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Classification of Stock Price Using Fundamental and Technical Analysis

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Abstract - Investors who want to make well-informed decisions face problems due to the constantly shifting nature of financial markets. Pattern identification becomes more difficult when analyzing high-dimensional data because quality patterns become more complex. Various machine learning approaches are frequently used in this complex situation to efficiently anticipate and categorize future data. However, customizing a computer for a particular portion of the dataset usually comes at a high cost. This study suggests a deep learning method to recognize various price patterns in the stock market by utilizing long short-term memory (LSTM) networks. LSTM networks are superior to conventional methods in capturing temporal dependencies and patterns in time-series data, as they may not require as much training cost for certain dataset segments. A thorough review of a company's data and economic indicators is part of the fundamental analysis component of the study. Technical analysis is also used to look at trading volumes, historical price movements, and different technical indicators. It aims to get over the limitations of traditional approaches by using LSTM model capabilities to find periodic relationships and patterns in stock market data.

Keywords* : *LSTM, Stock Patterns, Machine Learning, Stock Prediction, Technical Analysis

1. INTRODUCTION

In the fast-paced world of financial markets, making informed investment decisions is a big challenge. Investors and traders constantly seek tools and methodologies to predict and classify stock price movements, enabling them to maximize returns and minimize risks. Two key approaches have emerged as cornerstones of stock price analysis: fundamental analysis and technical analysis. Fundamental analysis focuses on evaluating a company's financial stability and other economic variables that may influence how well it performs. The rewards that investors may reap when market directions are correctly predicted are highlighted by the recent focus on stock market forecasts. The predictability of the stock market significantly influences trading and investment profits. A reliable system that forecasts the volatile stock market's direction empowers users to make well-informed judgments, enhancing their decision-making capabilities. Traditionally, traders have relied on patterns, and repetitive sequences in OHLC (Open, High, Low, Close) candlestick charts, as signals for buying and selling. A critical challenge in stock market research lies in categorizing and predicting stock price volatility patterns. Predicting stock price trends essentially involves classifying and forecasting patterns of stock price fluctuations. Professional traders typically analyze stocks for buy or sell decisions using either technical or fundamental research. Fundamental analysis involves examining a firm's core elements, such as market position, growth rates, revenues, and costs. In contrast, technical analysis relies solely on past price movements. Analysts seek patterns in price charts and estimate future price movements by employing various computations based on price data.

2. LITERATURE SURVEY

In machine learning, we often find that simple algorithms can produce impressive results compared to complex ones. Embracing this idea, our paper will use a Long Short-Term Memory (LSTM) model to predict short-term stock prices.

1. In the Research Paper, "Stock Chart Pattern Recognition with Deep Learning" used the exhibitions of CNN and LSTM for perceiving normal outline designs in a stock of verifiable information. It presents two normal examples, the technique used to assemble the preparation set, the brain network designs, and the exactness. According to this paper, the LSTM algorithm has achieved higher detection rates.

2. In this paper , the effectiveness of the Long Short-Term Memory (LSTM) and Bidirectional LSTM (BI-LSTM) models for stock price prediction is compared. Time series data and long-term dependencies are well-suited for the modified Recurrent Neural Network (RNN) known as LSTM. The LSTM's architecture—which includes memory cells, gates, and cell states—is covered in the paper. These components enable the LSTM to store information over time. By simultaneously taking into account past and future data, BI-LSTM, an improvement on LSTM, combines two LSTMs to boost sequence classification tasks. Using Yahoo Finance data for Google stock prices from 2004 to 2019, the methodology entails preparing the data and splitting it into training and testing sets. Google Collaboratory and TensorFlow are used in the study to train and evaluate the models. According to the results, BI-LSTM performs better than LSTM in terms of prediction accuracy and has lower RMSE values. The study emphasizes how crucial parameter adjustment is for maximizing model performance, including the number of epochs, hidden layers, and thick layers. Specific configurations of BI-LSTM, such as two thick layers, 64 units, and two hidden layers, show the greatest results for stock price prediction.

3. To optimize parameters and enhance stock market prediction, the study suggests a hybrid strategy that blends Long Short-Term Memory (LSTM) networks with Genetic Algorithms (GA). Recurrent neural networks (RNNs) of the LSTM type are excellent at identifying patterns in time series data related to finance. GA is used to optimize the time window size. LSTM parameters are shown as binary chromosomes in the GA determining the LSTM model's Mean Squared Error (MSE) and using it as the GA's fitness function. The dataset for the study is daily KOSPI stock index data from 2000 to 2016. Historical price/volume data and five technical indicators are utilized as input elements to forecast the next closing price of the day. The results indicate that when it comes to predicting the direction of S&P 500 stock returns, the GA-optimized LSTM performs better than the normal LSTM and other benchmarks like Random Forest and Deep Neural Networks. The hybrid GA-LSTM technique is a good fit for stock market prediction tasks, according to the authors.

4.The Long Short-Term Memory (LSTM) neural network is the main method used in Dou Wei's study "Prediction of Stock Price Based on LSTM Neural Network". The LSTM neural network, which is optimized by the Mini-Batch Gradient Descent (MBGD) algorithm is finally chosen by the study after it compares and evaluates several neural network prediction techniques. The opening price, closing price, lowest price, maximum price, date, and daily trading volume of three sample equities from China's stock market are among the important data gathered for the study. When paired with an attention mechanism, the LSTM neural network predicts stock price patterns with encouraging results. The model can nonetheless accurately anticipate stock values even though its predictions include a duration lag.

5. In order to predict future stock prices in the Indian share market, the research paper "Stock Price Prediction Using LSTM on Indian Share Market" examines the use of machine learning and data analysis approaches, particularly the LSTM (Long Short-Term Memory) model. The paper explores the difficulties in predicting the stock market, emphasizing the obstacles caused by a number of variables, including market rumors, investor emotions, and the fluctuating nature of the value of stocks. The suggested structure shows the potential of ML approaches to identify patterns and generate accurate forecasts by analyzing and predicting company growth using LSTM when combined with an algorithm. With high accuracy rates and reduced error, the paper's results demonstrate how well LSTM can predict stock values for companies like Google and Reliance.

6. Dev Shah, Wesley Campbell, and Farhana H. Zulkerine investigated the use of state-of-the-art technologies—Deep Neural Networks (DNN) and Long Short-Term Memory (LSTM) in particular—for stock market price forecasting. Daily training of both models and an evaluation of their accuracy and error rates were part of that inquiry. Notably, the DNN and the LSTM Recurrent Neural Network both performed brilliantly when it came to daily prediction, indicating that they are both appropriate for these kinds of tasks. By applying overfitting prevention techniques, they made certain that both models could successfully generalize to novel and more unstable datasets. Notably, the LSTM RNN outperformed the DNN in terms of weekly forecasts.

7. The research paper , describes a project that shows how LSTM networks can be used in real-world stock market analysis. To present a comprehensive overview of the market, the project uses a thorough data collection approach that integrates sentiment analysis of news stories, financial indicators, and social media data. Preprocessing methods for data, such as normalization with MinMaxScaler, are used to convert feature values to a standard scale and minimize bias. To avoid overfitting, a Sequential Keras model with Adam Optimizer and Dropout is used to create the predictive model. The accuracy of the model is assessed by comparing the actual and forecast share prices, which helps measure its performance.

8. In this, authors used 175 technical indicators produced with the TA-Lib toolkit and 15-minute candlestick data for multiple Brazilian stocks from 2008 to 2015 to train an LSTM model. Every trade day, the model was trained using data from the past ten months, and it was validated using data from the previous week to forecast if prices would rise or fall during the next fifteen minutes. Based on experiments conducted on data from December 2014, the LSTM model was able to forecast price fluctuations with up to 55.9% accuracy.

9. In this research focuses on creating a deep learning model that forecasts movement in the benchmark broad-based stock market index (NIFTY 50) of the National Stock Exchange of India using historical data from Infosys Ltd. and recurrent neural networks (RNN). Because the stock market is dynamic and complicated, impacted by a wide range of external variables such as national policies, economic circumstances, and investor feelings, the article emphasizes the significance of precise forecasting in the stock market. To forecast changes in the stock market, the study makes use of deep learning techniques such as LSTM and RNN, demonstrating the effectiveness of neural network models over more conventional approaches like ARIMA. The application of Support Vector Machine (SVM) is also investigated in this work.

10. This study examines three distinct approaches—linear regression, Auto-ARIMA, and long short-term memory (LSTM)—for stock price prediction utilizing machine learning and deep learning algorithms. To forecast the closing prices of Reliance Industries Limited (RIL) stock in the future, the paper used a linear regression model. 80 % of the data were used for training and 20% of it were used for testing. To predict the closing prices of the RIL stocks, the Autoregressive Integrated Moving Average (ARIMA) model—a popular time series forecasting method—was also employed in this work.30% of the data were used to test and train the ARIMA model. In addition, the study used a stacked long short-term memory model—a kind of recurrent neural network—to predict the closing prices of RIL stock. On 80% of the data, the LSTM model was trained, and on the remaining 20%, it was tested. The LSTM model performed better than the other two approaches, as evidenced by its computed RMSE value of 64.32.

In summary, all the researchers implemented various methods to learn about the stock trends of the market. They used numerous algorithms for this, including LSTM, RNN, and Support Vector Machine. Each of them implemented their strategies to forecast the stock price and tried to make an accurate decision.

3. PROPOSED SYSTEM AND ALGORITHM

In machine learning, it's common for researchers to find that less complicated algorithms can provide more remarkable outcomes than more complicated ones. In line with this notion, our study will forecast short-term stock values using a long-short-term memory (LSTM) model. A type of RNN termed LSTMs is useful for capturing long-term dependencies in time series prediction issues. The order of the input has a big impact on prediction because of these relationships. Each LSTM cell delivers an output after a multi-step process, in contrast to regular neurons. A separate memory in LSTMs called the cell state is used to retain pertinent historical data that helps with prediction. In the subsequent steps, structures known as gates alter the data stored in the cell state. First, the forget gate chooses whether to remove any information that is accessible. Next, the input gate and tanh layer determine which newly acquired data should be stored. Additionally, data is added and removed by earlier gates. Lastly, the data are subjected to the activation function, and the result is generated. demonstrated appreciable improvements, according to. LSTM networks have been used in the context of stock price prediction, utilizing news text data to predict price patterns. On the other hand, some research uses historical price data and stock indices to forecast price changes.

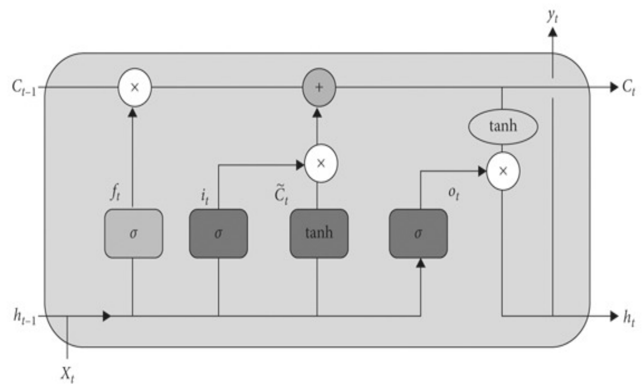

Fig -3.1: LSTM Architecture

$$i_t = \sigma(w_i[h_{t-1}, x_t] + b_i)$$
$$f_t = \sigma(w_f[h_{t-1}, x_t] + b_f)$$
$$o_t = \sigma(w_o[h_{t-1}, x_t] + b_o)$$

$i_t \rightarrow$ *represents input gate.*
$f_t \rightarrow$ *represents forget gate.*
$o_t \rightarrow$ *represents output gate.*
$\sigma \rightarrow$ *represents sigmoid function.*
$w_x \rightarrow$ *weight for the respective gate(x) neurons.*
$h_{t-1} \rightarrow$ *output of the previous lstm block(at timestamp $t-1$).*
$x_t \rightarrow$ *input at current timestamp.*
$b_x \rightarrow$ *biases for the respective gates(x).*

These are the equations for gates. The first equation is for the Input Gate which tells us what new information we're going to store in the cell state. The second is for the forget gate which tells the information to throw away from the cell state. The third one is for the output gate which is used to provide the activation to the final output of the LSTM block at timestamp 't'.

The equations for the cell state, candidate cell state, and the final output:

$$\tilde{c}_t = tanh(w_c[h_{t-1}, x_t] + b_c)$$
$$c_t = f_t * c_{t-1} + i_t * \tilde{c}_t$$
$$h_t = o_t * tanh(c^t)$$

ct => cell state(memory) at timestamp(t).

c`t => represents candidate for cell state at timestamp(t).

This project proposes an LSTM-based model for predicting price movements. LSTMs specifically avoid the long-term dependency issue. They pick up knowledge easily, and they have no trouble remembering it for a long period of time. In most recurrent neural networks, a sequence of neural network modules repeats itself. The approach involves leveraging a variety of technical indicators, commonly used in investment strategies. The goal is to evaluate the effectiveness of this method and test the hypothesis that the short-term memory capabilities of LSTM networks can yield superior results compared to traditional feed-forward networks.

Using LSTM For Stock Market Prediction:

1. LSTM networks are a good fit for analyzing the stock market because they are highly effective at recognizing and learning from historical trends in sequential data. Their ability to accurately identify volatility, periodic patterns, and trends in stock prices enables more accurate projections of future price movements.

2. Long-term dependencies: Traditional models have trouble capturing long-term dependencies in stock market data. LSTM networks may reliably predict future market trends by identifying pricing patterns from the past and using them to retain information across longer periods in memory cells and recurrent connections.

3. Handling variable-length input sequences: Stock market data is often widely spread and changing duration, with different stocks trading at different frequencies. Because LSTM networks can accept variable length input sequences, which enable them to adapt to changing time intervals and handle missing or unevenly spaced data points, they can make strong predictions even when the data is sparse or incomplete.

Proposed System: This project aims to develop a predictive model for Stock prices using Long Short-Term Memory (LSTM) networks. The model leverages historical stock price data to forecast future prices, providing valuable insights for investors and traders. The LSTM network's ability to capture temporal dependencies in sequential data makes it an ideal choice for this task. This overview presents the methodology and decision-making process employed in the study. The project includes a thorough planning and data collecting approach. It incorporates information from a variety of data sources, such as financial websites like Yahoo Finance and Nasdaq , to capture both quantitative and qualitative market elements. This approach provides an accurate understanding of the industry, enabling the development of trustworthy forecasting models.

The dataset has the following attributes:

Name - Name of the company

Symbol - This is short symbol of every company

Name:- Name of the company

Last Sale - Most recent price at which a stock was traded

Net Change - Indicates how much the stock's price has increased or decreased over that period

Country - Country to which the company belongs

IPO Year - Refers to the year in which a company makes its initial public offering

Sector - a sector refers to a group of companies that operate in the same industry or share similar business characteristics.

Volume - Volume refers to the total number of shares traded during a given period

In order to improve decision-making in the dynamic stock market environment and enable machine learning algorithms to draw insightful conclusions, extensive data gathering and preprocessing are prioritized in an effort to improve the accuracy and reliability of stock market forecasts.The MinMaxScaler has been used to normalize the data.A data preparation method called MinMaxScaler seeks to normalize feature values within a given range. Two steps in this process are carried out for each data value. First, the data value is deducted from the feature's minimum value. This change effectively shifts the entire range of values by guaranteeing that the minimum value becomes zero. After that, the outcome is divided by the range, which is computed as the variation between the feature's initial maximum and minimum values. By dividing by the range, the data values are scaled proportionately and brought inside the intended range, which is often between 0 and 1. The feature values are transformed to a similar scale by using the MinMaxScaler, which makes them comparable and eliminates any potential bias brought on by different scales. When using machine learning algorithms that are sensitive to feature scale, this normalization process is particularly helpful since it enables the algorithms to efficiently use the data and produce accurate estimations or classifications.

In the project implementation part, predictive model construction using machine learning techniques is described in detail. Additionally, model training is covered in this part, highlighting methods for maximizing model performance. To further develop the model, the predictive model combines the Sequential Keras model with the Adam Optimiser. The sequential approach was used in the implementation, which works well in situations where the layer stack is simple.

Because there is exactly one input tensor and one output tensor for each layer in this structure, data flows through the network linearly.

```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm_4 (LSTM)               (None, 60, 200)           161600

 lstm_5 (LSTM)               (None, 100)               120400

 dense_4 (Dense)             (None, 100)               10100

 dense_5 (Dense)             (None, 1)                 101

=================================================================
Total params: 292201 (1.11 MB)
Trainable params: 292201 (1.11 MB)
Non-trainable params: 0 (0.00 Byte)
```

Fig. 3.2 A description of the Sequential Model Layers

To reduce loss and improve model performance, optimizers are crucial algorithms that adjust a neural network's properties, such as layer weights and learning rate. Adaptive Moment Estimation, or Adam, is a well-liked optimizer that was created especially for deep neural network training. It combines the advantages of momentum-based stochastic gradient descent (SGD) and RMSprop, two additional optimization methods. Adam allows for quicker convergence in different areas of the parameter space by adjusting the learning rate according to the strength of the gradients for each parameter. Furthermore, Adam uses the moving average of gradients—as seen in SGD with momentum—to include the idea of momentum. By doing this, the optimizer can retain a memory of past gradients, which leads to updates that are smoother and may accelerate convergence. For training deep neural networks, Adam is an adaptive optimization technique that, in essence, combines the benefits of momentum-based SGD and RMSprop.

4. IMPLEMENTATION

A machine learning model was created to forecast stock prices. The model was optimized with the Adam optimizer using a mean squared error (MSE) loss function after being trained using a variety of setups. Throughout the course of the 10-epoch training phase, the model iterated over the whole dataset several times. With a batch size of 512 utilized, 512 data points were handled concurrently in each iteration. The model performed better during training, as evidenced by a decrease in the MSE loss from 0.0211 to 0.0015. The model's predictions after 10 epochs were evaluated.

The formula that we have used for making buy or sell decision in this model is;

```
if predicted[0]<predicted[-1] and y_high[-1]<predicted[-1]:
      buy="Yes"
 else:
      buy="No"
```

Make a buy decision based on the predictions. If the predicted price trend is increasing (the first predicted value is less than the last predicted value) and the final predicted value is higher than the last known high price (y_high[-1]) , then decide to buy ("Yes"). Otherwise, do not buy ("No").

Fig -4.1 Decision Whether To Buy Stock Or Not

It shows the maximum and minimum price in prediction with whether to purchase given stock using provided formula using which it shows whether to buy stock or not. And change in price of that stock.

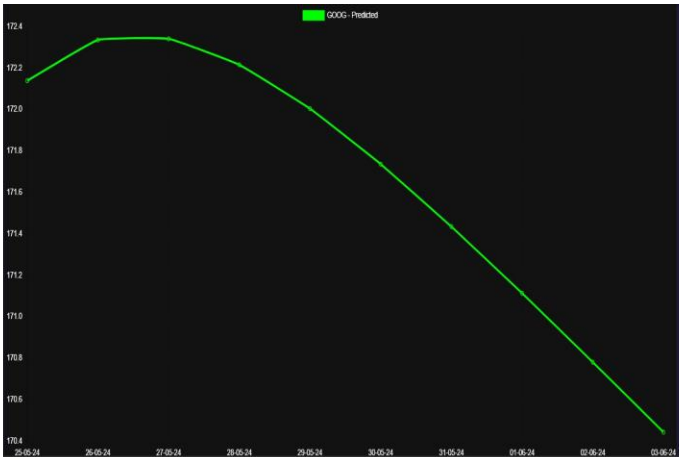

Fig -4.2 Predicted Price

And then the model shows the predicted price chart for the selected stock from the available list of stocks.

5. CONCLUSION

In conclusion, the world of financial experts revolves around the anticipation of stock market costs, driven by investors' keen interest in understanding the potential returns on their investments. This research study concludes with a thorough analysis of the use of machine learning methods in stock market analysis. It uses data from the real world to assess how well machine learning models function and presents a particular project as a practical example. In addition to addressing opportunities, the article promotes machine learning-based investment strategies and risk management approaches for stock market analysis. It places a strong emphasis on enhancing data quality and adjusting algorithms to changing market conditions. The conversation also looks at potential directions for further study, such as combining different algorithms and adding more data sources.

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