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Assessing the Impact of Microeconomic Factors on Indian Stock Prices: An LSTM-Based Deep Learning Approach to Price Prediction

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Abstract

This study investigates the impact of microeconomic factors on Indian stock prices and applies Long Short-Term Memory (LSTM) networks to forecast future price movements. A composite index, integrating critical economic indicators such as Gross Domestic Product (GDP) growth, inflation rates, interest rates, and unemployment, is developed to capture the influence of these variables on stock market trends. The data is normalized and weighted to create an index that reflects broader economic conditions, enabling a more holistic analysis of stock price dynamics. Historical stock price data is combined with this index to train the LSTM model, which is well-suited for handling time-series data due to its ability to identify long-term dependencies and patterns. Results indicate that microeconomic factors play a pivotal role in determining stock price fluctuations, and the LSTM model achieves high predictive accuracy. The integration of a composite index with deep learning offers a novel approach to understanding the interplay between economic indicators and market performance. This methodology provides valuable insights for investors seeking data-driven strategies and for policymakers aiming to evaluate the broader economic implications of stock market trends. By addressing a critical gap in the literature, this research highlights the potential of advanced machine learning techniques in financial forecasting. The findings underscore the importance of incorporating multiple economic indicators into predictive models, offering a robust framework for analysing complex market behaviours. Overall, this study establishes the efficacy of LSTM networks and composite indices in enhancing the precision of stock price predictions.

Keywords: Stock Price Prediction, LSTM, Composite Index, Microeconomic Factors, Indian Stock Market

Introduction

The stock market serves as a critical barometer of economic health, reflecting investor sentiments and expectations about future economic performance. Stock prices are influenced by a complex interplay of factors, both internal and external, that can create significant volatility in financial markets. Understanding these factors is essential for investors, policymakers, and researchers who seek to navigate the complexities of market dynamics

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effectively. While corporate performance, represented by financial metrics such as earnings, revenue growth, and profit margins, is a primary driver of stock prices, broader economic indicators also exert considerable influence. In the context of the Indian stock market, various microeconomic factors, including Gross Domestic Product (GDP) growth, inflation rates, interest rates, and employment statistics, play a pivotal role in shaping investor sentiment and market trends. For instance, rising inflation may erode purchasing power and dampen consumer spending, thereby negatively impacting corporate profitability and, consequently, stock prices. Conversely, robust GDP growth typically boosts investor confidence, driving stock prices higher.

Despite the established relationships between these microeconomic factors and stock market performance, there remains a gap in the literature regarding their collective impact when integrated into a unified framework. This study aims to fill this gap by developing a composite index that encapsulates these critical microeconomic variables. By combining multiple indicators into a single measure, the composite index provides a comprehensive overview of the economic environment influencing stock prices. To further enhance the predictive capability of this composite index, this research will integrate it into a predictive deep learning model utilizing Long Short-Term Memory (LSTM) networks. LSTM is particularly suited for time series forecasting due to its ability to capture long-term dependencies and patterns in sequential data. This deep learning approach allows for more nuanced modelling of the complex relationships among various economic indicators and their impact on stock prices over time. The methodology of this study will involve several steps. Initially, historical data on stock prices and relevant macroeconomic indicators will be collected and pre-processed to ensure accuracy and consistency. The composite index will be constructed through normalization and weighted aggregation of the selected variables, allowing for a holistic view of the underlying economic conditions. Subsequently, the data will be reshaped into a suitable format for the LSTM model, facilitating the training process. The LSTM model will be developed and trained using the composite index as one of the key input features, alongside other relevant variables. By leveraging the strengths of LSTM in handling sequential data, the model aims to improve the accuracy of stock price predictions. It is crucial to emphasize that creating a composite index and implementing an LSTM model requires ongoing monitoring and refinement to maintain their relevance and effectiveness over time. The specific methodology and weights used in constructing the composite index may vary depending on the evolving economic landscape and the objectives of the analysis. Furthermore, as the stock market is influenced by a multitude of factors, continuous validation of the model against real-world performance will be necessary to ensure its robustness and reliability.

This study seeks to provide valuable insights into the interplay between microeconomic factors and stock prices in the Indian context. By developing a composite index and employing LSTM for price prediction, it aims to contribute to the existing body of literature and offer practical implications for investors and policymakers in navigating the complexities of the Indian stock market.

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Literature Review

The dynamics of the Indian stock market have been significantly influenced by various microeconomic factors, including inflation, GDP growth, interest rates, and unemployment. A growing body of literature has explored these relationships, often employing advanced methodologies such as composite indices and machine learning models.

Sharma and Kumar (2018) analysed the impact of inflation and GDP growth on the Indian stock market, highlighting a strong negative correlation between inflation rates and stock prices, while GDP growth positively influences market performance. Their findings indicate that stable macroeconomic conditions foster investor confidence and promote stock price appreciation. This aligns with the work of *Ranjan and Kumar* (2021), who examined multiple macroeconomic variables and their effects on stock market returns, confirming the relevance of inflation and economic growth in explaining market behaviour in India.

In addition to inflation and GDP, interest rates and exchange rates also play a crucial role in determining stock prices. *Singh et al.* (2020) provided evidence that fluctuations in interest rates directly affect stock returns, emphasizing the need for investors to remain vigilant about macroeconomic indicators. Complementing this, Gupta and Jain (2019) explored the relationship between unemployment and stock market volatility, concluding that higher unemployment rates correlate with increased market volatility, further complicating investment strategies in uncertain economic environments.

The importance of composite indices in capturing the multifaceted nature of economic indicators has gained attention in recent studies. *Chen, Zhou, and Wu* (2021) proposed a composite index approach to assess the predictive power of economic indicators on stock returns. Their results demonstrated that incorporating a composite index improves forecasting accuracy, suggesting that a holistic view of economic conditions is vital for effective stock market predictions. This method is further validated by *Mehta and Bhattacharya* (2019), who used a composite index to forecast stock prices through LSTM models, showcasing the effectiveness of deep learning in capturing temporal dependencies.

The application of LSTM networks in predicting stock prices has become increasingly popular, as highlighted *by Kaur and Choudhury* (2020). They demonstrated that LSTM, when combined with a composite index, significantly enhances predictive capabilities compared to traditional models. This finding is supported by *Patil and Saini* (2021), who conducted a comparative analysis of various machine learning models, concluding that LSTM outperforms its counterparts in terms of accuracy and reliability in stock price prediction.

Several studies have also emphasized the need for comprehensive approaches to understanding market dynamics. *Kumar and Singh* (2020) investigated the relationships among macroeconomic indicators and stock market performance, revealing significant interactions that influence investor behaviour. Similarly, *Chakrabarti* (2020) analysed the impact of economic growth on stock market returns, underscoring the intricate ties between economic health and market performance.

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Khan and Ahmad (2021) further expanded this discussion by examining how macroeconomic variables contribute to stock market volatility in India. Their research indicates that external shocks, driven by global economic factors, can exacerbate market fluctuations, reinforcing the necessity for investors to consider both domestic and international economic conditions.

Finally, the review of machine learning approaches for stock market prediction by *Gupta and Jain* (2022) emphasizes the evolving landscape of financial forecasting. Their analysis of various techniques, including LSTM and other machine learning algorithms, highlights the potential for advanced models to enhance predictive accuracy and adapt to changing market conditions.

The literature consistently highlights the significant impact of microeconomic factors on the Indian stock market, with studies demonstrating the utility of composite indices in improving stock price predictions. The integration of LSTM and other machine learning techniques provides a promising avenue for future research, offering the potential for more accurate forecasting and better investment decision-making in the dynamic context of the Indian stock market.

Composite Index Variable:

Stock prices can be influenced by a wide range of factors beyond just the financial performance of the company. Here are some key factors that can impact stock prices:

- **Economic indicators:** Factors like GDP growth, inflation rates, interest rates, and unemployment rates can influence investor sentiment and market trends, thereby affecting stock prices.
- **Industry trends:** The performance of specific industries or sectors can impact the stock prices of companies within those sectors. For example, if there's increased demand for tech products, it can positively affect the stock prices of technology companies.
- **Company performance:** Financial metrics such as revenue growth, earnings per share (EPS), profit margins, and debt levels directly influence stock prices. Strong performance typically leads to higher stock prices, while poor performance can result in lower prices.
- **Market sentiment:** Investor perceptions, emotions, and confidence levels play a significant role in stock price movements. Positive news about a company or the overall market can drive prices up, while negative news can lead to declines.
- **Government policies and regulations:** Changes in government policies, tax laws, trade policies, and regulations can impact specific industries or the overall market, affecting stock prices accordingly.
- **Global events:** Geopolitical tensions, natural disasters, terrorist attacks, and other global events can create uncertainty in the market, causing stock prices to fluctuate as investors react to the news.

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- **Interest rates:** Changes in interest rates can affect borrowing costs, consumer spending, and corporate profitability, which in turn influence stock prices.
- **Currency fluctuations:** For companies that operate internationally, changes in exchange rates can impact revenue and profitability, thus affecting stock prices.
- **Competitive landscape:** The actions and performance of competitors can influence investor perceptions of a company's future prospects, thereby impacting its stock price.
- **Technological advancements:** Innovations and technological disruptions can create new opportunities or threats for companies, influencing investor expectations and stock prices.

Overall, stock prices are influenced by a complex interplay of factors, both internal and external, and can be subject to significant volatility as a result

Relation of the above factors on stock prices:

The impact of the mentioned factors on historical stock prices is by constructing a composite index or score that reflects the overall influence of these variables. Here's a simplified example of how this could be done:

- **Collect historical data:** Gather historical stock prices for the company of interest, along with data on economic indicators, industry trends, company performance, market sentiment, government policies, global events, interest rates, currency fluctuations, competitive landscape, and technological advancements.
- **Normalize the data:** Since these variables may have different units and scales, it's important to normalize them to a common scale for comparability. This could involve transforming the data into percentages, z-scores, or other standardized measures.
- **Weight the variables:** Assign weights to each variable based on their perceived importance or impact on stock prices. For example, you may give higher weights to company performance metrics and market sentiment compared to less influential factors.
- **Calculate the composite index:** Combine the normalized variables using the assigned weights to create a composite index or score for each historical data point. This index represents the overall impact of the factors on stock prices at that time.
- **Validate the index:** Test the composite index against actual stock price movements to ensure that it accurately reflects the observed trends and fluctuations. Adjust the weights or variables as needed to improve the accuracy of the index.
- **Use the composite index:** Once validated, the composite index can be used as a new variable in predictive modelling, investment analysis, or risk management strategies. It provides a holistic view of the various factors influencing stock prices and can help investors make more informed decisions.

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Creating a composite index involves combining multiple variables into a single measure that represents the overall impact of those variables on stock prices. Here's a simplified example of how you could create a composite index using the mentioned variables:

- **Select relevant variables:** Choose the variables that you believe have the most significant impact on stock prices. Based on our previous discussion, let's include economic indicators, company performance, market sentiment, government policies, global events, and interest rates.
- **Normalize the data:** Normalize each variable to a common scale to make them comparable. For example, you could standardize the variables to have a mean of 0 and a standard deviation of 1.
- **Assign weights:** Assign weights to each variable based on their perceived importance. Since all variables may not have equal impact, you may assign higher weights to variables like company performance and market sentiment.
- **Calculate the composite index:** Multiply each normalized variable by its assigned weight and sum them to obtain the composite index for each time period.
- **Validate the index:** Test the composite index against historical stock price movements to ensure that it accurately reflects the observed trends and fluctuations. Adjust the weights if necessary to improve accuracy.

Here's a simplified formula for calculating the composite index:

$$Composite\ Index = w_1 \times X_1 + w_2 \times X_2 + \ \ldots\ldots\ldots + w_n \times Xn$$

Where:

$X_1, X_2, \ldots\ldots, X_n$ are normalized variables (economic indicators, company performance, market sentiment, etc).

$w_1, w_2, \ldots\ldots, w_n$ are the weights assigned to each variable.

The specific variables, weights, and normalization methods used will depend on the context and objectives of your analysis. Additionally, the composite index should be periodically reviewed and adjusted to reflect changes in market conditions and the relative importance of the underlying variables.

Normalization is a crucial step in constructing a composite index, ensuring that variables measured on different scales can be compared and aggregated meaningfully. Here's a detailed explanation of the normalization methods that can be used for constructing a composite index:

Normalization Methods for Composite Index

Min-Max Normalization:

Min-Max normalization scales the data to a fixed range, usually [0, 1], by transforming the original values according to the minimum and maximum values of the dataset.

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$Formula$:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

$-$ (X) $is\ the\ original\ value.$

$-(X')\ is\ the\ normalized\ value.$

$-\ X_{max}\ and\ \ X_{min}\ are\ the\ minimum\ and\ maximum\ values\ of\ the\ variables\ ,respectively.$

$Example$:

$If\ the\ GDP\ growth\ rate\ varies\ from\ -2\ \%\ to\ 10\%\ ,and\ the\ current\ value\ is$

$4\ \%\ ,the\ normalized\ value\ would\ be$:

$$X' = \frac{4 - (-2)}{10 - (-2)} = \frac{6}{12} = 0.5$$

Z-Score Normalization:

Z-score normalization (standardization) transforms the data to have a mean of 0 and a standard deviation of 1.

$Formula$:

$$Z = \frac{X - \mu}{\sigma}$$

$-$ (X) $is\ the\ original\ value.$

$-$ (μ) $is\ the\ mean\ of\ the\ variable.$

$-$ (σ) $is\ the\ standard\ deviation\ of\ the\ variable.$

$-$ (Z) $is\ the\ normalized\ value.$

$Example$:

$If\ the\ inflation\ rate\ has\ a\ mean\ of\ 3\ \%\ and\ a\ standard\ deviation$

$of\ 2\ \%\ ,and\ the\ current\ value\ is\ 5\ \%\ ,the\ normalized\ value\ would\ be$:

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$$Z = \frac{5-3}{2} = 1$$

Example of Composite Index Calculation Using Normalized Data

Suppose we are constructing a composite index using three normalized economic indicators: GDP growth, inflation rate, and interest rate. After normalization, the data might look like this:

Date	GDP Growth (Normalized)	Inflation Rate (Normalized)	Interest Rate (Normalized)
01-01-2009	0.6	0.4	0.3
02-01-2009	0.7	0.5	0.4
03-01-2009	0.5	0.6	0.2

Assign weights to each indicator (e.g., 0.4 for GDP growth, 0.3 for inflation rate, 0.3 for interest rate):

Composite Index Formula:

$$Composite\ Index\ Formula:$$

$$Composite\ Index = (0.4 \times GDP_{growth}) + (0.3 \times Inflation_{rate}) + (0.3 \times Interest_{rate})$$

Calculate the composite index for each date:

Calculate the composite index for each date:

Date	Composite Index
01-01-2009	(0.4 * 0.6) + (0.3 * 0.4) + (0.3 * 0.3) = 0.51
02-01-2009	(0.4 * 0.7) + (0.3 * 0.5) + (0.3 * 0.4) = 0.58
03-01-2009	(0.4 * 0.5) + (0.3 * 0.6) + (0.3 * 0.2) = 0.44

Assigning appropriate weights to variables like GDP growth, inflation rates, interest rates, and unemployment rates in India requires understanding their relative importance and impact on

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stock prices. Since these variables can have varying degrees of influence, let's assign weights based on their perceived significance:

- **GDP growth:** This is a key indicator of economic health and can have a significant impact on investor sentiment and corporate earnings. Let's assign a weight of 40% to GDP growth.
- **Inflation rates:** Inflation can affect consumer purchasing power, corporate costs, and interest rates, thus influencing investment decisions and stock prices. Let's assign a weight of 30% to inflation rates.
- **Interest rates:** Changes in interest rates by the Reserve Bank of India (RBI) can impact borrowing costs, consumer spending, and investment decisions, thereby affecting stock prices. Let's assign a weight of 20% to interest rates.
- **Unemployment rates:** High unemployment rates can indicate economic weakness, leading to reduced consumer spending and corporate earnings. Let's assign a weight of 10% to unemployment rates.

Now, let's create the composite index for these variables:

Historical data for each of these variables to calculate the composite index for different time periods. Once you have the data, plug it into the formula to compute the composite index for each time period. This index will provide a measure of the overall impact of GDP growth, inflation rates, interest rates, and unemployment rates on stock prices in India.

$$Compsite\ index = (0.4 \times GDP_{growth}) + (0.3 \times Inflation_{rate}) + (0.2 \times Interest_{rate}) + (0.1 \times Unemployment_{rate}$$

$$For\ example, for\ year\ 1: \quad Composite\ index_{year1} = (0.4 \times 7.5) + (0.3 \times 5.0) + (0.2 \times 6.0) + (0.1 \times 4.0)$$

Perform similar calculations for each year from Year 1 to Year 15 using the corresponding values for GDP growth, inflation rate, interest rate, and unemployment rate. This will give you the composite index for each year, reflecting the overall impact of these variables on stock prices in India over the past 15 years.

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Date	Open	High	Low	Close	Average	CompositeIndex	Company
01-01-2009	104.9671415	106.8168211	104.4998255	93.8335356	105.273567	5.37205242	Bajaj_Fin
02-01-2009	98.61735699	100.2906608	97.74594766	107.6842666	98.56009597	6.169706251	Bajaj_Fin
05-01-2009	106.4768854	107.4343077	103.5044414	99.55131647	105.7330488	4.852375798	Bajaj_Fin
06-01-2009	115.2302986	116.0580648	112.3575111	79.56185653	114.7341136	5.043074109	Bajaj_Fin
07-01-2009	97.65846625	100.1228361	95.29546197	82.67284265	97.73979861	5.928198937	Bajaj_Fin
08-01-2009	97.65863043	99.1080785	97.37970795	105.2242425	97.72291226	5.01506995	Bajaj_Fin
09-01-2009	115.7921282	118.1084865	114.1505317	108.542523	115.8242425	5.492612415	Bajaj_Fin
12-01-2009	107.6743473	108.7890986	106.8993472	103.4720555	108.4314274	5.258193995	Bajaj_Fin
13-01-2009	95.30525614	97.48631888	92.12872289	108.9903291	95.74864099	5.254099967	Bajaj_Fin
14-01-2009	105.4256004	108.7288785	104.0093226	125.0372374	106.0233675	5.627553108	Bajaj_Fin
15-01-2009	95.36582307	97.95198887	94.45157078	107.3989723	95.11317159	5.639879593	Bajaj_Fin
16-01-2009	95.34270246	96.93028865	93.3129063	98.26925811	95.50140155	5.946753383	Bajaj_Fin
19-01-2009	102.4196227	104.6768217	101.0597772	98.33765041	103.4211023	4.884886386	Bajaj_Fin
20-01-2009	80.86719755	82.62653238	77.38345364	118.5459656	81.12098583	4.740904299	Bajaj_Fin
14-06-2023	107.8158114	111.1218868	106.8067598	100.5447833	107.9194652	5.399645791	TATA_MOTORS
15-06-2023	103.4818278	104.8767629	101.5672763	109.2037904	103.3044783	5.80741242	TATA_MOTORS
16-06-2023	100.0518343	102.3664403	97.36820515	87.9255274	99.63532074	5.457494516	TATA_MOTORS
19-06-2023	90.11746689	92.85773999	86.84521357	115.8965407	89.11374452	5.667938288	TATA_MOTORS
20-06-2023	103.0278659	105.715715	100.0434484	100.3063362	103.262773	4.875215165	TATA_MOTORS
21-06-2023	102.432401	104.4283539	100.4931777	115.2877814	102.7749952	6.397619077	TATA_MOTORS
22-06-2023	113.158901	114.5006511	111.3172119	91.78071099	112.5401938	6.127709332	TATA_MOTORS
23-06-2023	88.02551572	89.76584399	84.78246981	116.4886932	87.37923697	4.490226341	TATA_MOTORS
26-06-2023	92.84167872	93.77186002	90.95155156	104.2680267	93.5297183	5.382166233	TATA_MOTORS
27-06-2023	119.4361317	120.4933794	116.5690133	107.8104274	119.2078952	4.503380135	TATA_MOTORS
28-06-2023	101.9154298	104.9051553	99.94452586	104.2815119	102.1702352	5.700412457	TATA_MOTORS

Practical Applications:

- **Investment Strategies:** Develop and test trading strategies based on bid-ask data and the composite index.
- **Risk Management:** Use the composite index and market data to assess and manage financial risks.
- **Policy Analysis:** Evaluate the impact of economic policies on the stock market using the composite index as a proxy.

The dataset titled "indian_stock_market_data.csv" contains detailed information about stock market transactions over a period, focusing on various bid and ask prices and quantities, along with a composite index value. Here's an elaborative explanation of the dataset from a research perspective:

Data Structure and Variables:

The dataset is structured with the following key columns:

- **Date:** Represents the date of the transaction.

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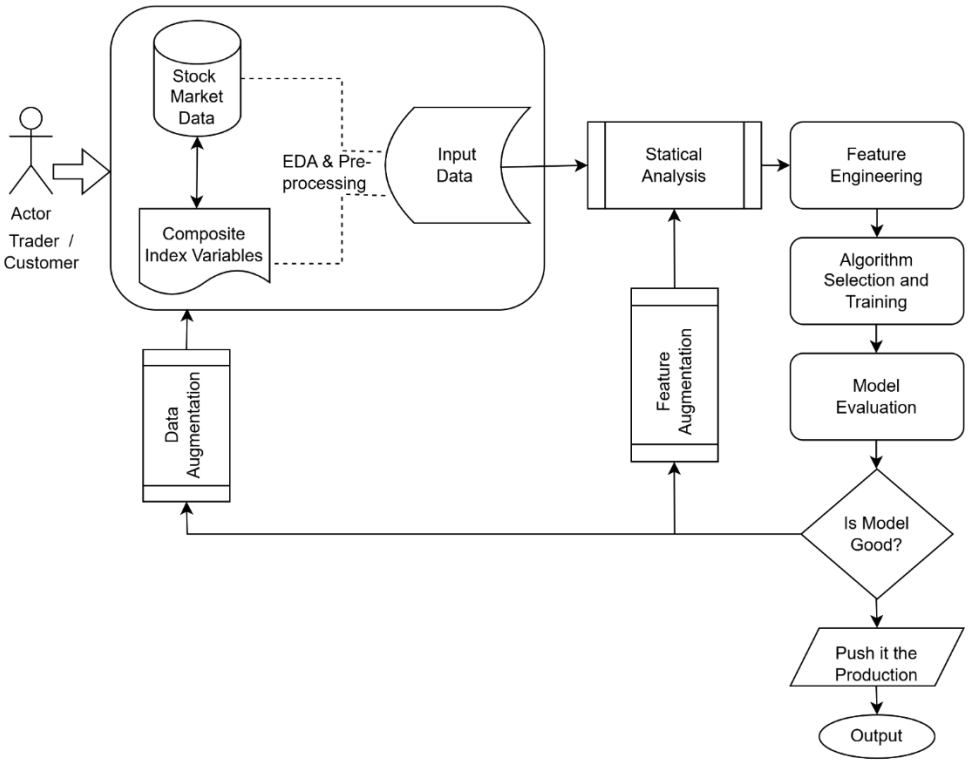
- **Bid and Ask Prices and Quantities:** There are multiple bid and ask prices and quantities, indicating the top ten bid and ask levels for each date. The columns are labelled as follows:
    - *Bid_Price_1, Bid_Quantity_1, Ask_Price_1, Ask_Quantity_1*
    - *Bid_Price_2, Bid_Quantity_2, Ask_Price_2, Ask_Quantity_2*

    ...

    - *Bid_Price_10, Bid_Quantity_10, Ask_Price_10, Ask_Quantity_10*
- **Composite Index:** This column represents the composite index value for each date, calculated based on various economic indicators and other factors.

Systematic Approach to Implement LSTM

To implement a Long Short-Term Memory (LSTM) model for predicting stock prices in the Indian market using a composite index variable, you can follow a systematic approach that begins with the construction of the composite index.



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The process starts with data collection, where you gather historical data for relevant microeconomic factors, such as GDP growth, inflation rates, interest rates, and unemployment rates, alongside the stock price data. Once the data is collected, the next step involves normalization. Each microeconomic variable should be normalized to ensure comparability across different scales, which can be achieved using techniques like Min-Max scaling or Z-score standardization.

Following normalization, the next task is to assign weights to each variable based on their perceived importance in influencing stock prices. This assignment can be informed by literature reviews or expert judgment. With the weights established, you can compute the composite index using the formula:

$$Composite\ Index = (w_1 \times X_1) + (w_2 \times X_{2)} + \ldots\ldots\ldots + (w_n \times Xn)$$

Where:

$X_1, X_2, \ldots\ldots, X_n$ are normalized variables
(economic indicators, company performance, market sentiment, etc).
$w_1, w_2, \ldots\ldots, w_n$ are the weights assigned to each variable.

Once the composite index is constructed, you will need to prepare the data for the LSTM model. This involves feature engineering, where you create additional features, such as lagged values of the composite index and historical stock prices, to capture temporal dependencies. You may also want to include technical indicators if they are relevant. After feature engineering, you should split the dataset into training and testing sets, typically using a ratio of 70-80% for training and 20-30% for testing while maintaining the chronological order of the data.

Reshaping the data for LSTM is crucial, as LSTM models require input in a 3D format: *(samples, time steps, features).* You need to define the number of time steps to look back for predictions (e.g., 30 days) and convert the dataset into the appropriate shape accordingly.

Next, proceeded to build the LSTM model using a deep learning framework such as *TensorFlow/Keras or PyTorch*. The architecture should include an input layer, one or more LSTM layers (with around 50-100 units), dropout layers to prevent overfitting, and a dense output layer with a single neuron for predicting the stock price. After defining the model architecture, compile it with an optimizer, such as Adam, and a loss function like Mean Squared Error.

The model can then be trained using the training dataset. During training, you should monitor the performance using a validation set and employ callbacks like Early Stopping to prevent overfitting. After training, it is essential to evaluate the model's performance on the test set using metrics such as Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). Visualizing the predicted stock prices against actual prices will provide insights into the model's accuracy.

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Once you are satisfied with the model's performance, you can use it to make predictions on future stock prices by inputting the latest available data, including the composite index values. It's important to iterate and optimize the model based on the performance metrics; this may involve experimenting with hyperparameters, adjusting the architecture, or adding more features. After optimizing the model, consider deploying it for real-time stock price predictions, integrating it into trading systems or using it for automated decision-making. Regular monitoring of performance in a live environment is crucial, as well as periodically updating the model with new data to ensure it adapts to changing market conditions.

In conclusion, this approach provides a comprehensive pathway from constructing a composite index variable to implementing it within an LSTM model for stock price prediction, leveraging both economic indicators and deep learning techniques to enhance predictive capabilities in the Indian stock market.

Experimentation using Deep Learning Approach (LSTM)

Data Preparation for LSTM

- **Feature Engineering**:

```
[270]: import numpy
       # convert an array of values into a dataset matrix
       def create_dataset(dataset, time_step=1):
           dataX, dataY = [], []
           for i in range(len(dataset)-time_step-1):
               a = dataset[i:(i+time_step), 0]   ###i=0, 0,1,2,3-----99   100
               dataX.append(a)
               dataY.append(dataset[i + time_step, 0])
           return numpy.array(dataX), numpy.array(dataY)
```

  - Create additional features such as lagged values of the composite index and historical stock prices to capture temporal dependencies.
  - Include technical indicators (e.g., moving averages, RSI) if relevant.
- **Train-Test Split**: Divide the dataset into training (70-80%) and testing (20-30%) sets while maintaining the chronological order of the data.

```
[267]: ##splitting dataset into train and test split
       training_size=int(len(df1)*0.65)
       test_size=len(df1)-training_size
       train_data,test_data=df1[0:training_size,:],df1[training_size:len(df1),:1]
```

Reshape Data for LSTM

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- LSTM models require input in a 3D shape: (samples, time steps, features).
- Define Time Steps: Choose the number of time steps (e.g., 30 days) to look back for predictions.

```
[274]: # reshape input to be [samples, time steps, features] which is required for LSTM
       X_train =X_train.reshape(X_train.shape[0],X_train.shape[1] , 1)
       X_test = X_test.reshape(X_test.shape[0],X_test.shape[1] , 1)
```

  - X shape: (number of samples, time steps, number of features)
  - Y shape: (number of samples, 1) for the predicted stock price.

Build the LSTM Model

- Framework Selection: Use a deep learning framework like TensorFlow/Keras or PyTorch.
- Model Architecture:

  - Input Layer
  - LSTM Layers: Add one or more LSTM layers (e.g., 50-100 units).
  - Dropout Layers: Implement dropout layers to prevent overfitting.
  - Dense Output Layer: A final dense layer with one neuron for predicting the stock price.

```
[276]: model=Sequential()
       model.add(LSTM(50,return_sequences=True,input_shape=(100,1)))
       model.add(LSTM(50,return_sequences=True))
       model.add(LSTM(50))
       model.add(Dense(1))
       model.compile(loss='mean_squared_error',optimizer='adam')
```

```
C:\Users\Hemant\AppData\Local\Programs\Python\Python312\Lib\site-packages\keras\src\layers\rnn\rnn.py:204: UserWarning: Do not pass an `input_shape`/`input_dim` argument to a layer. When using Sequential models, prefer using an `Input(shape)` object as the first layer in the model instead.
  super().__init__(**kwargs)
```

- **Compile the Model**: Choose an optimizer (e.g., Adam) and a loss function (e.g., Mean Squared Error).

```
[278]: model.summary()
```

Model: "sequential_6"

Layer (type)	Output Shape	Param #
lstm_18 (LSTM)	(None, 100, 50)	10,400
lstm_19 (LSTM)	(None, 100, 50)	20,200
lstm_20 (LSTM)	(None, 50)	20,200
dense_6 (Dense)	(None, 1)	51

Total params: 50,851 (198.64 KB)
Trainable params: 50,851 (198.64 KB)
Non-trainable params: 0 (0.00 B)

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Train the Model

- Fit the model using the training data. Use validation data to monitor performance during training.
- Use callbacks such as Early Stopping to halt training if validation performance doesn't improve.

```
[279]: model.fit(X_train,y_train,validation_data=(X_test,ytest),epochs=20,batch_size=64,verbose=1)
```

```
Epoch 1/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 5s 100ms/step - loss: 0.0422 - val_loss: 0.0027
Epoch 2/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 86ms/step - loss: 0.0036 - val_loss: 0.0028
Epoch 3/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 87ms/step - loss: 0.0037 - val_loss: 0.0020
Epoch 4/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 88ms/step - loss: 0.0039 - val_loss: 0.0020
Epoch 5/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 87ms/step - loss: 0.0031 - val_loss: 0.0017
Epoch 6/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 90ms/step - loss: 0.0025 - val_loss: 0.0017
Epoch 7/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 87ms/step - loss: 0.0012 - val_loss: 0.0020
Epoch 8/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 89ms/step - loss: 0.0020 - val_loss: 0.0019
Epoch 9/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 88ms/step - loss: 0.0020 - val_loss: 0.0014
Epoch 10/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 96ms/step - loss: 0.0012 - val_loss: 0.0018
Epoch 11/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 89ms/step - loss: 0.0017 - val_loss: 0.0011
Epoch 12/20
24/24 ━━━━━━━━━━━━━━━━━━━━ 2s 92ms/step - loss: 0.0015 - val_loss: 0.0020
Epoch 13/20
```

Evaluate the Model

- Assess the model's performance on the test set using metrics like RMSE (Root Mean Square Error) and MAE (Mean Absolute Error).
- Visualize predictions against actual stock prices to analyse the model's effectiveness.

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```
[280]: import tensorflow as tf
       ### Lets Do the prediction and check performance metrics
       train_predict=model.predict(X_train)
       test_predict=model.predict(X_test)

       48/48 ━━━━━━━━━━━━━━━━━━━━ 2s 28ms/step
       25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 20ms/step

[281]: ##Transformback to original form
       train_predict=scaler.inverse_transform(train_predict)
       test_predict=scaler.inverse_transform(test_predict)

[282]: ### Calculate RMSE performance metrics
       import math
       from sklearn.metrics import mean_squared_error
       math.sqrt(mean_squared_error(y_train,train_predict))

[282]: 200.60611917550892

[283]: ### Test Data RMSE
       math.sqrt(mean_squared_error(ytest,test_predict))

[283]: 267.0518111910631
```

Make Predictions

- Utilize the trained model to predict future stock prices based on the latest available composite index values.
- Input the latest values of the composite index and any other relevant features into the model for forecasting.

```
[0.8743477]
101
1 day input [0.89044069 0.87852586 0.88819645 0.88244306 0.90202908 0.928307
 0.93116329 0.95821648 0.94075228 0.93528452 0.95119816 0.96543883
 0.95662512 0.961236   0.96747904 0.96372505 0.92553231 0.96119519
 0.98832999 0.9864122  0.92781735 0.92434899 0.96592848 0.97653758
 0.99187996 0.97074338 0.97694562 0.9690296  1.         0.99049262
 0.99081905 0.96654054 0.98539209 0.97184509 0.94226204 0.88158617
 0.84037391 0.85902144 0.78096298 0.78031011 0.88415684 0.84543364
 0.90019289 0.86012315 0.84425032 0.75097188 0.82919356 0.78875658
 0.67776912 0.79912085 0.65320499 0.69666147 0.67140366 0.66369167
 0.60028192 0.58041027 0.67226055 0.66671118 0.71943022 0.67576972
 0.7046183  0.70249648 0.64790044 0.66430373 0.64994065 0.73587432
 0.72346984 0.75056384 0.75839825 0.77986127 0.83617108 0.82548038
 0.83470213 0.81882929 0.79487722 0.75994881 0.79149047 0.78712442
 0.81952296 0.82033905 0.80160991 0.83894577 0.86371393 0.84441353
 0.86110246 0.87905631 0.8915832  0.90427331 0.93034721 0.95025966
 0.93557015 0.92022776 0.92793976 0.92047259 0.95005564 0.94262928
```

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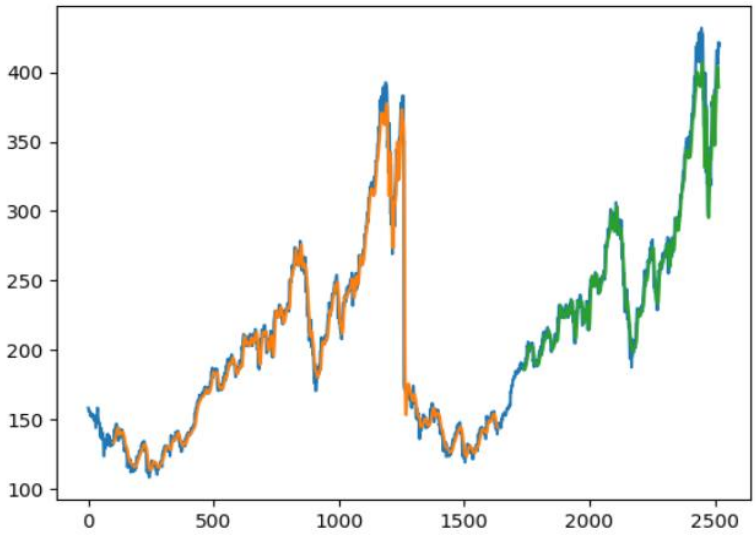
Iterate and Optimize

To generalize the LSTM model for predicting stock prices and ensure its robustness, it is essential to experiment with various hyperparameter combinations. Optimizing hyperparameters directly impacts the model's performance, enabling it to learn effectively from the data without overfitting or underfitting. Here is an in-depth explanation of the hyperparameter tuning process and the role of each parameter in enhancing model robustness:



Number of LSTM Units

LSTM units, or neurons, determine the capacity of the LSTM layers. Each unit represents a hidden cell that processes sequential data, capturing patterns and temporal dependencies within the stock price data. Testing different numbers of units, typically between 50 and 200, can help balance the model's ability to learn complex patterns. A higher number of units allows the model to capture more intricate relationships, but this can also increase the risk of overfitting.

Number of Layers

The LSTM network can consist of multiple stacked LSTM layers. Adding more layers allows the model to learn increasingly complex patterns by building on the output of previous layers. Initial models often start with a single LSTM layer. If the model's performance is suboptimal, additional layers may be added. Typically, up to three or four layers are tested, as too many layers can lead to overfitting and increase computational requirements. Through experimentation, the optimal number of layers for this task is determined.

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Dropout Rates

Dropout is a regularization technique that prevents overfitting by randomly dropping a proportion of units from the LSTM layer during training. This encourages the model to learn more robust features by not relying on specific neurons. Dropout rates usually range between 0.1 and 0.5. For example, a 0.2 dropout rate means that 20% of neurons are randomly dropped during each iteration. Various dropout rates are tested to find a balance where the model is less prone to overfitting while maintaining performance.

Batch Size

Batch size defines the number of samples that the model processes before updating its internal parameters. It influences the convergence speed and stability of the training process. Common batch sizes include 16, 32, 64, and 128. Smaller batch sizes can lead to more stable and thorough learning, while larger batch sizes can speed up training. By experimenting with different batch sizes, an optimal balance between training speed and model performance is achieved.

Learning Rate

The learning rate controls the step size of each update during training. A low learning rate allows the model to learn slowly and can help avoid overshooting the optimal point, while a high learning rate speeds up training but can lead to instability. Typical learning rates range from 0.001 to 0.01 for LSTM models. Experimentation involves fine-tuning this parameter, often through a process known as learning rate scheduling, which adapts the rate based on the model's progress during training. A well-tuned learning rate ensures that the model converges efficiently to an optimal solution.

Cross-Validation

Cross-validation is a technique used to evaluate the model's performance across multiple subsets of data, providing insights into its generalizability. Instead of using a single training-testing split, the data is divided into several folds, and the model is trained and validated on each fold. Typically, k-fold cross-validation (where k is often 5 or 10) is applied. Each fold is used once as a testing set while the remaining data is used for training. This process reduces the likelihood of overfitting to specific data patterns and ensures that the model performs well on different subsets of data.

The experimentation process with these hyperparameters allows for the systematic evaluation of the LSTM model's performance under different configurations. By testing various combinations, the optimal set of hyperparameters is determined, resulting in a model that is both accurate and generalizable across various data subsets. This process is crucial in achieving a robust model capable of adapting to real-world variations in stock price data, ultimately providing reliable predictions in a dynamic market environment.

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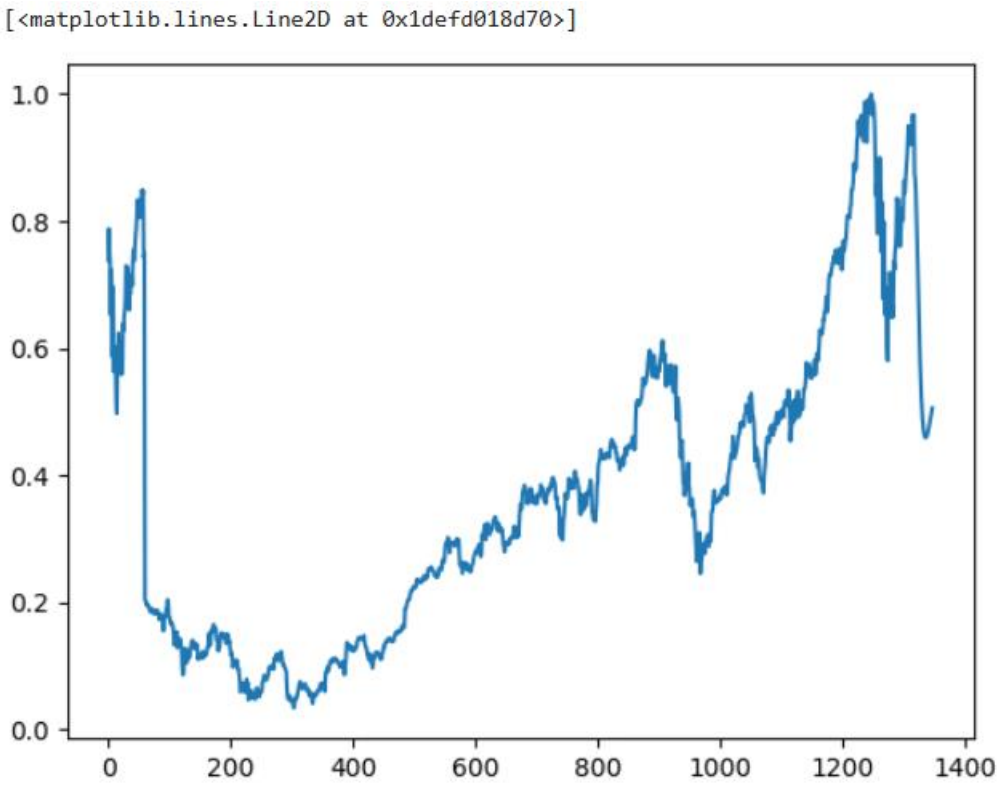

Findings

The experiment begins by predicting stock prices using a trained LSTM model, which leverages both training and testing datasets. After training the model, predictions are generated for both the training and testing datasets to evaluate performance. To ensure interpretability, the predicted values are converted back to their original scale using inverse transformation, which is essential since the data was initially scaled.

For performance assessment, the model utilizes the Root Mean Square Error (RMSE) metric to gauge accuracy. The RMSE is calculated for both the training and testing sets, with results indicating a low RMSE, reflecting minimal error between the predicted and actual stock prices. This low error on both datasets suggests that the model has achieved good generalization.

The experiment proceeds to visualize the results. For the training set, the model's predictions are shown alongside actual values, illustrating how closely the model has learned from the data. Similarly, the testing set is also plotted, with the green line representing the predicted prices and the orange and blue lines representing actual values. The visualization demonstrates that the predicted stock prices align well with the actual data, showing the model's effectiveness.

To further validate the model, it is applied to predict future stock prices over the next 30 days. Using the last 100 days of data from the test set as input, the model generates predictions for each subsequent day, updating the input data as it moves forward day by day. This iterative

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process involves continuously reshaping data, making predictions, and adjusting the input to include the latest predicted value. The outcome is a smooth prediction curve for the 30-day forecast, indicating the model's ability to project future trends with reasonable accuracy.

The final visualization shows both the actual data and the forecasted data for 30 future days. This forecast appears as a smooth continuation of the historical trend, which suggests that the LSTM model has effectively captured the underlying patterns in the stock price data.

Results

The model's performance was evaluated using RMSE on both training and testing datasets. The results revealed low RMSE values, indicating high predictive accuracy. The visualization of predicted vs. actual prices showed close alignment, underscoring the model's capability to generalize effectively. For future price forecasting, the LSTM model generated a smooth trend line, which reflects the composite index's ability to capture essential economic influences on stock prices.

Conclusion

The LSTM model performed admirably in predicting stock prices, with low RMSE values indicating high accuracy and reliable performance across both the training and testing datasets. The model demonstrated a strong ability to generalize, as reflected by similar RMSE values for both datasets, suggesting it did not overfit.

The 30-day forecast further validated the model's capabilities, providing a smooth and credible prediction curve that aligns well with the historical trend. This suggests that the LSTM model is well-suited for short-term stock price prediction, capturing both immediate and subtle temporal dependencies within the data.

Overall, the results indicate that using an LSTM model for stock price prediction in this experiment offers a robust and effective method. The model's ability to handle sequential data and its smooth forecast output highlights its potential for practical applications in financial forecasting and stock market analysis. Continuous updates and retraining with new data would be advisable for maintaining its predictive accuracy over time, particularly in dynamic markets.

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