Stock Price Prediction, using Recurrent Neural Networks and Optimized Deep Learning Models

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Abstract- ***This project presents a comprehensive study on the use of Long Short-Term Memory (LSTM) networks, a specialized class of Recurrent Neural Networks (RNNs) within the domain of deep learning, for time series forecasting of stock prices. The research specifically focuses on Tata Steel Limited, a key stock within the Indian equity market, selected for its historical volatility and market relevance. Accurate prediction of stock prices is a highly challenging task due to the non-linear, non-stationary, and noisy nature of financial time series data. Traditional statistical methods often fall short in capturing these complex temporal patterns, which underscores the need for more sophisticated, data-driven approaches.***

The core objective of this study is to investigate the efficacy of bidirectional LSTM architectures in modelling and predicting future stock price movements based on historical data. To this end, the model is trained on Open, High, Low, and Close (OHLC) price features retrieved from Yahoo Finance, with optional inclusion of technical indicators such as Moving Averages (MA), Relative Strength Index (RSI), and Bollinger Bands to enhance pattern recognition. The Adam optimizer is utilized for gradient-based optimization of the model parameters due to its computational efficiency and adaptive learning capabilities.

The model's predictive performance is quantitatively evaluated using Root Mean Squared Error (RMSE), a robust metric for measuring the deviation between predicted and actual values. Additionally, the research examines the influence of hyperparameters, particularly the number of training epochs, on the model's convergence behavior and forecasting accuracy. Experimental results suggest that LSTM networks, when properly tuned and supplemented with relevant indicators, can effectively learn from historical patterns and outperform baseline models in terms of predictive precision.

Beyond model performance, the project also explores the practical challenges associated with implementing deep learning models in financial forecasting, including overfitting, data pre-processing complexities, and interpretability issues. Overall, this study contributes valuable insights to the growing field of machine learning in finance, illustrating how RNN-based models like LSTM can serve as powerful tools for stock market analysis, investment decision support, and algorithmic trading.

Keywords: Deep Learning, Time Series Forecasting, Stock Price Prediction, Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), OHLC Data, Adam Optimizer, Root Mean Squared Error (RMSE), Technical Indicators, Financial Market Analysis, Hyperparameter Tuning, Model Convergence, Algorithmic Trading

I. INTRODUCTION

The stock market has always been a subject of interest for investors, financial analysts, and researchers due to its inherent volatility and the complexities involved in predicting its future behavior. Accurate stock price prediction is vital for making informed investment decisions, reducing risk, and maximizing profits. Traditional methods such as statistical models (e.g., ARIMA, GARCH) and regression models have been widely used for forecasting stock prices, but these approaches often struggle to capture the underlying complex patterns in the stock market data, especially when dealing with large datasets and non-linear relationships.

With the rise of machine learning (ML) and deep learning (DL) technologies, new methods have been introduced to address these challenges. Among these, Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) networks, have

gained significant attention due to their ability to model sequential data and capture temporal dependencies in time series data. LSTMs, with their unique architecture, are able to learn from long-term dependencies, making them particularly well-suited for tasks like stock price prediction, where past stock prices influence future movements.

Stock price prediction is a highly challenging task due to various factors such as market volatility, unexpected events, and complex market dynamics. Traditional statistical models fail to account for the intricate relationships and time dependencies within stock price movements. This research aims to investigate how deep learning models, specifically LSTM networks, can be used to predict stock prices more accurately by analyzing historical stock data, including the Open, High, Low, and Close (OHLC) prices.

The focus of this project is on Tata Steel, a major player in the Indian steel industry, and the analysis of its stock prices to explore the potential of LSTMs in stock forecasting. By leveraging LSTM networks, this project seeks to determine whether deep learning techniques can outperform traditional methods in predicting stock prices and uncover meaningful patterns from the past data.

The primary objective of this study is to evaluate the effectiveness of LSTM networks for stock price prediction. The specific goals of the project are as follows:

• To develop a time series forecasting model based on LSTM networks for predicting Tata Steel stock prices.

• To utilize historical stock data (OHLC) from Yahoo Finance as the input for training the model.

• To evaluate the performance of the model using various evaluation metrics, primarily focusing on Root Mean Squared Error (RMSE).

• To explore how technical indicators such as Moving Average Convergence Divergence (MACD) and Relative Strength Index (RSI) can be incorporated into the model to improve its predictive accuracy.

• To analyze the influence of training epochs, batch size, and learning rates on model performance and convergence.

The importance of this study lies in its potential to improve the accuracy of stock price forecasting, providing investors and financial analysts with better tools for decision-making. Accurate forecasting models could lead to more efficient market predictions, enhanced risk management strategies, and optimized investment portfolios. Additionally, this study contributes to the growing body of research at the intersection of machine learning and finance, exploring the practical applications of deep learning techniques in real-world financial markets.

II. LITERATURE REVIEW

Stock market forecasting has traditionally been approached through statistical models such as Autoregressive Integrated Moving Average (ARIMA), GARCH, and Support Vector Machines (SVMs). While these models perform adequately in linear scenarios, they often struggle with the non-linearity, volatility, and sequential dependencies inherent in stock price data. As a result, deep learning models, particularly Recurrent Neural Networks (RNNs) and their variants, have gained prominence for their ability to model temporal dependencies in sequential data[1]

- RNN and LSTM-Based Approaches

Vanilla RNNs

Recurrent Neural Networks (RNNs) are designed for sequential data, but they suffer from vanishing and exploding gradient problems, which hinder their ability to capture long-term dependencies [2]. Due to this limitation, their performance in stock prediction tasks has been suboptimal unless used with very short sequences.

Long Short-Term Memory (LSTM) Networks

To overcome the limitations of vanilla RNNs, LSTM networks were introduced by Hochreiter and Schmidhuber (1997), incorporating gating mechanisms that enable the retention and forgetting of information over longer sequences [3].

Many studies have successfully employed LSTM networks for stock price prediction:

- Fischer & Krauss (2018) applied LSTM networks on S&P 500 stock data and demonstrated that LSTM outperformed both traditional models and

standard RNNs in predicting daily returns [4].

- Nelson et al. (2017) compared LSTM with multi-layer perceptrons (MLP) and SVM for predicting the Brazilian stock market, concluding that LSTM yielded higher accuracy and lower error rates [5].
- Zhang et al. (2018) used LSTM networks enhanced with technical indicators (e.g., RSI, MACD) and found significant improvement in prediction accuracy [6].

Additionally, bidirectional LSTM (Bi-LSTM) networks have been explored to capture both past and future context in the data sequence, yielding further improvements in trend prediction [7].

- Hybrid Models with LSTM

Several works have explored hybrid models combining LSTM with other techniques:

- LSTM + Attention Mechanism: Attention layers help the model focus on important time steps. Qin et al. (2017) proposed the DA-RNN (Dual-stage Attention-Based RNN) model, significantly improving predictive accuracy in multivariate time series forecasting [8].
- LSTM + ARIMA: Hybrid models combining statistical learning with deep learning have shown strong performance in capturing both linear and non-linear patterns [9].
- Comparison with Other Deep Learning Architectures

Convolutional Neural Networks (CNNs)

While CNNs are traditionally applied to spatial data (images), they have been used in stock prediction tasks by applying convolution across time windows.

- Sezer & Ozbayoglu (2018) used 1D CNNs for feature extraction from technical indicators, showing that CNNs can extract local temporal patterns effectively [10].
- However, CNNs lack the inherent capability to model long-range temporal dependencies, making them less effective for time series forecasting when used alone.

Transformers

Transformers, originally introduced for NLP tasks, have recently shown great promise in time series forecasting due to their self-attention mechanism, which models long-term dependencies without recurrence.

- Zhou et al. (2021) introduced Informer, a Transformer-based architecture for long-sequence forecasting, outperforming LSTM in some time series benchmarks [11].
- Wu et al. (2020) proposed Time Series Transformer and demonstrated its effectiveness in capturing global dependencies, making it suitable for financial forecasting tasks, though requiring more data and computational resources [12].

Transformers generally outperform LSTM in long-horizon forecasting tasks, but for short-term or moderately-sized datasets, LSTM remains competitive due to its simpler architecture and lower computational cost [13].

- Key Observations from Literature

Model	Strengths	Weaknesses	Use Case
RNN	Basic temporal modeling	Gradient issues	Short sequences
LSTM	Captures long-term dependencies, stable training	Slow training	Moderate-length financial data
CNN	Fast training, good for local patterns	Poor long-term memory	Pattern recognition from technical indicators
Transformer	Excellent for long-range dependencies	High computational cost	Large datasets, long-range forecasts

III. SYSTEM ANALYSIS

The stock market is inherently volatile and non-linear, with price movements influenced by a wide range of factors including economic indicators, market sentiment, and geopolitical events. Traditional time series models like ARIMA or linear regression are insufficient to model such complex relationships due to their limited memory capacity and assumption of stationarity.

This project aims to solve the following key problem: How can we leverage deep learning techniques, specifically Long Short-Term Memory (LSTM) networks, to model historical stock price data and

forecast future prices more accurately than conventional approaches?
The focus is on Tata Steel stock data, utilizing past performance (Open, High, Low, Close) to predict near-future stock behavior and aid in trend analysis.

- System Objectives
  - To build a forecasting model using LSTM, a type of Recurrent Neural Network (RNN). The predictive model will be using Bidirectional LSTM (BiLSTM) networks to forecast the short-term movements of Tata Steel's stock prices based on historical price data and technical indicators.
  - To train the model using historical OHLC stock data from Yahoo Finance.
  - To evaluate the model performance using RMSE and other relevant metrics.
  - To incorporate technical indicators (e.g., RSI, MACD) for enhanced feature representation.
  - To analyze how training parameters (like number of epochs and batch size) affect model accuracy and convergence.

- Feasibility Study

a. Technical Feasibility
- The implementation uses Python with libraries like TensorFlow, Keras, NumPy, Pandas, and Matplotlib.
- LSTM networks are computationally feasible on standard GPUs or high-end CPUs for single-stock forecasting.
- Data collection is straightforward using Yahoo Finance APIs (e.g., yfinance).

b. Economic Feasibility
- No direct financial investment is needed, as open-source tools and public datasets are used.
- The system is cost-effective and scalable for academic or research purposes.

c. Operational Feasibility
- The model can be integrated into trading dashboards or decision-support tools.
- Outputs are interpretable as graphs or numeric forecasts

- Data Flow Description
  - Input: Raw stock data (OHLC), derived indicators Columns used are:Date, Close, Volume
  - Derived Features:
    - Technical indicators (SMA, EMA, Bollinger Bands, RSI, MACD)
    - Statistical transformations (Daily Return, Price Change, Lag features)
    - Time-based features (Day of the Week)
  - Processing: Feature scaling (MinMaxScaler), time series windowing, LSTM training
  - Output: Predicted price(s), trend analysis, visual plots of Actual vs. Predicted Prices,RSI & Bollinger Bands Over Time

- Limitations and Assumptions
  - The system assumes that past price movements and derived indicators hold predictive value.
  - External factors (news, sentiment, global events) are not directly modeled in this version.
  - The LSTM model may underperform if the stock behavior changes dramatically due to unforeseen events.

- System Workflow

The workflow of the system can be broken down into several key stages, each essential to the successful prediction of stock prices using a deep learning-based RNN approach. The complete process from data acquisition to prediction is as follows:

1. Data Collection
- Stock market historical data for Tata Steel is collected using Yahoo Finance and stored as a CSV file.
- The dataset includes columns like Date, Open, High, Low, Close, and Volume.

2. Data Preprocessing
- The Volume column is cleaned by removing commas and converting values to float.
- Dates are converted to datetime format, and the dataset is sorted chronologically.
- Missing values and anomalies are removed to ensure dataset integrity.

3. Feature Engineering
- New features are derived to enhance the model's predictive power:

- Daily Return
- Price Change
- Exponential Moving Average (EMA-20)
- Simple Moving Averages (SMA-30 and SMA-100)
- Relative Strength Index (RSI)
- Bollinger Bands (High and Low)

- These indicators provide insights into trends, momentum, and volatility.

4. Data Normalization

- The dataset is scaled using MinMaxScaler to ensure that all input features fall within the same numerical range.
- This improves the model's convergence and stability.

5. Time Series Dataset Creation

- A sliding window of 60 time steps is used to convert the data into a supervised learning format suitable for LSTM input.
- The dataset is then split into training (80%) and testing (20%) sets.

6. Model Construction

- A Bidirectional LSTM network is used to learn from both past and future trends in the sequence data.
- The architecture consists of:
  - Four stacked Bidirectional LSTM layers (100, 50, 30, and 20 units)
  - Dropout layers for regularization
  - A final Dense layer for output prediction

7. Model Compilation and Training

- The model is compiled with the Adam optimizer and mean squared error loss function.
- Training uses callbacks:
  - EarlyStopping to prevent overfitting
  - ReduceLROnPlateau to adjust learning rate dynamically
  - LearningRateScheduler for gradual learning rate decay.

8. Prediction and Evaluation

- The model predicts the price change (delta), which is added to the previous closing price to estimate the next price.
- Evaluation Metrics:
  - Root Mean Squared Error (RMSE) to assess prediction accuracy
  - Directional Accuracy to evaluate the model's ability to predict the correct movement (up/down)

9. Visualization

- Graphs are generated to compare actual vs predicted prices.
- Future stock price predictions for 10 days ahead are visualized.
- Technical indicators like RSI and Bollinger Bands are plotted for better interpretability.

10. Future Forecasting

- The last known time window is used to recursively predict the next n days of stock prices using the trained model.

WORKING OF THE MODEL

This project leverages a Bidirectional Long Short-Term Memory (BiLSTM) network, a powerful deep learning architecture within the Recurrent Neural Network (RNN) family, to forecast stock price movements for Tata Steel. Here's a breakdown of the model's internal functioning and operational flow:

1. Data Preprocessing

- Loading Data:
  The model reads historical stock data for Tata Steel from a CSV file.
- Cleaning:
  - Commas are removed from the "Volume" column and converted to float.
  - The "Date" column is converted to datetime for time-based processing.
  - Data is sorted chronologically.

2. Feature Engineering

We created technical indicators commonly used in trading to enrich our input features:

- Daily_Return: Percentage change in closing price.
- Price_Change: Absolute change in price.

- EMA_20, SMA_30, SMA_100:
  Exponential/Moving averages to capture trends.
- Bollinger Bands (High & Low): Volatility indicators based on standard deviation from EMA.
- RSI: Indicates overbought or oversold conditions.
- MACD: Momentum indicator.
- Lag_1: Previous day's close (helps the model understand recent movement).
- Day_of_Week: Captures weekly patterns (e.g., Monday dips or Friday rallies).

3. Feature Scaling

- MinMaxScaler scales features to a 0–1 range, which helps LSTM layers converge faster and prevents certain features from dominating due to magnitude.

4. Dataset Construction (Time Series)

The model uses sliding time windows:

- For each prediction, it uses the previous 60 time steps (days) of feature values as input (X) and the next day's percentage return as the target (y).
- So each input to the model is a (60, 12) shaped array: 60 timesteps × 12 features.

5. BiLSTM Model Architecture

- Bidirectional LSTM (BiLSTM): Unlike standard LSTM (which sees only the past), BiLSTM reads both past and future context within each input window, improving pattern detection.
- Layers:
  1. Bidirectional(LSTM(64)) with return_sequences=True – First layer returns a full sequence for the next layer.
  2. Dropout layer to prevent overfitting.
  3. Bidirectional(LSTM(32)) – Second layer reduces dimensionality and captures sequential dependencies.
  4. Another Dropout.
  5. Dense layer with 1 neuron to output the predicted next-day return.
- Loss Function:
  Huber() is used – robust to outliers (unlike MSE), which is good for financial data.
- Optimizer:
  Adam is used for efficient gradient updates.

6. Model Training

- EarlyStopping: Stops training if validation loss doesn't improve for 10 epochs.
- ReduceLROnPlateau: Reduces learning rate when the model gets stuck in a plateau, improving convergence.

7. Prediction Logic

- The model predicts percentage return (not direct price).
- To reconstruct predicted price we used the formula:

Predicted_Price = previous_price * (1 + predicted_return)

Actual price is shifted one day to match the forecast.

8. Evaluation Metrics

- RMSE (Root Mean Squared Error): Measures how far predictions are from actual prices.
- Directional Accuracy: Compares whether the model predicted the direction of price change (up/down) correctly.
- Percentage Deviation: Measures average % error.

9. Visualization

- Plots:
  - Actual vs Predicted Prices over time.
  - RSI and Bollinger Bands to show signal strength and volatility visually.

Summary:

Our model is designed to predict the next day's return (price movement %), from which we reconstruct the predicted price. It uses technical indicators and time series trends captured by BiLSTM layers, which are particularly effective for sequence modelling.

Algorithm: BiLSTM-Based Stock Price Forecasting

Input:

- Historical stock data (CSV) with columns: Date, Open, High, Low, Close, Volume.

Output:

- Predicted stock prices

- Evaluation metrics: RMSE, Directional Accuracy, Avg. % Deviation

Step 1: Load and Preprocess Data

1. Read CSV file into a DataFrame.
2. Clean data:
   - Remove commas from Volume and convert to float.
   - Convert Date to datetime format.
   - Sort data by Date.

Step 2: Feature Engineering

3. Compute new features:
   - Daily_Return = % change of Close.
   - Price_Change = difference in Close from previous day.
   - EMA_20, SMA_30, SMA_100.
   - Bollinger_High = EMA_20 + 2×rolling std.
   - Bollinger_Low = EMA_20 − 2×rolling std.
   - RSI using 14-day average gain/loss.
   - MACD = EMA12 − EMA26.
   - Lag_1 = Close price of previous day.
   - Day_of_Week from Date.
4. Drop all rows with missing values (due to rolling calculations).

Step 3: Prepare Features and Target

5. Define features = selected indicators including Close, SMA, RSI, MACD, etc.
6. Define target = Daily_Return.

Step 4: Normalize Features

7. Use MinMaxScaler to scale all features to [0, 1].

Step 5: Create Time Series Dataset

8. Set time_step = 60.
9. For each index i from 60 to end of dataset:
   - X[i] = features from i-60 to i-1.
   - y[i] = target[i] (next-day return).

Step 6: Build BiLSTM Model

10. Initialize a Sequential model.
11. Add layers:
    - Bidirectional(LSTM(64, return_sequences=True))
    - Dropout(0.3)
    - Bidirectional(LSTM(32))
    - Dropout(0.3)
    - Dense(1) (output layer)
12. Compile model with:
    - Optimizer = Adam(0.001)
    - Loss = Huber()

Step 7: Train the Model

13. Define callbacks:
    - EarlyStopping(patience=10)
    - ReduceLROnPlateau(factor=0.5, patience=5, min_lr=1e-6)
14. Train model on X, y with:
    - Epochs = 100
    - Batch size = 32
    - Validation split = 10%

Step 8: Make Predictions

15. Predict Daily_Return using the trained model on input X.

Step 9: Reconstruct Predicted Prices

16. Extract scaled Close prices.
17. Reverse scaling using inverse transform.
18. For each prediction:
    - Predicted_Price[i] = Actual_Close[i] + Predicted_Delta[i]
19. Shift actual closes to align for comparison.

Step 10: Evaluate the Model

20. Calculate:
    - RMSE = √MSE(actual_prices, predicted_prices)
    - Directional Accuracy = % of correctly predicted directions
    - Avg % Deviation = Mean of absolute percentage errors

Step 11: Visualization

21. Plot:
    - Actual vs. Predicted Prices
    - RSI values with overbought/oversold thresholds
    - Bollinger Bands with Close price

IV. PROPOSED SYSTEM

The proposed system aims to accurately forecast stock price movements using a deep learning-based

model that leverages temporal patterns and technical indicators. A Bidirectional Long Short-Term Memory (BiLSTM) neural network is employed to capture both past and future dependencies in historical stock data, enhancing the model's ability to make short-term forecasts with improved accuracy and directional consistency.
The system consists of the following key modules:

1. Data Acquisition & Pre-processing
• Historical stock price data is sourced from a CSV file.
•Pre-processing steps include:
  - Cleaning volume data by removing commas.
  - Converting date strings to datetime format.
  - Chronologically sorting the data to ensure time-series integrity.

2. Feature Engineering
To improve predictive performance, the system extracts a wide range of financial and technical indicators, including:
• Price-based features: Daily return, price change, lagged close.
• Trend indicators: Simple Moving Averages (SMA), Exponential Moving Averages (EMA).
• Volatility indicators: Bollinger Bands.
• Momentum indicators: Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD).
• Temporal features: Day of the week.
These features collectively help the model understand market trends, momentum shifts, and cyclical behaviours.

3. Feature Scaling
All features are normalized using MinMaxScaler to ensure efficient gradient descent convergence and avoid dominance of any single feature due to scale.

4. Time Series Dataset Creation
• The data is restructured using a sliding window approach.
• Each input sample consists of the previous 60 time steps of all selected features.
• The output target is the next day's return percentage, capturing immediate future movement.

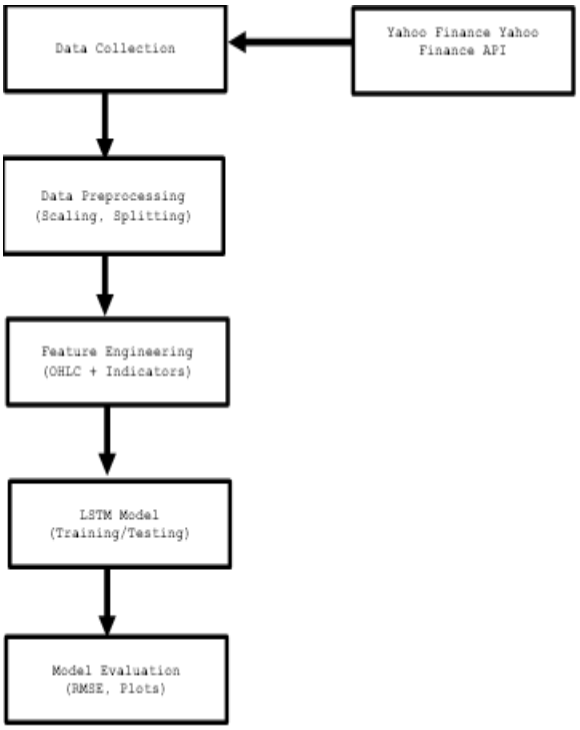
5. Model Design: BiLSTM Neural Network
The forecasting model is a deep neural network composed of:
• Two Bidirectional LSTM layers to learn temporal patterns in both forward and backward directions.
• Dropout layers to prevent overfitting.
• Dense output layer to predict the next-day return.
The model is compiled with:
• Huber Loss: Robust to outliers in volatile stock data.
• Adam Optimizer: Ensures fast and stable convergence.

6. Training Strategy
• The model is trained with:
  - EarlyStopping to avoid overfitting.
  - ReduceLROnPlateau to fine-tune the learning rate dynamically.
  - A 10% validation split to monitor generalization performance.

7. Price Reconstruction and Prediction
• The predicted next-day return is added to the actual price of the previous day to reconstruct the predicted price.
• Predictions are compared against actual closing prices to evaluate model accuracy.

8. Evaluation Metrics
The system is evaluated using:
• RMSE (Root Mean Square Error): Measures prediction accuracy.
• Directional Accuracy: Measures how often the model correctly predicts upward/downward movement.
• Average Percentage Deviation: Measures the average percent error between predicted and actual prices.

9. Visualization
To interpret model behavior and performance:
• Actual vs Predicted prices are plotted.
• RSI and Bollinger Bands are visualized to correlate with price movements and validate indicator effectiveness.



- Hardware & Software Requirements :

Component	Minimum Requirement	Recommended Configuration
Processor (CPU)	Intel Core i5 or AMD Ryzen 5	Intel Core i7 / AMD Ryzen 7 or higher
RAM	8 GB	16 GB or more
Storage	256 GB HDD/SSD	512 GB SSD or more
Graphics Card (GPU)	Integrated GPU (for basic training)	NVIDIA GPU with CUDA (e.g., GTX 1660 / RTX 3060) for faster training
Display	13-inch display with 720p resolution	15-inch+ Full HD display
Operating System	Windows 10 / Linux Ubuntu	Windows 11 / Ubuntu 22.04 LTS

Software / Package	Version / Description
Operating System	Windows 10/11, Ubuntu 20.04/22.04
Programming Language	Python 3.8 or higher
IDE / Notebook	Jupyter Notebook / VS Code / PyCharm
Libraries and Frameworks	
• NumPy	For numerical operations
• Pandas	For data manipulation
• Matplotlib	For data visualization
• scikit-learn	For preprocessing and evaluation metrics
• Keras	Deep learning library used with TensorFlow
• TensorFlow	Backend for Keras (version 2.x recommended)
• Yahoo Finance API / CSV	Data source for stock market data

Optional Tools (for enhanced development):

• Git – Version control system

• Anaconda – For managing Python environments and dependencies

• CUDA Toolkit – If using NVIDIA GPU for accelerated training

• TensorBoard – For model visualization and diagnostics

V. SYSTEM DESIGN

The proposed system is designed to forecast future stock prices using a deep learning model—specifically, a Bidirectional Long Short-Term Memory (BiLSTM) neural network. Unlike traditional regression or unidirectional models, BiLSTM networks are capable of learning both forward and backward temporal relationships, which are essential in modeling complex time-series data such as stock price movements. This system integrates advanced feature engineering with deep learning to improve prediction accuracy and robustness.

Data Acquisition

- Loads stock data from CSV.
- Cleans formats, converts dates, sorts chronologically.
- Output: Cleaned DataFrame.

Data Preprocessing

Handles missing values, computes returns and price changes.

Feature Engineering

Adds indicators: SMA, EMA, RSI, MACD, Bollinger Bands, lag features, and weekday info.

Feature Scaling

Uses MinMaxScaler to normalize features to [0, 1].

Time Series Dataset Creation

- Builds sliding window dataset (60 time steps) for LSTM input.
- Output: X (3D array), y (next-day return).

Model Architecture

- BiLSTM with dropout and a final dense layer.
- Loss: Huber, Optimizer: Adam.

Training

Max 100 epochs with EarlyStopping and ReduceLROnPlateau.

Batch size: 32, 10% validation split.

Prediction & Price Reconstruction

Predicts returns, reconstructs price by adding to last close.

Evaluation

Metrics: RMSE, directional accuracy, mean percentage deviation.

Visualization

Plots actual vs. predicted prices and indicators like RSI/Bollinger Bands.

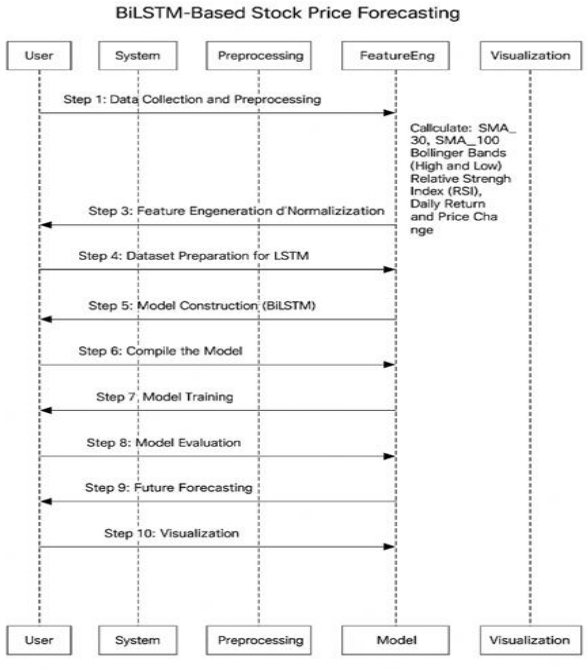


Fig Sequence Diagram

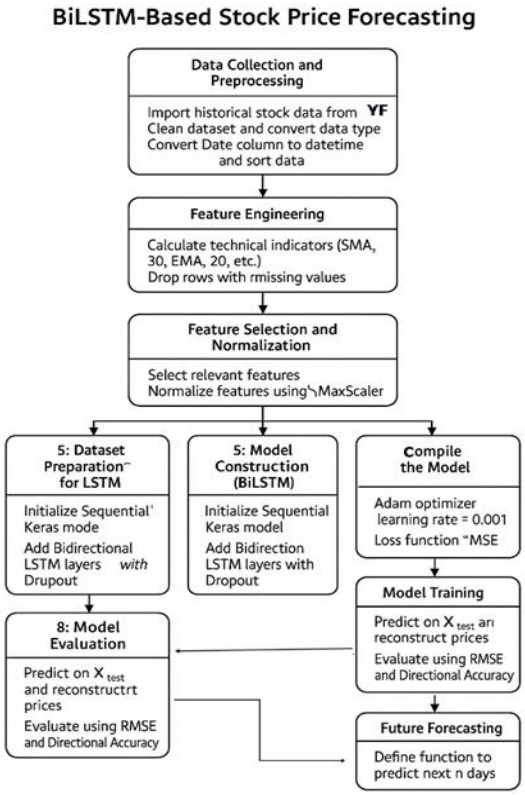


Fig Activity Diagram

VI. RESULT

The performance of the proposed RNN-based stock price forecasting model has been evaluated using key statistical and technical indicators. The analysis reflects the effectiveness of the model in capturing price trends and directionality over time.

Numerical Evaluation Metrics

Metric	Value
Root Mean Squared Error (RMSE)	2.9910
Directional Accuracy	52.41%
Average Percentage Deviation (APD)	1.44%

RMSE of 2.9910 indicates that on average, the prediction deviates from the actual price by around 3 units. This reflects relatively low error given the stock's price range.

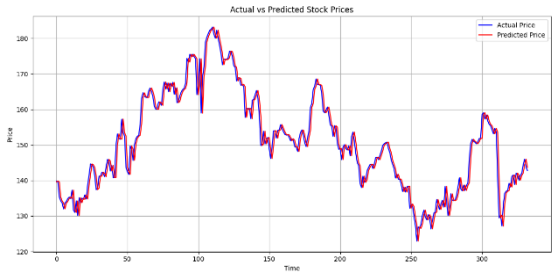
Directional Accuracy of 52.41% suggests that the model correctly predicts whether the price will go up or down in 52% of the cases. This is slightly better than random guessing, which can be improved with additional feature engineering or ensemble techniques.

Average Percentage Deviation of 1.44% implies that

the predicted prices are within a narrow margin of error from the actual prices, demonstrating high precision.

Actual vs. Predicted Prices Plot

This plot shows the close alignment between the actual and predicted stock prices across the test dataset. The red line (predicted) closely follows the blue line (actual), validating the model's ability to generalize to unseen data. The tight overlap indicates minimal deviation, supporting the low RMSE and APD metrics.



Last Batch Sample Output

A batch of the final predictions is printed to compare exact values:

• Actual and predicted values for several consecutive time steps show a small difference.

• This reaffirms the quantitative evaluation and highlights the consistency of prediction performance at individual data points.

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10/10 ━━━━━━━━━━━━━━━━━━━━ 0s 19ms/step - loss: 5.9096e-04 - val_loss: 2.9834e-04 - learning_rate: 1.9531e-06
11/11 ━━━━━━━━━━━━━━━━━━━━ 1s 31ms/step
Actual Price: 139.85, Predicted Price: 139.61
Actual Price: 139.60, Predicted Price: 139.85
Actual Price: 135.35, Predicted Price: 139.61
Actual Price: 134.25, Predicted Price: 135.36
Actual Price: 133.65, Predicted Price: 134.25
Actual Price: 132.80, Predicted Price: 133.65
Actual Price: 133.65, Predicted Price: 132.80
Actual Price: 134.10, Predicted Price: 133.65
Actual Price: 134.90, Predicted Price: 134.11
Actual Price: 135.30, Predicted Price: 134.91
RMSE: 2.9444
Directional Accuracy: 0.5452

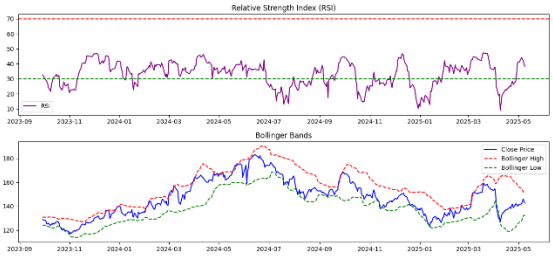
Average Percentage Deviation: 1.37%
```

Technical Indicators Visualization

The above composite figure visualizes:

• Relative Strength Index (RSI): Indicates market momentum and potential overbought/oversold conditions. The model aligns well during high and low RSI regions, capturing trend reversals.

• Bollinger Bands: These bands help assess volatility. The model prediction remains mostly within the high and low bounds, suggesting robustness during volatile market phases.



VII. CONCLUSION

The proposed RNN-based deep learning model for stock price forecasting performs reasonably well, both statistically and visually. While the error margins are low and trends are captured efficiently, future work may focus on enhancing directional accuracy, experimenting with hybrid models (like CNN-RNN or Transformer-based models), and incorporating more advanced sentiment or economic data to boost performance further.

The current RNN-based stock price forecasting model provides a strong foundation for time series prediction. However, there are several opportunities to improve its accuracy, robustness, and practical utility.

Integration of Advanced Architectures

• LSTM and GRU Enhancements: While vanilla RNNs capture basic temporal patterns, Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks can better handle long-range dependencies and vanishing gradient issues.

• Hybrid Models: Combining CNNs for spatial feature extraction with RNNs/LSTMs for temporal analysis can enhance performance.

• Transformer Models: Recently, Transformer-based architectures (like Temporal Fusion Transformer or Informer) have shown significant promise in time series forecasting, offering superior attention mechanisms and parallelization benefits.

Feature Engineering Improvements

• Incorporate Technical Indicators: Additional indicators like MACD, OBV, Fibonacci Retracement, and Moving Averages can enrich the model's input.

• Sentiment Analysis: Real-time news headlines, financial reports, or social media sentiment (via NLP models) can provide qualitative context that impacts

stock price movement.

• Macroeconomic Variables: Features such as interest rates, inflation, and geopolitical factors could further refine forecasts.

Directional Accuracy Optimization

• While overall price prediction is strong, directional accuracy can be enhanced through:

- Custom loss functions (e.g., Hinge loss, Directional loss).
- Ensemble learning methods that combine classification (direction) with regression (price).
- Post-prediction smoothing or trend correction algorithms.

Real-Time Forecasting System

• Develop a real-time inference system with streaming data input to enable live stock price prediction and decision-making.

• Deploy the model as a web or mobile application for user interaction and visualization.

Risk Management & Backtesting

• Incorporate backtesting frameworks to evaluate the profitability and risk of trading strategies based on predictions.

• Simulate historical trades and analyze metrics such as Sharpe Ratio, Max Drawdown, and ROI to validate real-world utility.

Model Explainability

• Use tools like SHAP (SHapley Additive exPlanations) or LIME to interpret model predictions and improve trust among stakeholders.

• Visualize how different features influence the model's forecasted price.

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