Penny Stock Prediction in Indian Markets using LSTM

a. Satwik Sokey

AIML
(of Affiliation)
Manipal University Jaipur
Jaipur, India
satwik.219310266@muj.manipal.edu

***Abstract*— This research paper investigates the groundbreaking application of Artificial Intelligence (AI) in the prediction of the values of highly volatile penny stocks. With the advancements in machine learning, there have been significant developments in time series analysis, creating numerous opportunities for the hedge fund industry. This study is centered on the utilization of AI for forecasting the fluctuations in the prices of volatile commodities that are traditionally challenging to predict. We delve into the technical intricacies of AI-driven time series prediction, its practical use in forecasting financial market trends, and its impact on enhancing user engagement. The research reveals how AI can be leveraged in the field of investment banking, providing advantages for investment bankers, hedge funds, and individual investors looking to enhance their investment strategies. These findings pave the way for future research in this emerging field, underscoring the transformative potential of AI in democratizing access to financial markets.**

***Keywords*— Artificial Intelligence, Machine Learning, Stock Prediction, Time Series Analysis, Long Short Term Memory**

I. INTRODUCTION

Within the dynamic realm of investment banking, the incorporation of artificial intelligence (AI) has ushered in a new era of capabilities for forecasting the values of commodities, enhancing risk assessment, and facilitating broader participation for both individuals and businesses to harness its advantages. Among these groundbreaking AI applications, one of the most transformative is the utilization of Recurrent Neural Networks with LSTM layers for predicting stock prices. This cutting-edge technology empowers investors and hedge funds alike to make informed decisions, ultimately optimizing their financial returns.

The act of forecasting penny stock prices is not merely a novel method for streamlining the investment process; it is also a tool that magnifies the capacity of investors to make well-informed investment choices tailored to their specific needs. Through the ability to anticipate the fluctuations in penny stock prices, individuals can harness this knowledge to optimize their financial gains. This innovative approach signifies a departure from conventional investment practices, where decisions are typically grounded in extensive market research spanning months and accumulated years of industry experience.

The utilization of this technology is fundamentally reshaping our approach to stock market analysis and investment strategies, providing valuable foresight into the future behavior of exceptionally volatile assets, such as penny stocks. It introduces a degree of independence to the realm of investing that was previously beyond reach. Naturally, like any advanced technology, it presents notable technical challenges. However, the potential benefits and the pioneering essence of this concept strongly indicate that it represents a highly promising and thrilling field for exploration.

This research paper extensively investigates the application of Recurrent Neural Networks, specifically those based on LSTM, for forecasting the directional trends (upward or downward) in the realm of penny stocks. It comprehensively explores the foundational technologies, advantages, obstacles, and prospective developments in this emerging facet of financial market prediction. By illuminating the complexities inherent in machine learning-driven forecasting, this paper seeks to enrich the comprehension and progression of this thrilling application of machine learning within financial markets.

II. LITERATURE REVIEW

Previous Studies	Methodology	Outcome
K. Chen, Y. Zhou and F. Dai, "A LSTM-based method for stock returns prediction: A case study of China stock market,"	The past study employed a methodology where historical data underwent a transformation into sequences spanning 30 days. Each sequence consisted of ten learning features, and the labeling involved a learning rate over a period of three days.	The authors asserted that the model enhanced accuracy from 14.3% to 27.2% when compared to a random prediction approach.
W Bao, J Yue, and Y Rao, "A deep learning framework for financial time series using stacked autoencoders and long-short term memory"	Utilized Haar wavelet transformation for noise reduction in financial time series data, applied stacked autoencoders for deep feature learning, and used LSTM to predict stock index closing prices. The prediction exclusively relied on fundamental data (open, close, low, and high), excluding macroeconomic and technical indicators.	The average R score for the LSTM model on the S&P 500 fell below 88%. Roondiwala et al. also applied the LSTM model to NIFTY 50 data spanning from 2011 to 2016 [5].
Thomas Fischer, Christopher Krauss, "Deep learning with long short-term memory networks for financial make predictions"	Fischer and Krauss employed LSTM networks to address the classification challenge associated with predicting the directional movements of constituent stocks within the S&P 500 index, spanning the period from 1992 to 2015.	The authors found that the LSTM network effectively extracted meaningful information from financial time series data, outperforming random forests, standard deep networks, and logistic regression in prediction accuracy and daily returns after transaction costs.
Qiu J, Wang B, Zhou C (2020) Forecasting stock prices with long-short term memory neural network based on attention mechanism.	Applied an LSTM-based model to historical datasets of S&P 500, DJIA, and Hang Seng Index. Their unique approach incorporated an attention mechanism to extract information from news, assisting in price fluctuation assessment. Before prediction, they used a wavelet transformation for data denoising. The attention-based LSTM framework predicted the opening index price using solely fundamental market data.	The proposed model exhibited enhanced fitting capabilities and improved accuracy in prediction outcomes. Consequently, it holds promising application prospects and stands as a highly competitive option among existing models.
A Yadav, C Jha, A Sharan, "Optimizing LSTM for time series prediction in Indian stock market"	Yadav et al. employed an LSTM model with multiple hidden layers on Indian stock market data, eliminating trend and seasonality components, with the aim of predicting the closing price.	Their conclusion was that the prediction accuracy was superior in the single-layer LSTM model.
Yakup Kara, Melek Acar Boyacioglu, Ömer Kaan Baykan, Predicting direction of stock price index movement using artificial neural networks and support vector machines: The sample of the Istanbul Stock Exchange	Kara et al. employed both support vector machine (SVM) and artificial neural network methodologies to forecast daily movements in the Istanbul Stock Exchange National 100 Index during the period spanning 1997 to 2007. The authors specifically opted for ten technical indicators as the input variables for their predictive model.	Experimental findings indicated that the artificial neural network model consistently outperformed the SVM model in terms of average performance.
D. Karmiani, R. Kazi, A. Nambisan, A. Shah and V. Kamble, "Comparison of Predictive Algorithms: Backpropagation, SVM, LSTM and Kalman Filter for Stock Market,"	Karmiani et al. conducted a comparative analysis of LSTM, Backpropagation, SVM, and Kalman filter methodologies for stock price prediction. Their study focused on the stock prices of nine selected companies in the prediction process.	LSTM emerged as the optimal selection in terms of accuracy in predictions with minimal variance.
Yu, Pengfei Yan, Xuesong (2020) Stock price prediction based on deep neural networks	Yu and Yan utilized a combination of phase-space reconstruction and LSTM modeling to predict stock prices across various market environments, including the S&P 500, DJIA, Nikkei 225, Hang Seng Index, China Securities Index 300, and ChiNext index. The model focused exclusively on historical price data, and its performance was compared with Multilayer Perceptron, Support Vector Regressor, and ARIMA models.	The authors asserted that the LSTM model demonstrated superior performance compared to other models when applied to S&P 500 data.

III. STOCK PREDICTION USING LSTM NETWORKS

A. *Definition and Overview*

Stock market prediction is the act of trying to determine the future value of a company stock or other financial instrument traded on an exchange [1]. Traditionally, this prediction process relies on methods such as stock analysis and comprehensive market research.

Penny stocks are common stocks valued at less than one dollar, and therefore highly speculative [2].The penny stock market has demonstrated considerable volatility, rendering it a high-risk arena where substantial gains come hand in hand with the potential for significant losses.

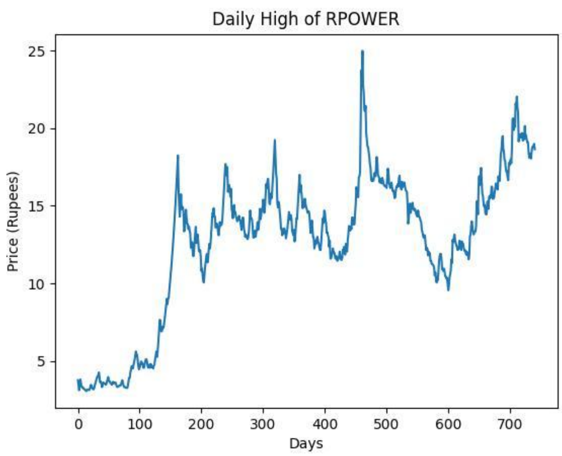
LSTM (Long Short-Term Memory) is a recurrent neural network (RNN) architecture widely used in Deep Learning. It excels at capturing long-term dependencies, making it ideal for sequence prediction tasks [3]. The Long Short-Term Memory (LSTM) network comprises three essential gates: the Forget Gate, the Input Gate, and the Update Gate. The Forget Gate employs a sigmoid-activated neural network to discern the relevant features within the incoming data, effectively filtering out less important information. The Input Gate enables the cell to assimilate new information from the input, and the Output Gate carries forward the updated information from the current timestamp to the next while also delivering the cell's output at the final iteration. LSTM fine-tunes the gate weights to ensure the production of precise and reliable results.

This approach is grounded in the principles of exemplar-based learning. The artificial intelligence system is trained with an extensive historical dataset spanning three years, focusing on penny stock Reliance Power (RPOWER), which has garnered notable investor interest due to its promising profit potential. Following the training phase, the AI leverages this acquired expertise to generate forecasts for the stock's future values within a specified time frame.

IV. Methodology:

A. Data Collection

For this project, Reliance Power, a penny stock that has garnered significant attention from investors due to its potential for substantial gains, was chosen as the subject of analysis. Despite its notoriety in the financial markets, the stock has exhibited a persistent trading price of approximately 16 Rupees.[4]

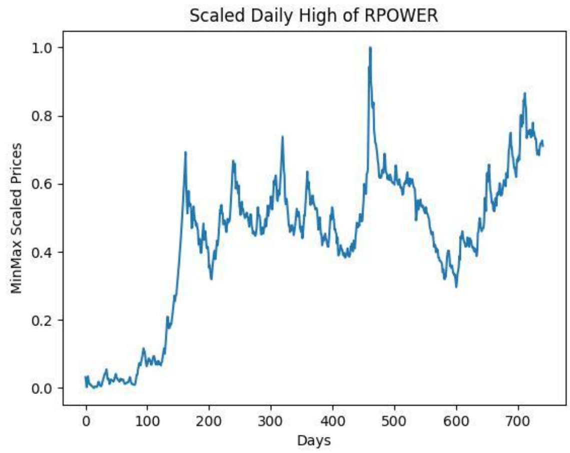


(Fig. 1) Graphical Representation of the Daily High Values for RPOWER Stock

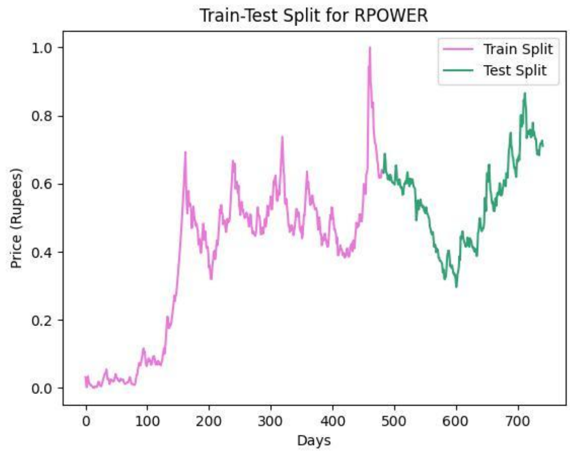
The study employed the daily high prices of the stock over the last three years as the primary data source for predictive modeling. The data was sourced from Google Finance, ensuring data reliability.

B. Data Pre-Processing

To prepare the historical data for LSTM analysis, it was initially scaled to fit within the range of [0, 1], as LSTM cells are sensitive to the data range. Following this scaling, the data was partitioned into training and testing sets for the neural network. The training data was subsequently structured into a dataset with appropriate labels, resulting in a dataset comprising 343 rows and 100 features after all preprocessing steps.



(Fig. 2) Visual Representation of MinMax Scaled Daily High Values for RPOWER Stock



(Fig. 3) Graphical Representation of the Train-Test Split Conducted on RPOWER Stock

C. Neural Network

The predictive model utilized in this study is a sequential model featuring LSTM cells in its hidden layers, with a dense cell used for generating output. The neural network was configured to process 100 historical entries at a time, producing the predicted value based on this input. The model underwent training for a total of 100 epochs.

D. Tools and Techniques Used:

1) Deep Learning Frameworks

We employed powerful deep learning frameworks such as TensorFlow and Keras, which serve as the cornerstone for constructing, evolving, and instructing the LSTM model, underscoring their pivotal contribution to shaping the model's structure and capabilities.

2) LSTM Model

The predictive model applied in this research is a sequential architecture that incorporates LSTM cells within its hidden layers. A dense layer is employed for generating the final output. The model encompasses three hidden layers, with each layer containing 50 LSTM cells, and a concluding dense layer that aggregates output from all 50 LSTMs in the preceding layer to produce the ultimate result. This model comprises a sum of 50,851 trainable parameters. The model evaluates its loss in each epoch using the Mean Squared Error algorithm and fine-tunes its weights utilizing the Adaptive Moment Estimator (Adam).

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 100, 50)           10400

 lstm_1 (LSTM)               (None, 100, 50)           20200

 lstm_2 (LSTM)               (None, 50)                20200

 dense (Dense)               (None, 1)                 51

=================================================================
Total params: 50851 (198.64 KB)
Trainable params: 50851 (198.64 KB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

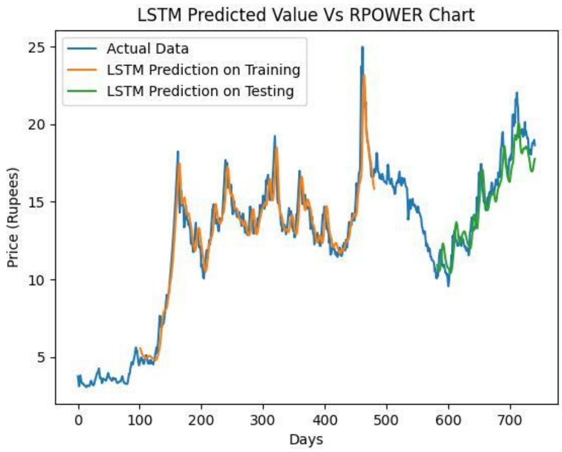
(Fig. 4) Comprehensive Overview of the Employed LSTM Network Architecture for Penny Stock Prediction

3) Training

The model was subjected to an extensive training regimen encompassing 100 epochs, with each epoch structured into 6 distinct batches, drawing from the training dataset. This rigorous training process aimed to refine the model's understanding and predictive capabilities. After the culmination of these 100 training epochs, the model demonstrated remarkable performance metrics, with a training loss of 0.0012 and a validation loss of 0.0023, underscoring its aptitude for capturing essential patterns and optimizing its predictive accuracy.

V. Results and Discussions

After the training phase concluded, the Root Mean Squared Error (RMSE) for the model's predictions was carefully examined. It was found that the RMSE values for the training and testing datasets were notably low, measuring 12.4 and 14.05, respectively. These low RMSE scores underscore the model's effectiveness, particularly when applied to the inherently turbulent realm of penny stocks in Indian financial markets.



(Fig. 5) Visualization of Predictions on Training Dataset (Yellow), Predictions on Testing Dataset (Green), and Actual Prices of RPOWER Stock

This achievement not only highlights the model's aptitude for handling the complexities of penny stock prediction but also suggests that it holds substantial promise for more comprehensive and extensive utilization. The next logical step in this research would involve broadening the model's scope to incorporate a diverse range of penny stocks, thereby creating a more versatile and generalized predictive framework that can offer valuable insights into this dynamic financial landscape.

VI. Conclusion

In conclusion, our investigation has unveiled the significant promise that LSTM-based networks hold when it comes to the realm of penny stock prediction. The findings from our research affirm that these networks possess the capacity to navigate the intricate landscape of predicting penny stock prices with remarkable accuracy.

Looking ahead, we are poised to enter the next phase of our project with a heightened sense of purpose. Our objective is to create a more comprehensive and versatile model, one that can accommodate a diverse array of penny stocks for training. This next step is pivotal in our pursuit to evaluate the feasibility and adaptability of the proposed LSTM networks, as we endeavor to construct predictive models that can effectively capture the nuances and subtleties of the penny stock market.

Our research not only serves as a testament to the potential advantages that LSTM networks can offer to financial analysts, investors, and traders, but also underscores the ever-evolving landscape of financial market prediction. It is clear that the future holds even more opportunities for the application of LSTM-based methodologies in expanding our understanding and capabilities in the dynamic world of penny stocks. Our work not only contributes valuable insights but also sets the stage for more extensive and inclusive applications, ultimately benefiting those who seek to navigate the complexities of the penny stock market.

References

[1] Stock Market Prediction (Wikipedia) **https://en.wikipedia.org/wiki/Stock_market_prediction**

[2] Penny Stocks **https://www.google.com/search?q=what+are+penny+stocks&rlz=1C1CHZN_enIN946IN948&oq=what+are+penny+stocks+&gs_lcrp=EgZjaHJvbWUyBggAEEUYOdIBCTEzMzg1ajBqN6gCALACAA&sourceid=chrome&ie=UTF-8**

[3] LSTM **https://www.analyticsvidhya.com/blog/2021/03/introduction-to-long-short-term-memory-lstm/#:~:text=LSTM%20(Long%20Short%2DTerm%20Memory,ideal%20for%20sequence%20prediction%20tasks**

[4] Reliance Power (RPOWER) (Youtube) **https://www.youtube.com/watch?v=xQMJRMzpBgU**

[5] M Roondiwala, H Patel, S Varma, "Predicting Stock Prices Using LSTM" **https://www.researchgate.net/profile/Murtaza-Roondiwala/publication/327967988_Predicting_Stock_Prices_Using_LSTM/links/5bafbe6692851ca9ed30ceb9/Predicting-Stock-Prices-Using-LSTM.pdf**