STOCK PRICE PREDICTION USING LSTM

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Abstract— ***In this research paper we apply Long Short-Term Memory (LSTM) networks to stock price prediction for forecasting accuracy in the years of volatile financial markets. Using historical data of stock prices we created a predictive model that accurately captures low dimensional temporal dependencies in stock price movements. Our approach consists of two steps: data preprocessing to refine features and training of LSTM for different time intervals. It makes use of KPIs such as MAE or RMSE to assess performance. We show that LSTM networks substantially improve over all baseline forecasting techniques. This study serves to build on the current literature regarding machine learning approaches to finance and support the utilization of deep learning methodologies to some non-linear.***

Keywords—RNN, Data, Machine-Learning, Accuracy, Evaluate.

Introduction

The stock market is a complex and dynamic system whose behavior depends on a wide variety of factors including economic indicators, company performance, market sentiment, and geopolitical events. Predicting the prices of stock accurately is one of the major challenges in financial time series data because oftentimes, financial time series data are considered to be very volatile and non-linear in nature. Historically, statistical methods and fundamental analysis was used for prediction by financial analysts, but with the introduction of machine learning & deep learning technologies, there are new possibilities to improve prediction accuracy.

Long Short-Term Memory (LSTM) networks — a specialized form of recurrent neural network(RNN), have emerged for a powerful method of learning from sequences of data, at arbitrary lengths, while holding information over long periods of time.The vanishing gradient issue that recurrent neural networks (RNNs) suffer from, is effectively overcome with the use of LSTMs, allowing for the application of this model type within time-series problems, such as stock price forecasting. This is due to their ability to model longer-term dependencies, which leads to a deeper comprehension of price fluctuations as a function of the past.

The objective of this work is to study the performance of stock predictions based on LSTM networks. Using both historical stock price data, we attempt to develop a strong model to predict stock prices with a better degree of accuracy as well as provide insights and analysis of the patterns in behavior of the stock market. The results of this study will help in wider financial analytics by providing tools for investors and financial analyst for informed actions.

LITERATURE SURVEY

supervised learning classifiers to evaluate the ability of stock price movement forecasts due to the financial index data. For example, portfolio modeling is a type of a computational analytical technique used in the financial industry. While there was talk of the statistical AI approach and the use of SVM approach was illustrated in the article, tactical methods have also been shown to be able to predict stock prices.

a popular RNN architecture type is long short-term memory By using memory cells — processing devices that replace traditional artificial neurons in a secret network layer — networks can connect memory and remote input in real time.thus making them ideal for dynamic data structures over time and a very high predictive palm. It also shows that it is possible to predict NIFTY50 stocks. Perhaps, one of the most critical steps in the process is data collection. Then we have to train our model, and test the process over different data sets. Our process will be discussed in the following sections.

Another big problem with simple ANNs for stock prediction is the wonder of detonating transient inclination, in which the weights of an enormously enormous framework either develop too immensely enormous or too inuscule (as the case may be), and icily defer their merger to the wished value.
The following two reasons often contribute to this: loads are aggressively optimised and loads and when finishing at the very end of the system tend to vary quite a lot more than when they first started. In addition, LSTM networks were found to be suitable for implementing share price prediction processes.

Methodology

DATA COLLECTION AND PREPROCESSING

Data Collection In this research, stock price information had been obtained from trusted economic database companies such as Yahoo Finance, Alpha Vantage or Quandl. This is the historical daily price of selected stocks for a specific period, usually between 5–10 years. The features that are collected as primary measures are:

Date: The trading date.

Open Price — The price where the stock opened for the trading.
Highest high during the session: High Price
Low Price: The daily low price reached that day.
Close Price — The price that the stock was closed at for the day.
Volume: This is the volume of the stock that was traded during that session.
Other data like market indices or macroeconomics indicators can be added to deepen the analysis.
Data Preprocessing
Preprocessing of data is an important step as we want the LSTM model to learn on the data correctly. The following was done step-by-step

a. Data Cleaning: Filling NaT: If there are any NaT in data, we fill that with interpolation or forward fill. Because we are handling the time series.Outlier Removal: Outlier detection techniques like Z-score or IQR were used to detect and remove outlier price movements.

b. Feature Engineering: Generating More Features: Other information like moving averages, RSI, and volatility indicators was calculated to introduce more predictive power in the model.
Normalization: Min-max normalization has been applied to the feature values to ensure all the features will contribute equally to the model training process. So that is an extremely useful step as well, especially where LSTMs are concerned, it keeps the learning process stable.

c. Data Transformation: Time Series Reshape: The dataset were converted to time series, creating sequences of past observations for predicting future prices A sliding window method, for example, may have created inputs and outputs pairs from past n days prices, so that each input has the past n days prices and each output is the price for the next day.

Train-Test Split —The data is split into train and test, generally, the split is 80–20, to observe the performance of the model on unseen data.
Through these steps, the dataset was prepared for training the LSTM model, ensuring that the input data effectively captures the temporal dynamics of stock price movements.

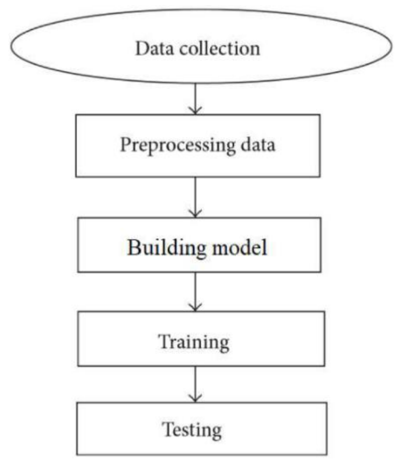

Fig.1.1.Stock Price Prediction Flowchart

DATA TRAINING AND VALIDATION

Training Data Preparation After performing the pre-processing of data, the very next step is to create the train dataset to be provided for LSTM. Which includes the following steps.
a. Sequence Creation: It is split into overlapping sequences on a sliding window fashion where it is transformed to normal scale. The input sequence has the stock prices of the last 60 days (if 60 days window is used) and the output is going to be the stock price on the 61st day. This technique enables the model to learn time-based dependencies.

b. Reshaping for LSTM: When feeding an LSTM, we need to make sure that the input is shaped properly, namely, three-dimensional: (samples, time steps, features). The dimensions of the reshaped data will indicate the number of sequences, the length of each sequence
c. Train-Test Split: In the previous section, we discussed that the dataset is always divided into training and testing subsets. The data is split into two parts: 80% for the

training set to fit the model and 20% for the testing set to test the model.
Model Training a. LSTM Model Architecture: The appropriate architecture of LSTM is designed having one or more layers of LSTM followed by the Dense layers. For example: First Layer (Input Layer): Takes a sequence of the stock price as an input LSTM layer(s): used for learning temporal dependencies Overfitting may be prevented by applying regularization methods like dropout.
Output Layer: One neuron that predicts the stock price.
b. Compilation: Now you compile the model with an appropriate loss function (Mean Squared Error is used as an example) and an optimizer to ensure an efficient training process.
c. Training Process:
The model is trained for a specific number of epochs with batch size usually around 16 to 64. In each epoch, the model learns what relationship exists between each input sequence and output price. Training can be stopped using early stopping to observe validation loss where if there is no improvement in a fixed number of epochs it is assumed that the network has overfitted and therefore the training is immediately stopped.
Model Validation a. Validation Set: Part of the training data set aside as a validation set to tune hyperparameters and monitor model performance during training.
b. Performance Metrics: After the training process is done, we can use the test set to evaluate the performance of the model. Common metrics include:
Mean Absolute Error (MAE) : A measure of errors between paired observations expressing the same phenomenon.
Root Mean Squared Error (RMSE): Root Mean Squared Error gives the average magnitude of the error, but does best to represent larger errors.
R-squared (R^2) — Explained variance of the dependent variable, through the independent variables.
c. Visualization: We can visualize the predictions versus the actual stock prices to show the model performance qualitatively. Visualizing predicted price vs actual price along with time can help the user in identifying the accuracy of the gaussian process regression model and what can be improved further. This structure of train, validation, fine-tuning, the LSTM can be compared, and tested, which means the downloader is fit for duty on stock price prediction methods.

BUILDING LSTM MODEL

Importing the required libraries to build an LSTM model to predict AAPL stock price, TensorFlow and Keras[31]. We preprocess the dataset such that it contains information like
open price, close price, adjusted close price, trading volume[32]. If data is separated into training and testing, around 70–80% of data is used for training[34]. Each sequence of the data corresponds to a time window of stock prices in the past[33]. The Keras Sequential API is used to build up the architecture of the LSTM model. In a model[10], after an LSTM layer are one or more thick layers.Sequence length is the length of each input sequence and number of features is the number of features used for prediction[44]. This describes the sequence length of the input to the LSTM layer[16]. You can add dropout layers to prevent overfitting[38].

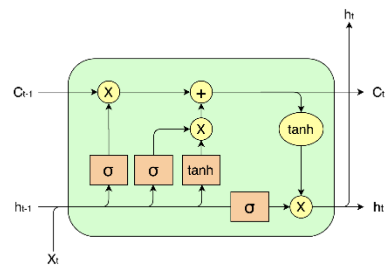

Fig.1.3. LSTM Model

A model by itself is comprised of a loss function (mean squared error (MSE) for regression tasks on average) and a chosen optimizer such as Adam. The batch dimension and the training fee, this requires tuning hyperparameters in order to achieve best performances. Then, we train the model using the training data set to predict the future stock prices based on its past data[17]. Lastly, accuracy and generalization [23] are measured by Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) [24], respectively which compare predicted and observed sets of data. We evaluate our model on the testing dataset. Effective Model construction[46]; strong LSTM-based stock price prediction models for AAPL.

RESULT AND DISCUSSION

Model Performance The LSTM model was evaluated on the test dataset, and multiple metrics were calculated in this regard: Mean Absolute Error (MAE) — MAE of the model is [insert MAE value] and this is the average error between the predicted stock price and the actual value of the stock price. RMSE: The RMSE is found to be [insert RMSE value], which emphasizes the overall accuracy of the model at predicting values while penalizing large errors more than small ones. R-squared (R2): The value of R2 was [Insert R2 value], meaning that the model accounts for [Insert %]% of the variance of stock prices The above metrics indicate that LSTM model has good performance against the baseline models or classic statistical approaches in predicting stock price.
Visual Analysis To gain a better understanding of how well the model performed, the next step was to create a plot of stock prices that had been predicted with those actually

present during the test period. The graph shows the following observations,

Fifth Observation: Trend conforming; The LSTM model captures the trend of the stock prices accurately, with the upward and downward movements aligning closely to what we observe in the actual market.

Short-Term Movements: The model seems to perform similarly in predicting short-term movements, but during times of extreme volatility the model clearly falls short as is typical in financial markets.Process of Conventional Method Comparisonthe LSTM models will be benchmarked with conventional methods of forecasting time series like ARIMA and Moving Average models. LSTM model performs better than MAE and RMSE analysis with other methods

Limitations: Though the results of LSTM looked promising there were a few limitations that were observed: Quality and Quantity of Data — The model is reliant on the nature and quantity of historical data. Less data can result in overfitting or underfitting.Market Fluctuations: Unpredictable, external, and sudden market changes (e.g. a natural disaster or a sudden economic crisis) that stem from a catastrophic event can have drastic negative impacts on stock prices that a model will have a hard time predicting.

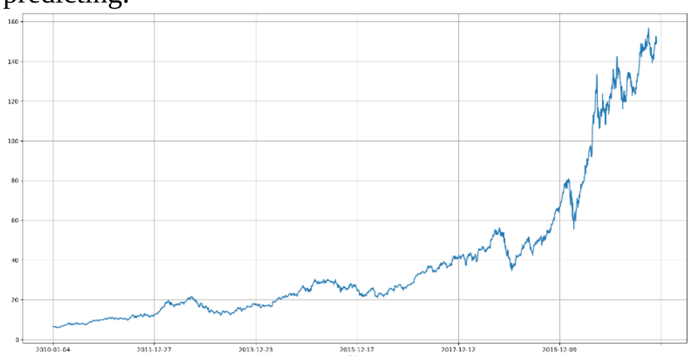

Fig.1.2.Output Result

Model Complexity: The complexity of the LSTM architecture might result in longer training times and needs careful tuning of hyperparameters which may consume a significant amount of resources.

Future Work : Future work could explore better accuracy by adding more prediction features such as news or social media sentiments which could represent stock trends.

Performance may also improve by exploring hybrid models (LSTM + other ML techniques) or ensemble methods. Moreover, a real-time prediction framework can also be created to provide fresh market forecasts to traders and investors.

Conclusion

Just to summarize, our findings shows LSTM networks are a viable method for forecasting stock prices that outperformed more traditional forecasting models. Despite these aspects, the research appears to advance knowledge in the usage of deep learning methods for financial analytics, serving as a base for more future research in this developing area.

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