LSTM Based Stock Price Prediction on Daily Charts

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***Abstract*—The incorporation of fundamental ratios for predicting the stock price, such as price to book (PB), price to sales (PS) and Price to earnings(PE), alongside historical price data has gained considerable attention in stock price prediction. This study aims to investigate the effectiveness of utilizing these fundamental ratios in conjunction with Long-Short Term Memory (LSTM) model for predicting stock prices. In particular, we chose three large-cap companies that are listed in the National Stock Exchange (NSE), in India. scripts such as Reliance, Tata Consultancy Services (TCS), and Imperial Tobacco Company (ITC) are selected as case studies. Historical price data and fundamental ratios are collected over a specific period of the past year i.e. march 2022 to march 2023. To ensure accurate predictions, the collected dataset undergoes pre-processing techniques. By incorporating both fundamental ratios and historical price data into LSTM model, this study aims to explore the potential benefits of combining these factors for improved stock price prediction in terms of the chosen metrics like Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE).**

***Index Terms*—Stock Price Prediction, Fundemental ratios, Deep Learning.**

I. Introduction

Predicting stock prices on a dialy basis is formidable challenge, given the inpredictible volatile nature of the financial markets [1]. To address this issue, sophisticated methods are needed to extract insights from vast historical data that is present. Deep learning evolved as promising tool to deal with vast historical data including the fundemental ratios, particularly LSTM models has garnered attention for its prowess in capturing the temporal dependencies and offering dependable predictions. LSTM's [2]aptitude for learning long-term patterns makes it a promising candidate for providing reliable forecasts in the dynamic and turbulent stock market. A study conducted by Selvin *et al.* [3] with various deep learning (DL) models such as Recurrent Nueral Network(RNN), LSTM, and Convulutional Nueral Network (CNN). These models were employed to evaluate the performance of NSE-listed companies using a sliding window approach. They trained these models to predict stock prices for Infosys, TCS, and Cipla in the short term (less than an year). The research demonstrated the CNN model's ability to detect shifting trends, ultimately concluding that it was the most effective model. On the similar lines, Khare *et al.* [4] worked on the Chinese Stock Index (CSI) 300 Index. They used an LSTM model that considered market data and performed investorsentiment analysis. Initially, they categorized stock market posts as positive, negative, or neutral using a sentiment classification method. Then, they used these post sequences to analyze the overall market sentiment. Additionally, they created a deep neural network model with multiple layers, while testing it achieved a high accuracy of 87.86% by combining 90% of the training data with 10% of the test data, outperforming other methods like Support Vector Machine (SVM) by at least 6%.

An article by Li *et al.* [5] discusses using regression analysis and artificial neural networks (ANN) to develop stock market prediction apps. They worked with 210 days of historical data and 30 days of testing data for one scrip. They presented two methods for analyzing stock market data firstly, they used regression analysis to predict future stock prices, and secondly, they applied ANN's. To assist investors, analysts, or any individual interested in investing in the stock market [6]. The ussage of RNN and LSTM parlley seams to be the most useful technique to give them a good understanding of the future prediction of the stock price movement. Shen *et al.* (2020) [7] conducted extensive assessments on commonly employed ML models and in their study, determined that our suggested solution surpasses others, mainly due to the incorporation of comprehensive feature engineering techniques. In a study conducted by Ya Gao *et al*. (2021) [8] introduces a novel model aimed at optimizing stock forecasting. The model incorporates a wide range of technical indicators, including investor sentiment indicators and financial data [9]. To address the multitude of influencing factors affecting stock prices, the researchers employ dimension reduction techniques, specifically deep learning LASSO and PCA approaches. Additionally, the study compares the performance of two popular neural network models, LSTM and GRU, for stock market forecasting across various parameters. The experiments conducted yield two main findings: (1) both LSTM and GRU models demonstrate efficient stock price prediction capabilities, with no clear superiority of one over the other, and (2) among the two dimension reduction methods, the neural models utilizing LASSO exhibit superior prediction abilities compared to those using PCA. V Kranthi Sai Reddy *et al.* [10] in (2018) presents a ML model that involves training a model using available stock data to acquire intelligence and subsequently utilize that knowledge for accurate predictions. Specifically, this study employs a ML technique named as Support Vector Machine (SVM) to forecast stock prices across various markets, including both large and small capitalizations. The analysis encompasses datasets with different frequencies, ranging from daily to up-to-the-minute prices. SVM algorithm proves effective in handling large volumes of data collected from global financial markets and mitigates the issue of overfitting. An intelligent linear regression approach was used by Mohammad Mekayel Anik *et al* [11]. in 2020 to forecast future stock prices. They were successful in achieving their objectives, and the model accuracy is excellent enough that stock value predictions might be made using it.

In this research paper, we delve into the application of LSTM-based machine learning models [12] for predicting the stock prices of three prominent Indian companies, viz. Reliance, TCS, and ITC. By analyzing companies from diverse sectors, our aim is to provide a complete analysis of stock price dynamics across different industries. Recognizing the significance of fundamental financial indicators in stock price prediction, we incorporate key financial ratios such as PE, PB, and PS ratios as additional features in our predictive framework. By combining these fundamental indicators with historical price data, we to enhanced the accuracy and robustness of our predictions. This research contributes to the expanding knowledge on stock price prediction using ML techniques. Incorporating fundamental financial ratios alongside historical price data, we aim to provide investors and analysts with valuable insights into potential future price movements. Additionally, our comparative analysis across different companies broadens the applicability of our models, paving the way for more comprehensive and accurate predictions in real-world investment scenarios.

The rest of the article is arranged as follows: Section 2 introduces the methodology, Section 3 discusses about system architecture and LSTM algorithm, Section 4 discusses the results, and Section 5 concludes the paper with future scope.

II. Methodology

Long Short Term Memory Model (LSTM)

The LSTM architecture represents a transformative leap in DL model, addressing the persistent challenge of vanishing gradients that hindered traditional RNNs. Distinguished by its unique memory cell with output, forget, and input gates, LSTM enables selective storage and retrieval of information across extended sequences. In LSTM, the forget gate discards irrelevant data, the input gate stores valuable information, and the output gate controls predictions. This makes LSTM a powerful tool for tasks like time series analysis and natural language processing. Its proficiency lies in nuanced pattern recognition within sequential data, solidifying its status as a fundamental asset in contemporary deep learning methodologies.

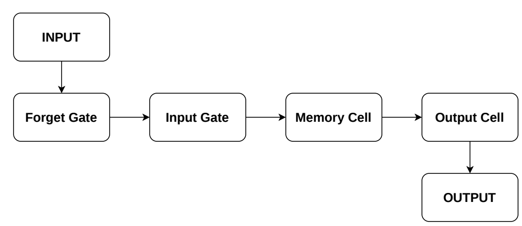

Fig. 1. Long Short Term Memory Unit

LSTM's prowess is illustrated by its capacity to capture long-term dependencies, making it instrumental in applications such as sentiment analysis, speech processing, stock price prediction, and machine translation. This architecture has revolutionized deep learning, transcending the limitations of traditional RNNs and becoming a powerful tool due to its memory cell and gating mechanisms.

In the initial phase of this study, our focus is on comprehensive data gathering and preparation. We aim to source historical stock price data for prominent entities like Reliance, TCS, and ITC from reliable financial platforms such as screener and Yahoo Finance. This dataset will encapsulate daily closing prices, trading volumes, and crucial financial ratios such as PE, PB, and PS over a predefined one-year timeframe from march 2022 to march 2023. Our meticulous approach includes essential preprocessing steps, encompassing data interpolation for handling missing values, normalization of numeric variables, and ensuring overall data consistency.Transitioning to feature engineering, our strategy incorporates thoughtful consideration of short- and long-term trends in stock prices. We leverage historical price data alongside fundamental financial ratios (PE, PB, and PS ratios) as input features for the LSTM model. Notably, our exploration extends beyond the traditional incorporation of Simple Moving Average (SMA) and Exponential

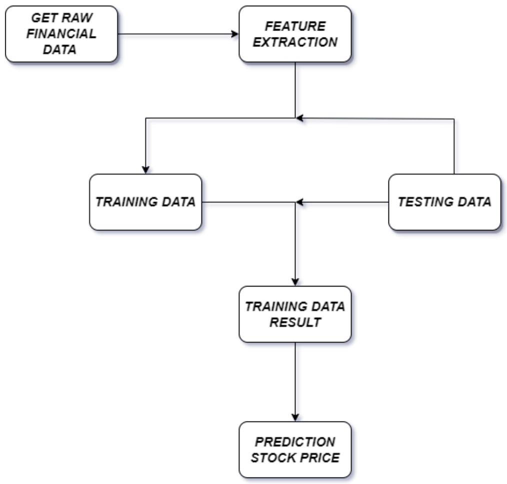

Fig. 2. System flow diagram

Moving Average (EMA) indicators [13] . By introducing these financial ratios into our model, we aim to scrutinize their impact on predictive accuracy and thoroughly assess their role in enhancing stock price forecasting. The crux of our methodology revolves around LSTM model development. We opt for Long Short-Term Memory (LSTM) neural networks, a specialized subset of RNN's, recognized for their adept capture of sequential dependencies and patterns inherent in time series data. The model training process involves the utilization of the meticulously preprocessed dataset, coupled with fine-tuning of critical hyperparameters such as the number of LSTM layers, hidden units, and learning rate to optimize overall performance. The culmination of our research journey involves a robust evaluation and comparison of our LSTM model. We employ pertinent evaluation metrics, including mean squared error (MSE), root mean squared error (RMSE), and mean absolute percentage error (MAPE), to gauge the model's predictive accuracy rigorously. Additionally, we undertake a comparative analysis, critically examining the LSTM model's performance against relevant benchmark models. This comprehensive approach ensures a thorough understanding of the model's efficacy in the context of stock price forecasting.

III. System Architecture

The objective of this research is to employ a deep learning architecture, specifically Long-Short Term Memory (LSTM), to forecast future stock prices. The dataset used in this study is sourced from Yahoo Finance and encompasses stock data from March 2022 to March 2023.

The primary focus of the proposed method is to predict the closing price of companies for the following day.we have used yahoo for fetching our data. The dataset comprises daily information for the listed companies, including opening price, closing price [14] high and low prices, volume, as well as various financial ratios such as price-to-earnings (PE), price-to-book (PB), and price-to-sales (PS) ratios.To conduct the analysis and prediction, historical data for these companies was collected and employed for research purposes.

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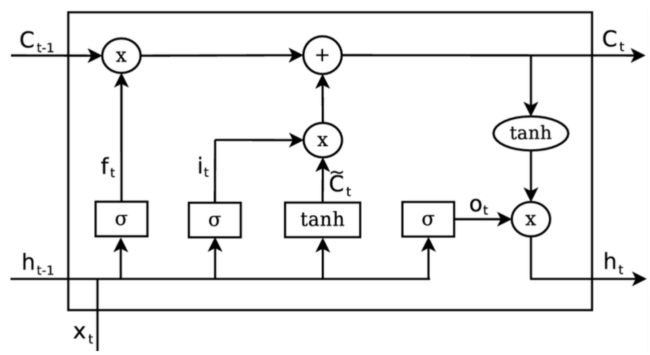

Fig. 3. LSTM Architecture

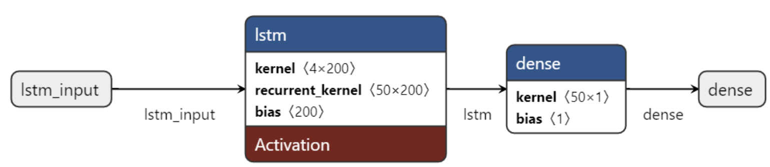

Fig. 4. LSTM Model Training

A. Algorithm:Stock price prediction using LSTM

Algorithm 1 Stock price prediction using LSTM

Import the necessary libraries

Compile historical stock price information for each company, including the closing price, PE ratio, PB ratio, and PS ratio

Clean up the data

Apply the LSTM model

Forecast share prices

Take PE, PB, and PS ratios into account

Machine learning training mode

Assess the model

Display the outcomes.

If necessary, repeat steps 4 through 9 with various parameter settings.

IV. Results and Discussions

After implementing Algorithm A, The result graph contains two subplots within a single figure to compare actual and predicted values. Figure 5, Fig. 6, and Fig. 7 represent the comparison of actual and predicted stock prices over 30 days for ITC, Reliance, and TCS respectively.

In Fig. 5(a), the actual and predicted values are plotted with solid lines, representing the respective data points. The x-axis shows the number of days, while the y-axis shows the value of the stock (ITC). In Fig. 5(b), the gradients of the actual and predicted values are plotted as lines. The actual gradients are shown in red, and the predicted gradients are shown in green. Number of days is represented in X- ais, wherein y-axis represents the gradient percentage. This representation provide easy visual comparision for the actual changes in stock value each day against the predicted value on the same day. Figure 6 and Fig. 7 follow similar analogy.

To enhance readability, the code ensures that the legends do not cover the plots. The tight layout() function adjusts the spacing between the subplots, optimizing the arrangement of the visual elements. These visualizations provide valuable insights into the model's performance in predicting trends. They allow us to assess how closely the predicted values align with the actual values and how well the gradients capture the underlying patterns in the data. In summary, the provided code enables an effective comparison between actual and predicted values using clear and separate subplots. This facilitates a comprehensive understanding of the model's performance in predicting trends.

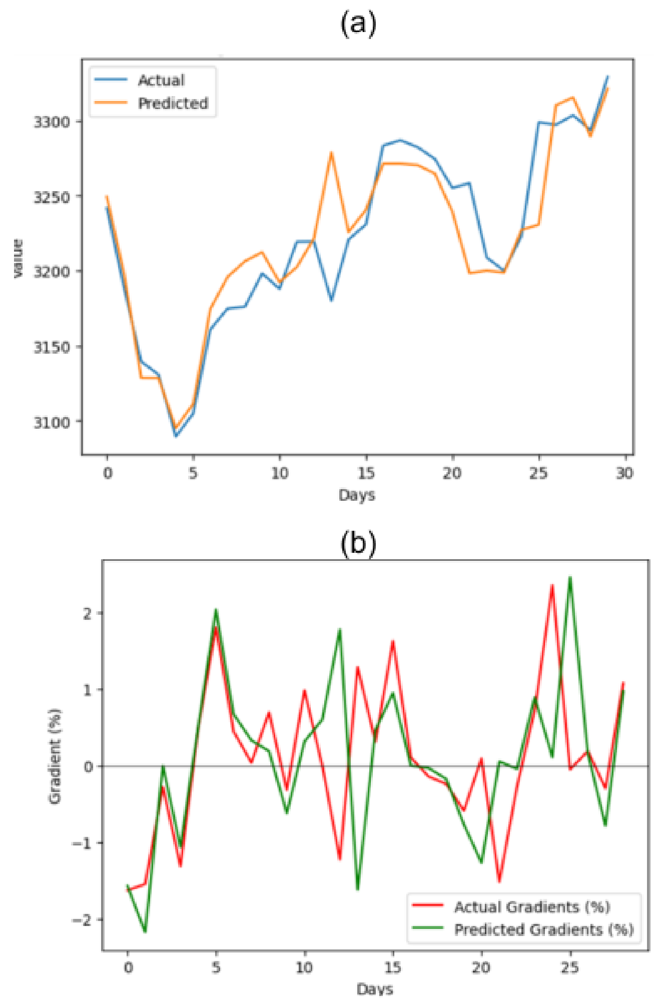

Fig. 5. For ITC, Fig. (a) shows comparison of predicted and actual stock price and Fig. (b) shows predicted and actual daily percentage changes in the stock price for 30 days.

Table 1 compares the RMSE (Root Mean Square Error) and MAPE (Mean Absolute Percentage Error) values of an LSTM model's predictions for three companies Reliance, TCS, and ITC. The predictions are closer to the actual values as can be observed from table 1.

TABLE I
Comparison of RMSE and MAPE for LSTM model.

	Relaince	TCS	ITC
RMSE	38.330	37.260	5.066
MAPE	1.390	0.995	1.039

Lower values for RMSE and MAPE [8] indicate higher prediction accuracy. The LSTM model achieves the lowest RMSE for ITC, indicating that it performs the best in predicting ITC's stock prices compared to Reliance and TCS. Likewise, the LSTM model achieves the lowest MAPE for TCS, suggesting that it provides more accurate predictions for TCS's stock prices compared to Reliance and ITC. In summary, the LSTM

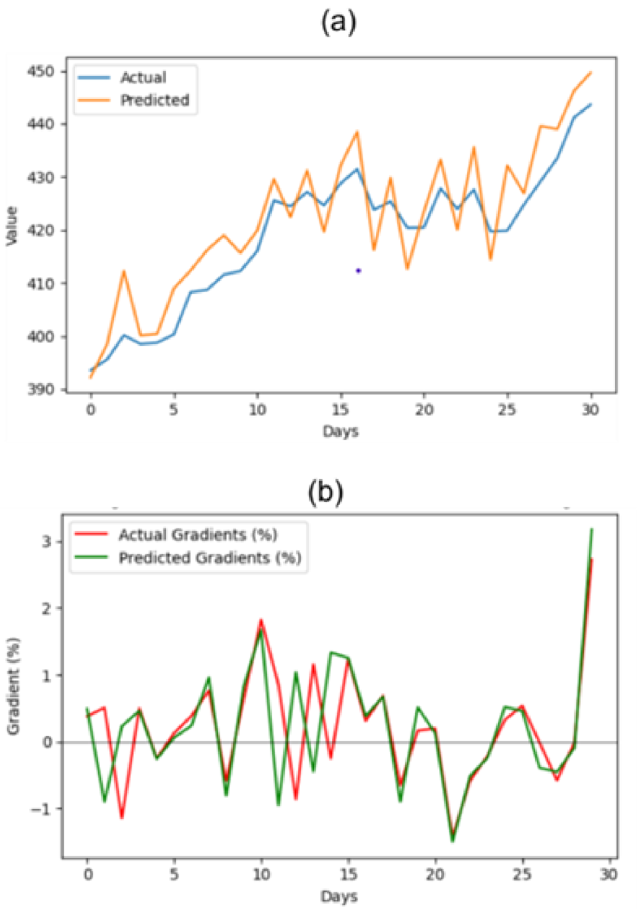

Fig. 6. For Relaince, Fig. (a) shows comparison of predicted and actual stock price and Fig. (b) shows predicted and actual daily percentage changes in the stock price for 30 days.

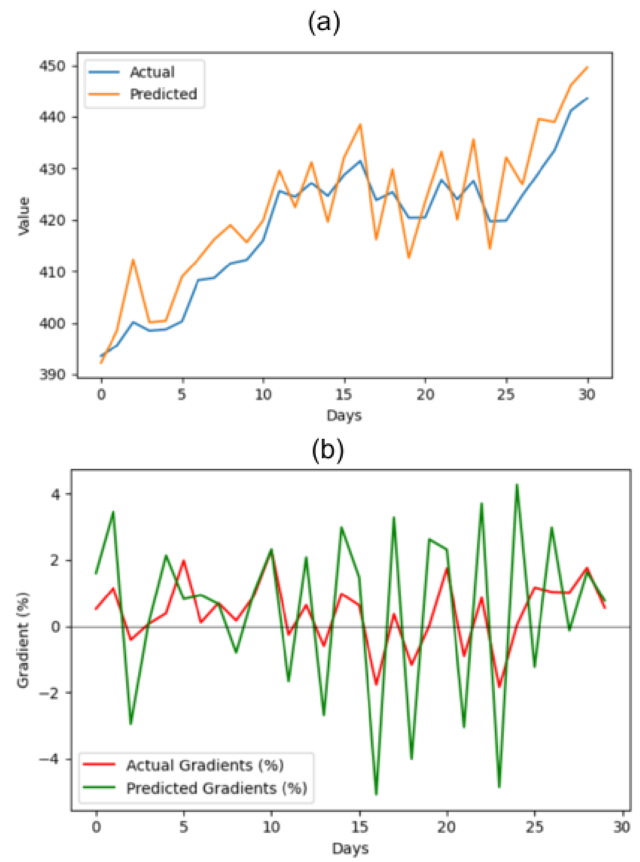

Fig. 7. For TCS, Fig. (a) shows comparison of predicted and actual stock price and Fig. (b) shows predicted and actual daily percentage changes in the stock price for 30 consecutive trading days.

model demonstrates superior performance in terms of RMSE for ITC and in terms of MAPE for TCS, underscoring its effectiveness in predicting the stock prices of these companies.

V. Conclusion

This study demonstrates the significant potential of employing AI techniques, specifically the LSTM model, to predict stock prices. By incorporating essential fundamental ratios such as PE, PB, and PS, the prediction accuracy is further enhanced. The outcomes of this research can essentially help the algo-traders to incorporate these ratios into their algorithms for better prediction of prices so that they can update their stop losses accordingly either upside or downside.For investors and market participants who aim to make well-informed decisions within the ever-changing landscape of stock markets. Future studies may examine the use of additional sophisticated DL algorithms and inclusion of the sentiment analysis in future may be the direction to go as we know that in india stocks move more by the sentiments that surpases the fundementals and technicals often.

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