APPLICATION OF LSTMAND RNN IN PREDICTING STOCK MARKET TRENDS

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Abstract— **When someone plan their investment, it is not easy for them to follow the overall daily updates and analysis the complete past records as an investor. They often fall into trap of choosing their known or recommended stocks instead of choosing a stock that has potential for giving them better result and profit based on analysis. Learning to forecast the stock market's investing strategies requires in-depth research of a large amount of data. We believe that the application of AI and machine learning techniques, which are now more prevalent than traditional methodology and approaches, can improve stock market forecasting. A recent breakthrough is the usage of ML in the current scenario of stock market forecasting. By training from previous values, this system generates projections depending on the stock market's current values indexes. Machine learning itself employs a variety of models to support and confirm prediction. The study focuses on machine learning using LSTM along with RNN for valuation of stock. Factors include volume, open, close, low, and high. Making it extremely challenging to predict future price changes. To comprehend the long-term dependency of stock prices, deep learning approaches, such as the LSTM approach, are utilised to gather lengthier data reliance and overall stock change patterns.**

Keywords— **Stock Market, Prediction, LSTM, RNN, unsupervised.**

I. INTRODUCTION

Machine learning-based stock price prediction enables to determine the worth of company stocks and various financial resources that will be sold on a market in future. Making share price predictions is only done for financial gain. It's challenging to forecast how the stock market will behave. The prediction also takes into consideration biological and psychological elements in addition to rational and illogical behaviours. These elements work together to create a turbulent and dynamic stock market. Therefore, it might be challenging to predict stock prices accurately.

Through the online platforms provided by brokers, anyone may purchase or sell stocks, currencies, shares, and derivatives in the market, which is a dynamic and complicated process. With the stock market, investors may purchase shares of publicly listed corporations by transacting on exchanges or off-exchange markets. Investing in this market offers investors the opportunity to become rich since it entails very minimal risk, as opposed to starting a new firm or requiring high-paying employment. Numerous variables influence the stock market, contributing to its high degree of volatility and unpredictability.

Proposed paper aims to explain a method a different strategy to forecasting share market values. Instead of fittingthe records to a particular model, suggested model employing machine learning architectures to detect the latent dynamics present in the data. The model uses machine learning designs like LSTM, Convolutional CNN, and the combined approach of LSTM + CNN for price forecasting of NSE listed businesses and differentiating their performance. Long-standing Sling window approach was applied, and root mean square error was used to assess effectiveness This paper proposes a time series models for forecasting, such as ARIMA or GARCH models, The practical efficacy of several time series prediction algorithms has been demonstrated. The bulk of algorithms used today are built upon RNNs, namely A unique type of RNN is Long-Short Term Memory (LSTM), and Gated Recurrent Units (GRU), another special type of RNN which is shown in figure 1. The stock market frequently uses time-series data, and various academics have investigated this area and created numerous models. In proposed research, an LSTM is employed to forecast the share cost.

II. LITERATURE REVIEW

One kind of recurrent neural network known as a Long Short-Term Memory (LSTM) is used to understand order dependence in prediction of sequence scenarios. Because it can retain previous data, the LSTM is quite useful for stock value predictions. This is because predicting the value of stocks in the future is dependent on their historical pricing.

Massive volumes of price data for the stock market are created and updated instantaneously[1]. People may either earn money on the stock market or lose all of their life savings in this difficult and intricate system. An effort is made to anticipate the stock market trend in this research. Two different kinds of models were developed: one for monthly forecasting and the other for daily forecasting. Using supervised machine learning methods, the models are created. The first model, the daily prediction model, takes sentiment and past price into account. Up to 70% accuracy has been seen in a daily prediction model that uses supervised machine learning methods. A monthly prediction model compares the trends of any two months to find patterns. Analysis shows that there is least correlation between a month's trend and next month's trend.

Stock Closing Price Prediction Using MLT[2]. Mehar Vijha, Arun Kumar, Deeksha Chandolab, and Vinay Anand Tikkiwal. It is very difficult to get precise projections of market returns because of how volatile and non-linear the stock markets are. Programmable estimate systems have become more good at anticipating fluctuations in stock prices as a result of the rising use of artificial intelligence and computer technologies. In this research, random forest and artificial neural network techniques were used to forecast the closing prices of five companies from different industrial sectors. The stock's open, high, low, and close prices are utilised to create new variables that are then included into the model. The models are assessed using RMSE and MAPE, two popular strategic metrics.

This problem is addressed in the article was the feasibility of stock market prediction using artificial intelligence for sentiment analysis is studied. [4], which was proposed by Surbhi Soni1, Ashok Kumar Shirvastava2, and Deepak Motwani. With minimal effort and great efficacy, real-world problems are being resolved utilising AI and ML techniques. Today, investing in the stock market is a profitable choice when the power of ML is applied to sentiment analysis to forecast the moment of the stock. Forecasting the share trading is a challenging task since it is dependent on a numberof factors, including as investor emotion, stock market synchrony, economic fundamentals, likewise social media sentiment. Proposed article presents a summary of different stock price forecasting and sentiment models in addition to AI advancements and applications in the financial industry. Some of the techniques for the stock market forecasting include Long Short Term Memory (LSTM), ARIMA model Recurrent Neural Network (RNN), linear regression, and k-Nearest Neighbours.

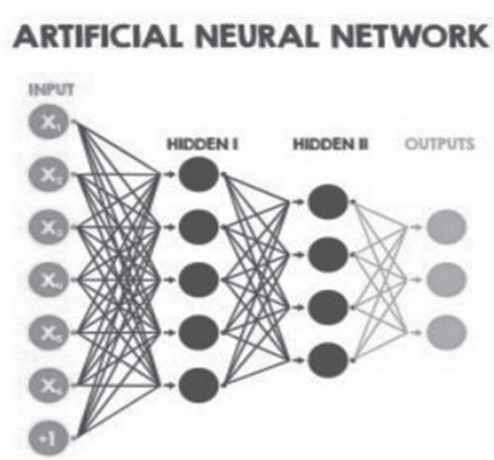


Figure 1: ANN

Leonardo dos Santos Pinheiro & Mark Dras's Character-based Neural Language Model for Event-based Trading: Stock Market Prediction using DL [5]. Machine learning recently became very popular to be utilized as a technique for assessing financial text data, thanks to some spectacular results in stock price forecasts . This conclusion has imposed implications for the Efficient Markets Hypothesis (EMH), which forms the basis of much economic theory. This research looks into RNN with character-level language and here model pre-training is used for stock market forecasting, during both intraday and interday. In order to predict directional changes in the Standard & Poor's 500 index, for individual companies as well as for the index as a whole, this method is competitive with the most advanced methods currently in use.

III. RELATED TERMINOLOGIES

Before going through the proposed paper, one should have a clear understanding of some related terminologies like LSTM , RNN, CNN, time series analysis, technical analysis, fundamental analysis, etc.

A. *RNN* : Future input to the same nodes from some nodes may be influenced by their output in An artificial neural network that can create loops through connections between nodes and is a member of the RNN family. This allows it to exhibit temporal dynamic behaviour. Using their internal state (memory), the RNNs, which descended feeding neural networks forward, can handle sequences of different lengths as input. As a result, they may be used to tasks like speech recognition or connected, unsegmented handwriting recognition. Since recurrent neural networks are Turing complete, they can potentially run any programme to handle any input sequence.

B. *CNN* : Deep Learning teaches robots or computers to perceive, categorise, and learn from experience in a manner comparable to that of the human brain. Deep Learning is shown as an effective method of assessing large amounts of data. Convolutional neural networks, or Often used for object recognition in deep learning, CNNs are a subtype of artificial neural networks. recognition and classification in photos. As a result, Deep Learning recognises objects in an image using a CNN. CNNs are widely used for a wide range of tasks and tasks, including as video analysis, image processing, computer vision, obstacle detection for self-driving cars, and speech recognition for natural language processing.

C. *LSTM :* Information persistence is made possible by A deep learning, sequential neural network called Long Short-Term Memory Networks. The vanishing gradient issue that RNNs encounter can only be resolved by a certain type neural network, recurrent. Schmidhuber and Hochreiter created LSTM to address the issue using conventional rnn and machine learning methods. The Keras library in Python may be utilised to implement LSTM.

1. Assume for the moment that when you watch a movie or read a tale, you are able to recall the events of the previous scene or chapter. They retain previous knowledge and apply it to the current input, much like RNNs. RNN has the disadvantage of not being able to recall long-term dependence because of the decreasing gradient.

2. *LSTM Architecture* – LSTM performs at a high level very similarly to an RNN cell. Using the LSTM network is demonstrated here the functions perform inside. As shown in the picture below, the LSTM network design is separated into three parts, each of which serves a particular purpose.

   Whether or whether the data from the previous timestamp has to be remembered determined in the first section. This cell attempts to learn new information using the input from the second part. After then, the cell transmits the updated data using the current timestamp of the third segment to the subsequent timestamp. One LSTM cycle is regarded as one single-time step.

3. *Forget Gate*— A neural network of LSTM cell's first action is to choose if to retain the data or throw away the data obtained from the previous time step. The gate of the forget formula is displayed below.

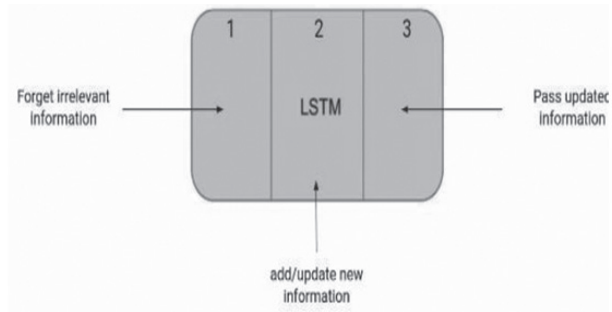
   $Ft = \sigma (Yt * vf + it\text{-}1 * xf)$
   Yt : input of the current timestamp.
   vf : suitable weight for the input
   $it\text{-}1$: The preceding timestamp's concealed state
   xf : It really consists of the weight matrix related to the hidden state.

   It then goes via a sigmoidal function. Consequently, Ft will change as value 1 and 0. This Ft is affected by the succeeding multiplier's cell state.

D. *Analysis of Time Series* — A series of time is a predetermined group of numerical observations that a system collects over a predetermined period of time, such daily,weekly, monthly, or sometimes yearly. Specialised models have been used to analyse, characterise, and interpret the collected time-series data, and certain presumptions are based on shifts and anomalies in the process of data collection. These shifts and probabilities include, but are not limited to, changes in trends, seasonal demand spikes, certain recurring changes, non-systematic changes in usual patterns, etc.

All of the previous, recent, and presently gathered data is utilised as input in the time series forecasting, which uses sophisticated mathematically driven algorithms to generate future trends, seasonal changes, irregularities, and the like. Time series forecasting also becomes faster, more accurate, and more productive over time using machine learning.

IV. PROPOSED METHODOLOGY



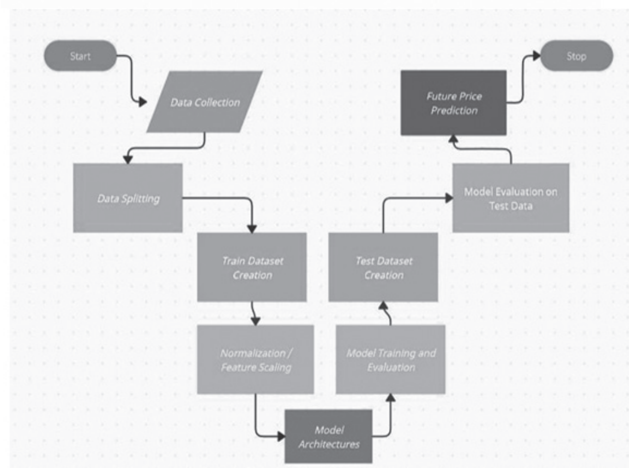


Figure 2: Flowchart

1. System Model

In this subsection, outline the high-level process this proposed model followed to predict the open price of Tesla stock using Simple RNN and LSTM models.

Data Loading and Preprocessing: Proposed model loaded the Tesla stock price data using pandas. The data includes columns such as Date and Open price. Suggested model ensured that the Date column was in a datetime format for time-based analysis which is shown in Figure 2.

Data Splitting: With a split ratio of 70% for training and 30% for validation, this model separated the training and validation datasets. Data Splitting step is essential to evaluate model's performance effectively.

Feature Scaling: Proposed model normalized the Open price values using Min-Max scaling, which scales the values between 0 and 1. This normalization is crucial for training neural network models.

B. Architecture

Detail the architecture of both the Simple RNN and LSTM models suggested model employed for open price prediction:

Table 1: Time Series Dataset

	date	date_block_num	shop_id	item_id	item_price	item_cnt_day
0	02.01.2013	0	59	22154	999.00	1.0
1	03.01.2013	0	25	2552	899.00	1.0
2	05.01.2013	0	25	2552	899.00	-1.0
3	06.01.2013	0	25	2554	1709.05	1.0
4	15.01.2013	0	25	2555	1099.00	1.0

Simple RNN Model:

1. Architecture Overview: The model which is proposed constructs a Simple RNN model which can be used for predicting open prices.
2. Layer Configuration: The proposed model will use specifically four layers of Simple RNN cells that will include tanh activation functions. Each layer is going to layer which will experience dropouts at a rate of 0.2.
3. Output Layer: The model concludes with a single Dense output layer.
4. Model Compilation: “adam” optimizer and the MSE loss function is used in this model to prepare the suggested model.
5. Training: 50 epochs on 32-piece batch size is used to train the model . The model which is proposed here will monitor the training loss and accuracy over epochs.

LSTM Model:

1. Architecture Overview: with figure 3 the model which is proposed here implements an LSTM Model for open price prediction. LSTM is known for handling long-term dependencies more effectively than the usual RNN.
2. Layer Configuration: The LSTM Model which is being used here comprises of 2 LSTM layers which is followed by Dense layers for prediction . Every LSTM layer contains 64 units, while the second LSTM layer returns sequences during the final step of prediction .
3. Model Compilation: Just like the simple RNN model this model was compiled by using the Optimizer “adam” and MSE loss.

Training: The LSTM model used was trained for 10 epochs.

V. EXPERIMENTATION AND ANALYSIS

A. Experimental Setup

Here we will describe the setup of our experiments, that includes the hardware, the software, and the tools which will be used to conduct the experiments.

Hardware and Software Environment:

A suitable hardware and software environment needs to be established In order to successfully implement LSTM and RNN machine learning models to predict the stock market, and also to facilitate the development, training, and evaluation processes of the model. The following components were utilized:

Hardware Environment:
RAM: 32 GB, 16 GB
Processor: Core i7, AMD Ryzen 9
Graphics Processing Unit: NVIDIA GeForce RTX 3080 with 10 GB VRAM

A. Software Environment:

A comprehensive software environment that encompasses different programming languages, libraries, and tools facilitates the development and exectution of the predictive model . In this research these software components are utilized:

B. Experimental Parameters

1. Date: The date is the chronological information which is essential for time-series analysis and sequential data processing.
2. Open: This column serves as the primary target variable for the prediction task, as model aim to forecast the future open price based on historical data.
3. High: The stock’s highest price throughout the trading day. The High provides the insights into the price volatility and also the potential price trends.
4. Low: The Low is considered to be the stock’s lowest price during the day of trading Just like the “High” column, the “Low” column indicates the price range and the potential fluctuations of the market.

C.Performance Evaluation

1. Model Evaluation:

With the figure 3. shown Loss and Accuracy Plotting: Model evaluated the training process of both the Simple RNN and LSTM models. The graph shown below plots the training loss and accuracy over epochs, thereby providing the insights into the model’s convergence and performance.

1. Future Price Prediction:

Next Day Prediction: The proposed model demonstrates how can the trained model be used in predicting the open price for a future date. Suggested model prepared the necessary input data by selecting the last 50 days’ open prices and scaling them for model input.

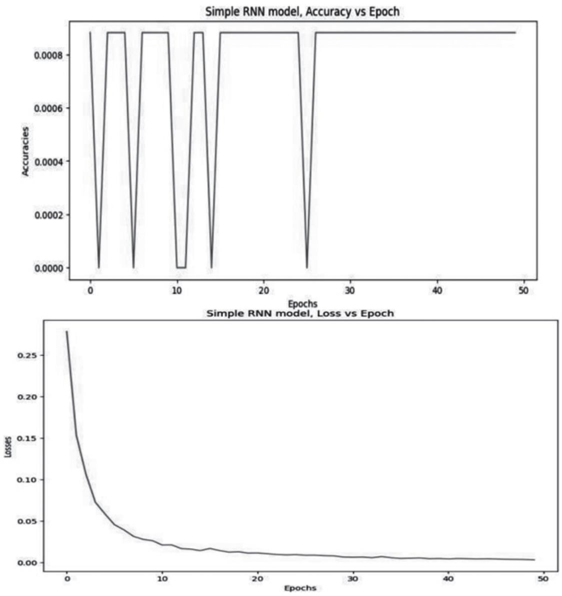


Figure 3: RNN Loss Vs Epoch

Table 2: RNN Comparison

Days	Anticipated closing price on the next day	True closing cost
1	3049.85	3111.75
2	2848.77	3153.7
3	2934.06	3195.1
4	2683.15	3117.85
5	3086.26	3174.6

CONCLUSION AND FUTURE SCOPE

This study explors the effectiveness of LSTM RNN-based machine learning models for predicting stock market trends, specifically by focusing on open price prediction for Tesla stock. By implementing both in concurrency ,this model can be used to gain insights into their separate capabilities for capturing temporal dependencies within time-series financial data.

The results obtained from this experiment demonstrate how potential LSTM-based models can be for stock market prediction tasks.

The LSTM model used here outperformed the Simple RNN model, which thereby highlights the significance of capturing long-term dependencies along with complex patterns that ultimately influence stock prices.

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