A PROJECT ON

LSTM BASED STOCK PRICE PREDICTION USING MACHINE LEARNING APPLICATION

Submitted in partial fulfillment of the requirement for the award of the degree of

BACHELOR OF TECHNOLOGY

IN

INFORMATION TECHNOLOGY

Submitted by:

Mohit Negi	**1918907**
Tarun Kumar Dhiman	**1918917**
Rishabh Aggarwal	**1918909**
Shourya Kapoor	**1918914**

Under the Guidance of

Dr. NOOR MOHD
(ASSOCIATE PROFESSOR)

Project Team ID: ID No – MP22IT03

Department of Computer Science and Engineering
Graphic Era (Deemed to be University)
Dehradun, Uttarakhand

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CANDIDATE'S DECLARATION

We hereby certify that the work which is being presented in the Synopsis entitled **"LSTM based Stock price prediction using machine learning application"** in partial fulfillment of the requirements for the award of the Degree of Bachelor of Technology in Information Technology in the Department of Computer Science and Engineering of the Graphic Era (Deemed to be University), Dehradun shall be carried out by the undersigned under the supervision of **Dr. NOOR MOHD**, ASSOCIATE PROFESSOR, Department of Computer Science and Engineering, Graphic Era (Deemed to be University), Dehradun.

Mohit Negi	1918907	_____
Tarun Kumar Dhiman	1918917	_____
Rishabh Aggarwal	1918909	_____
Shourya Kapoor	1918914	_____

The above-mentioned students shall be working under the supervision of the undersigned on the **"LSTM BASED STOCK PRICE PREDICTION USING MACHINE LEARNING APPLICATION"**

_____ _____

Supervisor **Head of the Department**

Internal Evaluation (By DPRC Committee)

Status of the Synopsis: Accepted / Rejected

Any Comments:

Name of the Committee Members: **Signature with Date**

Abstract

In this project, we propose a machine learning solution for stock market prediction by utilizing the Long Short-Term Memory (LSTM) architecture. Predicting stock market movements accurately is a challenging task due to the inherent complexity and volatility of financial markets. Our project aims to leverage the power of LSTM, a specialized recurrent neural network architecture, to capture and model the temporal dependencies in stock market time series data.

The system design involves collecting historical stock market data, including price and volume information, from reliable financial data sources. This data is preprocessed and transformed to create a suitable input format for the LSTM model. The LSTM architecture, with its ability to retain and learn from long-term dependencies, is trained on the historical data to capture patterns and relationships that influence stock market movements.

To evaluate the performance of our stock market prediction model, we employ appropriate evaluation metrics and testing methodologies. We assess the accuracy, precision, and recall of the predictions, comparing them against actual stock market trends. Additionally, we analyze the model's ability to generalize by conducting back testing and validation on unseen data.

Throughout the project, we emphasize scalability and efficiency by utilizing parallel computing techniques and optimizing the LSTM model's architecture. The project also addresses the ethical considerations surrounding stock market prediction and emphasizes the importance of responsible and informed decision-making in financial markets.
By harnessing the power of LSTM and machine learning, our project aims to contribute to the development of robust and accurate stock market prediction models. The outcomes of this project can potentially benefit investors, financial institutions, and policymakers by providing valuable insights for informed decision-making in the dynamic world of stock markets.

Acknowledgement

Any achievement, be in scholastic or otherwise does not depend solely on the individual effort but on the guidance, encouragement and co-operation of intellectuals, elders and friends. A number of personalities in their own capacity have helped me in carrying out this project work.

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Mohit Negi	1918907
Tarun Kumar Dhiman	1918917
Rishabh Aggarwal	1918909
Shourya Kapoor	1918914

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Chapter 1

Introduction and Problem Statement

Stock market has received widespread attention from investors. How to grasp the changing regularity of the stock market and predict the trend of stock prices has always been a hot spot for investors and researchers. The rise and fall of stock prices are influenced by many factors such as politics, economy, society and market. For stock investors, the trend forecast of the stock market is directly related to the acquisition of profit. The more accurate the forecast, the more efficiently it can avoid risks. For listed companies, the stock price not only reflects the company's operating conditions and future development expectations, but also an important technical index for the analysis and research of the company. Stock forecasting research also plays an important role in the research of a country's economic development. Therefore, the research on the intrinsic value and prediction of the stock market has great theoretical significance and wide application prospects. The main purpose of this paper is to design a deep network model to predict simultaneously the opening price, the lowest price and the highest price of a stock on the next day according to the historical price of the stock and other technical parameter data. Therefore, it is proposed an LSTM based deep recurrent neural network model to predict the three associated values (so it is called the associated neural network model, and abbreviated as associated net model). The associated net model is compared with LSTM and LSTM-based deep recurrent neural network, and verify the feasibility of the model by comparing the accuracy of the three models.

Chapter 2

Background/ Literature Survey

2.1 INTRODUCTION

There have been various studies on predicting stock prices using different techniques. For instance, support vector machines have been applied to construct a regression model of historical stock data and predict stock trends [1]. Another study used particle swarm optimization to optimize the parameters of support vector machines, resulting in a robust prediction of stock values [2]. However, this method requires a long time to calculate.

LSTM, combined with naive Bayesian methods, has been used to extract market emotion factors and improve the accuracy of stock price prediction, especially in different time scales and with other variables [3]. Additionally, the integration of emotional analysis models with LSTM time series learning models can yield a robust model for predicting the opening price of stocks [11]. Furthermore, Jia [12] demonstrated the effectiveness of LSTM for predicting stock profits.

Real-time wavelet denoising has been combined with LSTM networks to predict the east Asian stock index and correct some of the logical defects present in previous studies [13].

It is common for researchers to use various machine learning techniques for stock price prediction. For instance, support vector machines have been used to build a regression model of historical stock data to predict stock trends. Particle swarm optimization algorithms have also been used to optimize the parameters of support vector machines to predict stock values robustly. LSTM has been combined with the naive Bayesian method to extract market emotion factors, and the emotional analysis model integrated with the LSTM time series learning model to obtain a robust time series model for predicting the opening price of stocks, which has improved the accuracy of prediction.

Researchers have also used bagging methods to combine multiple neural network methods to predict Chinese stock index. Although this method has different accuracy for the prediction of different stock indexes, the prediction on close is unsatisfactory. Other techniques that have been used for stock price prediction include the evolutionary method, deep belief network with inherent plasticity, convolutional neural network, and a forward multi-layer neural network

model. Overall, the combination of different machine learning techniques can improve the accuracy of stock price prediction, but each method has its own advantages and disadvantages.

Other methods that have been used include the bagging method, which combines multiple neural network methods to predict the Chinese stock index. An evolutionary method has been used to predict the change trend of stock prices. The deep belief network with inherent plasticity has been used to predict the stock price time series. Convolutional neural networks have been applied to predict the trend of stock prices. A forward multi-layer neural network model has been created for future stock price prediction by using a hybrid method combining technical analysis variables and basic analysis variables of stock market indicators and BP algorithm. Furthermore, an effective soft computing technology has been designed for the Dhaka Stock Exchange (DSE) to predict the closing price of DSE. Comparison experiments with artificial neural networks and adaptive neural fuzzy reasoning systems have shown that this method is more effective than others. Overall, there are many methods.

2.2 EXISTING METHODS

2.2.1 Stock Market Prediction Using Machine Learning

Stock trading has become a significant activity in the finance world today. The prediction of stock prices involves attempting to forecast the future values of stocks from various companies traded on financial exchanges using different financial instruments. This paper focuses on utilizing machine learning, a well-known computer technology, for stock price prediction. The study employs technical analysis, fundamental analysis, and time-series analysis, commonly used by stockbrokers to make stock price predictions.

Python is the programming language used for implementing the machine learning models. The proposed approach in this paper utilizes machine learning techniques, specifically Support Vector Machine (SVM), to predict stock prices for both large and small capitalizations. The study gathers historical stock data and applies machine learning algorithms to extract patterns and insights, which are then utilized to generate predictions. The research considers data from three different markets and incorporates different time frequencies, including daily and up-to-the-minute prices.

2.2.2 Forecasting the Stock Market Index Using Artificial Intelligence Techniques

The weakest form of the Efficient Market Hypothesis suggests that it is not possible to forecast the future price of any stock or asset based on historical price data. According to this form of the hypothesis, the market behaves randomly, making any form of prediction impossible. Additionally, financial forecasting is challenging due to the complex and unpredictable nature of events in the financial system.

The objective of our project is to develop software that utilizes Artificial Intelligence techniques or different models to predict the future price of the stock market index. Three major techniques, namely neural networks, support vector machines, and neuro-fuzzy systems, are implemented for forecasting the future price of the global stock market exchange index using historical price information.

Machine Learning techniques are well-suited for handling the complexities of the financial system and are commonly used in financial time-series forecasting. To benchmark the Machine Learning techniques, two specific techniques, Recurrent Neural Networks (RNN) and Long-Short Term Memory (LSTM), are utilized. The experiment involves using input datasets consisting of previous historical data in CSV format. The relevant information required to predict the future stock prices includes the closing time, opening time, and any updates over the time period. By analyzing this data, the developed mechanism has the capability to predict the future stock prices accurately, taking into account transaction costs associated with trading in the market.

2.2.3 Indian stock market prediction using artificial neural networks on tick data

The stock market serves as a platform for trading company stocks and assets at agreed-upon prices. The supply and demand of shares influence the stock market, making it one of the most active and exciting sectors of business in every country. Nowadays, individuals participate in the stock market directly or indirectly through brokers or trading applications like OctaFX and Olymp Trade. As a result, understanding market trends has become crucial. With the stock market's evolution, people have developed a greater interest in stock price forecasting. However, due to the dynamic nature of the market, predicting stock prices accurately and

quickly is a challenging task. The stock market's fluctuations make it difficult to make accurate guesses about price movements.

Previous work in the field of stock prediction has proposed effective methods for learning representations of recent events, capturing both syntactic and semantic information from text corpora. These methods have demonstrated their effectiveness for tasks such as script event prediction. However, one limitation is that different events extracted from raw texts often lack common-sense knowledge, such as the intentions and emotions associated with the events. This common-sense knowledge is valuable for distinguishing event pairs, particularly when there are subtle differences in their surface realizations. To address this issue, this research proposes incorporating external common-sense knowledge related to the intent and sentiment of the occurred events.

2.2.4 The Stock Market and Investment

The increased integration of European finance markets is expected to lead to a stronger correlation between equity prices in different European countries. This integration process may also foster convergence in various economic aspects, including investment and consumption. Based on our RNN model, we have observed a positive correlation between changes in equity prices and investment. As a result, it is advisable for monetary authorities to closely monitor the reactions of share price markets to monetary policy and their impact on the overall business cycle.

Chapter 3

Objectives

The purposed work are as follow:

- Stock markets play a crucial role in helping companies raise capital. When a company decides to go public, it offers shares of its ownership to the public through an initial public offering (IPO) or a direct listing. These shares are then traded on a stock exchange.
- The stock market can provide an opportunity for individuals to generate personal wealth. Investing in stocks allows individuals to participate in the ownership and growth of publicly traded companies, potentially benefiting from their success.
- Stock markets do serve as indicators of the state of the economy. They reflect the overall health and performance of the economy and provide valuable insights into economic trends and conditions. Here's how stock markets act as indicators.
- The stock market is a widely used platform for individuals to invest their money in companies with high growth potential. Investing in stocks allows individuals to participate in the ownership and success of publicly traded companies, potentially benefiting from their growth and profitability.

Chapter 4

Possible Approach/ Algorithms

4.1 Long short-term memory work.

Long short-term memory network (LSTM) is a type of recurrent neural network (RNN) that is capable of processing sequential data. LSTM is a specialized network architecture that includes three “gates” (shown in Fig. 1): the input gate, the forget gate, and the output gate. These gates allow information to enter the LSTM’s network and be selected according to specific rules. Only the information that conforms to the algorithm will be kept, while the information that does not conform will be forgotten through the forgetting gate.

The gate allows information to be passed selectively, and the default activation function of the LSTM network is the sigmoid function, as shown in Eq. 1. The LSTM can selectively add or delete information for neurons through its gating units. The gating unit consists of a sigmoid layer and a pointwise multiplication operation, which can learn to regulate the flow of information by controlling the values of the sigmoid layer. The input gate controls how much new information is added to the cell state, while the forget gate determines how much previous information is retained. The output gate determines how much information is output from the cell state. The LSTM architecture allows it to capture long-term dependencies and prevent the vanishing gradient problem that occurs in traditional RNNs, making it well-suited for time series prediction tasks.

Tanh and sigmoid function: The concept of sigmoid function and the tanh function in LSTM is basically maintaining the control flow of data passing or processing through cell state, cell state is considered as a memory block the does actual processing work, which is also known as memory block or **gate** of the network which filter the information to the cell’s state or working.

In LSTM, the sigmoid function is used as an activation function in the gating units. The sigmoid function is used to regulate the flow of information into and out of the cell state. The sigmoid function is defined as:

$$\sigma(x) = 1 / (1 + e^{-x})$$

where x is the input to the sigmoid function and σ(x) is the output. Sigmoid function representation is shown in figure 4.1.

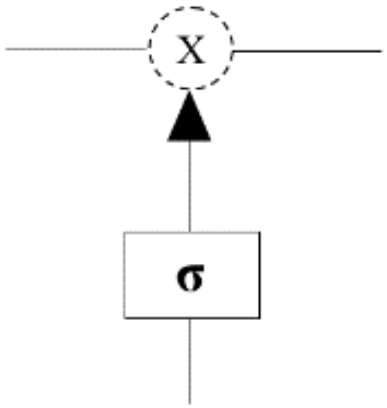

Fig 4.1 Representation of sigmoid function

In LSTM, the sigmoid function is used in the input gate, forget gate, and output gate. The input gate regulates the flow of new information into the cell state, while the forget gate controls the amount of old information that is retained in the cell state. The output gate controls the amount of information that is output from the cell state. The sigmoid function ensures that the values of the gates are between 0 and 1, so that the gates can act as binary switches.

LSTM network can add and delete the information according to the process.

Sigmoid function: $\sigma(x) = 1/(1+e^{-x})$

Tanh function: $\tanh(x) = (e^{x} - e^{-x})/(e^{x} + e^{-x})$

4.2 Gated recurrence unit.

The Gated Recurrent Unit (GRU) is a variant of the Long Short-Term Memory (LSTM) network, which is a type of recurrent neural network (RNN). Similar to LSTM, GRU also uses gating mechanisms to selectively update and reset the hidden state of the network, allowing it to better handle long-term dependencies in sequential data.

A GRU unit has two gates, a reset gate and an update gate. The reset gate controls how much of the previous hidden state is forgotten, while the update gate controls how much of the new input is used to update the current hidden state. The equations for a GRU unit can be written as:

r_t = σ(W_r[x_t, h_{t-1}] + b_r)

$z_t = \sigma(W_z[x_t, h_{t-1}] + b_z)$

$\tilde{h}t = \tanh(W[x_t, r_t \odot h\{t-1\}] + b)$

$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$

where x_t is the input at time step t, h_{t-1} is the hidden state at the previous time step, r_t is the reset gate activation, z_t is the update gate activation, $\tilde{h}_t$ is the candidate hidden state, h_t is the new hidden state at time step t, W and b are the learnable weight matrix and bias vector, respectively, and σ is the sigmoid activation function. The symbol ⊙ denotes element-wise multiplication. The representation of LSTM is shown in figure 4.2 .

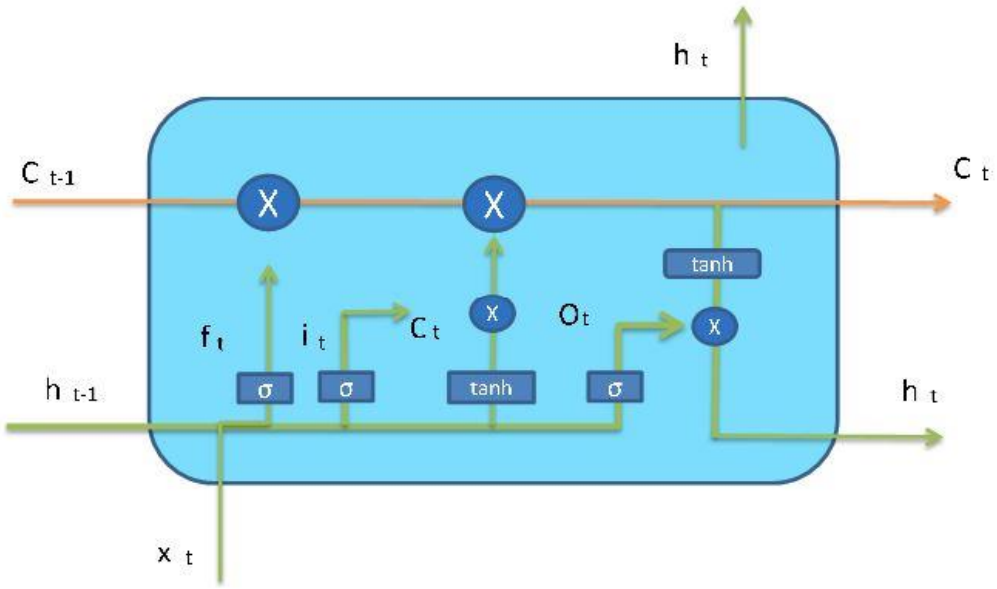

Fig 4.2 Long short term memory model representation

4.3 LSTM (Long Short-Term Memory) Architecture

Long Short-Term Memory (LSTM) is a type of recurrent neural network (RNN) architecture that is designed to overcome the vanishing gradient problem and capture long-term dependencies in sequential data. It was introduced by Hochreiter and Schmidhuber in 1997.

The basic building block of an LSTM is the LSTM cell, which consists of several key components:

1. Cell State (Ct): It is the memory of the LSTM and is passed along from one time step to another, allowing the network to capture long-term dependencies. The cell state can be modified through various gates in the LSTM.

2. Hidden State (ht): Also known as the output or the short-term memory of the LSTM. It is the information that the LSTM cell outputs at each time step based on the input and the cell state.

3. Input Gate (i): Determines how much new information should be stored in the cell state at the current time step. It takes input features and the previous hidden state as inputs and produces an output between 0 and 1.

4. Forget Gate (f): Controls what information should be discarded from the cell state. It takes input features and the previous hidden state as inputs and produces an output between 0 and 1.

5. Output Gate (o): Determines how much information from the cell state should be exposed as the output or hidden state of the LSTM. It takes input features and the previous hidden state as inputs and produces an output between 0 and 1.

6. Cell State Update: Calculates the new candidate values to update the cell state based on the current input and the previous hidden state. It combines the input gate and the candidate values to update the cell state.

The LSTM architecture consists of multiple LSTM cells arranged in a sequential manner, with the output of one LSTM cell being fed as input to the next LSTM cell in the sequence. This allows the LSTM to capture dependencies across different time steps.

LSTMs can have variations such as stacked LSTMs, bidirectional LSTMs, and attention-based LSTMs, which enhance their ability to model complex sequential data. These variations involve stacking multiple layers of LSTMs, processing sequences in both forward and backward directions, or incorporating attention mechanisms to focus on important parts of the input sequence.

Overall, LSTM architectures have proven to be effective in a wide range of tasks such as natural language processing, speech recognition, machine translation, and time series analysis, where modeling long-term dependencies is crucial.

Gate representation in LSTM is architecture shown in figure 4.3 below.

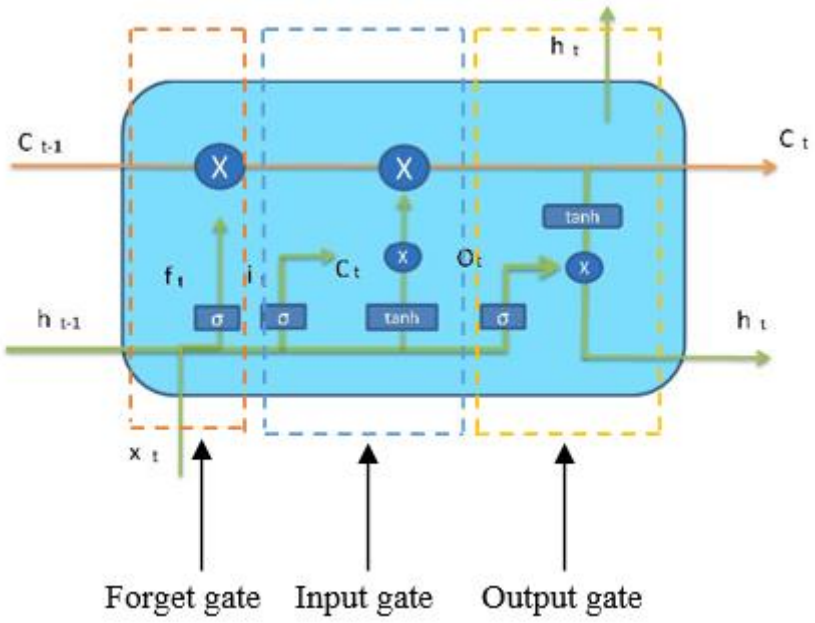

Fig 4.3 forget gate, input gate and output gate representation

4.4 Using RSME for prediction.

RMSE (Root Mean Square Error) is a commonly used metric for evaluating the performance of regression models, including those used for stock price prediction. While LSTM (Long Short-Term Memory) networks are popular for time series forecasting tasks, including stock price prediction, they can also be evaluated using RMSE.

Here's a general approach to using RMSE for prediction in stock price prediction using LSTM:

Data Preparation: Prepare your stock price dataset by dividing it into training and testing sets. Typically, you would use historical stock price data to train your LSTM model and reserve a portion of the data for testing.

LSTM Model Training: Build and train an LSTM model using your training dataset. The LSTM network takes historical stock price data as input and learns to make predictions based on the patterns it finds in the data.

Prediction: Use the trained LSTM model to make predictions on the testing dataset. Input the historical stock price data, and the LSTM model will generate predicted values for the corresponding time steps.

Calculation of RMSE: Once you have the predicted values from the LSTM model and the actual values from the testing dataset, calculate the RMSE to evaluate the performance of the

model. RMSE measures the average magnitude of the differences between predicted and actual values.

The formula for calculating RMSE is as follows:

RMSE = sqrt(mean((predicted - actual)^2))

Remember to replace the 'predicted_values' and 'actual_values' arrays with your own predicted and actual values obtained from the LSTM model.

By using RMSE, you can assess the accuracy of your LSTM model for stock price prediction. Lower RMSE values indicate better performance, as they represent smaller average differences between predicted and actual values.

4.5 Streamlit usage

Streamlit is a popular Python library that allows you to create interactive web applications for data science and machine learning projects. It provides a simple and intuitive way to build and deploy your LSTM project with a user interface. Here's an example of how you can use Streamlit for an LSTM project:

Install Streamlit: Start by installing Streamlit using pip or conda. Open your command prompt or terminal and run the following command.

Define Streamlit Widgets: Within the main function, you can add Streamlit widgets and UI elements to interact with your LSTM model. For example, you can include file upload buttons for uploading the stock price dataset, sliders for adjusting hyperparameters, and buttons to trigger predictions.

Load and Preprocess Data: Use Streamlit widgets to allow the user to upload the stock price dataset. Preprocess the data as required, such as scaling or normalizing the values.

Split the Data: Split the preprocessed data into training and testing sets, based on the desired split ratio or time periods.

Build and Train the LSTM Model: Use Streamlit widgets to allow the user to adjust hyperparameters or model configurations. Train the LSTM model using the training dataset.

Prediction and Result Display: Implement the logic to make predictions using the trained LSTM model. Display the predicted results alongside the actual values using Streamlit components like data tables, line charts, or plots.

Run the Streamlit App: Open your command prompt or terminal, navigate to the directory where your lstm_app.py script is located, and run the following command.

This command starts the Streamlit development server and launches your LSTM application in your default web browser.

Interact with the Streamlit App: Once the app is running, you can interact with the Streamlit widgets and explore the predictions made by your LSTM model based on the user's inputs.

4.6 Libraries used in Stock Prediction

The system will be built using the following technologies:

Python: Python is a widely adopted programming language renowned for its versatility in data analysis and machine learning applications. It boasts an extensive collection of libraries and tools that expedite the creation of sophisticated software solutions. Python's emphasis on readability and simplicity renders it well-suited for constructing the proposed framework.

Pandas: Pandas is an open-source library in Python that offers robust capabilities for data manipulation and analysis. It equips users with convenient data structures and functions that facilitate efficient handling of structured data. When it comes to stock prediction, Pandas proves valuable in tasks such as data ingestion from diverse sources, data preprocessing, including data cleaning and handling missing values, and transforming the data into a suitable format for analysis. Additionally, Pandas provides functionalities for data aggregation, filtering, and merging, empowering researchers to thoroughly explore and prepare the data for integration with machine learning algorithms.

Streamlit: Streamlit is a user-friendly Python library used for creating interactive web applications. It simplifies the process of building data-driven dashboards, visualizations, and user interfaces. In the context of stock prediction, Streamlit can be utilized to create an intuitive interface that enables users to input parameters**,** visualize predictions, and explore different aspects of the model's performance. It allows for quick and easy deployment of machine learning models, enabling users to interactively experiment and observe the model's predictions on live or historical stock data.

NumPy: NumPy (Numerical Python) is an essential library in Python that plays a pivotal role in scientific computing. It furnishes a potent N-dimensional array object, accompanied by an extensive collection of mathematical functions, facilitating efficient execution of numerical computations. In the realm of stock prediction, NumPy finds utility in various tasks, including data manipulation, statistical analysis, and mathematical operations. It enables seamless handling and manipulation of numerical data, empowering researchers to execute calculations on large datasets and support diverse mathematical operations crucial for training and evaluating machine learning models.

4.7 Data flow diagram.

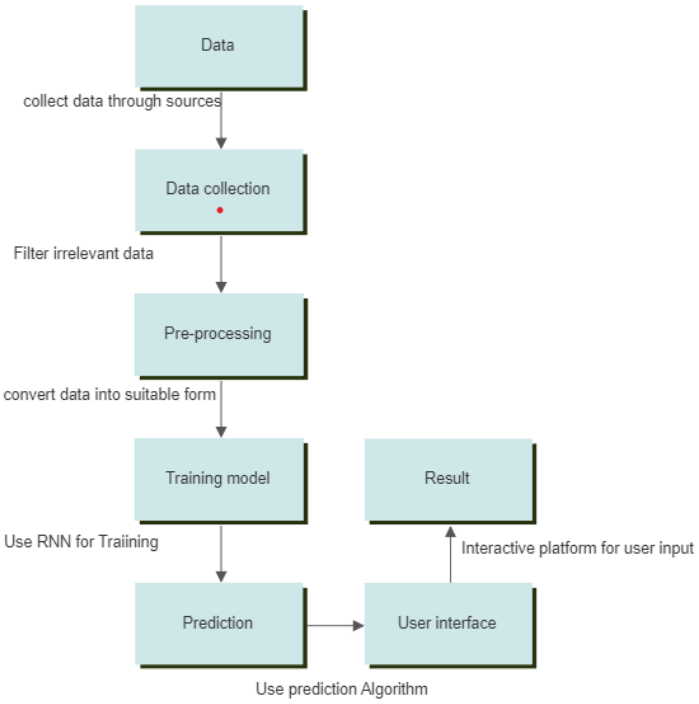

Fig. 4.4 Data flow diagram

Chapter 5

Conclusion

In conclusion, our research project utilized LSTM and the Granger causality test to gain insights into predicting trends in the Indian stock market by incorporating foreign market data. The LSTM model effectively captured the complex patterns and fluctuations present in the Indian stock market, showcasing its efficacy in forecasting future trends.

Additionally, the application of the Granger causality test enhanced our understanding of the causal relationships between the Indian stock market and foreign market variables. Our findings highlighted significant influences originating from specific foreign markets, emphasizing the importance of considering international factors when analyzing the dynamics of the Indian market.

Visualizations derived from our analysis, such as line graphs, candlestick plots, and network diagrams, provided stakeholders with a comprehensive understanding of projected trends in the Indian stock market. These intuitive visual representations enabled users to interpret and analyze the data effectively, facilitating well-informed decision-making.

It is important to acknowledge the limitations of our analysis, including assumptions made during model training, potential data quality and availability issues, and the possibility of unaccounted factors impacting stock market performance. Future research should aim to address these limitations to further refine our understanding of Indian stock market dynamics.

In summary, our project highlights the potential benefits of using LSTM and the Granger causality test to predict trends in the Indian stock market by incorporating foreign market data. The insights gained from this research have practical implications for investors, policymakers, and financial institutions, equipping them with valuable tools to make informed decisions in the dynamic global financial landscape.

Chapter 6

Code

```
import tensorflow
import math
import streamlit as st
import numpy as np
import pandas as pd
import pandas_datareader as data
from sklearn.preprocessing import MinMaxScaler
from keras.models import load_model

import yfinance as yf
yf.pdr_override()
from pandas_datareader import data as pdr

import matplotlib.pyplot as plt
plt.style.use('fivethirtyeight')
st.title('Stock trend Prediction USING trained model')


user_binput= st.text_input("Ticker",'AAPL')
start = '2010-01-01'
end='2023-03-09'

df = pdr.get_data_yahoo(user_binput, start, end )
#describing the data
st.subheader('Date from 2010 to 2023')
st.write(df.describe())
#Visulaisation
st.subheader('closing price')
fig =plt.figure(figsize=(12,6))
plt.plot(df.Close)
st.pyplot(fig)
```

```
#moving Average
st.subheader('Closing price vs 60 days MA')
ma60=df.Close.rolling(60).mean()
fig =plt.figure(figsize=(12,6))
plt.plot(ma60)
plt.plot(df.Close)
st.pyplot(fig)


st.subheader('Closing Price vs 60 days MA and 120 MA')
ma60=df.Close.rolling(60).mean()

ma120=df.Close.rolling(120).mean()
fig =plt.figure(figsize=(12,6))
plt.plot(ma60,'r')
plt.plot(ma120, 'g')
plt.plot(df.Close, 'b')
plt.legend(['ma60','ma120','close'],loc='lower right')
st.pyplot(fig)


data=df.filter(['Close'])
#convert dataframes to a numpy array
dataset= data.values
#get the number rows to train model
training_data_len=math.ceil( len(dataset) * .8)#which give us 80 % of data to train

scaler = MinMaxScaler(feature_range=(0,1))
scaler_data = scaler.fit_transform(dataset)
train_data = scaler_data[0:training_data_len ,:]
```

```
model=load_model('prediction.h5')
test_data =scaler_data[training_data_len - 60: , :] # this is from index 2132 2192
#create the new sets x_test and y test
x_test =[]
y_test = dataset[training_data_len:, :]
for i in range(60,len(test_data)):
  x_test.append(test_data[i-60:i,0])
  #convert the data to a numpy array
x_test=np.array(x_test)
#reshape the data
x_test =np.reshape(x_test, (x_test.shape[0], x_test.shape[1],  1))
#get the model predicted price value
prediction= model.predict(x_test)
prediction= scaler.inverse_transform(prediction)
#get the root mean square erroe (RMSE)
rmse=np.sqrt(np.mean(prediction - y_test)**2)


train = data[ : training_data_len]
valid=data[training_data_len :]
valid['prediction']=prediction
fig2=plt.figure(figsize=(12,6))
plt.title('New predict model')
plt.xlabel('Date',fontsize=18)
plt.ylabel('Close peice inin rs',fontsize=20)
plt.plot(train['Close'])
plt.plot(valid[['Close','prediction']])
plt.legend(['Train','Val','prediction'],loc='lower right')
st.pyplot(fig2)

# Forecast the next 10 days

forecast = []

# Get the last 60 days' data from the original dataset
last_60_days = data[-60:].values.reshape(-1,1)
# Scale the data
last_60_days_scaled = scaler.transform(last_60_days)

for i in range(10):
  # Reshape the data to a 3-dimensional array
  X_test = last_60_days_scaled.reshape(1,60,1)
  # Predict the next day's value
  pred_price = model.predict(X_test)
  # Invert the scaling to get the actual value
  pred_price = scaler.inverse_transform(pred_price)
  # Append the predicted value to the forecast list
  forecast.append(pred_price[0][0])
  # Shift the data by one day
  last_60_days_scaled = np.append(last_60_days_scaled[1:], pred_price, axis=0)

# Print the forecast values
print(forecast)

#get the model predicted price value
prediction= model.predict(x_test)
prediction= scaler.inverse_transform(prediction)

#get the future time steps
future_time_steps = st.slider('Select future time steps:', 1, 251, 10, 1)
future_days = np.arange(len(data), len(data) + future_time_steps, 1)

```

```
#get the root mean square erroe (RMSE)
rmse=np.sqrt(np.mean(prediction - y_test)**2)

#iyplot the data
train = data[ : training_data_len]
valid=data[training_data_len :]

#extend the x-axis values to include the future time steps
valid_future = valid.tail(future_time_steps)
valid_future.index = future_days
valid['new_prediction'] = prediction

# convert the x-axis values of train and valid to days
train_days = np.arange(len(train))
valid_days = np.arange(len(train), len(data))

#plot the actual and predicted values
fig3=plt.figure(figsize=(20,10))
plt.title('New predict model')
plt.xlabel('Days',fontsize=18)
plt.ylabel('Close price in rs',fontsize=20)
plt.plot(train_days, train['Close'])
plt.plot(valid_days, valid[['Close']])
plt.plot(future_days, valid_future[['Close']])
plt.plot(valid_days, valid[['new_prediction']])
plt.legend(['Train','Actual','Future', 'Predicted'],loc='lower right')
#get the future time steps
future_time_steps = st.slider('Select future time steps:', 1, 251, 10, 1,key='future_time_steps_slider')
future_days = np.arange(len(data), len(data) + future_time_steps, 1)

#get the root mean square erroe (RMSE)
rmse=np.sqrt(np.mean(prediction - y_test)**2)

#iyplot the data
train = data[ : training_data_len]
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train_days = np.arange(len(train))
valid_days = np.arange(len(train), len(data))

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plt.title('New predict model')
plt.xlabel('Days',fontsize=18)
plt.ylabel('Close price in rs',fontsize=20)
plt.plot(train_days, train['Close'])
plt.plot(valid_days, valid[['Close']])
plt.plot(future_days, valid_future[['Close']])
plt.plot(valid_days, valid[['new_prediction']])
plt.legend(['Train','Actual','Future', 'Predicted'],loc='lower right')
# set x-axis limits based on the slider value
xmin = 0
xmax = len(data) + future_time_steps
plt.xlim([xmin, xmax])

st.pyplot(fig3)
```
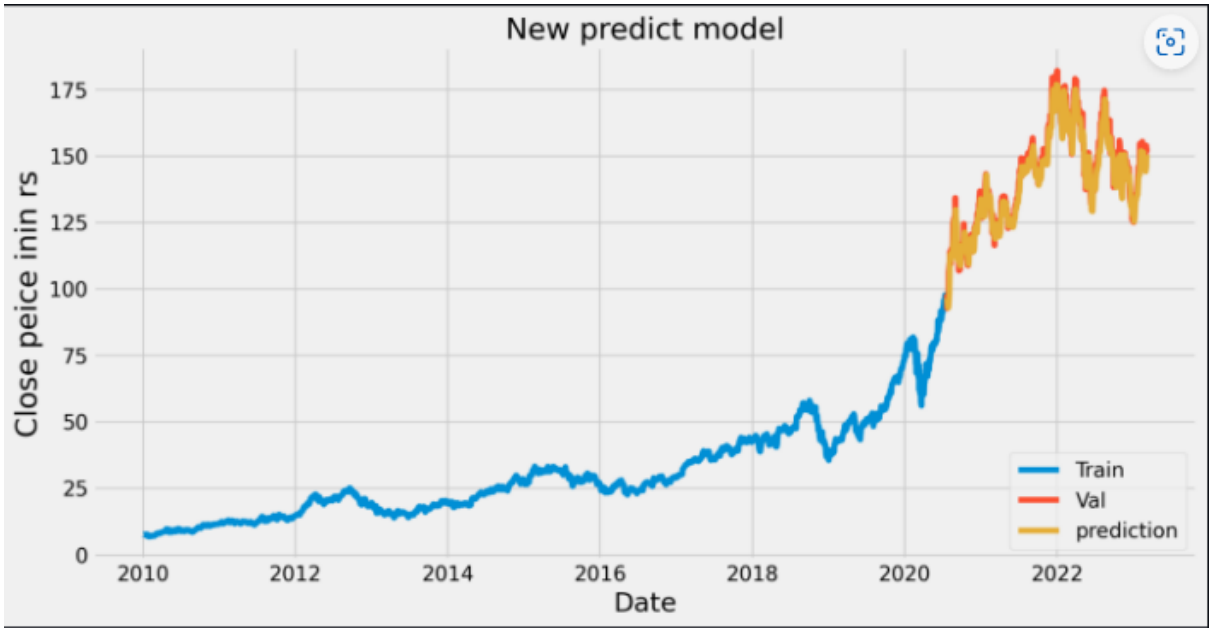

```python
import plotly

from datetime import date

import yfinance as yf
from prophet import Prophet
from prophet.plot import plot_plotly
from plotly import graph_objs as go

START = "2015-01-01"
TODAY = date.today().strftime("%Y-%m-%d")

st.title('STOCK PREDICTION USING HISTORY PRICE FBPROPHET')

stocks = ('GOOG','AAPL','MSFT','GME')
selected_stock = st.selectbox('Select dataset for prediction', stocks)

n_years = st.slider('Years of prediction:', 1, 4)
period = n_years * 365


@st.cache_data
def load_data(ticker):
    data = yf.download(ticker, START, TODAY)
    data.reset_index(inplace=True)
    return data


data_load_state = st.text('Loading data...')
data = load_data(selected_stock)
data_load_state.text('Loading data... done!')


st.subheader('Raw data')
st.write(data.tail())

# Plot raw data
def plot_raw_data():
  fig = go.Figure()
  fig.add_trace(go.Scatter(x=data['Date'], y=data['Open'], name="stock_open"))
  fig.add_trace(go.Scatter(x=data['Date'], y=data['Close'], name="stock_close"))
  fig.layout.update(title_text='Time Series data with Rangeslider', xaxis_rangeslider_visible=True)
  st.plotly_chart(fig)

plot_raw_data()

# Predict forecast with Prophet.
df_train = data[['Date','Close']]
df_train = df_train.rename(columns={"Date": "ds", "Close": "y"})

m = Prophet()
m.fit(df_train)
future = m.make_future_dataframe(periods=period)
forecast = m.predict(future)

# Show and plot forecast
st.subheader('Forecast data')
st.write(forecast.tail())

st.write(f'Forecast plot for {n_years} years')
fig1 = plot_plotly(m, forecast)
st.plotly_chart(fig1)

st.write("Forecast components")
fig2 = m.plot_components(forecast)
```

LSTM model prediction

```
import numpy as np
import pandas as pd
import yfinance as yf
from sklearn.preprocessing import MinMaxScaler
from keras.models import Sequential
from keras.layers import LSTM, Dense
from keras.callbacks import ModelCheckpoint

# Set the random seed for reproducibility
np.random.seed(42)

# Define the ticker symbol and the date range
ticker = 'AAPL'
start_date = '2010-01-01'
end_date = '2023-03-09'

# Fetch the historical stock data using yfinance
data = yf.download(ticker, start=start_date, end=end_date, progress=False)

# Prepare the data
scaler = MinMaxScaler(feature_range=(0, 1))
scaled_data = scaler.fit_transform(data['Close'].values.reshape(-1, 1))

# Split the data into training and testing sets
train_data = scaled_data[:int(0.8 * len(data))]
test_data = scaled_data[int(0.8 * len(data)):]

# Define the number of time steps for the LSTM model
time_steps = 60

# Prepare the training data
X_train, y_train = [], []
for i in range(time_steps, len(train_data)):
    X_train.append(train_data[i - time_steps:i, 0])
    y_train.append(train_data[i, 0])
X_train, y_train = np.array(X_train), np.array(y_train)

# Reshape the input data for LSTM (samples, time steps, features)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1))

# Define the LSTM model architecture
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
model.add(LSTM(units=50))
model.add(Dense(units=1))

# Compile the model
model.compile(optimizer='adam', loss='mean_squared_error')

# Define a checkpoint to save the best model during training
checkpoint = ModelCheckpoint('prediction.h5', monitor='val_loss', save_best_only=True, mode='min', verbose=1)

# Train the model
model.fit(X_train, y_train, epochs=50, batch_size=32, validation_split=0.2, callbacks=[checkpoint])

# Save the trained model
model.save('prediction.h5')
```

Result of prediction


New predict model
Close peice inin rs
175
150
125
100
75
50
25
0
2010
2012
2014
2016
2018
2020
2022
Date
Train
Val
prediction

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