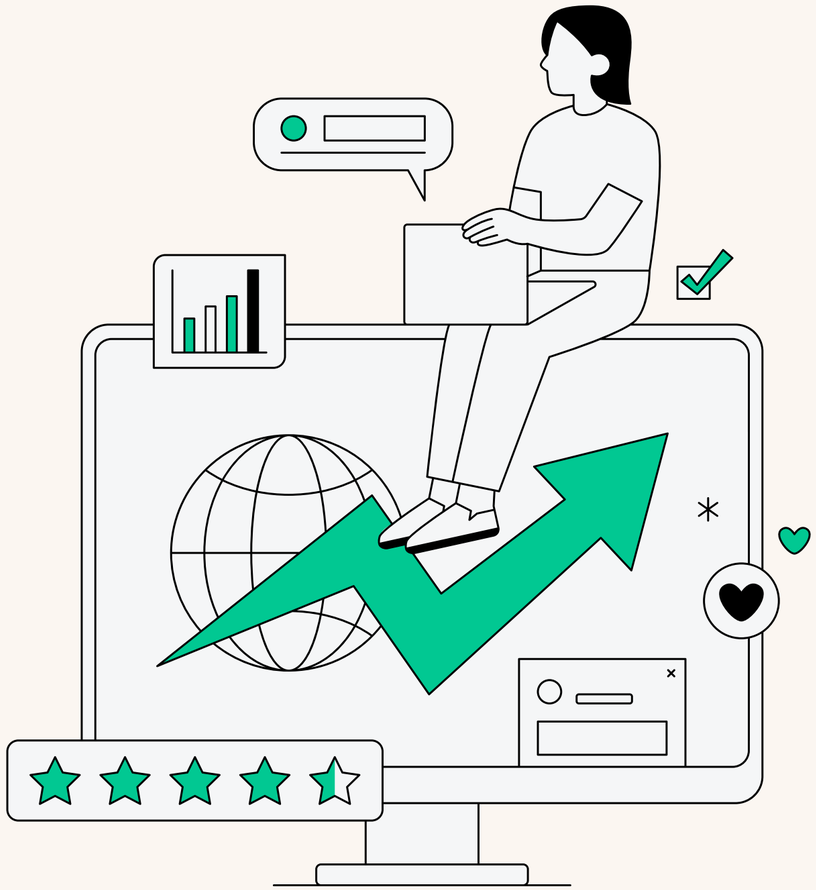
Stock Prediction

using LSTM algorithm



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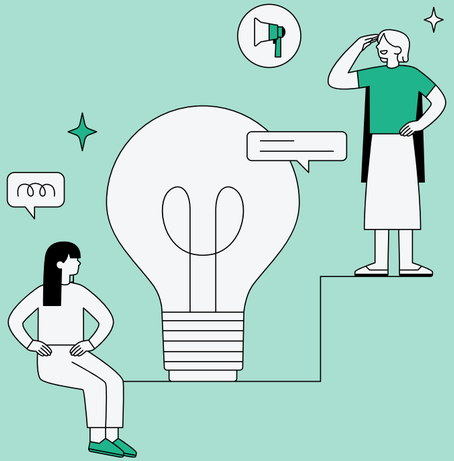
Motivation



The accurate prediction of stock prices has a significant role to play in the present economic world.

However, stocks have an ever-changing nature coupled with a risk factor that always seems much of a gamble, making it worthwhile for researchers to analyze them with machine learning algorithms.

We thus seek to develop a machine-based model replacing the traditional yet unreliable time-series forecasting to predict the stocks from the past historical data of a firm and to uncover the underlying patterns to improve the accuracy of the prediction of the model.

Literature Survey

Paper	Year	Author	Proposed Work	Drawback
Stock Market Prediction Using Machine Learning Algorithms.	2019	Sadia, K. Hiba, Aditya Sharma, Adarrsh Paul	Proposes a prediction system based on Machine Learning algorithm Support Vector Machine (SVM) and Random Forest Classifier	In stock prediction, where data can be highly nonlinear, SVM's reliance on linear boundaries might not capture complex patterns effectively.
A new approach of stock price prediction based on logistic regression model.	2009	Gong, Jibing, and Shengtao Sun	A Logistic Regression based model using feature index values and significant time-effectiveness has been proposed	Logistic regression assumes a linear relationship between the independent variables and the log-odds of the dependent variable.

Literature Survey

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Predicting trend in stock market exchange	2016	Khan, W., M. A. Ghazanfar, M. Asam, A. Iqbal	A prediction model where they measure the best algorithm before and after applying the Principal Component Analysis (PCA)	KNN requires storing the entire training dataset in memory, making it computationally expensive, especially for large datasets.
Machine learning approach in stock market prediction	2017	Deepak, Raut Sushrut, Shinde Isha Uday	Customize the features in ANN and then it is tested on the Support Vector Machine (SVM), which is a binary classifier.	ANNs are prone to overfitting, especially when the model capacity (number of parameters) is high relative to the amount of training data.

Literature Survey

Paper	Year	Author	Proposed Work	Drawback
Stock price prediction using CNN-sliding window model	2017	Selvin, Sreelekshmy, R. Vinayakumar, E. Gopalakrishnan, Vijay Krishna Menon	They evaluate the model performance based on percentage error. They train their model on Infosys' stock prices and can predict the stock prices of TCS and Cipla.	CNN can overfit the training data and feature selection for the CNN is also critical. Poor feature selection can lead to ineffective predictions.
Stock market's price movement prediction with LSTM neural networks.	2017	Nelson, David MQ, Adriano CM Pereira, and Renato A. de Oliveira	Get a dividend gain in predicting the price but can increment it if variance could be less and make the LSTM model perform well.	Overlook subtle patterns or fail to predict sudden shifts in market dynamics. LSTM models can be implemented better.

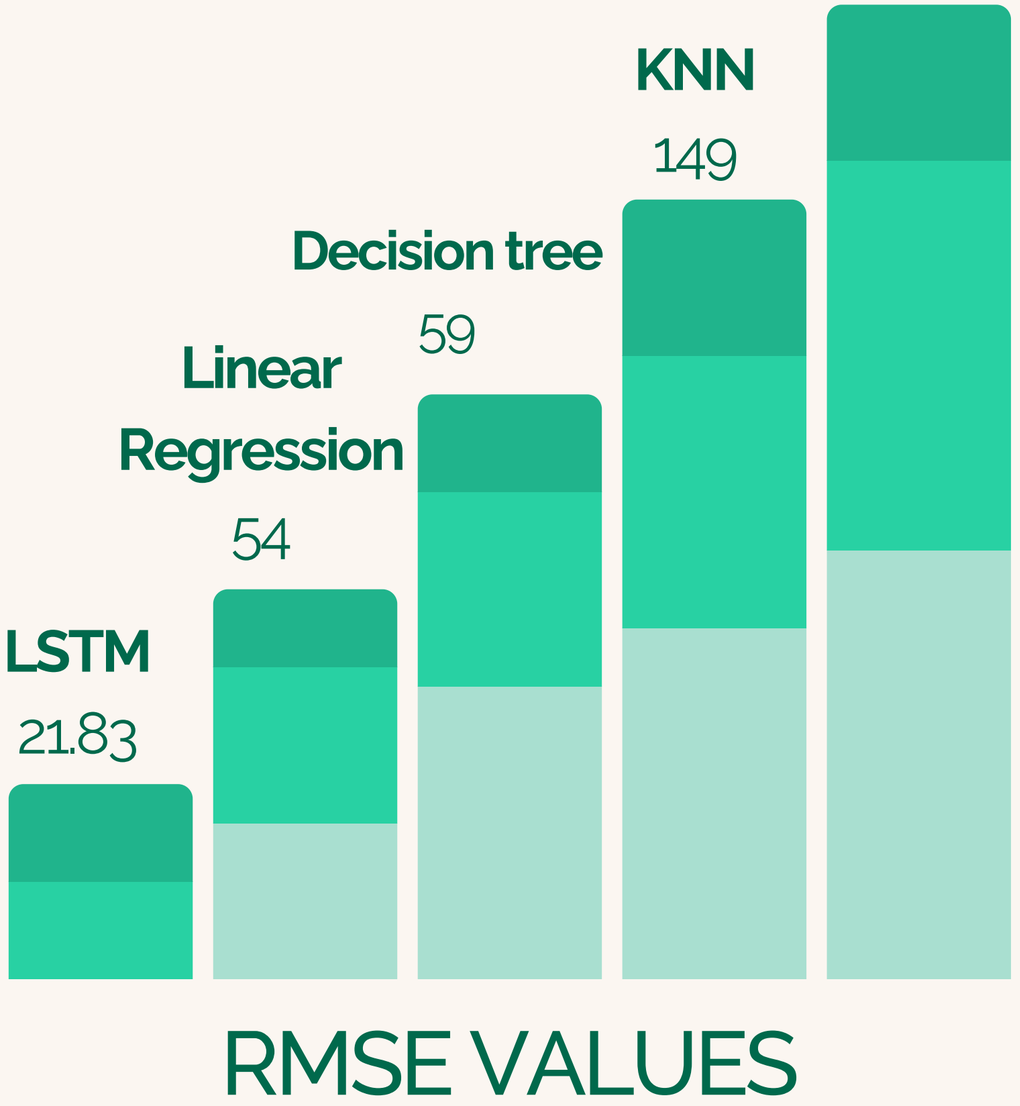
Literature Survey

Paper	Year	Author	Proposed Work	Drawback
Prediction models for Indian stock market	2016	Nayak, Aparna, MM Manohara Pai, and Radhika M. Pai	Combined the historical data with the sentiments like news/tweets of a company.This type of dataset, Decision Tree performs better than Logistic Regression and SVM.	SVM performance can be sensitive to the choice of the kernel and the regularization parameter. Selecting appropriate values for these parameters can require extensive tuning and cross-validation, which can be computationally expensive.

Limitations

LSTM model is the best proposed model as it can depict the near representation of predicted values from the actual stock price value and has the least RMSE value.

Whereas Linear Regression, Decision Tree and KNN cannot predict the prices as accurately as LSTM.



Objective

01. Preprocess the data to handle missing values, normalize the features, and create appropriate input sequences for the LSTM model.

02. Construct LSTM-based neural network architecture for stock price forecasting, optimizing hyperparameters for improved accuracy.

03. Evaluate the model's performance on a separate validation or test dataset to assess its ability to generalize to unseen data.

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Dataset - General features

01.

DATE gives the date corresponding to which the stock prices are stored..

02.

OPEN is the opening price at which the market opens, i.e., the price for which the first trading executes.

03.

HIGH represents the highest price at which the stock has reached on the given day.

04.

LOW represents the most economical value at which the stock has concluded on the day. .

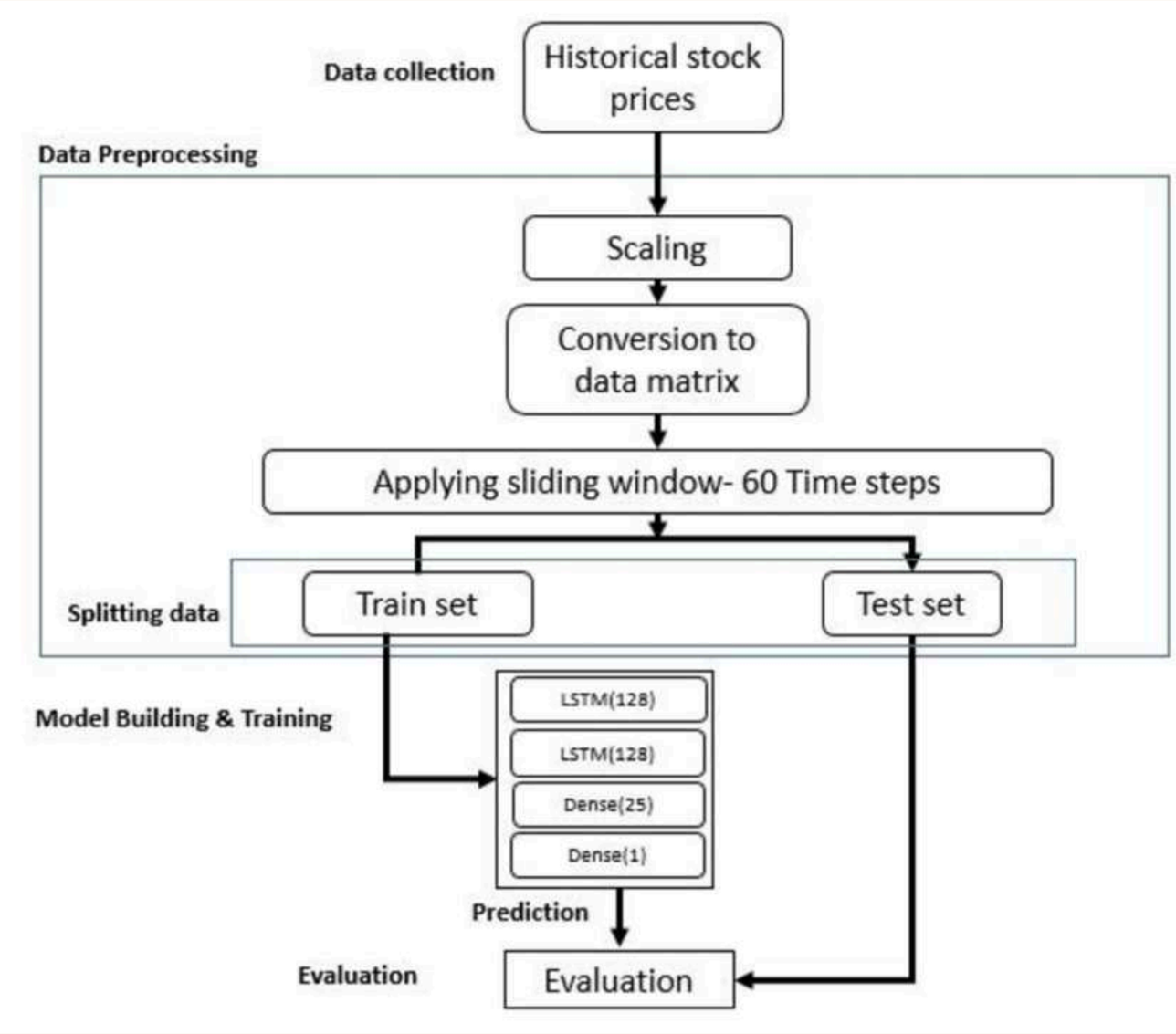
05.

CLOSE is the closing price, and it is the most crucial price as it is the closing price for the given period.

06.

ADJ CLOSE price is the price that is quoted by the data provider after reviewing any corporate actions like dividends or stock splits.

Architecture Diagram



Methodologies

Data Preprocessing

- Scaling
- Slidingwindow approach Labeling
- Splitting of dataset

Input Dataset

Date	Open	High	Low	Close	Adj Close	Volume
2004-08-19	49.813286	51.835709	47.800831	49.982655	49.982655	44871300
2004-08-20	50.316402	54.336334	50.062355	53.952770	53.952770	22942800
2004-08-23	55.168217	56.528118	54.321388	54.495735	54.495735	18342800
2004-08-24	55.412300	55.591629	51.591621	52.239193	52.239193	15319700
2004-08-25	52.284027	53.798351	51.746044	52.802086	52.802086	9232100

Scaling

Scale the features to a range suitable for the activation function of the neural network.

Commonly, the Min-Max scaling method is used to scale the features between 0 and 1.

Scaling ensures that each feature contributes equally to the model's learning process and prevents features with larger magnitudes from dominating the model.

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$$

Sliding window approach labelling

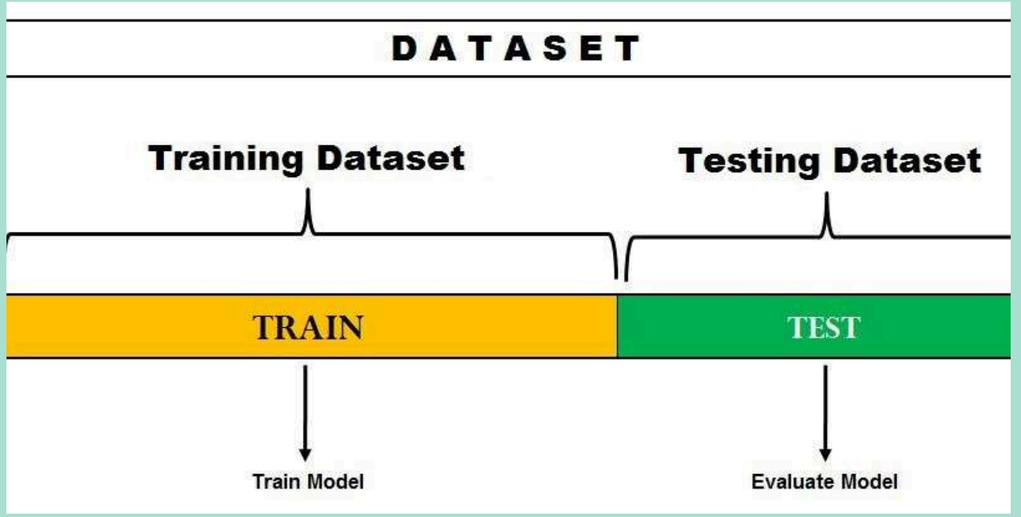
Convert the time series data into input-output pairs suitable for training a sequence prediction model like LSTM.

In the sliding window approach, you create input sequences (X) and corresponding output labels (y) by sliding a window of a fixed size over the time series data.

For example, if you're using a window size of 60 time steps, each input sequence contains the historical values of the selected features for the past 60 time steps, and the corresponding output label is the value of the target feature at the next time step.

This process effectively converts the time series data into a supervised learning problem.

Splitting of dataset



We distribute the dataset in the training phase and in the testing phase, where 80% of the data goes to the training phase and 20% of the data goes to the testing phase.

In the training phase, the model gets coached on the data and then the testing data gets tested on the trained model so that it can predict the stock price more accurately

Methodologies

LSTM Model

- Building model
- Compiling model
- Evaluating model

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LSTM

- LSTM stands for Long Short Term Memory is a deep neural network..
- In LSTM, the hidden layers that generally all neural network uses are replaced with memory cells, a series of gates.
- These gates decide whether to pass the detailed information to the next cell or ignore it. There are three gates in LSTM

01. **Input Gate**

02. **Forget Gate**

03. **Output Gate**

Memory cells containing gates

01.

At forget gate the input is combined with the previous output to generate a fraction between 0 and 1, that determines how much of the previous state need to be preserved . An activation output of 1.0 means “remember everything” and activation output of 0.0 means “forget everything.”

02.

Input gate operates on the same signals as the forget gate, but here the objective is to decide which new information is going to enter the state of LSTM. The output of the input gate (again a fraction between 0 and 1) is multiplied with the output of tan h block that produces the new values

03.

At output gate, the input and previous state are gated as before to generate another scaling fraction that is combined with the output of tanh block that brings the current state. This output is then given out. The output and state are fed back into the LSTM block.

Compiling Model

The loss function, also known as the cost function or objective function, quantifies the difference between the predicted output of the model and the actual target values. Its purpose is to measure how well the model is performing on a given task.

MSE is one of the most commonly used loss functions in regression tasks, including stock price prediction. It calculates the average squared difference between the predicted values and the true values.

Compiling Model

Backpropagation is used to update the weights of the neural network in order to minimize the loss function. Gradients of the loss with respect to the model's parameters are computed and used to adjust the weights through gradient descent optimization algorithms like Adam

Adam (Adaptive Moment Estimation) is an optimization algorithm commonly used to update the parameters of a neural network during training

Implementation

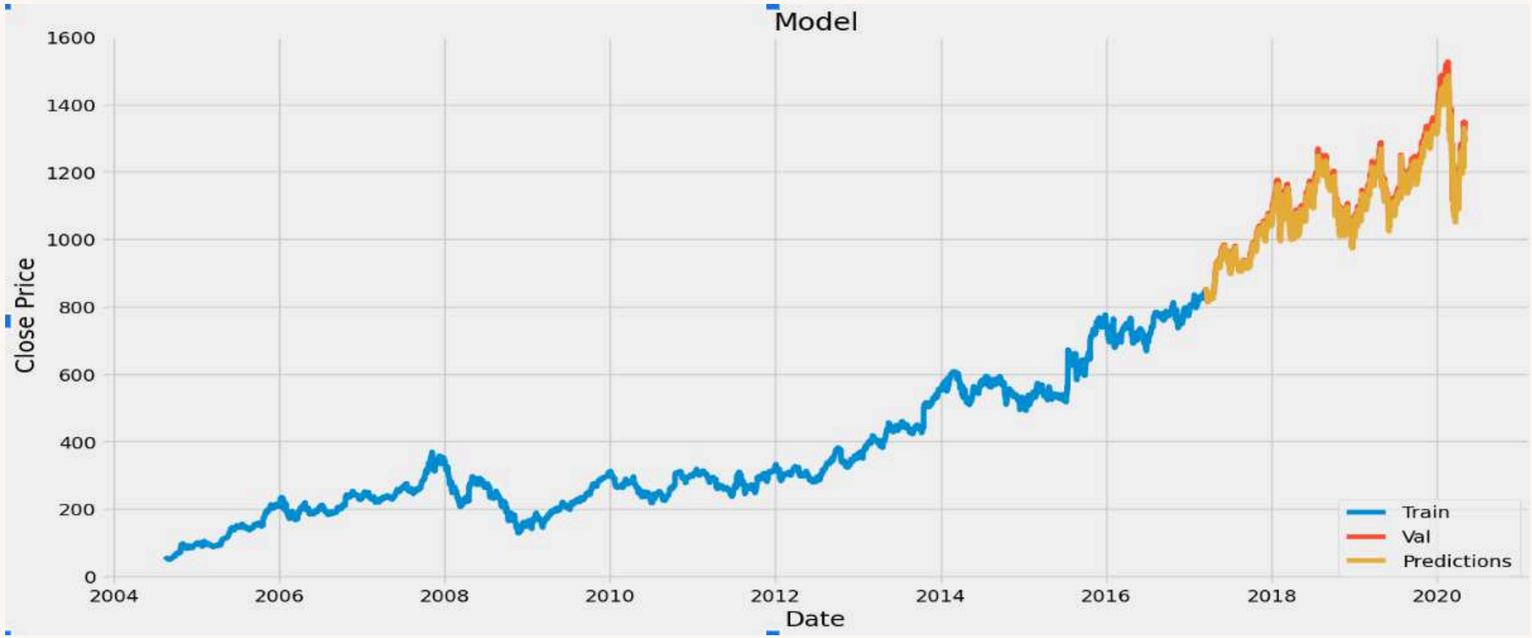
We have employed Keras library to implement the LSTM model, which works sequentially, which means layers are sequentially added one after the other.

Consequently, we have used four layers of the LSTM model in which the first two layers take the input of 50 set.

The third layer, usually known as the "Dense" layer, serves as the connection between the second layer and the next Dense layer, which is the output layer

Ultimately, for compiling the model, we consider the two parameters – Adam optimizer and loss function as mean square error

Evaluation Graph



By using the LSTM model the predicting stock values (represented using orange colour) are almost accurately equal to the valid value which is represented using red colour

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Thank you very much!