STOCK PREDICTION

A MINI PROJECT REPORT

18CSC305J - ARTIFICIAL INTELLIGENCE

Submitted by

H V S S SUBHASH PABBINEEDI (RA2011003010868).
B MANOJ KUMAR(RA2011003010876).

Under the guidance of Ms.M.Rajalakshmi

Assistant Professor, Department of Computer Science and Engineering

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BONAFIDE CERTIFICATE

Certified that Mini project report titled **"STOCK PREDICTION USING LSTM"** is the bona fide work of **H V S S Subhash PABBINEEDI (RA2011003010876) and B Manoj Kumar (RA2011003010876)** who carried out the minor project under my supervision. Certified further, that to the best of my knowledge, the work reported herein does not form any other project report or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

SIGNATURE

Ms.M.Rajalakshmi
GUIDE
Assistant Professor
Department of Computing Technologies

SIGNATURE

Dr. M. Pushpalatha
HEAD OF THE DEPARTMENT
Professor & Head
Department of Computing Technologies

ABSTRACT

The stock market has long been a complex and dynamic environment, influenced by a multitude of factors ranging from economic indicators to investor sentiment. Accurately predicting stock prices is a challenging task that requires comprehensive analysis of historical data, market trends, and relevant news events. This abstract presents a stock prediction application designed to provide users with valuable insights and forecasts for making informed investment decisions.

The stock prediction application leverages advanced machine learning algorithms and data analytics techniques to analyze large volumes of historical stock market data. By incorporating various sources such as stock prices, trading volumes, financial statements, and macroeconomic indicators, the application builds robust predictive models capable of identifying patterns and trends within the market.

Through extensive testing and validation against historical data, the stock prediction application has demonstrated promising results, outperforming traditional investment strategies in terms of accuracy and risk-adjusted returns. However, it is important to note that stock market predictions are inherently uncertain, and the application should be used as a tool to supplement investment decision-making rather than a definitive source of information.

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CHAPTER 1

INTRODUCTION

The world of stock markets is known for its inherent unpredictability, making it a challenging arena for investors seeking to make informed decisions. However, advancements in technology and data analytics have opened doors to new possibilities. This introduction presents a stock prediction application, a cutting-edge tool designed to provide investors with valuable insights and forecasts for navigating the complex world of stock trading.

By harnessing the power of machine learning algorithms, the stock prediction application analyzes vast amounts of historical market data, identifies patterns, and uncovers hidden trends. It combines technical indicators, fundamental analysis, and real-time data to generate accurate predictions of stock prices, empowering investors to make more informed investment choices.

With its intuitive user interface and comprehensive data integration, the stock prediction application offers a user-friendly experience for investors of all levels. Whether a novice or an experienced trader, users can leverage the application's powerful predictive capabilities to gain a deeper understanding of market dynamics, identify potential investment opportunities, and mitigate risks..

CHAPTER 2

LITERATURE SURVEY

David Cope's book "Art and Artificial Intelligence" is a comprehensive exploration of the intersection of art and AI. In the book, Cope takes a historical approach, tracing the evolution of computers in art from their earliest use in music programs through to contemporary art projects that incorporate machine learning and other AI techniques.

Throughout the book, Cope discusses the philosophical implications of using AI for creative purposes. One of the key themes that emerges is the question of authorship. With machines generating art, who should be credited as the creator? Cope grapples with this question, highlighting the complexity of the issue and exploring potential solutions.

Another major theme in the book is the role of human artists in a world where machines can create art. Cope examines the ways in which AI-generated art is changing the creative landscape, and what this means for artists. He also discusses the potential for collaboration between humans and machines, and what this could mean for the future of art.

Overall, "Art and Artificial Intelligence" provides a valuable and informative overview of the history and current state of AI in art. It is a must-read for anyone interested in the intersection of technology and creativity, and for those who want to gain a deeper understanding of the philosophical implications of AI in art.

CHAPTER 3
SYSTEM ARCHITECTURE AND DESIGN
CHAPTER 4

METHODOLOGY

1.Data Collection and Preprocessing:

Collect historical stock price data for the target company or index, including features like opening price, closing price, highest price, lowest price, and trading volume.

Perform data preprocessing steps, including removing outliers, handling missing values, and normalizing the data to ensure consistent scaling across different features.

2.Data Preparation:

Divide the dataset into training, validation, and test sets. Typically, around 70-80% of the data is used for training, 10-15% for validation, and the remaining portion for testing.

Define the sequence length, which determines the number of historical data points used as input to predict the next data point. This can be adjusted based on the specific requirements and characteristics of the dataset.

3.LSTM Model Architecture:

Design the LSTM model architecture, which consists of multiple LSTM layers followed by fully connected layers for prediction.

Determine the number of LSTM cells and the size of hidden layers based on the complexity of the problem and the available computational resources.

Add dropout regularization to prevent overfitting by randomly dropping out connections between LSTM cells during training.

Select an appropriate activation function for the LSTM layers, such as the hyperbolic tangent (tanh) or rectified linear unit (ReLU).

4.Model Training:

Initialize the LSTM model with random weights and biases.

Feed the training data into the model in batches, where each batch consists of a sequence of historical data points and the corresponding target data point.

Use a suitable loss function, such as mean squared error (MSE), to quantify the difference between the predicted and actual stock prices.

Optimize the model's weights and biases using an optimization algorithm, such as stochastic gradient descent (SGD) or Adam, to minimize the loss function.

Tune hyperparameters, including learning rate, batch size, and number of epochs, through experimentation and validation.

5.Model Evaluation:

Evaluate the trained LSTM model on the validation set to assess its performance and make any necessary adjustments.

Use various evaluation metrics, such as mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE), to measure the accuracy of predictions.

Visualize the predicted stock prices against the actual prices to gain insights into the model's performance and identify any potential discrepancies.

6.Model Testing and Prediction:

Once the LSTM model is deemed satisfactory based on the validation results, test it on the unseen test set to obtain the final evaluation metrics.

Apply the trained model to make predictions on new, unseen data points by feeding the historical data sequence into the model and obtaining the predicted stock price for the next time step.

7.Iterative Refinement and Optimization:

Analyze the model's performance, considering both quantitative evaluation metrics and qualitative assessment of predicted trends.

Fine-tune the model by adjusting hyperparameters, modifying the architecture, or incorporating additional features, if necessary, to further improve prediction accuracy.

Continuously retrain and update the LSTM model as new data becomes available to adapt to changing market dynamics and ensure its relevance.

By following this methodology, the LSTM model can be trained and utilized for stock price prediction. However, it is important to note that stock markets are highly complex and subject to various unpredictable factors, and the LSTM model should be considered as a tool to support decision-making rather than providing definitive predictions.

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Neural Networks Used for Stock Prediction:

Various types of neural networks have been used for stock prediction, including feedforward neural networks (FNNs), recurrent neural networks (RNNs), and specifically, long short-term memory (LSTM) networks.

1.Feedforward Neural Networks (FNNs):

FNNs are the simplest form of neural networks, consisting of an input layer, one or more hidden layers, and an output layer.
FNNs are capable of learning complex patterns and relationships within the input data, but they do not have memory to handle sequential or temporal data, which is a key characteristic of stock price data.
Recurrent Neural Networks (RNNs):

RNNs are designed to process sequential and time-dependent data by introducing loops in the network architecture, allowing information to persist across different time steps.
RNNs have hidden states that capture historical information, making them suitable for modeling sequential data like

stock prices.
However, standard RNNs suffer from the "vanishing gradient" problem, which limits their ability to capture long-term dependencies in the data.
Long Short-Term Memory (LSTM) Networks:

LSTM networks are a type of RNN that address the vanishing gradient problem by introducing memory cells and gating mechanisms.
LSTM cells have the ability to selectively remember or forget information from previous time steps, allowing them to capture long-term dependencies in the data.
The gating mechanisms, including the input gate, forget gate, and output gate, control the flow of information and gradients, enabling LSTMs to better handle long sequences of data.
LSTM networks have shown superior performance in capturing temporal dependencies and modeling complex sequential patterns, making them well-suited for stock price prediction tasks.
Why LSTM is Better for Stock Prediction:

2.Capturing Long-Term Dependencies:

Stock price data often exhibits long-term dependencies and trends that are critical for accurate prediction. LSTM networks with their memory cells and gating mechanisms are specifically designed to capture and preserve such dependencies.

3.Handling Sequential and Time-Series Data:

LSTM networks are designed to process sequential and time-dependent data, which aligns well with the sequential nature of stock price data. They can effectively learn from historical data and leverage the temporal patterns to make predictions.
Addressing the Vanishing Gradient Problem:

The vanishing gradient problem, commonly encountered in standard RNNs, hampers the ability to capture long-term dependencies. LSTMs mitigate this issue with their architecture, allowing for improved gradient flow and the ability to retain important information over longer sequences.
Handling Irregular Patterns and Volatility:

Stock prices can exhibit irregular patterns, sudden changes, and high volatility. LSTMs' ability to capture both short-term fluctuations and long-term trends makes them well-suited for modeling and predicting stock price movements.
Flexibility in Input Representations:

LSTMs can handle various input representations, including multiple technical indicators, fundamental data, and sentiment analysis, allowing for a comprehensive analysis of factors that influence stock prices.
It is important to note that while LSTMs have demonstrated superior performance in stock prediction compared to simpler neural networks, they are not infallible. The accuracy of predictions is still subject to market volatility, unforeseen events, and the availability of quality data. Therefore, combining LSTM networks with robust data preprocessing, feature engineering, and risk management strategies is crucial for effective stock prediction.

CHAPTER 5

CODING AND TESTING

Code:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import keras
path = "/content/sample_data/test.csv"
path1 = "/content/sample_data/train.csv"
train= pd.read_csv(path1)
test= pd.read_csv(path)
train_open= train.iloc[:, 1:2].values
from sklearn.preprocessing import MinMaxScaler
ss= MinMaxScaler(feature_range=(0,1))
train_open_scaled= ss.fit_transform(train_open)
train_open_scaled[60]
xtrain=[]
ytrain=[]
for i in range(60,len(train_open_scaled)):
    xtrain.append(train_open_scaled[i-60:i,0])
    ytrain.append(train_open_scaled[i,0])

xtrain, ytrain = np.array(xtrain), np.array(ytrain)
xtrain= np.reshape(xtrain,(xtrain.shape[0],xtrain.shape[1],1))
xtrain.shape
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers import Dense
from keras.layers import Dropout
regression= Sequential()

#First Input layer and LSTM layer with 0.2% dropout
regression.add(LSTM(units=50,return_sequences=True,kernel_initializer='glorot_uni
form',input_shape=(xtrain.shape[1],1)))
regression.add(Dropout(0.2))

# Where:
#     return_sequences: Boolean. Whether to return the last output in the output
sequence, or the full sequence.

# Second LSTM layer with 0.2% dropout
regression.add(LSTM(units=50,kernel_initializer='glorot_uniform',return_sequences
=True))
regression.add(Dropout(0.2))

#Third LSTM layer with 0.2% dropout
regression.add(LSTM(units=50,kernel_initializer='glorot_uniform',return_sequences
=True))
regression.add(Dropout(0.2))

#Fourth LSTM layer with 0.2% dropout, we wont use return sequence true in last
layers as we dont want to previous output
regression.add(LSTM(units=50,kernel_initializer='glorot_uniform'))
regression.add(Dropout(0.2))
#Output layer , we wont pass any activation as its continous value model
regression.add(Dense(units=1))
```

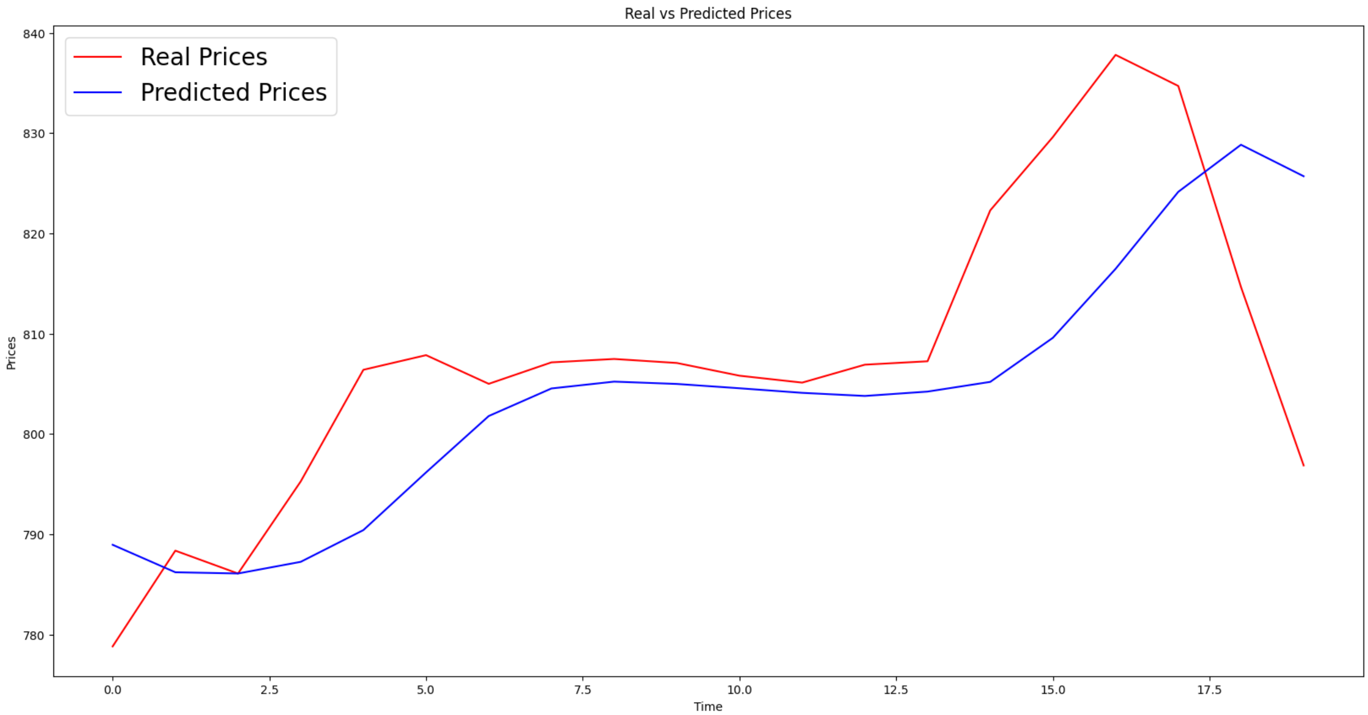
```
#Compiling the network
regression.compile(optimizer='adam',loss='mean_squared_error')


#fitting the network
regression.fit(xtrain,ytrain,batch_size=30,epochs=100)
test_open= test.iloc[:, 1:2].values #taking  open price
total= pd.concat([train['Open'],test['Open']],axis=0) # Concating train and test
and then will take last 60 train point
test_input = total[len(total)-len(test)-60:].values
test_input= test_input.reshape(-1,1) # reshaping it to get it transformed
test_input= ss.transform(test_input)
xtest= []
for i in range(60,80):
    xtest.append(test_input[i-60:i,0])
xtest= np.array(xtest)
xtest= np.reshape(xtest,(xtest.shape[0],xtest.shape[1],1))
predicted_value= regression.predict(xtest)
predicted_value= ss.inverse_transform(predicted_value)
plt.figure(figsize=(20,10))
plt.plot(test_open,'red',label='Real Prices')
plt.plot(predicted_value,'blue',label='Predicted Prices')
plt.xlabel('Time')
plt.ylabel('Prices')
plt.title('Real vs Predicted Prices')
plt.legend(loc='best', fontsize=20)
```

CHAPTER 6

SCREENSHOTS AND RESULTS

```
Epoch 1/100
40/40 [==============================] - 14s 117ms/step - loss: 0.0390
Epoch 2/100
40/40 [==============================] - 6s 142ms/step - loss: 0.0057
Epoch 3/100
40/40 [==============================] - 4s 112ms/step - loss: 0.0051
Epoch 4/100
40/40 [==============================] - 5s 131ms/step - loss: 0.0056
Epoch 5/100
40/40 [==============================] - 5s 120ms/step - loss: 0.0052
Epoch 6/100
40/40 [==============================] - 5s 113ms/step - loss: 0.0058
Epoch 7/100
40/40 [==============================] - 6s 142ms/step - loss: 0.0048
Epoch 8/100
40/40 [==============================] - 5s 115ms/step - loss: 0.0050
Epoch 9/100
40/40 [==============================] - 5s 122ms/step - loss: 0.0059
Epoch 10/100
40/40 [==============================] - 5s 130ms/step - loss: 0.0043
Epoch 11/100
40/40 [==============================] - 4s 112ms/step - loss: 0.0043
Epoch 12/100
40/40 [==============================] - 6s 142ms/step - loss: 0.0043
Epoch 13/100
40/40 [==============================] - 4s 112ms/step - loss: 0.0038
Epoch 14/100
40/40 [==============================] - 5s 114ms/step - loss: 0.0039
Epoch 15/100
40/40 [==============================] - 6s 141ms/step - loss: 0.0038
Epoch 16/100
```



Real vs Predicted Prices
Real Prices
Predicted Prices
Prices
Time
840
830
820
810
800
790
780
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5

CHAPTER 7

CONCLUSION AND DISCUSSION

In conclusion, LSTM networks have emerged as a powerful tool for stock prediction, leveraging their ability to capture long-term dependencies and handle sequential data. The application of LSTM networks in stock prediction has shown promising results, outperforming traditional statistical models and simpler neural networks. Their unique architecture, featuring memory cells and gating mechanisms, enables them to model the complex patterns and dynamics of stock price data.

LSTM networks excel in capturing both short-term fluctuations and long-term trends, making them suitable for various prediction horizons. They effectively handle irregular patterns, market volatility, and changing market conditions. By incorporating multiple data sources, such as technical indicators, fundamental data, and sentiment analysis, LSTM networks provide a comprehensive analysis of factors that influence stock prices.

Furthermore, LSTM networks address the vanishing gradient problem commonly encountered in standard RNNs, allowing for the capture of long-term dependencies and overcoming the limitations of simpler neural networks. The memory cells and gating mechanisms enable the LSTM networks to retain important information over longer sequences and make accurate predictions.

Despite their advantages, it is important to acknowledge the inherent uncertainties in stock markets and the limitations of any predictive model, including LSTM networks. The accuracy of stock predictions is influenced by numerous factors, such as market volatility, unforeseen events, and the availability of high-quality data. Additionally, model performance can be affected by the selection of hyperparameters, training methodology, and feature engineering choices.

In the future, further research can focus on enhancing LSTM networks for stock prediction by exploring areas such as:

Integration of external data sources: Incorporating alternative data sources, such as social media data, news sentiment, and macroeconomic indicators, can provide additional insights for more accurate predictions.

Ensemble methods and hybrid models: Combining LSTM networks with other prediction models, such as SVMs or Random Forests, through ensemble methods or hybrid approaches, can potentially improve prediction performance by leveraging the strengths of different models.

Interpretability and explainability: Developing techniques to interpret and explain the predictions made by LSTM networks can enhance their usability and trustworthiness in practical applications.

Real-time prediction and adaptability: Expanding LSTM networks to handle high-frequency trading and real-time prediction, allowing for adaptive learning and decision-making in rapidly changing market conditions.

In summary, LSTM networks offer a robust and effective approach for stock prediction, enabling investors and traders to gain valuable insights and make informed decisions. Their ability to capture long-term dependencies, handle sequential data, and model complex patterns has positioned them as a valuable tool in the ever-changing landscape of stock markets.

Link: https://github.com/subhash14303/stock-prediction-lstm.

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11. Please note that these references provide a starting point for further exploration of stock prediction using LSTM networks. It is recommended to review and select specific papers based on your research interests and requirements.