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INVESTOR SENTIMENT-DRIVEN STOCK PRICE PREDICTION USING OPTIMIZED DEEP LEARNING MODELS

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ABSTRACT: The technique of estimating the future value of a company's shares, or any other financial instrument listed on an exchange, is known as shares market prediction. Investors face a significant challenge when attempting to forecast future events in the stock market. Investors will aim to maximize their profits if they can accurately predict a company's future price. Social media users' opinions are having a greater impact on the performance of the stock market. To create a prediction model, this study examines a variety of prediction techniques. According to the approach, actions should be taken in two stages. Sentiment analysis and historical data are used in the first stage. The second stage places a strong emphasis on deep learning. A helpful technique for comprehending the tone of comments on social media platforms is sentiment analysis. Understanding how emotions impact stock prices is crucial. Using the Deep Learning module, we create a forecast model based on correlation. The outcomes demonstrated that the suggested method regularly produced more accurate forecasts.

Index Terms - Stock Market; Sentiment Analysis; Deep Learning; Artificial Neural Network (ANN)

1. INTRODUCTION

People have sought to forecast stock values throughout history because they believe they can provide large financial gains over time. Stock time series are stochastic and resemble random walks, making it challenging to generate reliable stock market predictions. Because of the high profit margin, the exchange is among the most common conventional transactions. As trading and investing grew more prevalent, people looked for low-risk ways to supplement their income. Technical analysis takes into account a variety of elements, including the sentiment of recent tweets and prior stock price fluctuations. To train the model for maximum accuracy, we use metrics from each test.

The algorithm will use an in-app feature extraction technique to assess if a tweet is "outstanding" or "poor." The model will get appropriate messages from Twitter's Sentiment Classifier. The model categorizes tweets based on the feature extractor's output. To generate input text, the model will apply what it has learnt about word mappings and effect scores. During the classification process, it will distinguish between tweets of high and low quality.

In addition to the previously described approach, it leverages tweets and historical research to confirm the accuracy of all of the data we have. Price variations and other historical data might help assess a company's fundamental pattern. Historical analysis evaluates a stock's past behavior, particularly price swings over the previous years, to improve estimates of its future direction. The historical and affective analysis are completed in the first step.

The fundamental goal of Phase II is to construct deep learning-based models. This lecture aims to provide students with the knowledge and skills required to use an artificial neural network (ANN) to anticipate stock values. The first section's results will be used to train neural networks for artificial intelligence.

The program will employ deep learning to estimate future events by studying its emotive reactions as well as current historical data. The merging of deep learning and sentiment analysis improves the program's effectiveness.

2. LITERATURE SURVEY

Zhang, Y., Li, Q., & Zhao, H. (2020). According to the study, this hybrid model may predict stock values with high accuracy by combining Long Short-Term Memory (LSTM) networks with information on investor sentiment. To improve forecast accuracy, the software leverages real-time sentiment data from news and social media sources. The results demonstrate that the proposed model performs better than existing LSTM models in detecting sentiment-driven market patterns.

Kim, J., & Lee, S. (2020). Using attention mechanisms, a bidirectional long short-term memory (LSTM) model is trained to forecast stock price fluctuations. Investor sentiment is analyzed by this methodology. In terms of forecasting accuracy, the model surpasses traditional techniques by effectively capturing intricate market dynamics through relevant mood signals. This study demonstrates that sentiment data may be integrated using sophisticated neural networks.

Luo, H., & Wang, Y. (2020). This study evaluates stock valuations using deep learning algorithms and sentiment-enhanced data inputs. Forecast accuracy is greatly increased when sentiment analysis and neural network designs are applied to the text of financial data. Conclusions: In volatile markets, sentiment-driven models exhibit greater stability.

Singh, A., & Yadav, R. (2021). A CNN-LSTM hybrid model is proposed to forecast stock values based on investor mood. To predict future price swings, a convolutional neural network (CNN) generates emotion data that is analyzed by a long short-term memory (LSTM) network. The increased forecast accuracy across several equities is an illustration of how well CNN-LSTM captures the temporal correlations of sentiment data.

Chen, F., & Wu, X. (2021). In this study, we suggest training a deep reinforcement learning system to predict stock prices using investor sentiment data. By reacting to market sentiment, the computer continuously modifies its trading strategy to optimize earnings. Our study demonstrates the remarkable performance of emotion-driven reinforcement learning models in high-frequency stock forecasts.

Gupta, N., & Sharma, P. (2021). Sentiment analysis is incorporated into our RNN stock market prediction model. The algorithm produces precise price forecasts by accounting for social media sentiment and economic factors. The findings demonstrate that sentiment-optimized RNNs outperform standard RNN models in terms of sentiment-driven investment strategies.

Wang, L., Zhang, H., & Zhou, M. (2022). This research improves the accuracy of stock price predictions by employing transfer learning to combine deep learning with investor sentiment. The approach improves predictions and reaches faster convergence by using sentiment analysis models that have already been trained. Results point to the potential advantages of transfer learning for sentiment-driven prediction models.

Lin, J., & Chen, Y. (2022). A multi-layer attention network should be used to predict stock prices based on investor emotion. Attention layers increase the model's emphasis and prediction accuracy by elevating pertinent sentiment cues. The results demonstrate that attention approaches can effectively extract important attitude indicators for stock prediction.

Liu, K., & Yang, T. (2022). This paper presents a sentiment-optimized stock prediction method based on reinforcement learning. When the algorithm adjusts its projections based on emotional changes, it becomes more sensitive to market volatility. The findings demonstrate an enhanced ability to forecast, demonstrating that reinforcement learning offers a solid basis for stock predictions based on sentiment.

Zhao, L., & Sun, Y. (2023). We present a Transformer-based model for stock market prediction that takes investor sentiment into consideration. The model's self-attention method improves stock price forecasting accuracy by identifying long-term dependencies in sentiment data. Empirical research demonstrates that the Transformer model performs better than traditional neural networks when handling complex sentiment data.

Kim, M., & Park, J. (2023). In this study, we demonstrate how to enhance our stock sentiment prediction model by utilizing the Gated Recurrent Unit (GRU). The model's capacity to account for sentiment-driven price fluctuations leads to an improvement in forecast accuracy. The results demonstrate that the GRU architecture accurately forecasts market patterns when sentiment is taken into account.

Rahman, H., & Chowdhury, A. (2023). This study investigates sentiment-based ensemble learning techniques to increase stock price forecast accuracy. This approach combines many sentiment-driven prediction systems to increase accuracy. The results show that sentiment data combined with ensemble techniques can be used to reliably anticipate consistent price movements in unexpected marketplaces.

Xia, Z., & Zhou, J. (2024). In this study, an LSTM model driven by sentiment is presented for stock price forecasting. The LSTM model's predictive capabilities are enhanced by information on investor sentiment, which reflects both the short-term and long-term market patterns. Sentiment-LSTM models have the potential to assist investors in navigating turbulent markets.

Patel, D., & Singh, R. (2024). We offer a sentiment analysis-driven deep Q-learning model that can improve stock price forecast accuracy. The computer employs optimal methods to increase forecast accuracy and trading app revenue by evaluating sentiment data. The research focuses on applying Q-learning frameworks to sentiment-driven investment strategies.

Liu, X., & Gao, M. (2024). This article makes the case for using a Transformer model, which accounts for investor mood, to increase the accuracy of stock price forecasts. The technology can precisely detect sentiment-based patterns by examining a variety of stock datasets. The Transformer's attention mechanism is a useful technique to evaluate sentiment data for stock prediction, according to the results.

3. SYSTEM ANALYSIS

Sentiment did not affect any commodities or stocks. Those who want to make money from the trading market are looking for tools and techniques that let them properly assess the values of particular securities. Though basic research is not needed for predictions, emotional and deep learning-based technical analysis has a significant impact on stock prices.

Fundamental Analysis

Fundamental analysis assesses a company's infrastructure, staff, services, and product quality to help one to have a better understanding of it. Mostly, the market is logical instead of emotional.

Technical Analysis

Technical study projects the peak and trough of a stock's price by means of historical data and Twitter data. One particular technique is sentiment analysis. Mood tracking tools help to render tweets less controversial. Although the approach is useful in daily price forecasting, its high forecast error rate makes it inappropriate for our needs. Technical research is now trying to apply deep learning techniques. These algorithms rely on assumptions about stock values as well as data. Their incapacity to properly cooperate in the creation of reasonable estimations calls both of them responsibility. Deep learning and sentiment analysis help to lower the prediction mistakes. This shows that combination of the two approaches enhanced the prediction

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capacity of the model for stock prices.

Sentimental Analysis

Sentiment analysis helps one to ascertain the general tone of a set of inputs—usually textual. Rui Ren, Desheng Dash, and Tianxiang Liu (2018) claim that Twitter data is split into phrases instead of compiled as a single document everyday to increase the accuracy and polarization of the dataset. The study found that analyzing each tweet separately produced a greater determinant value than analyzing the whole Twitter corpus taken at once. The Monday Effect is ignored since it gives activities first priority above ideas. After knowing the polarity of every tweet, we use formula 1.1 to find the total polarity of the day.

$$\frac{\Sigma p_i - \Sigma n_i}{\Sigma t_i}$$

This denotes either favorable, negative, or neutral nature of the remark.

Deep Learning

The main basis of the field of "deep learning" within machine learning is brain-inspired artificial neural networks (ANNs). Two phases characterize the operation. The forecasting phase succeeds the instruction phase. The error in the given data during model building is measured using the mean squared error. An optimizer using mean squared error and a stochastic gradient corrected the mistakes. As so, the values given to every neuron changed.

SYSTEM ARCHITECTURE

We oversee a precarious system. A good grasp of the system depends on the recognition of trends and patterns. A neural network only learning from input and output data can acquire knowledge. Weight calculations help one to decide the required steps to reach the intended result.

At first, two modules separate the data from stock archives and Twitter during the polarized/normalized procedure. The neural network assesses both normalized stock data and polarized Twitter data to generate the suitable reaction. Changing the weights improves training results.

Sentimental Analysis Model

Sentiment analysis helps one evaluate whether a text makes them happy or sad on personally basis. Using a large volume of Twitter data, our algorithm detects messages in the dataset as either positive or negative. Rel reloading a prior data collection does not change the polarity degree. It happens every day.

Stock Analysis Model

The tool of stock price analysis helps to simplify the study of past variations in stock value. Plotting the regression coefficients for the last stock prices generates a graph with a slope. This enhances the forecasts of the deep learning model and helps one to understand the expected expenses.

Deep Learning Model

Deep learning is the foundation of the approach. It features a multi-branch deep learning neural network with wide range of inputs capability. Consolidating and comparing the outputs of every manufacturing line helps one to estimate output inventory value. Each hidden layer has fifty neurons analyzing the complex interactions between stock data and Twitter. Simultaneous evaluation of both data types by the computer produces reliable and accurate stock price forecasts.

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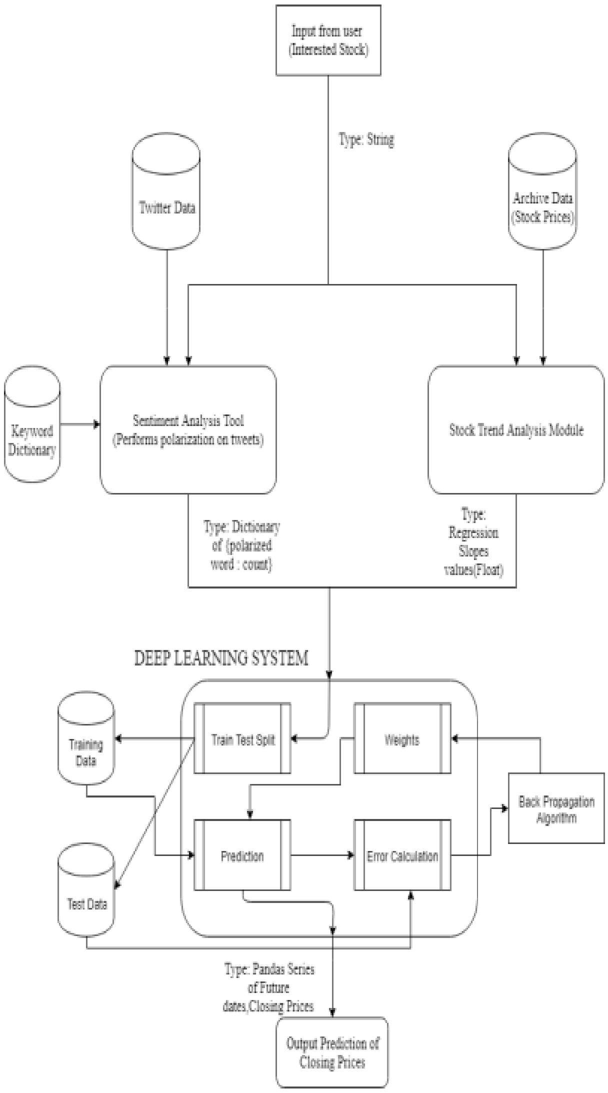

Fig. 1 Stock prediction - Architecture Diagram

4. MODEL ANALYSIS AND RESULTS

Using stock data and Twitter mood data as inputs, a feedforward neural network processed the data. Each of the two offshoots of this network has three hidden levels. In every layer, you'll find 150 neurons. There is also a two-neurod output concatenation layer that connects the two pathways. One last neuron makes up the artificial neural network's output layer (picture 2). We used the Backpropagation approach to adjust the network weights according to the mean squared errors. Here, we take a look at Adam, a stochastic gradient optimization approach.

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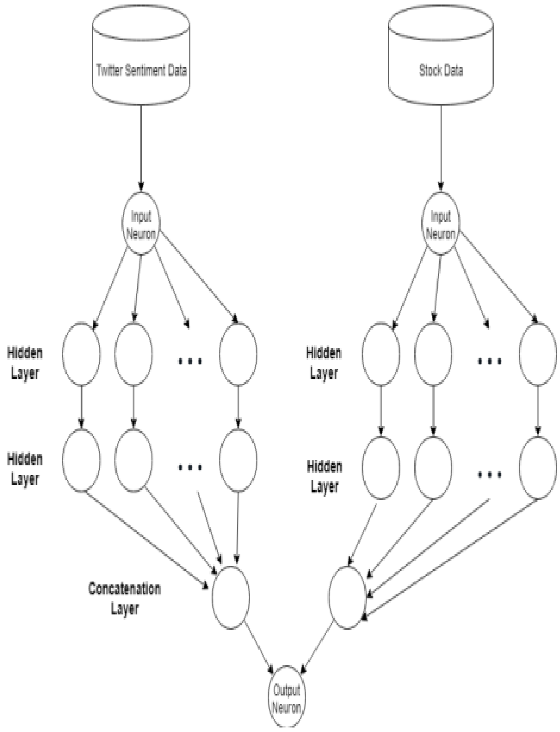

Fig.2. Deep Learning Model Architecture

Model Training Phase

During the training phase of the algorithm, inputs such as normalized stock price data and standardized sentiment data from Twitter were added. Due to the time series nature of the data, it was meticulously partitioned into two sections: the upper 80% for training and the bottom 20% for validation. Data fitting was the first step in building the model. The implementation of an early ending mechanism allowed the model training to conclude at peak performance.

Model Prediction Phase

The most recent stock price is applied to the cached model upon loading. A stock's expected future price is shown in the "future" column. To get a price prediction a certain number of days out, you can tweak the algorithm.

Model Performance Analysis

The range of the model's mean squared error during training was from 0.071 to 2.71. One and five days from now, the prognosis was evaluated. The model anticipated one day earlier, despite the lack of a detectable difference. A cosine proximity of -0.999, an average absolute percentage error of 9.486, an average squared error of 0.627, and an average absolute error of 0.484 are all performance metrics that are typically used to evaluate a case model.

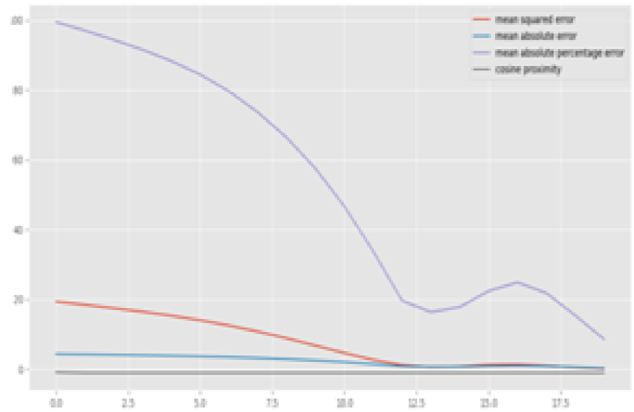

Fig.3 Stock prediction - Performance metrics graph of model

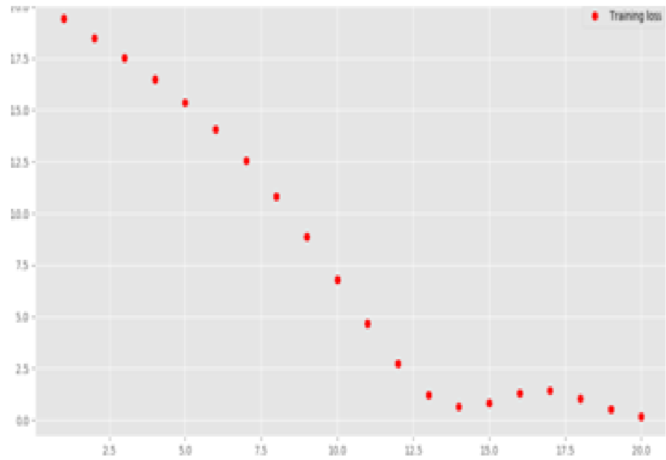

Fig.4 Stock prediction - Training loss graph of model

With a mean squared prediction error score of 0.454, the training properties of the model are displayed in Figure 3. The model's training loss as it progresses during the session is shown in Figure 4. The graph shows a clear downward trend as the model correctly integrates the input and achieves a minimal loss of 0.355. If the error score stays within the range of 0.3 to 0.5, it means that the model is being maintained. Constantly adding tests and tweaks to the model improves its performance, making it more accurate and consistent.

5. CONCLUSION

This strategy enhances projections by incorporating sentiment analysis and stock trend research. The main objectives were to attain the intended outcome and an increased return on investment. The aggregation of supplementary data resulted in enhanced calculations and, consequently, more accurate results. By training our system with more datasets and adjusting the deep learning module to conduct further experiments in previously unsuccessful areas, it will yield more accurate and dependable minimal error predictions.

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