

A PROJECT REPORT
on
“Stock Prediction Using LSTM”

Submitted to
KIIT Deemed to be University

In Partial Fulfilment of the Requirement for the Award of

BACHELOR’S DEGREE IN
INFORMATION TECHNOLOGY
BY

Rajdeep Thakur	2206113
Sumandeep Sahoo	2206302
Anshuman Ghosh	2206074
Debdip Chatterjee	2206087
Tathagato Bhattacharjee	2206145
Smruti Ranjan Rout	2206131

UNDER THE GUIDANCE OF
MR. PRASENJIT MAITI



SCHOOL OF COMPUTER ENGINEERING
KALINGA INSTITUTE OF INDUSTRIAL TECHNOLOGY
BHUBANESWAE, ODISHA -751024
April 2025

KIIT Deemed to be University

School of Computer Engineering
Bhubaneswar, ODISHA 751024



CERTIFICATE

This is certify that the project entitled
“Stock Prediction Using LSTM”

submitted by

RAJDEEP THAKUR	DEBDIP CHATTERJEE
SUMANDEEP SAHOO	TATHAGATO BHATTACHARJEE
ANSHUMAN GHOSH	SMRUTI RANJAN ROUT

is a record of bonafide work carried out by them, in the partial fulfilment of the requirement for the award of Degree of Bachelor of Engineering (Computer Science & Engineering OR Information Technology) at KIIT Deemed to be university, Bhubaneswar. This work is done during year 2024-2025, under our guidance.

Date: / /

(Mr. Prasenjit Maiti)
Project Guide

Acknowledgements

We are profoundly grateful to **MR. PRASENJIT MAITI** of **KIIT University** for his expert guidance and continuous encouragement throughout to see that this project rights its target since its commencement to its completion.

RAJDEEP THAKUR

SUMANDEEP SAHOO

ANSHUMAN GHOSH

DEBDIP CHATTERJEE

TATHAGATO BHATTACHARJEE

SMRUTI RANJAN ROUT

ABSTRACT

This project report details the development and implementation of a stock prediction model using Long Short-Term Memory (LSTM) neural networks. In an effort to bridge the gap between traditional technical analysis and modern machine learning techniques, our system fetches real-time financial data, computes technical indicators such as Exponential Moving Average (EMA) and Parabolic SAR, and constructs market signals. These signals are then used to train an LSTM model to predict the direction of stock prices. Experimental results, including accuracy, loss metrics, and a confusion matrix, are discussed. The study demonstrates that deep learning techniques can enhance the predictive power in volatile financial markets.

Keywords: Stock Prediction, LSTM, Technical Indicators, Deep Learning, Financial Forecasting

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Chapter 1

Introduction

In today's fast-paced financial markets, the ability to predict stock price movements is a significant advantage. Traditional technical analysis uses historical data and pre-defined indicators to generate trading signals; however, these methods often fall short in capturing the non-linear patterns inherent in stock prices. With advancements in machine learning, particularly deep learning, there is an opportunity to improve forecasting accuracy by learning from complex temporal data.

This project focuses on the development of a predictive model using Long Short-Term Memory (LSTM) networks. The system integrates financial data fetched via APIs, computes technical indicators such as EMA and Parabolic SAR, and constructs a feature set to train the LSTM. This approach aims to provide more robust predictions compared to conventional methods, thus offering potential improvements in trading strategies and risk management.

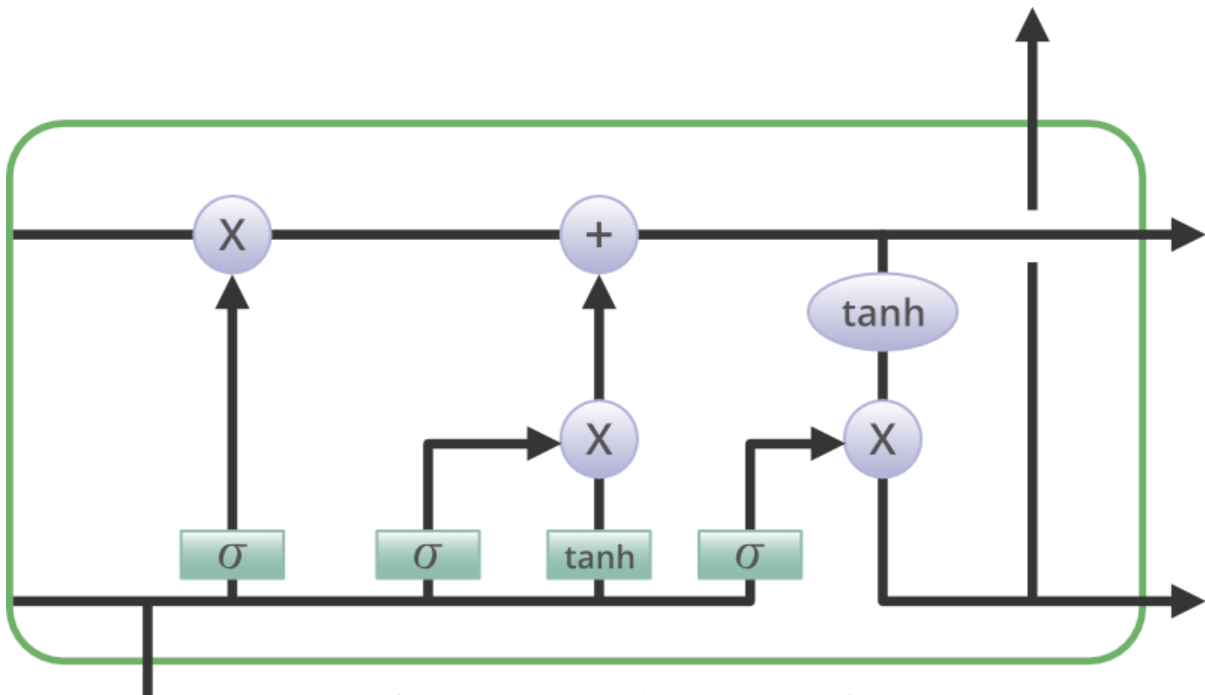


Figure 1.1: Structure of an LSTM Network

1.1 Problem Statement

Stock market fluctuations exhibit high volatility, making it difficult for investors to make informed decisions. Conventional forecasting techniques fail to account for sudden market shifts and non-stationary characteristics. This project aims to build an advanced predictive model leveraging LSTM networks to analyze financial data and generate accurate stock price predictions. The key challenges addressed include:

- Handling high volatility and noise in stock price movements.
- Integrating various technical indicators for improved predictive accuracy.
- Managing real-time data streaming and API integration for financial data retrieval.

1.2 Objectives of the Study

The primary objectives of this project are:

1. To develop a predictive model utilizing LSTM networks for stock price forecasting.
2. To preprocess financial time series data and compute key technical indicators such as Exponential Moving Average (EMA) and Parabolic Stop and Reverse (SAR).
3. To evaluate the performance of the model against traditional forecasting methods.
4. To enhance trading strategies through improved forecasting accuracy and risk assessment.

1.3 Significance of the Study

The significance of this study lies in its potential applications in financial decision-making, automated trading systems, and portfolio management. Accurate stock price prediction helps investors optimize their strategies, reducing risks and improving returns. The integration of LSTM networks allows for capturing intricate dependencies in financial data, making it a promising approach for market analysis.

Additionally, the research highlights the importance of feature engineering in stock price prediction. By leveraging technical indicators alongside historical price data, the model can enhance its predictive capabilities. The study also emphasizes the need for real-time data processing, which is crucial for traders who rely on up-to-date market insights.

Chapter 2

Basic Concepts/ Literature Review

2.1 Overview of Technical Indicators and Deep Learning in Finance

2.1.1 Exponential Moving Average (EMA)

The Exponential Moving Average (EMA) is a crucial technical indicator used in financial markets to smooth price data and identify trends. Unlike the Simple Moving Average (SMA), which assigns equal weight to all data points, EMA gives exponentially greater weight to more recent prices, making it more responsive to new data. The EMA is calculated using the following formula:

$$EMA_t = (P_t \times \alpha) + (EMA_{t-1} \times (1 - \alpha))$$

where:

- EMA_t is the Exponential Moving Average at time t ,
- P_t is the closing price at time t ,
- $\alpha = \frac{2}{N+1}$ is the smoothing factor,
- N is the selected time period.

By adjusting the smoothing factor, traders can fine-tune EMA sensitivity to price movements. Shorter EMAs react faster to price changes, whereas longer EMAs provide a smoother representation of the trend.

2.1.2 Parabolic SAR (Stop and Reverse)

The Parabolic SAR (PSAR) is designed to identify potential trend reversals in financial markets. It places a series of dots above or below the price chart to indicate the direction of the trend. The calculation involves an acceleration factor (AF) that increases as the trend progresses:

$$PSAR_t = PSAR_{t-1} + AF \times (EP - PSAR_{t-1})$$

- $PSAR_t$ is the value at time t ,
- AF is the acceleration factor (typically starting at 0.02 and increasing to a maximum of 0.2),
- EP is the extreme price (highest high or lowest low of the trend).

The PSAR system assists traders in identifying stop-loss points and optimal trade exits, thereby improving risk management.

2.1.3 Long Short-Term Memory (LSTM) Networks

LSTMs are an advanced form of recurrent neural networks (RNNs) designed to handle sequential data. Traditional RNNs suffer from vanishing gradient problems, making them inefficient for long-term dependencies. LSTMs overcome this limitation by introducing memory cells and gating mechanisms. The key equations governing LSTM operations are:

Forget Gate:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

Input Gate:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

$$\tilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

Cell State Update:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \tilde{C}_t$$

Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

$$h_t = o_t \cdot \tanh(C_t)$$

where:

- x_t is the input at time t ,
- h_{t-1} is the previous hidden state,
- W and b are weight matrices and biases,
- σ is the sigmoid activation function,
- \tanh represents the hyperbolic tangent activation.

LSTMs have been widely used in stock price forecasting due to their ability to learn complex temporal dependencies from past data.

2.1.4 Literature Review

Numerous studies have explored the effectiveness of deep learning in financial markets. A study by Fischer and Krauss (2018) demonstrated that LSTMs outperform traditional models such as ARIMA and GARCH in stock price prediction. Another study by Bao, Yue, and Rao (2017) found that hybrid deep learning models, which integrate LSTMs with technical indicators like EMA and PSAR, yield better accuracy than standalone methods.

Empirical findings suggest that leveraging LSTMs alongside technical indicators enhances predictive accuracy, enabling traders to make informed decisions. Figure 1 illustrates the conceptual workflow of integrating EMA, PSAR, and LSTMs in stock forecasting.

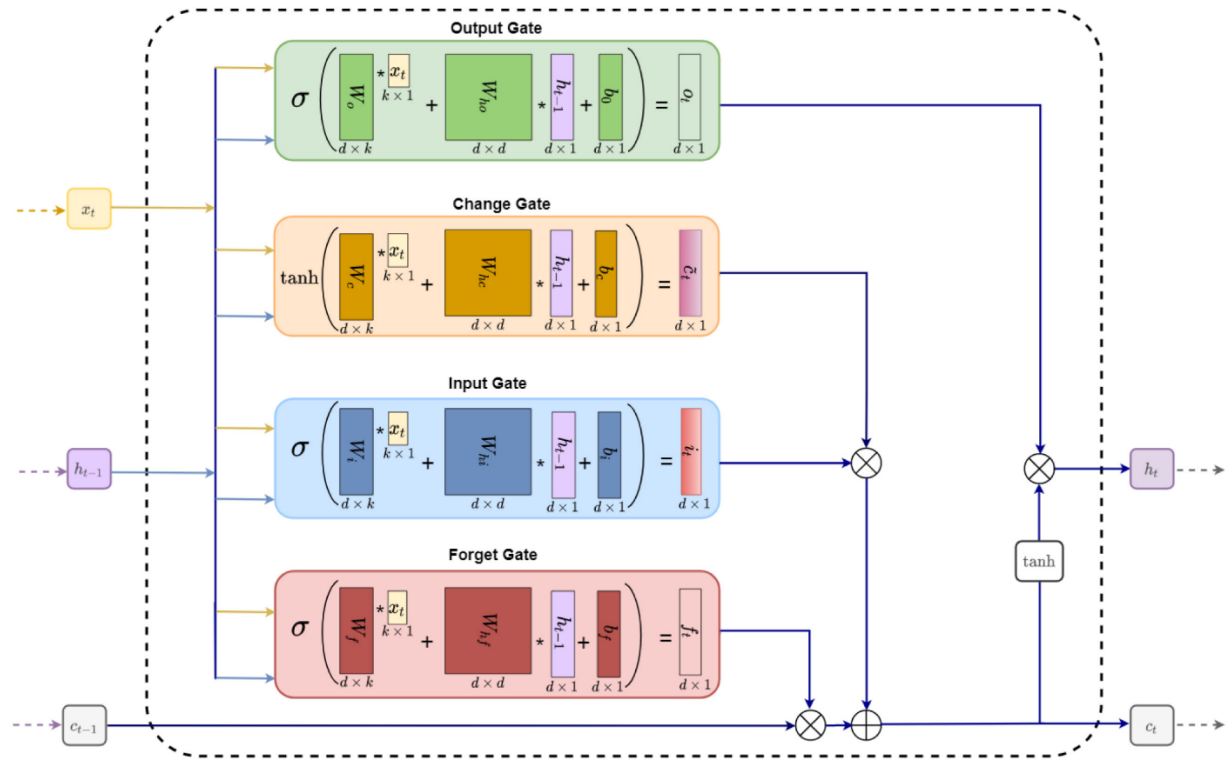


Figure 2.1.4: LSTM Cell: Gate Mechanisms for Memory and State Update.

In conclusion, integrating traditional technical indicators with modern deep learning models offers a powerful framework for financial forecasting, potentially leading to improved trading strategies and reduced risk.

Chapter 3

Problem Statement / Requirement Specifications

The primary objective of this project is to design and implement a system that predicts stock price movement direction using a deep learning model. The project is structured to address the following issues:

- **Problem Statement:**
Traditional technical analysis techniques often fail to capture the non-linear and temporal dependencies in stock price movements. This project proposes a solution that integrates technical indicators with an LSTM model to improve prediction accuracy.

3.1 Project Planning

The project is divided into several modules:

- **Data Fetching:** Collecting historical stock data using APIs.
- **Technical Indicator Computation:** Calculating EMA and Parabolic SAR to form the basis of signal construction.
- **Signal Construction:** Generating market signals (e.g., trend and return) that serve as features for the predictive model.
- **Model Development:** Building and training an LSTM network to forecast stock movement.
- **Evaluation:** Analyzing model performance using metrics like accuracy, loss, and confusion matrix.

3.2 Project Analysis

The system requirements are defined as follows:

- **Functional Requirements:**
 1. Fetch and process historical stock data.
 2. Calculate relevant technical indicators.
 3. Construct features for machine learning.
 4. Train an LSTM model for binary classification (upward or downward movement).
 5. Evaluate and validate the model performance.
- **Non-functional Requirements:**
 1. The system should be modular and scalable.
 2. Ensure efficient computation to handle large datasets.
 3. The model should generalize well on unseen data.

3.3 System Design

3.3.1 Design Constraints

- Hardware/Software:**
 The project is implemented in Python and leverages libraries such as TensorFlow, Keras, and scikit-learn. It is designed to run on standard computing systems equipped with a GPU for accelerated training.
- Experimental Setup:**
 The system is tested using historical stock data obtained through the Yahoo Finance API. Data preprocessing includes handling missing values and scaling features.

3.3.2 System Architecture OR Block Diagram

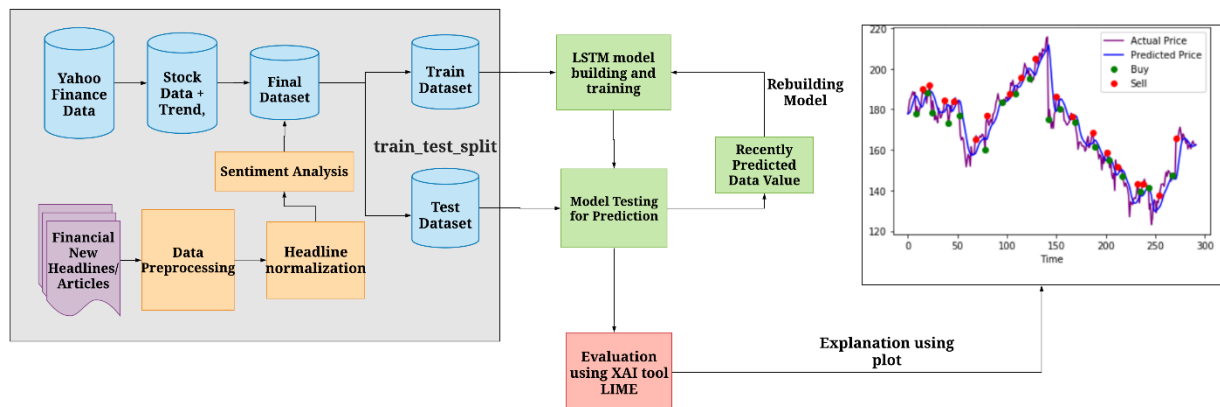


Figure 3.3.2: Stock Price Prediction using LSTM and Sentiment Analysis.

The system architecture comprises six modules:

1. Data Fetching Module: Retrieves stock data.
2. Technical Indicators Module: Computes EMA and Parabolic SAR.
3. Signal Construction Module: Generates feature signals.
4. Sequence Creation Module: Prepares data sequences for the LSTM.
5. LSTM Model Training Module: Constructs and trains the neural network.
6. Result Evaluation Module: Assesses model performance using various metrics.

A block diagram illustrating the flow from data retrieval to prediction can be provided as an appendix in the final submission.

Chapter 4

Implementation

4.1 Methodology OR Proposal

The project implementation is divided into the following key steps:

1. **Data Fetching:**
Historical stock data is fetched using the Yahoo Finance API via the `fetch_data` function. This module ensures that data is properly formatted and cleaned for further processing.
2. **Technical Indicator Computation:**
The functions `calculate_ema` and `calculate_parabolic_sar` compute the EMA and Parabolic SAR respectively. These indicators are crucial for identifying market trends and reversals.
3. **Signal Construction:**
The `construct_signals` function integrates the computed indicators with additional features like trend, return, and volume. This enriched dataset forms the basis for the predictive model.
4. **Sequence Creation for LSTM:**
The `create_sequences_multifeature` function prepares the time-series data in sequences suitable for input into the LSTM network. Each sequence is accompanied by a target label indicating the market direction.
5. **LSTM Model Training:**
The LSTM model is built using the `build_lstm_model` function and trained via `train_lstm_model`. Early stopping and dropout techniques are employed to prevent overfitting, and the model's performance is evaluated using accuracy and loss metrics.
6. **Model Evaluation:**
Model predictions are compared with actual outcomes using a confusion matrix, ensuring the reliability of the forecasting system.

4.2 Testing OR Verification Plan

Testing was conducted at multiple levels:

- **Unit Testing:**
Individual functions for data fetching, indicator computation, and sequence creation were tested with sample datasets.
- **Integration Testing:**
The complete pipeline—from data retrieval to model training—was tested end-to-end.
- **Validation:**
A separate validation dataset (20% of the total data) was used to evaluate the model, with metrics such as accuracy, loss, and confusion matrix generated to verify performance.

4.3 Result Analysis OR Screenshots

- **Training and Validation Metrics:**

The model achieved promising accuracy rates during training and validation. Graphs of training/validation loss and accuracy, along with the confusion matrix, provide visual evidence of the model's performance.

- **Sample Output:**

Logs from the system indicated the number of data points processed, shapes of the training sequences, and the performance metrics after model training.

We are predicting **Tesla's stock** movements from 2023 to 2025 using an LSTM-based model. The analysis includes key indicators such as EMA and PSAR, along with features like trend, volume, and daily return. The visualizations generated include:

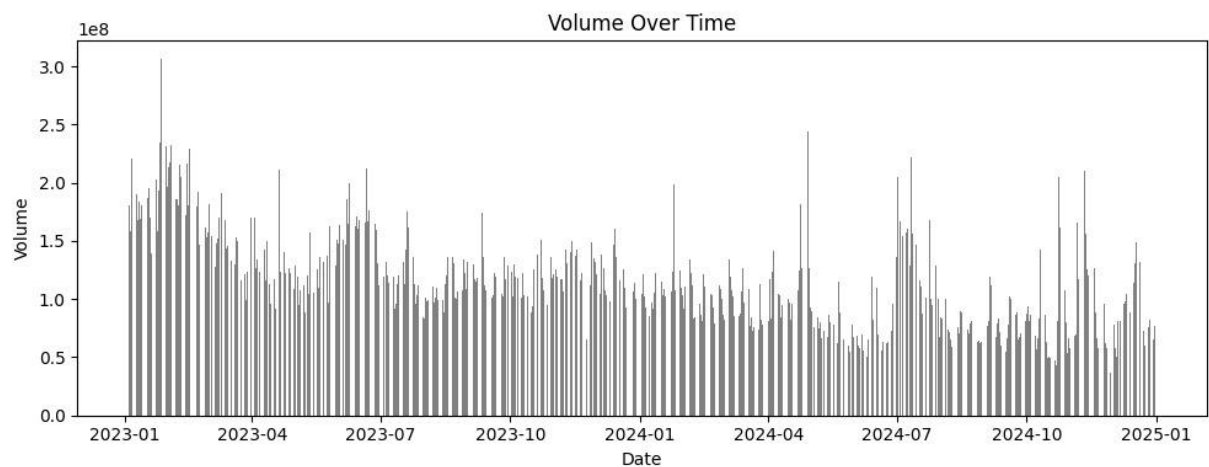


Figure 4.3.1: Volume Over Time

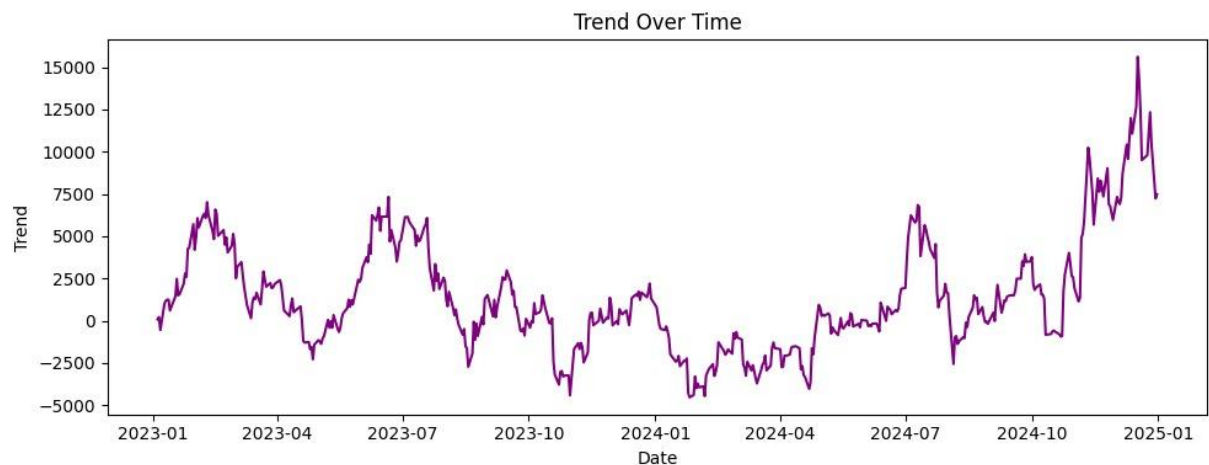


Figure 4.3.2: Trend Over Time

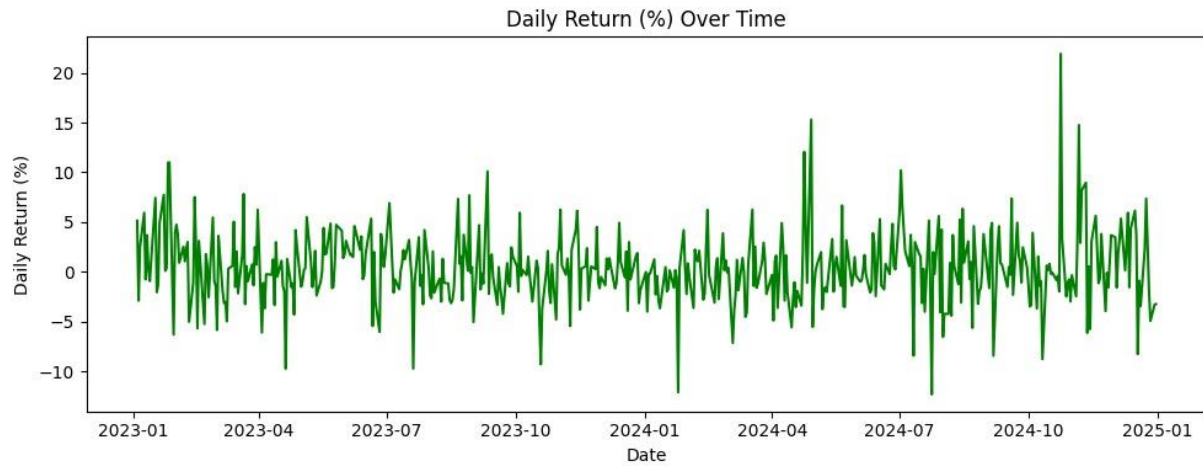


Figure 4.3.2: *Daily Return (%) Over Time*

4.4 Quality Assurance

Quality assurance was ensured through:

- Code reviews by peers and mentors.
- Adherence to coding standards and best practices.
- Rigorous testing using diverse datasets.
- Early stopping and dropout layers in the LSTM model to mitigate overfitting.

Chapter 5

Standards Adopted

5.1 Design Standards

5.1.1 Software Architecture Standards

The project follows a **Modular and Layered Architecture**, ensuring separation of concerns and maintainability. The architecture is divided into:

- **Data Collection Layer:** Responsible for fetching financial data from APIs.
- **Feature Engineering Layer:** Computes technical indicators such as EMA and Parabolic SAR.
- **Prediction Layer:** Implements the Long Short-Term Memory (LSTM) model for stock price forecasting.
- **Visualization & Reporting Layer:** Presents predictions using graphical representations.

This architecture follows Model-View-Controller (MVC) principles where data processing, business logic, and presentation layers are separated to enhance scalability.

5.1.2 UI/UX Standards

For the front-end, the project adheres to **Material Design Guidelines** for UI consistency. The following best practices are followed:

- Responsive design using **Bootstrap & CSS Flexbox**.
- Consistent color scheme ensuring accessibility compliance (WCAG 2.1 AA standard).
- User-friendly navigation and intuitive layout to enhance usability.

5.1.3 Documentation & Version Control Standards

The project employs:

- **Unified Modeling Language (UML)** for system design, including Use Case Diagrams and Sequence Diagrams.
- **Git Version Control (GitHub/GitLab)** with proper commit messages adhering to Conventional Commits.
- **IEEE 830-1998** Standard for Software Requirements Specification (SRS) documentation.

5.2 Coding Standards

5.2.1 Programming Language and Style Guide

The project is implemented using **Python** for the backend and **JavaScript (React.js)** for the frontend. The adopted coding standards include:

- **Python Coding Standards:**
 - Follow **PEP 8 (Python Enhancement Proposal 8)** for coding style.
 - Use **Docstrings** (PEP 257) for function documentation.
 - Apply **Type Hints** (PEP 484) to improve code readability.
 - Maintain modularity by organizing code into reusable classes and functions.
- **JavaScript Coding Standards:**
 - Follow **Airbnb JavaScript Style Guide**.
 - Use **ESLint** for static code analysis.
 - Maintain component-based development using **React.js Functional Components**.
 - Ensure asynchronous operations use **async/await** for readability and error handling.

5.2.2 Naming Conventions

- Variables: snake_case for Python (price_data), camelCase for JavaScript (priceData).
- Constants: Uppercase (API_KEY).
- Function Names: Verb-based (fetch_data(), computeEMA()).
- Class Names: PascalCase (StockPredictor).

5.2.3 Security Standards

- Implement **OAuth 2.0** for API authentication.
- Use **Environment Variables** to store sensitive credentials.
- Prevent **SQL Injection & XSS Attacks** through proper input sanitization.

5.3 Testing Standards

5.3.1 Unit Testing

Each module is tested independently to ensure correctness. The following frameworks are used:

- **pytest** for backend (Python).
- **Jest** for frontend (JavaScript/React).

Test cases are designed based on IEEE 829-2008 Standard for Software Test Documentation, ensuring:

- **Test Case ID:** Unique identifier for each test case.
- **Description:** Clear explanation of what is being tested.
- **Expected Output:** The correct outcome that should be observed.
- **Actual Output:** The observed outcome.
- **Pass/Fail Status:** Whether the test case succeeded or failed.

5.2.2 Integration Testing

Integration testing ensures seamless interaction between modules. Mock testing is used to simulate API responses. The following techniques are applied:

- **Black-box Testing:** Testing without knowledge of internal code.
- **White-box Testing:** Verifying logic flows and dependencies.

5.2.3 Performance & Load Testing

To ensure the system handles large datasets efficiently, **Apache JMeter** is used to simulate heavy API calls and analyze response times. Key Performance metrics include:

- **Throughput:** Number of requests processed per second.
- **Latency:** Time taken for data retrieval.
- **Scalability:** Ability to handle increasing loads.

5.2.4 Security Testing

Security Vulnerabilities are tested using:

- **OWASP ZAP (Zed Attack Proxy)** for penetration testing.
- **SonarQube** for static security analysis.
- **SSL/TLS Security Analysis** for secure data transmission.

Chapter 6

Conclusion and Future Scope

6.1 Conclusion

This project demonstrates the effectiveness of integrating technical analysis with deep learning to predict stock market trends. The developed LSTM model, trained on features derived from EMA, Parabolic SAR, and other market indicators, shows promising results in forecasting stock price direction. The project not only provides a robust framework for financial forecasting but also underscores the potential of deep learning techniques in solving real-world problems.

6.2 Future Scope

Future work can focus on:

- **Expanding the Feature Set:** Incorporating additional indicators and alternative data sources such as news sentiment analysis.
- **Model Enhancement:** Experimenting with more complex deep learning architectures (e.g., bi-directional LSTM, attention mechanisms) to further improve prediction accuracy.
- **Real-Time Implementation:** Deploying the model in a real-time trading environment with live data feeds.

Risk Management: Integrating risk assessment modules to aid in portfolio management decisions.

References

- [1] McKinney, W. (2017). Python for Data Analysis. O'Reilly Media.
- [2] Harris, C. R., et al. (2020). "Array programming with NumPy." *Nature*, 585(7825), 357-362.
- [3] Hunter, J. D. (2007). "Matplotlib: A 2D graphics environment." *Computing in Science & Engineering*, 9(3), 90-95.
- [4] Waskom, M. (2021). "Seaborn: statistical data visualization." *Journal of Open Source Software*, 6(60), 3021.
- [5] Abadi, M., et al. (2016). "TensorFlow: A system for large-scale machine learning." 12th USENIX Symposium on Operating Systems Design and Implementation (OSDI 16), 265-283.
- [6] Chollet, F. (2017). *Deep Learning with Python*. Manning Publications.
- [7] Pedregosa, F., et al. (2011). "Scikit-learn: Machine learning in Python." *Journal of Machine Learning Research*, 12, 2825-2830.

STOCK MARKET PREDICTION USING LSTM

TATHAGATO BHATTACHARJEE
2206145

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I was responsible for Modules 1 and 2, which involved data fetching, cleanup, and implementing technical indicators such as the Exponential Moving Average (EMA) and Parabolic SAR (PSAR). I ensured that historical stock data was correctly retrieved using Yahoo Finance and processed for further analysis. Additionally, I worked on computing the EMA to capture market trends and implementing the PSAR for detecting trend reversals. Through this, I learned the significance of technical indicators in stock prediction and the importance of data preprocessing in machine learning. Debugging real-time financial data inconsistencies was an insightful challenge.

Individual contribution to project report preparation: I contributed to writing Chapters 1 and 2, detailing the project's introduction, background, objectives, and data preprocessing methodologies.

Individual contribution for project presentation and demonstration: I contributed to explaining the data collection and preprocessing steps, ensuring that the audience understood how raw stock data was prepared for model training. I also demonstrated the technical indicators' role in feature extraction.

Full Signature of Supervisor:

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Full signature of the student:

.....

STOCK MARKET PREDICTION USING LSTM

SMRUTI RANJAN ROUT
2206131

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I collaborated on Modules 1 and 2, focusing on ensuring that stock market data was fetched accurately and preprocessed for further analysis. My role involved cleaning data, handling missing values, and integrating technical indicators such as EMA and PSAR into the dataset. Working on financial time-series data helped me understand the challenges of real-world data processing, especially handling gaps in financial datasets. I also learned the importance of feature engineering in improving machine learning model performance.

Individual contribution to project report preparation: I contributed to writing Chapters 1 and 2, covering project objectives, methodology, and preprocessing techniques.

Individual contribution for project presentation and demonstration: I helped prepare slides related to data acquisition and preprocessing. During the demonstration, I explained how the technical indicators were computed and their significance in predicting stock trends.

Full Signature of Supervisor:

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Full signature of the student:

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STOCK MARKET PREDICTION USING LSTM

RAJDEEP THAKUR
2206113

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I was responsible for Modules 3, 4 and 5, where I constructed trading signals, created sequences for the LSTM model, and built and trained the deep learning model. I also integrated all modules in the main execution. My work involved feature engineering, creating input sequences for LSTM and implementing early stopping to prevent overfitting. Through this, I gained valuable insights into deep learning models for time-series forecasting, the importance of data scaling, and optimizing neural network architectures for better accuracy.

Individual contribution to project report preparation: I wrote Chapters 4 and 5, detailing the model architecture, training procedures, and evaluation metrics.

Individual contribution for project presentation and demonstration: I presented the core machine learning model, explaining how the LSTM network was designed, trained, and optimized. I also demonstrated the model's predictions and validation results.

Full Signature of Supervisor:

.....

Full signature of the student:

.....

STOCK MARKET PREDICTION USING LSTM

ANSHUMAN GHOSH
2206074

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I contributed to Module 6, where I worked on the data visualization and analysis of model outputs. My role involved plotting feature correlations, trends, and other key metrics. Through this, I learned how different technical indicators influence stock price movements and how visualization techniques help in understanding model predictions. I also analyzed model performance by examining accuracy and confusion matrices.

Individual contribution to project report preparation: I contributed to writing Chapter 3, explaining the feature extraction and data transformation processes.

Individual contribution for project presentation and demonstration: I presented the data visualization part, demonstrating how different financial indicators and model predictions were analyzed using heatmaps, trend graphs, and correlation matrices.

Full Signature of Supervisor:

.....

Full signature of the student:

.....

STOCK MARKET PREDICTION USING LSTM

DEBDIP CHATTERJEE
2206087

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I worked on Module 7 alongside Anshuman Ghosh, focusing on visualizing financial trends and analyzing prediction results. My primary role involved ensuring that key market trends were accurately represented through various charts. I also helped interpret the results from our machine learning model and compare them with actual stock movements. This helped me understand the impact of different market factors on model predictions.

Individual contribution to project report preparation: I contributed to writing Chapter 3, discussing the role of financial indicators and their effect on prediction accuracy.

Individual contribution for project presentation and demonstration: I assisted in presenting the graphical insights, demonstrating how data visualization techniques helped in evaluating model effectiveness.

Full Signature of Supervisor:

.....

Full signature of the student:

.....

STOCK MARKET PREDICTION USING LSTM

SUMANDEEP SAHOO
2206302

Abstract: This project aims to develop an intelligent stock prediction system by integrating technical indicators with advanced deep learning techniques. The objective is to leverage historical financial data to compute key indicators such as EMA and Parabolic SAR, construct predictive signals, and train an LSTM-based model for forecasting market trends. Through modular design and collaborative development, the project demonstrates an innovative approach to addressing the challenges of volatile financial markets while providing valuable insights for trading strategies.

Individual contribution and findings: I was responsible for developing and refining the frontend website that interfaced with our ML model. My role involved designing a user-friendly UI that allowed users to input stock symbols and view model predictions in real time. Integrating the backend ML model with the frontend was a key challenge, requiring seamless data transfer and visualization. This experience enhanced my understanding of full-stack development and API integrations for ML-based applications.

Individual contribution to project report preparation: I contributed to writing Chapter 6, detailing the frontend design, API integration, and user interaction features.

Individual contribution for project presentation and demonstration: I demonstrated the working of the frontend application, showcasing how users can interact with the model's predictions. I also explained the integration process and the technologies used for frontend development.

Full Signature of Supervisor:

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Full signature of the student:

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Stock Prediction Using LSTM

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