Project Report

On

Deep Learning Approach to Mitigate Financial Risk

Submitted
In partial fulfilment
For the award of the Degree of

PG-Diploma in Big Data Analytics

(C-DAC, ACTS (Pune))

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ABSTRACT

This project explores the application of deep learning techniques to predict stock prices and mitigate financial risk. By leveraging a Long Short-Term Memory (LSTM) model, we analyse historical stock market data to forecast future prices. Our approach begins with fetching data from the Yahoo Finance API, which is then stored in a MySQL database to ensure efficient data management and retrieval.

The core of our methodology involves training the LSTM model on the historical data to capture long-term dependencies and trends. We then forecast stock prices for the upcoming month, providing valuable insights into potential market movements and associated risks.

The predicted results are visualized through an interactive Streamlit app, which offers functionalities for fetching data, training the model, forecasting prices, and displaying various risk metrics. This interactive platform allows users to dynamically explore the data and gain a comprehensive understanding of the financial risks involved.

To further enhance the analysis, we utilize Tableau for advanced visualization. This integration enables the creation of detailed dashboards and reports, offering a holistic view of stock market trends and facilitating informed decision-making and strategic investment planning.

Our project demonstrates the potential of combining advanced deep learning models with modern data visualization tools to address complex financial challenges. By providing a robust tool for financial risk mitigation, we aim to support investors in making data-driven decisions and navigating the uncertainties of the stock market.

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Chapter 1
Introduction

1.1 Introduction

In the volatile world of stock markets, predicting future price movements is a critical challenge for investors and financial analysts. Traditional methods often fall short in capturing the complex patterns and dependencies in financial data. This project addresses this gap by leveraging advanced deep learning techniques to enhance the accuracy of stock price predictions and mitigate financial risk.

Our approach utilizes a Long Short-Term Memory (LSTM) model, known for its ability to handle sequential data and capture long-term dependencies. By fetching historical stock data from the Yahoo Finance API and storing it in a MySQL database, we ensure efficient data management and retrieval. The LSTM model is then trained on this data to forecast future stock prices.

The need for this project arises from the limitations of conventional forecasting methods and the increasing demand for more accurate and reliable financial predictions. By providing a robust tool for predicting stock prices, we aim to support investors in making informed decisions and navigating market uncertainties.

The benefits of our project are multifaceted:

- **Enhanced Prediction Accuracy**: The LSTM model improves the accuracy of stock price forecasts by capturing complex patterns in historical data.

- **Interactive Visualization**: The use of a Streamlit app allows users to dynamically fetch data, train the model, forecast prices, and visualize results, making the process user-friendly and interactive.

- **Comprehensive Risk Analysis**: By incorporating risk metrics users gain a deeper understanding of potential financial risks.

- **Advanced Insights**: The integration of Tableau and Power BI for advanced visualization provides detailed dashboards and reports, offering a holistic view of market trends and aiding strategic investment planning.

Overall, this project demonstrates the potential of combining deep learning models with modern data visualization tools to address complex financial challenges and support data-driven decision-making in stock trading.

1.2 Objective

The objectives of the project work are as -

1. **Data Collection and Preprocessing**:
    - **Fetch Historical Data**: Gather historical stock price data from the Yahoo Finance API, covering a period of five years. This data includes daily prices, trading volumes, and other relevant financial indicators.
2. **Model Training and Forecasting**:
    - **Train LSTM Model**: Use the pre-processed data to train a Long Short-Term Memory (LSTM) model. LSTM is chosen for its ability to capture long-term dependencies and patterns in time series data, making it ideal for stock price prediction.
    - **Predict Stock Prices**: Utilize the trained LSTM model to forecast stock prices for the next 30 days. These predictions provide insights into potential future market movements and trends.
3. **Risk Categorization**:
    - **Categorize Stocks**: Based on the predicted stock prices, categorize stocks into different risk levels. For example, stocks with high predicted volatility might be categorized as high-risk, while more stable stocks might be categorized as low-risk.
    - **Risk Assessment**: Provide a detailed risk assessment for each stock, helping investors understand the potential risks associated with their

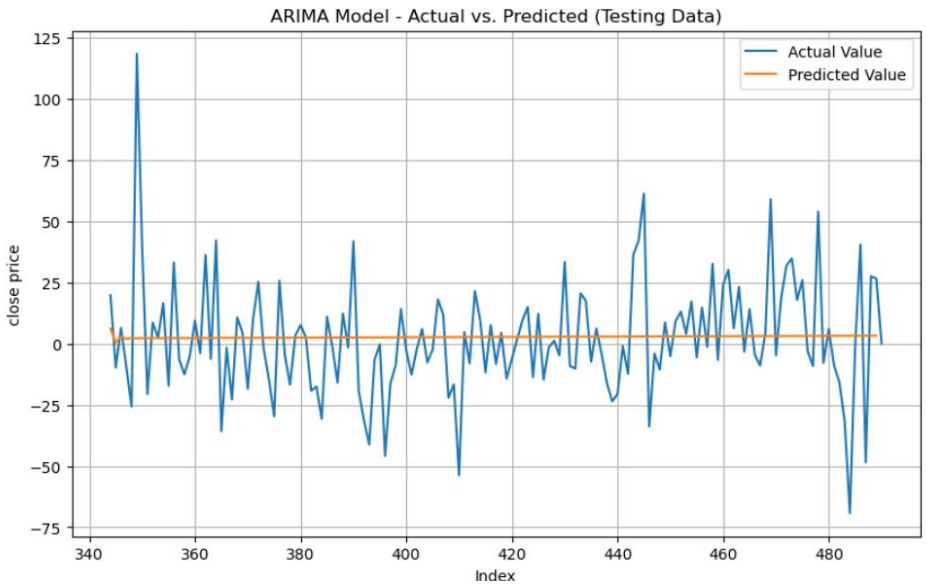
investments.

4. **User Interface Development**:
    - **Develop Streamlit App**: Create an interactive application using Streamlit. This app allows users to input stock symbols and view the predicted prices and associated risk levels in an intuitive manner.
    - **User-Friendly Interface**: Ensure the app is user-friendly and accessible, making it easy for investors to interact with the predictions and risk categorizations.
5. **Data Visualization**:
    - **Create Dashboards in Tableau and Power BI**: Develop interactive dashboards using Tableau and Power BI to visualize the forecasted stock prices and risk levels. These dashboards provide a clear and intuitive representation of the data, making it easier for users to interpret and understand.
    - **Visual Insights**: Use various charts, graphs, and other visual elements to present the data in a way that highlights key insights and trends.

Chapter 2

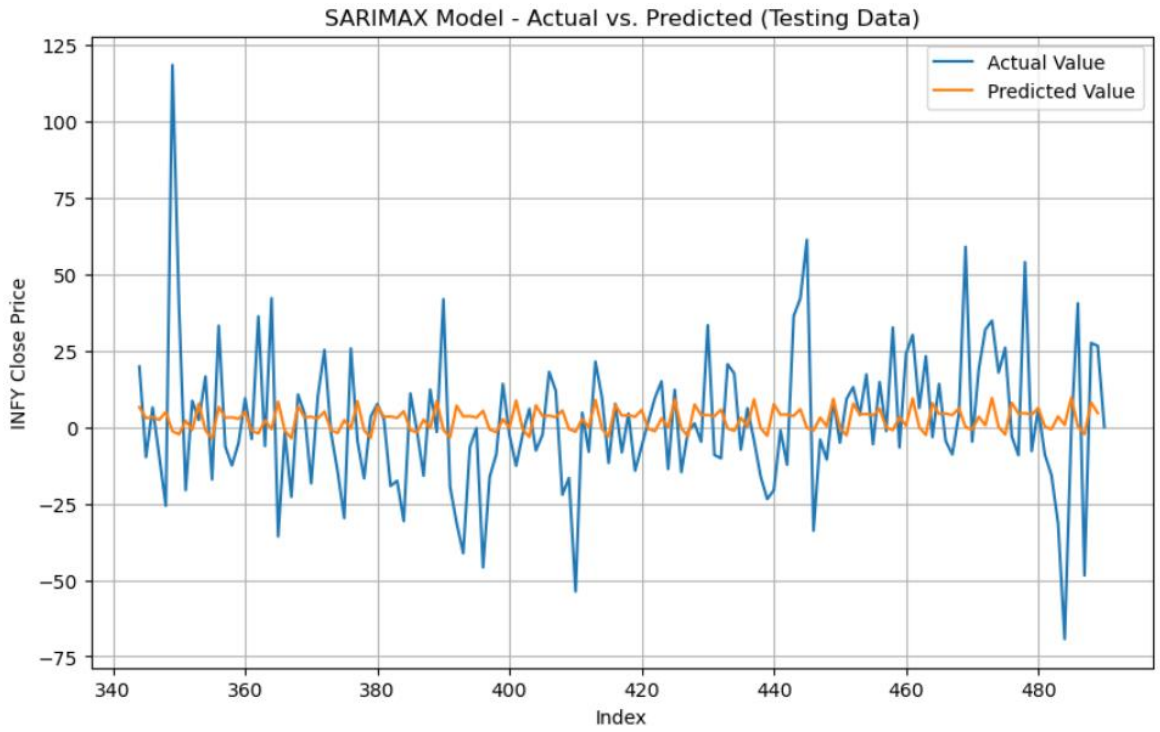
Comparative Analysis

Comparative Analysis of Time Series Forecasting Models: ARIMA, SARIMA, and LSTM




```
RMSE: 23.545967804941494
MAE: 17.307664641677206
R-squared: 0.0023065844335615 76
```

ARIMA




```
RMSE: 23.861024620548225
MAE: 17.399243351420502
R-squared: -0.024571313307482523
```

SARIMAX

In this section, we compare the performance of three time series forecasting models: ARIMA, SARIMAX, and LSTM, to elucidate why LSTM emerges as the superior choice for stock price prediction in our project.

ARIMA and SARIMAX Models

ARIMA (AutoRegressive Integrated Moving Average) is a classical time series forecasting model suitable for stationary data where the mean and variance are constant over time. It effectively captures linear trends and cyclic patterns but can be limited in handling more complex data behaviours. SARIMAX (Seasonal

AutoRegressive Integrated Moving Average with eXogenous regressors) extends ARIMA by including seasonal components and external regressors, which makes it adept at managing seasonal variations and additional influencing factors.

Despite their strengths, both ARIMA and SARIMAX face significant challenges when dealing with non-linear patterns and long-term dependencies inherent in financial time series data. These models rely on linear assumptions and stationarity, which can be restrictive for stock price data that often exhibits complex, non-linear behaviors. Additionally, ARIMA and SARIMAX models require meticulous parameter tuning and can be sensitive to hyperparameter choices, impacting their overall forecasting performance.

LSTM Model

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to capture long-term dependencies and non-linear relationships in sequential data. LSTMs excel in learning and modeling complex patterns within time series data, making them particularly effective for stock price prediction, where market trends and interactions can be highly non-linear. LSTMs are equipped with memory cells and gating mechanisms that enable them to retain and process information over extended periods, allowing for a more nuanced understanding of the temporal dynamics in financial data. This capability is crucial for predicting stock prices, which often involve intricate and non-linear trends that traditional models like ARIMA and SARIMAX may not fully capture.

Why LSTM is Preferable

1. **Non-linearity Handling**: LSTMs are capable of modeling non-linear relationships and complex patterns in stock price movements. Unlike ARIMA and SARIMAX, which are linear models, LSTMs can address the non-linear trends and interactions present in financial data, offering a more accurate representation of market behavior.

2. **Long-Term Dependencies**: LSTMs are designed to manage long-term dependencies within time series data. This is particularly beneficial for stock price forecasting, where understanding the prolonged effects of past data is essential. In contrast, ARIMA and SARIMAX may struggle with capturing such long-term dependencies due to their reliance on linear assumptions and fixed lags.

3. **Flexibility and Adaptability**: LSTMs can incorporate a wide range of features and inputs, including historical prices, trading volumes, and other financial indicators. This flexibility allows LSTMs to leverage a broader spectrum of information compared to ARIMA and SARIMAX, which are constrained by specific forms of lagged observations and seasonal components.

4. **Robustness to Stationarity Assumptions**: Unlike ARIMA and SARIMAX, LSTMs do not require the data to be stationary. This robustness makes LSTMs more applicable to real-world financial data, which often does not meet the strict assumptions of constant mean and variance required by traditional models.

Chapter 3

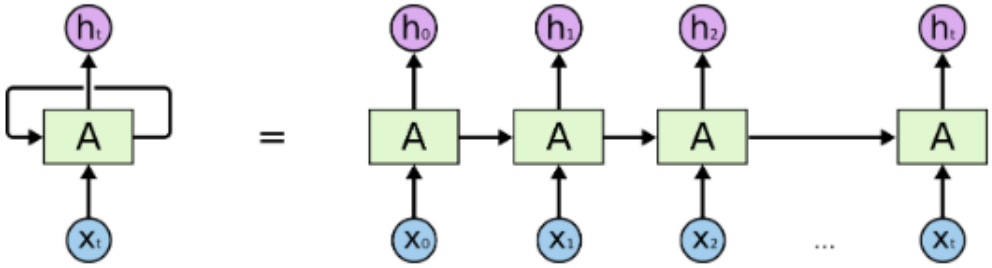
Methodology and Techniques

3.1 Methodology:

3.1.1 RNN

Recurrent Neural Networks (RNNs) are a type of artificial neural network designed to recognize patterns in sequences of data, such as time series, speech, or text. Unlike traditional feedforward neural networks, RNNs have connections that form directed cycles, allowing them to maintain a 'memory' of previous inputs. This makes them particularly well-suited for tasks where context and sequential information are crucial. RNNs use a hidden state to capture information about the sequence, which is updated at each time step based on the current input and the previous hidden state. They employ three sets of weights: input weights, recurrent weights, and output weights, and typically use non-linear activation functions like tanh or ReLU. Training RNNs involves calculating the loss over the entire sequence and using Backpropagation Through Time (BPTT) to compute gradients. However, RNNs can suffer from vanishing or exploding gradients, making training difficult. Advanced architectures like Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU) address these issues by including mechanisms to control the flow of information and gradients, effectively capturing long-term dependencies. RNNs are widely used in applications such as time series prediction, natural language processing, and speech recognition. In your project, using an LSTM model helps predict stock prices by capturing temporal dependencies in historical stock data, providing a comprehensive solution for mitigating financial risk when combined with data visualization tools like Streamlit and Power BI.

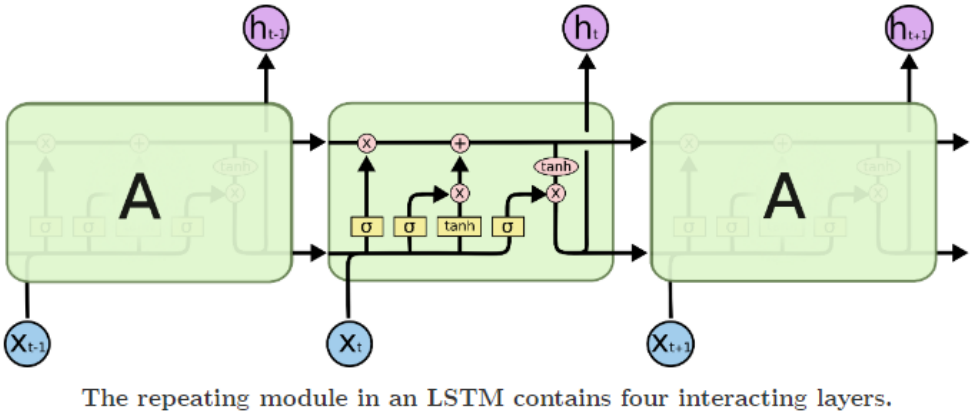
Fig.1 RNN



An unrolled recurrent neural network.

3.1.2 LSTM

To build and train an LSTM model for predicting stock prices and mitigating financial risk, start by collecting historical stock data using the Yahoo Finance API and storing it in a MySQL database. Preprocess the data by normalizing it and creating sequences of 60 days of historical data. Split the data into training and test sets. Design the LSTM model with two LSTM layers, each followed by a Dropout layer to prevent overfitting, and a Dense layer for the output. LSTM layers are particularly effective because they include memory cells that can store information for long periods, addressing the vanishing gradient problem common in traditional RNNs. These memory cells are controlled by three gates: the input gate, which decides what new information to store; the forget gate, which determines what information to discard; and the output gate, which controls what information is output from the cell. Compile the model using the Adam optimizer and Mean Squared Error loss function. Train the model with early stopping to avoid overfitting, using a validation split of 20%. After training, use the model to forecast stock prices for the next 30 days by iteratively predicting the next day's price and updating the input sequence. Visualize the forecasted prices using Streamlit for an interactive dashboard, providing a comprehensive solution for financial risk mitigation.



The repeating module in an LSTM contains four interacting layers.

Fig 2. LSTM Architecture

3.2 Dataset

To build a dataset for predicting stock prices and mitigating financial risk, start by collecting historical stock data for Nifty 50 companies using the Yahoo Finance API. This data includes key financial metrics such as open, high, low, close, adjusted close prices, and trading volume for each stock. Store the collected data in a MySQL database for efficient retrieval and management. Preprocess the data by normalizing the stock prices to a range between 0 and 1, and handle any missing values using techniques like forward fill or interpolation. Perform feature engineering to create additional predictive features such as moving averages and volatility measures, which provide valuable insights into stock performance and risk. Split the dataset into training, validation, and test sets to evaluate the model's performance accurately. The training set is used to train the machine learning model, the validation set is used to tune the model's hyperparameters, and the test set is used to assess the model's performance on unseen data. This structured approach ensures that the dataset is robust and comprehensive, ready for use in predictive modeling and financial risk assessment. By leveraging tools like yfinance, pandas, and sqlalchemy, you can efficiently manage and analyze large datasets, providing valuable insights into stock price movements and associated risks. This methodology ensures a well-prepared dataset that supports effective stock price prediction and financial risk mitigation.

3.1.3 Model Description

Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to effectively capture long-term dependencies in sequential data. They address the vanishing gradient problem that traditional RNNs face, making them particularly suitable for tasks involving time series prediction, natural language processing, and speech recognition. The core of an LSTM is its memory cell, which retains information over long periods. This cell is crucial for remembering values across arbitrary time intervals. LSTMs use three types of gates to control the flow of information: the input gate, which determines which new information is added to the memory cell; the forget gate, which decides what information from the memory cell should be discarded; and the output gate, which controls what information is output from the memory cell.

In your project, the LSTM model is designed with two LSTM layers. The first LSTM layer has 50 units and is set to return sequences, which means it outputs the full sequence of hidden states for each input time step. This is followed by a Dropout layer with a dropout rate of 0.2 to prevent overfitting. The second LSTM layer also has 50 units but does not return sequences, meaning it only outputs the hidden state at the last time step. This is followed by another Dropout layer with a dropout rate of 0.2. A Dense layer with a single unit is added as the output layer, responsible for producing the final prediction.

The model is compiled using the Adam optimizer and Mean Squared Error (MSE) as the loss function. The Adam optimizer is chosen for its efficiency and ability to handle sparse gradients. Early stopping is implemented to prevent overfitting, monitoring the validation loss and stopping training if it does not improve for 10 consecutive epochs. The best weights are restored at the end of training. The model is trained on the training dataset with a validation split of 20%, involving 100 epochs with a batch size of 32. The training is performed silently (verbose=0) to avoid cluttering the output.

After training, the model is used to forecast stock prices for the next 30 days. The forecasting process involves preparing the last 60 days of scaled data as the input

sequence for the model. The model predicts the next day's price, which is then appended to the input sequence, and the process is repeated for 30 iterations to generate the forecast for the next 30 days. The forecasted prices are transformed back to the original scale using the inverse transform of the scaler.

The forecasted prices are visualized using Streamlit, an interactive web application framework. The results are displayed in a line chart, allowing users to hover over the chart to see the forecasted prices. This visualization provides a comprehensive view of the predicted stock prices and helps in assessing financial risk. By leveraging the advanced capabilities of LSTM networks, your project can effectively predict stock prices and provide valuable insights for financial risk mitigation. The combination of data preprocessing, model training, and interactive visualization ensures a robust and comprehensive solution for financial analysis.

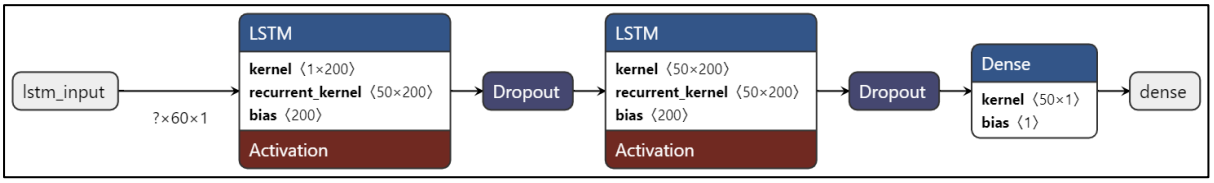


Fig 3. Model Visualization

```
[9]: # Print model summary
     model.summary()
```

```
Model: "sequential_1"
```

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 60, 50)	10,400
dropout_2 (Dropout)	(None, 60, 50)	0
lstm_3 (LSTM)	(None, 50)	20,200
dropout_3 (Dropout)	(None, 50)	0
dense_1 (Dense)	(None, 1)	51

```
Total params: 91,955 (359.20 KB)
Trainable params: 30,651 (119.73 KB)
Non-trainable params: 0 (0.00 B)
Optimizer params: 61,304 (239.47 KB)
```

Fig 4. Model Summary

Chapter 4

Implementation

1. Use of Python Platform for writing the code with **Keras**, **TensorFlow**, **Streamlit**
2. Hardware and Software Configuration:

Hardware Configuration:

- CPU: 16 GB RAM, Octa core processor
- GPU: 4 GB Nvidia's RTX 3050 Ti

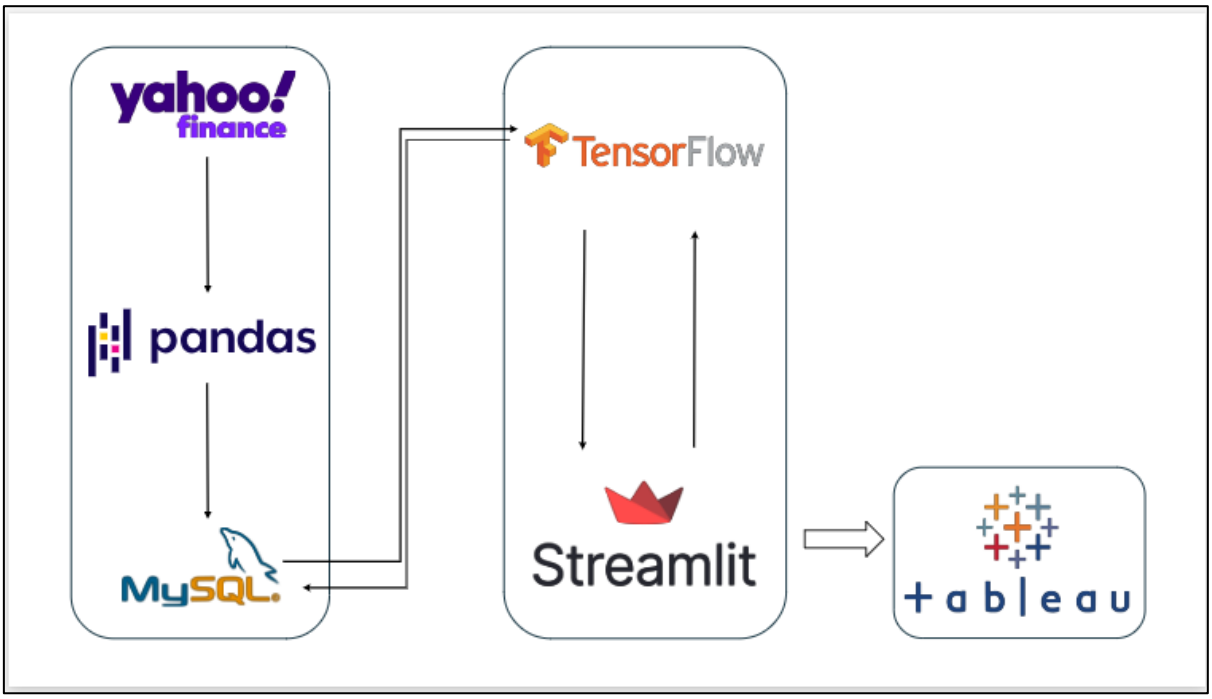


Fig 5. Project Architecture

Software Required:

- **Jupyter Notebook**:
  Jupyter is a web-based interactive development environment for Jupyter notebooks, code, and data.
  Jupyter is flexible: configure and arrange the user interface to support a wide range of workflows in data science, scientific computing, and machine learning.
  Jupyter is extensibleand modular: write plugins that add new components and integrate with existing ones.

- **MY SQL** : **Database Management System**
  The project utilizes **MySQL Server** as its primary relational database management system (RDBMS) due to its scalability, ACID compliance, and efficient handling of structured data. MySQL ensures data integrity and supports complex queries essential for diverse data management needs.

  Programming Libraries
  Python serves as the project's primary programming language, supported by essential libraries:
  SQLAlchemy: A Python SQL toolkit and ORM library facilitating database interactions, query execution, and schema management.
  pymysql: A Python MySQL client library enabling secure and efficient communication between Python and MySQL, handling SQL queries and database transactions seamlessly.

- **Tableau**
  Tableau is utilized in the project for data visualization and analytics. It offers intuitive dashboards and interactive visualizations, facilitating insightful data exploration and presentation. Tableau connects seamlessly with various data sources, including MySQL, enabling real-time data analysis and reporting. Its robust features for data blending, drill-down analysis, and dashboard creation empower users to derive meaningful insights from complex datasets efficiently.

- **Power BI**
  Power BI serves as a key tool for data modeling, visualization, and business intelligence in the project. It provides powerful data integration

```
# Function to fetch data from Yahoo Finance and save to MySQL
def fetch_data_from_yahoo():
    # Define the tickers for Nifty 50 companies
    nifty_50_tickers = [
        "RELIANCE.NS", "TCS.NS", "HDFCBANK.NS", "INFY.NS", "ICICIBANK.NS", "HINDUNILVR.NS",
        "KOTAKBANK.NS", "LT.NS", "AXISBANK.NS", "ITC.NS", "BAJFINANCE.NS", "SBIN.NS",
        "HCLTECH.NS", "BHARTIARTL.NS", "ASIANPAINT.NS", "HDFCLIFE.NS", "MARUTI.NS", "SUNPHARMA.NS",
        "ULTRACEMCO.NS", "WIPRO.NS", "NTPC.NS", "ADANIGREEN.NS", "TITAN.NS", "NESTLEIND.NS",
        "POWERGRID.NS", "DIVISLAB.NS", "ONGC.NS", "JSWSTEEL.NS", "ADANIPORTS.NS", "GRASIM.NS",
        "TECHM.NS", "TATAMOTORS.NS", "BAJAJ-AUTO.NS", "COALINDIA.NS", "HEROMOTOCO.NS",
        "DRREDDY.NS", "BPCL.NS", "TATASTEEL.NS", "SHREECEM.NS", "CIPLA.NS", "BRITANNIA.NS",
        "SBILIFE.NS", "ADANIENT.NS", "APOLLOHOSP.NS", "HINDALCO.NS", "TATACONSUM.NS",
        "M&M.NS", "INDUSINDBK.NS", "UPL.NS", "BAJAJFINSV.NS", "VEDL.NS"
    ]
    # Fetch data for the last 2 years
    data_frames = []
    for stock in nifty_50_tickers:
        data = yf.download(stock, period='2y', interval='1d')
        data['Ticker'] = stock
        data.reset_index(inplace=True)
        data_frames.append(data)
```

capabilities, connecting easily with MySQL and other data sources. Power BI's drag-and-drop interface and interactive visuals allow for intuitive report creation and dashboard development. It supports advanced analytics through its DAX (Data Analysis Expressions) language and integrates well with Microsoft ecosystem tools, enhancing collaboration and data-driven decision-making processes within the project.

Fig 6. Data fetch code

```
# Function to fetch data for a selected ticker
def fetch_data(selected_ticker):
    query = f"SELECT Date_time, Close FROM nifty_data_002 WHERE Ticker = '{selected_ticker}' ORDER BY Date_time"
    data = pd.read_sql(query, engine)
    data['Date_time'] = pd.to_datetime(data['Date_time'])
    data.set_index('Date_time', inplace=True)
    return data

# Function to build and train the LSTM model
def train_model(X_train, y_train):
    model = Sequential()
    model.add(LSTM(50, return_sequences=True, input_shape=(X_train.shape[1], 1)))
    model.add(Dropout(0.2))
    model.add(LSTM(50, return_sequences=False))
    model.add(Dropout(0.2))
    model.add(Dense(1))  # Output layer

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

    early_stopping = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)
    model.fit(X_train, y_train, epochs=100, batch_size=32, validation_split=0.2, callbacks=[early_stopping], verbose=0)

    return model
```

Fig 7. Train_model function

Streamlit UI :

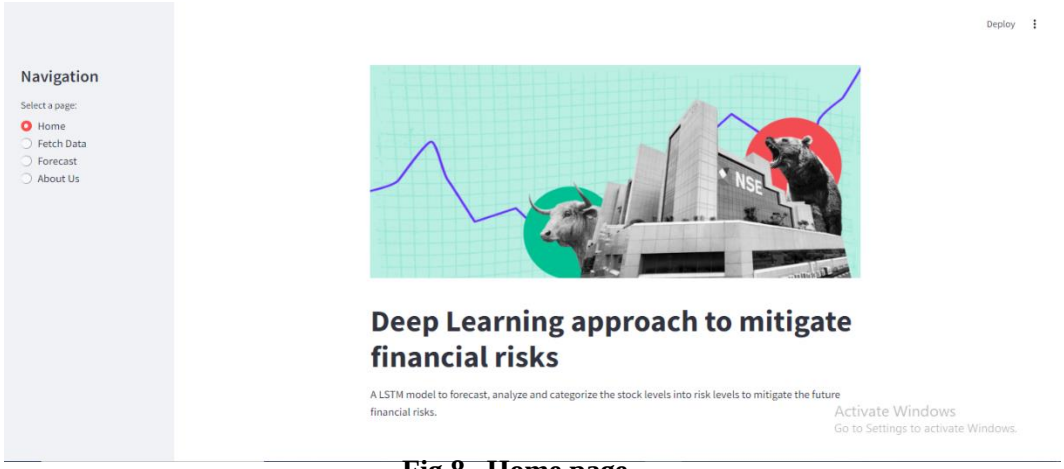


Fig 8. Home page

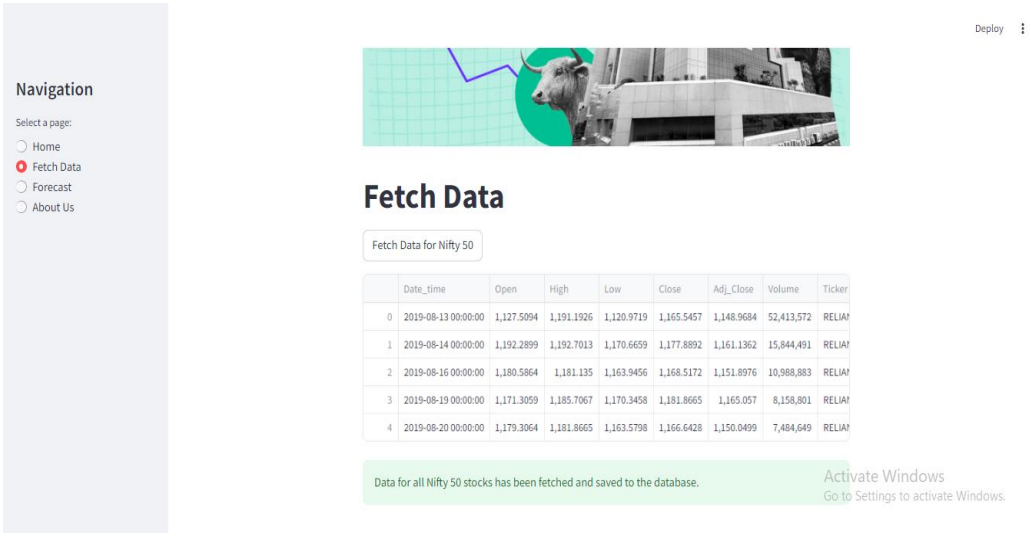


Fig 9. Fetched data

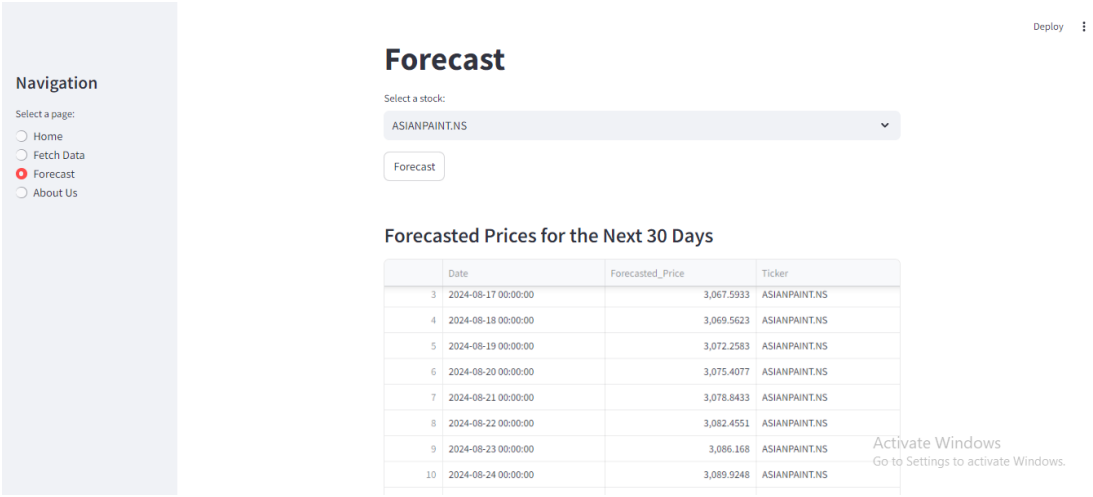


Fig 10. Forecasted data

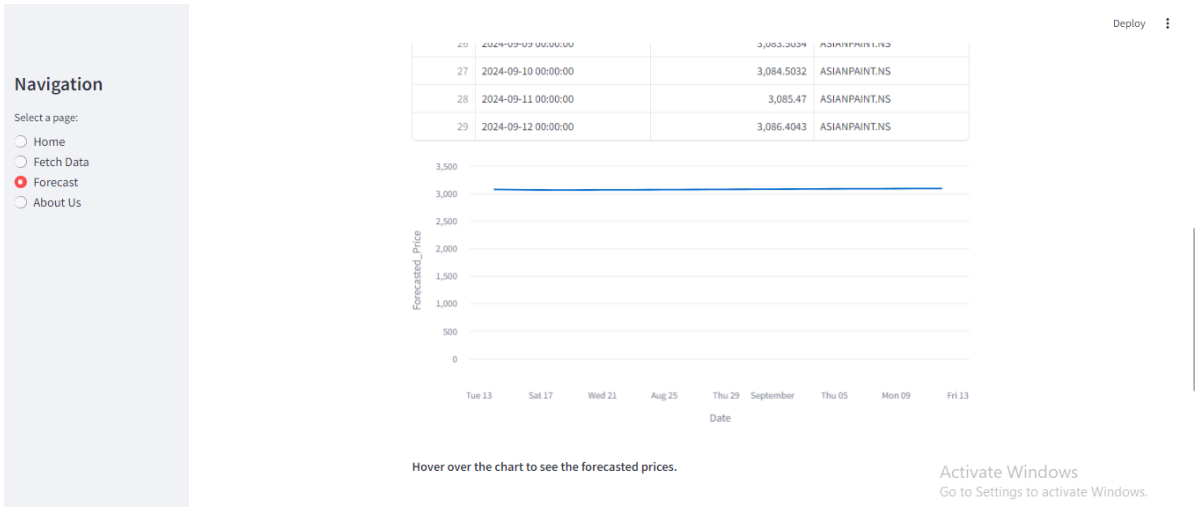
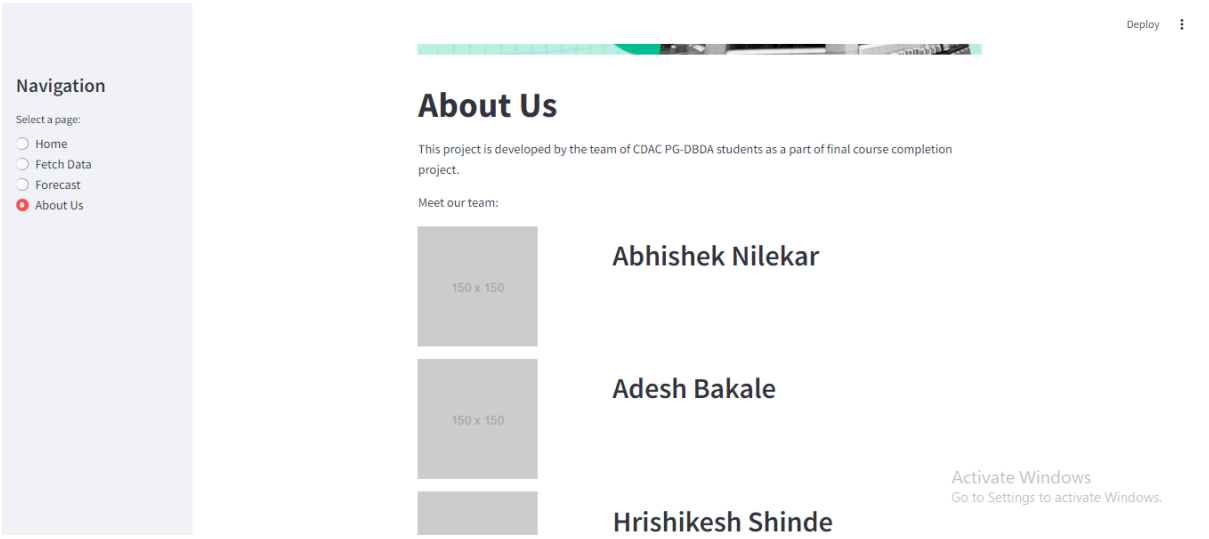


Fig 11. Forecasted Line Graph

Fig 12. Risk Matrix

Fig 13. About Us



Chapter 5

Results

Accuracy score

```
[10]: print(f'Mean Absolute Error: {mae:.2f}')
      print(f'Mean Squared Error: {mse:.2f}')
      print(f'Root Mean Squared Error: {rmse:.2f}')
      print(f'R2 Score: {r2:.2f}')

      Mean Absolute Error: 29.94
      Mean Squared Error: 1567.64
      Root Mean Squared Error: 39.59
      R2 Score: 0.96
```

Fig 14. Accuracy Score

Some Predicted Results –

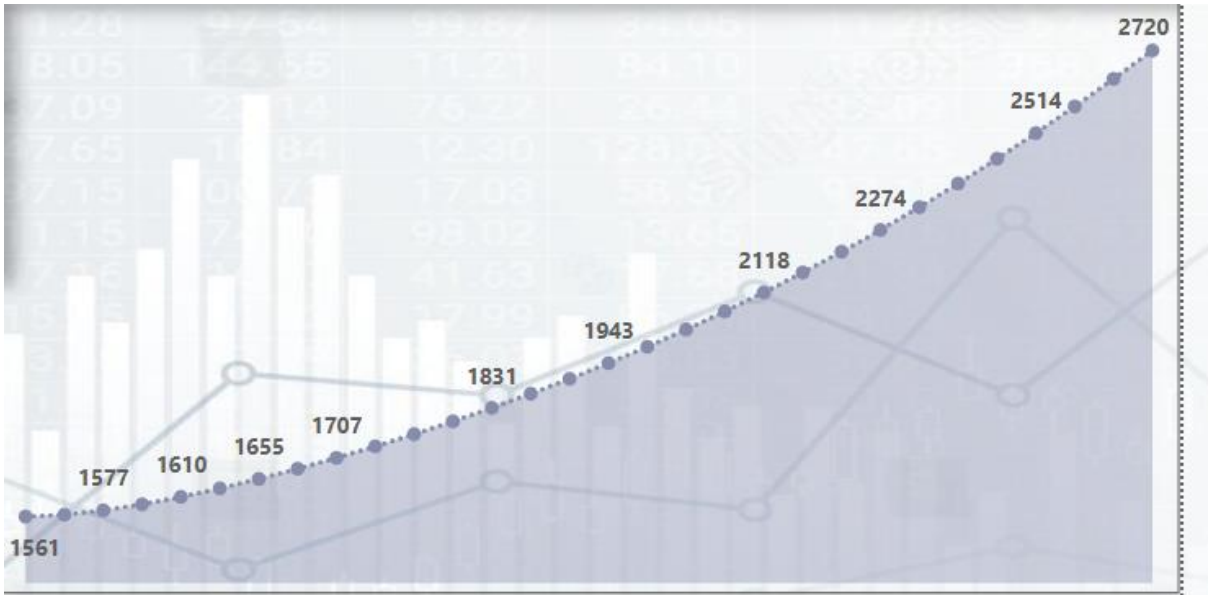


Fig 15. BHARTIARTL.NS prediction

Fig 16. ADANIGREEN.NS prediction

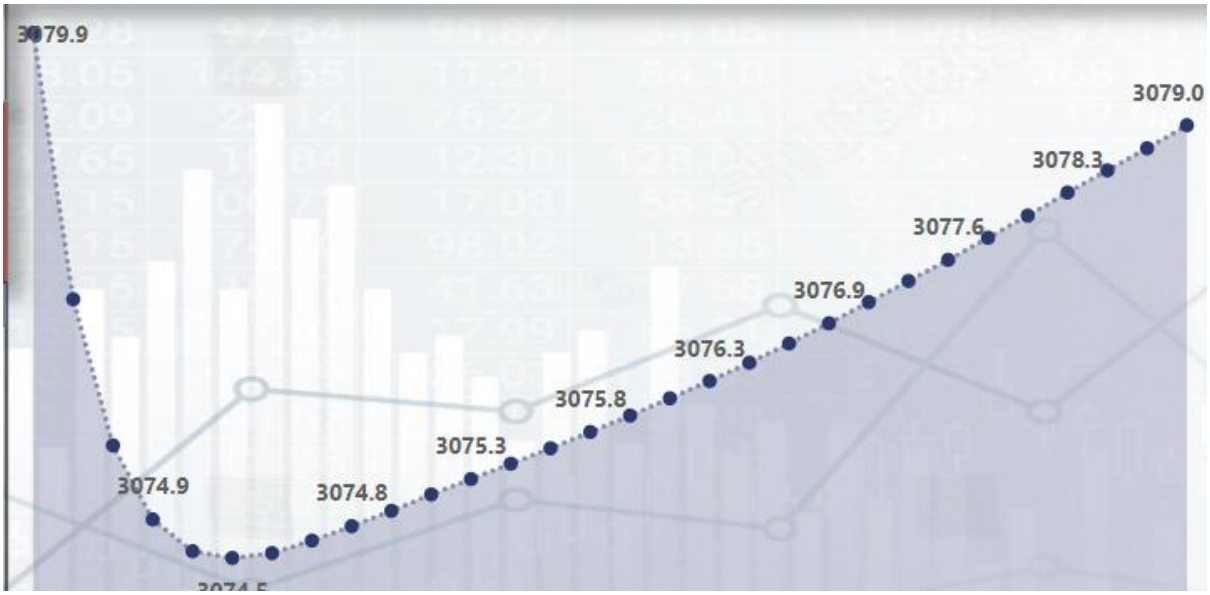


Fig 17. ASIANPAINTS .NS prediction

5.2 Dashboards:

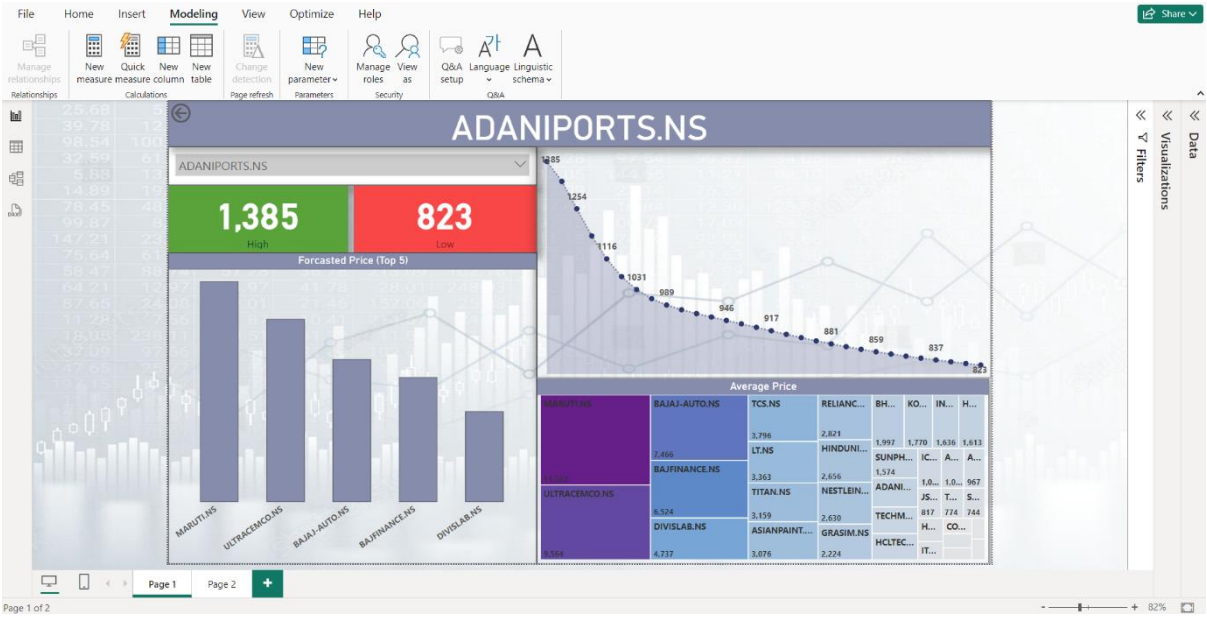


Fig 18. Power Bi

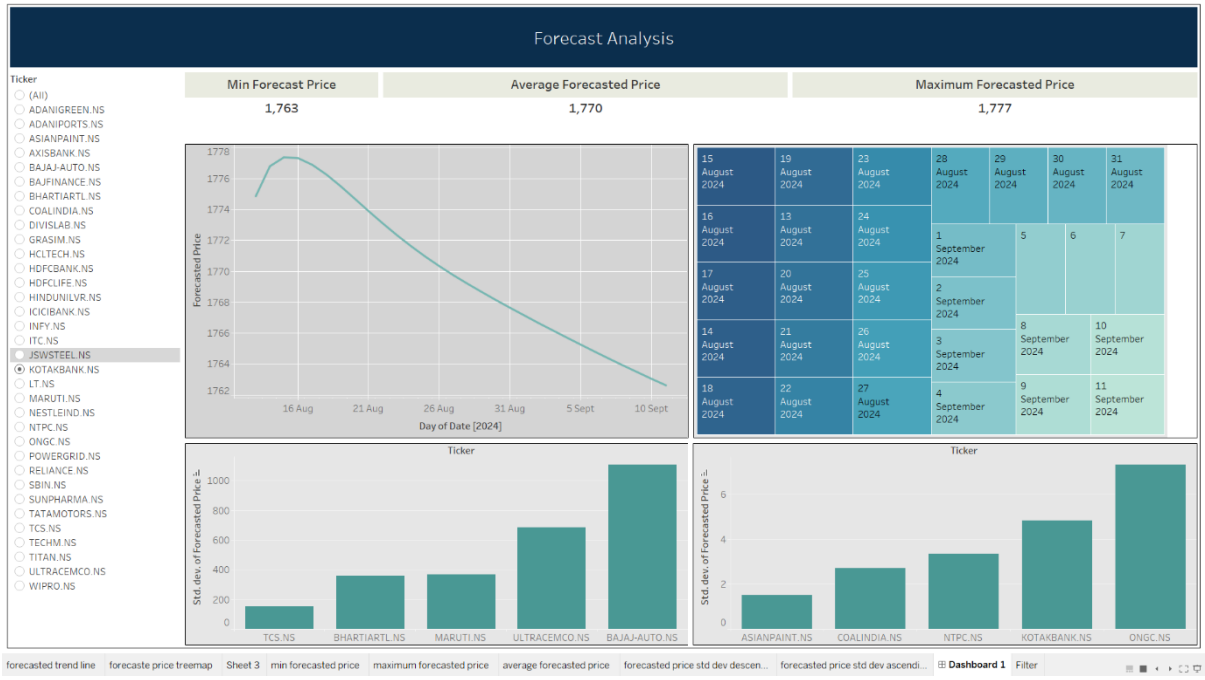


Fig 19. Tableau

Chapter 6

Conclusion

6.1 Conclusion

In this project, we have successfully implemented a comprehensive approach to stock price prediction and risk assessment using advanced data analysis and machine learning techniques. The key outcomes of the project are summarized as follows:

Data Collection and Preprocessing: We gathered historical stock price data from the Yahoo Finance API, covering a five-year period. This dataset included daily prices, trading volumes, and other relevant financial indicators. The data **preprocessing** phase ensured that the dataset was clean, normalized, and ready for model training.

1. **Model Training and Forecasting**: We employed a Long Short-Term Memory (LSTM) model, which proved to be highly effective for capturing the long-term dependencies and patterns inherent in time series data. The trained LSTM model was able to forecast stock prices for the next 30 days, providing valuable insights into potential future market movements and trends.

2. **Risk Categorization**: Based on the LSTM model's predictions, we categorized stocks into different risk levels. This risk categorization was crucial in distinguishing between high-risk stocks with high predicted volatility and low-risk stocks with more stable predictions. The detailed risk assessments offer investors a clearer understanding of potential investment risks.

3. **User Interface Development**: We developed an interactive application using Streamlit, allowing users to input stock symbols and view both predicted prices and associated risk levels. The app is designed to be user-friendly and accessible, enhancing the overall user experience and enabling investors to easily interact with the predictions and risk categorizations.

4. **Data Visualization**: Interactive dashboards were created using Tableau and Power BI, which effectively visualized the forecasted stock prices and risk levels. These visualizations provided clear and intuitive representations of the data, highlighting key insights and trends. The use of various charts and graphs facilitated a better understanding of the data, making it easier for users to interpret the results.

5. In conclusion, this project has demonstrated the power of integrating machine learning with interactive visualization tools to provide a robust framework for stock price prediction and risk assessment. The combination of an LSTM model for forecasting and intuitive visualizations for risk categorization offers valuable insights for investors, aiding them in making informed investment decisions. The development of a user-friendly interface further enhances the accessibility of these insights, making sophisticated financial analysis more approachable and actionable.

6.2 Future Enhancement –

While the current project has established a solid foundation for stock price prediction and risk assessment, several enhancements could further improve its capabilities and user experience:

6. **Model Optimization and Expansion**: Future work could involve refining the LSTM model and exploring other advanced models such as Transformer-based architectures or ensemble methods. Incorporating additional features like macroeconomic indicators or sentiment analysis from financial news could enhance prediction accuracy.
7. **Real-Time Data Integration**: Implementing real-time data feeds and predictions would allow users to receive up-to-date insights and adjust their strategies dynamically. This could involve integrating live stock price updates and refining the forecasting model for real-time application.
8. **Advanced Risk Assessment Metrics**: Expanding the risk assessment framework to include more sophisticated metrics, such as Value at Risk (VaR) or Conditional Value at Risk (CVaR), could provide a more comprehensive analysis of potential investment risks.
9. **User Interface and Experience**: Enhancing the Streamlit app with additional features, such as personalized investment recommendations, alerts for significant price changes, and more detailed risk analysis reports, could further enrich the user experience.
10. **Scalability and Performance**: Optimizing the application for scalability to handle a larger number of users and stocks simultaneously, and improving performance to ensure faster response times, would be beneficial for widespread adoption.

Chapter 7

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