long Short-Term Memory) algorithm and GRU (Gated Recurrent Unit). This method also employs better time intervals of size 1min,5min,15min to update the data from many sites in order to predict the future movements. Sentiment analysis on text from Twitter and various news headlines aids in fundamental analysis. We train 2 separate models (LSTM and GRU) using the ensemble approach on deep learning

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algorithms while considering technical and fundamental characteristics in order to integrate and attain the features from both models for real-time stock market prediction.
In terms of long-term price prediction versus short-term price prediction, the models will perform admirably with respectable directional accuracy. In addition, we suggested using the cutting-edge Rainbow DQN approach, which surpasses all other algorithms in terms of Return on Investment, to predict buy/sell signals.
The system's benefits include:

- It provides the most accurate results;
- It exceeds all other systems in terms of return on investment;
- It lowers market risk and contributes to individual profit.

Algorithms Used:

A. Deep Learning Time Series Model

EnsembleLSTM and GRU are the deep learning models in use. The sentiment score was derived from news headlines using an encoder network, and GRU was trained on it. This training was then applied to inference for forecasting. LSTM was trained on historical data. By calculating the average output from both networks, the Ensemble was completed. An important role in choosing the region of memory that will be used for generating future judgements or predictions is played by the gates that make up an LSTM cell's four gates and a GRU cell's two gates. A pretrained Encoder-Decoder Network calculates sentiment scores for all of the news headlines acquired every minute; the average of these scores is considered for that specific news item.

GRU was trained on columns "Closing Price, Sentiment Score, Volume" in the form "batch_X, batch_Y" where batch_X = x[i] to timestamp, a static parameter, and batch_Y = x[i] + 1 to timestamp + 1, a time step forward. LSTM was trained on preprocessed real-time data on the columns "Closing Price, Volume," whereas GRU was trained on columns "C" The layer size was 128 i.e. the number of LSTM cells, and the timestamp size was 4 i.e. the distance between any two results from the same batch. For the GRU network, comparable hyper-parameters were considered. To reverse the normalized data and restore the original scale of the data, inverse transform is applied to the model's forecast.

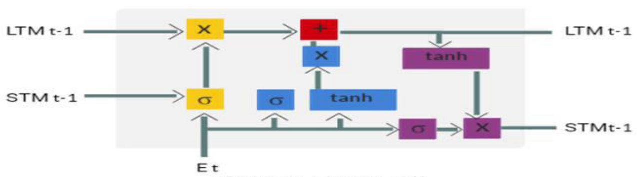

Figure 2. LSTM cell

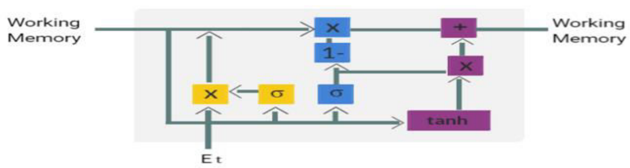

Figure 3. GRU cell

Fig 3.1 GRU CELL

B. DQN Rainbow

The most recent advancement in the field of reinforcement learning is the off-policy deep learning algorithm known as Rainbow DQN [15]. The Ensemble Deep Learning technique's anticipated closing price is utilized to predict buy/sell signals using Rainbow DQN.
We will use an Artificial Neural Network rather than a CNN as the basic model to train on the data, in contrast to the design suggested by the authors of the paper Due to the fact that stock data is not of the picture kind, these changes as well as a few others have been made. Seven essential Q learning algorithm algorithms from reinforcement learning make up Rainbow.

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Firstly, the base algorithm Deep Q learning [16] gave rise to the concept of using deep learning represented as nonlinear function approximators to calculate value actions based directly on the observation from the environment and find optimal parameters for such function approximators using gradient descent. Agents learn to take action with the help of these neural networks and maximize reward.

IV. METHODOLOGY

The National Stock Exchange of India's website, which includes prices structured in 1-day intervals, and Alpha Vantage, a financial API, which offers intraday data structured in 1-minute, 5-minute, and 15-minute intervals, will be the sources of the data used to train and test the models. For sentiment analysis, data like news headlines will be gathered from various business websites. We'll consider several news headlines being fetched instantly each minute. LSTM and GRU are the deep learning models in use. The emotion score will be derived from news headlines using an encoder network, and GRU will be trained on it. This training is then applied to inference for forecasting. LSTM will be trained on historical data. Calculating the average output will be used to complete the Ensemble from both the networks.

An important role in choosing the region of memory that will be used for generating future judgements or predictions is played by the gates that make up an LSTM cell's four gates and a GRU cell's two gates. Every minute, a pretrained encoder-decoder network calculates sentiment scores for all of the news headlines that are obtained; the average of these scores is considered for that minute. These sentiment ratings are provided to the GRU model as training data after being mapped with their respective closing prices based on the moment at which they were obtained. Before training the model, the sentiment score will be computed during inference.

On pre-processed real-time data on columns, LSTM will be trained.

{Closing Price, Volume}, whereas GRU will be trained on columns {Closing Price, Sentiment Score, Volume} in the form {batch_X, batch_Y} where;

batch_X = x[i] to timestamp, a static parameter

batch_Y = x[i] + 1 to timestamp + 1, a time step ahead

The timestamp size is 4 (the distance between any two values from the same batch), and the layer size is 128 (the number of LSTM cells). For the GRU network, comparable hyper-parameters will be considered. To reverse the normalized data and restore the original scale of the data, inverse transform is applied to the model's forecast.

The most advanced method in the field of reinforcement learning is the off-policy deep learning algorithm known as Rainbow DQN. The Ensemble Deep Learning technique's anticipated closing price is utilized to predict buy/sell signals using Rainbow DQN.

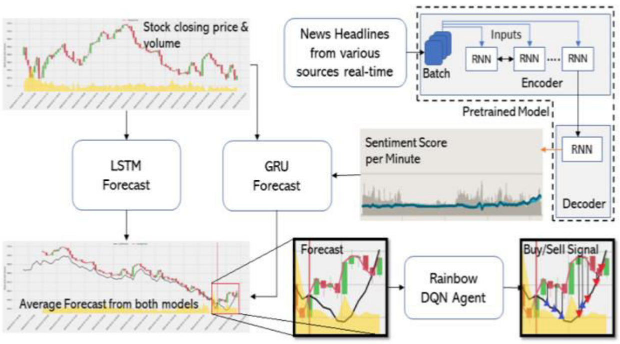

Fig 4.1 Working architecture

The news data from various other business sources is first fed to an encoder decoder network to calculate sentiment scores on a real-time basis, and then given as an input to GRU that is then trained on sentiment score and historical data to forecast price. The average of the results from both models is then calculated. The historical data extracted using the Alpha Vantage API will be fed to an LSTM which is trained on it to forecast closing price in real-time. This average forecast is then used to predict buy and sell signals by a Rainbow agent.

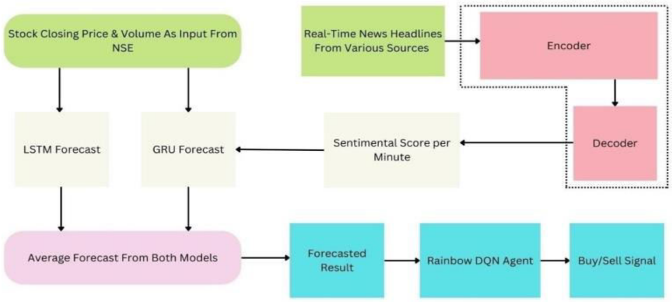

Fig 4.2 Detailed working architecture

V.RESULTS

Fig5.1Homepage

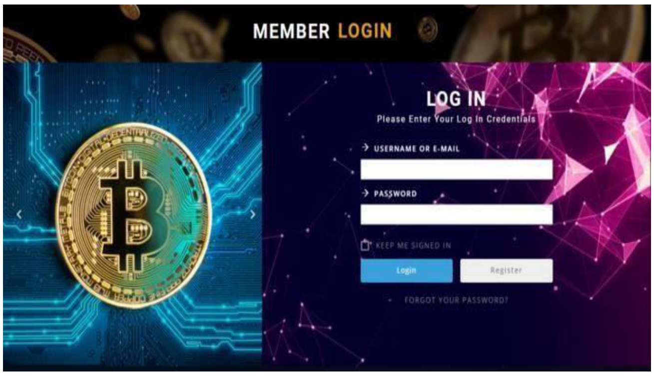

Fig5.2Loginpage

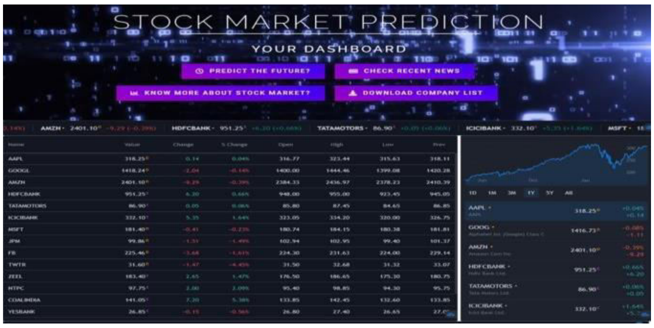

Fig5.3 Dashboard of User.

Fig5.4PredictionPage

Fig5.5 ResultsPage

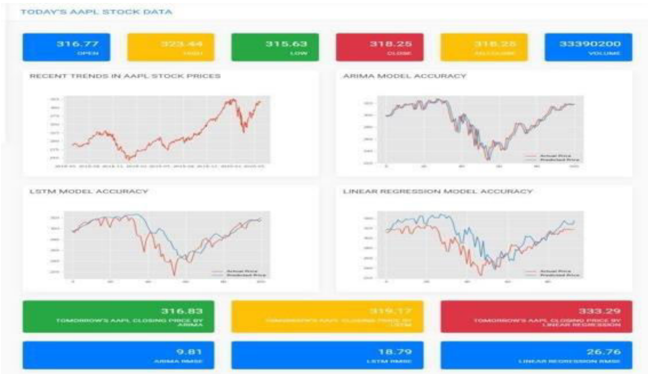

Fig5.6OverallResultsPage

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VI.CONCLUSION AND FUTURE SCOPE

In this study, we trained 2 separate models (LSTM and GRU) using the ensemble approach on deep learning algorithms, considering technical and fundamental characteristics, and combined and obtained the features from both models for real-time stock market prediction. When compared to long-term price prediction, the short-term price prediction performed admirably with respectable directional accuracy. We also suggested using a cutting-edge method called Rainbow DQN to forecast buy/sell signals because it surpassed all other systems in terms of Return on Investment.

In spite of these findings, the model did not perform well with high volatility and consequently value accuracy. For more accurate findings, multiple models can be combined or more parameters can be considered. Fast Fourier Transform and Decomposition are examples of mathematical models [23]. The final architecture that is being presented can also be utilized to create trading bots. The ability to predict the stock market has been constantly increasing, and upcoming technological breakthroughs may produce more accurate outcomes than were previously possible. In comparison to a standard Artificial Neural Network with Rainbow DQN algorithm, an LSTM [24] base model may perform better. We did not include distributional RL in our implementation, even though it could greatly enhance our agent's current performance.

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