CHAPTER 1:
INTRODUCTION TO COMMODITY PRICE PREDICTOR

1.1 INTRODUCTION

The fluctuation of vegetable prices has become a persistent issue, driven by various factors such as demand fluctuations, supply chain disruptions, seasonal changes, and external influences. These variations pose significant challenges to consumers and businesses alike. For medium-scale buyers and small food businesses, these unpredictable price changes not only complicate budgeting but also affect profitability and long-term financial planning. Sudden price hikes can lead to increased food costs, impacting their ability to remain competitive and sustain their operations.

Commodity Price Predictor for Vegetables is a project aimed at addressing these challenges by leveraging predictive analytics to forecast future vegetable prices. The primary objective of this project is to empower small-scale businesses with accurate and timely price predictions. By analyzing historical data, market dynamics, and real-time variables, the model provides actionable insights, helping businesses plan budgets more effectively, mitigate the impact of price fluctuations, and maintain profitability.

Predictive analysis plays a crucial role in this project, as it enables businesses to anticipate future trends by identifying patterns and relationships within data. Utilizing advanced machine learning techniques, particularly the Long Short-Term Memory (LSTM) model, this project offers a robust solution for forecasting. LSTM, a specialized type of recurrent neural network (RNN), is designed to handle sequential data efficiently. Its ability to remember long-term dependencies and process time-series data makes it particularly suitable for predicting vegetable prices, where past trends and seasonal patterns are vital for accurate forecasts.

Through this project, small businesses gain access to a powerful predictive tool that was previously available only to larger enterprises with advanced analytical capabilities. By bridging this gap, the **Commodity Price Predictor** not only supports better decision-making but also contributes to a more equitable market environment. This initiative exemplifies how machine learning and predictive analytics can be harnessed to solve real-world problems and drive positive societal impact.

1.2 PURPOSE

The purpose of the **Commodity Price Predictor for Vegetables** is to provide small-scale food businesses and medium-scale buyers with an effective and reliable tool to forecast vegetable prices. This project aims to address the challenges posed by unpredictable price fluctuations, which disrupt budgeting, reduce profitability, and make financial planning difficult for these businesses.

By leveraging machine learning techniques, specifically the Long Short-Term Memory (LSTM) model, the project analyzes historical price data, seasonal trends, and market dynamics to deliver accurate and actionable price predictions. The goal is to empower small businesses with insights that enable them to:

1. **Improve Budget Planning**: Predictive analytics helps small businesses allocate resources efficiently and plan their expenses better in the face of volatile market conditions.
2. **Enhance Profit Margins**: With prior knowledge of potential price changes, businesses can make strategic purchasing and inventory decisions to minimize costs and maximize earnings.
3. **Level the Playing Field**: Small businesses often lack access to sophisticated forecasting tools available to larger organizations. This project bridges that gap by offering an accessible solution tailored to their needs.

1.3 DESCRIPTION

The **Commodity Price Predictor** is a machine learning-driven project designed to forecast vegetable prices with high accuracy, using historical data, seasonal trends, and market dynamics. This project aims to address the challenges faced by small-scale businesses and medium-scale buyers due to unpredictable price fluctuations. By utilizing advanced predictive analytics, it offers a user-friendly and accessible solution to support better decision-making and financial planning.

Key Features

1. **Data-Driven Insights:**

The project utilizes historical price data, seasonal patterns, and external factors to create an extensive dataset for analysis. This ensures the predictions are rooted in real-world market trends.

2. **Predictive Modeling with LSTM:**

   At the core of the project lies the Long Short-Term Memory (LSTM) model, a type of recurrent neural network (RNN) that excels in handling sequential and time-series data. The LSTM model captures long-term dependencies and identifies subtle trends in the data, enabling precise price forecasts.

3. **Interactive User Interface:**

   The project includes an interactive web interface where users can input specific vegetables to view their predicted prices for the next three days. The interface is designed for accessibility, ensuring ease of use for small business owners with minimal technical expertise.

4. **Real-Time Predictions:**

   By integrating real-time data from market sources, the model continuously refines its predictions, providing users with up-to-date insights to make informed decisions.

5. **Accessible and Scalable Solution:**

   The project is designed to be cost-effective and scalable, making it suitable for small-scale businesses that often lack access to sophisticated forecasting tools.

CHAPTER 2:

LITERATURE SURVEY

2.1. REAL-TIME SURVEY OF VEGETABLE COMMODITY PRICES

2.1.1. Introduction

This chapter details the real-time survey conducted to gather comprehensive data on vegetable commodity prices from various areas within a 10 km radius around RR Nagar. The survey aimed to capture pricing trends and variations across diverse locations, including local markets, supermarkets, and roadside vendors. By exploring multiple areas, the study provides a holistic view of the factors influencing vegetable pricing in the region. This data serves as a crucial foundation for the development and validation of the commodity price prediction model.

2.1.2. Objectives

The objectives of the real-time survey were:

1. To collect up-to-date price information for commonly consumed vegetables across multiple vendors in a 10 km radius around RR Nagar.
2. To examine price variability across different types of shops and locations within the specified area.
3. To identify factors such as supply chain dynamics, seasonal trends, and consumer demand that influence pricing.
4. To create a reliable and region-specific dataset for training and testing the commodity price prediction model.

2.1.3. Methodology

- SurveyLocations:
  The survey was conducted across various areas within 10km radius of R R Nagar including Uttarahalli, Kengeri, BEML Layout, Banashankari and Nagarabhavi. A diverse mix of food trucks, food stalls and cafes were included.
- DataCollectionPeriod:
  Data was collected over two weeks to account for daily and weekly price fluctuations.
- Approach:
  - Prices for essential vegetables (e.g., tomatoes, onions, potatoes, beans) were recorded systematically.

- Vendor-specific data, including shop type, location, and sourcing practices, were documented.
- Brief interviews with shopkeepers provided qualitative insights into pricing strategies and customer preferences.
- Data was recorded using a structured format to ensure consistency and ease of analysis.

2.1.4. Findings

1. Regional Price Variations:
   - Prices varied significantly across the surveyed areas, with supermarkets typically charging higher rates than roadside vendors.
   - Local markets closer to wholesale hubs exhibited lower prices due to reduced transportation costs.
2. Key Influencing Factors:
   - Seasonal availability played a major role in pricing, with certain vegetables showing substantial fluctuations.
   - Supply chain issues, such as delays from wholesalers and increased transportation costs, were common drivers of price hikes.
   - Demand patterns varied by location, with urban areas showing a preference for premium-quality produce.
3. Consumer Preferences:
   - Customers in suburban areas favored affordability, while those in urban localities prioritized freshness and quality, even at higher prices.
   - Roadside vendors reported higher sales volumes but lower profit margins compared to supermarkets.
4. Shopkeeper Insights:
   - Many shopkeepers expressed concerns about rising wholesale prices and inconsistent supply, particularly for highly perishable vegetables.
   - Strategies such as bulk purchasing and sourcing from multiple suppliers were commonly employed to manage costs.

2.1.5. Challenges and Limitations

- Data Collection Challenges:
  - Price variability within the same day and across different areas made it difficult

to standardize the dataset.

- Some vendors were hesitant to share detailed information about their pricing or sourcing strategies.

- External Factors:
  - Unpredictable weather conditions during the survey period impacted the availability and pricing of certain vegetables.
  - Local events or market-specific factors occasionally influenced prices temporarily.

Commodity Price Predictor App

S.NO	Submit Date	Name of the owner / business	Type of the business	Location	How will you purchase the vegetables often..?	How much do you spend on vegetables..?	Have you experienced the cost difference..?	Would you like to have an app that predicts the vegetable prices in advance to help you plan the purchase..?	How much savings would you expect if price prediction were accurate..?	What are the other features you want to include in the app..?	How would you rate our project / application..?	Overall Feedback or suggestions
1	20-11-2024 21:01:53	Manju Kumar,Cafe Acacia(2020)	Cafe	SJBIT	Daily	₹1000/per day	Yes	Yes	25%	No Answer	Good	It will help to make some profit
2	20-12-2024 12:11:06	Food adda	Food Truck	Nagarbhavi	Daily	1400	Yes	Yes	10%	No Answer	Very Good	No Answer
3	20-12-2024 12:15:04	KRISHNA TEJA K	Food Truck	RR NAGAR	Daily	10000	Yes	Yes	3000 to 5000	No Answer	Very Good	Vvvv good
4	20-12-2024 12:19:46	Juice and snacks junction	Cafe	BEML LAYOUT	Daily	2000	Yes	Yes	Atleast 5 percent	No Answer	Very Good	No Answer
5	20-12-2024 12:22:01	Vomika momo	Food stall	Nagarbhavi	Weekly	1350	Yes	Yes	No Answer	No Answer	Very Good	No Answer
6	20-12-2024 12:22:58	Snacks and more	Cafe	Nagarbhavi	Daily	1400	Yes	Yes	No Answer	No Answer	Very Good	No Answer
7	20-12-2024 12:24:05	Bakasura bandi	Small scale restaurant	Nagarbhavi	Daily	2500	Yes	Yes	No Answer	No Answer	Very Good	No Answer
8	20-12-2024 12:26:22	Bangarpet chats	Food stall	BEML LAYOUT	Daily	1900	Yes	Yes	No Answer	No Answer	Very Good	No Answer
9	20-12-2024 12:27:26	KRISHNA TEJA K	Food Truck	BANGALORE	Monthly	10000	Yes	Yes	5000	No Answer	Very Good	Vvvvv good
10	20-12-2024 12:27:42	Naga chay snacks	Cafe	Banashankari	Daily	1400	Yes	Yes	No Answer	No Answer	Good	No Answer
11	20-12-2024 12:30:11	Salt and pepper	Cafe	BEML LAYOUT	Daily	1600	Yes	Yes	No Answer	No Answer	Neutral	No Answer
12	20-12-2024 12:36:06	Bhavana Suresh	Food stall	Hoysala circle	Daily	700 to 800	Yes	Yes	200 to 300	No Answer	Very Good	Everything is good
13	20-12-2024 12:36:35	Kanish Rishab D	Food Truck	Beml Layout	Daily	900-1000	Yes	Yes	200	nothing	Very Good	Awesome
14	20-12-2024 12:38:12	Uncle rolls cafe	College canteen	Sjb college Kengeri	Daily	1360	Yes	Yes	No Answer	No Answer	Very Good	No Answer
15	20-12-2024 12:39:25	Harihar veg biryani	Small scale restaurant	Uttarahalli	Daily	1000	Yes	Yes	No Answer	No Answer	Very Good	No Answer
16	20-12-2024 12:39:42	Sneha food court	Food Truck	Bengaluru	Daily	1000	Yes	Yes	40%	No Answer	Very Good	It's good
17	20-12-2024 12:42:54	Dimpu's manchuri and more	Food stall	Kengeri	Daily	1590	Yes	Yes	No Answer	No Answer	Very Good	No Answer
18	20-12-2024 12:44:03	Dilli ka dil	Cafe	Beml layout	Daily	1300	Yes	Yes	No Answer	No Answer	Very Good	No Answer
19	20-12-2024 12:44:54	Vasantha eats	Food Truck	Kengeri	Daily	1300	Yes	Yes	No Answer	No Answer	Very Good	No Answer
20	20-12-2024 12:46:02	Chandu Dhaba	Food Truck	Uttarahalli	Daily	1200	Yes	Yes	No Answer	No Answer	Very Good	No Answer
21	20-12-2024 12:48:38	Madeshwara Bhel Puri	Food Truck	Uttarahalli	Daily	900	Yes	No	No Answer	No Answer	Neutral	No Answer
22	20-12-2024 12:55:21	Alen	Cafe	Earth	Weekly	100000	Yes	No	150000	Nothing	Very Good	Super fantastic marvellous
23	20-12-2024 12:58:41	NGT	Food stall	Bengaluru	Weekly	1200	Yes	Yes	30%	No Answer	Very Good	Nice
24	20-12-2024 13:01:24	Desi masala	Cafe	Bengaluru	Weekly	1500	Yes	Yes	35%	No Answer	Very Good	Good
25	20-12-2024 13:04:08	Shiva egg rice	Food Truck	Bengaluru	Weekly	700	Yes	Yes	30%	No Answer	Good	Good
26	20-12-2024 13:05:14	Tasty Cafe	Cafe	SJBIT	Daily	1400	Yes	Yes	15%	No Answer	Good	It's good
27	20-12-2024 13:06:51	69 cafe	Cafe	Bengaluru	Weekly	1000	Yes	Yes	40% 40%	No Answer	Very Good	No Answer
28	20-12-2024 13:07:47	Like cafe	Cafe	Kengeri	Weekly	1200	Yes	Yes	20%	Nothing	Good	Nothing
29	20-12-2024 13:08:56	Mint and Mayos	Cafe	Uttharahalli	Daily	1000	Yes	Yes	400	No Answer	Neutral	No Answer
30	20-12-2024 13:09:26	Clours cafe	Cafe	Bengaluru	Weekly	1000	Yes	Yes	40%	No Answer	Very Good	No Answer
31	20-12-2024 13:12:00	Bachelor's Fried rice	Food Truck	Banashankari	Daily	1600	Yes	Yes	500	No Answer	Neutral	No Answer
32	20-12-2024 13:14:17	Baigan barta	Food stall	Banashankari	Daily	1700	Yes	Yes	No Answer	No Answer	Very Good	No Answer
33	20-12-2024 13:15:45	Hotel Ganesh	Food stall	Benguluru	Weekly	1500	Yes	Yes	40%	No Answer	Very Good	No Answer
34	20-12-2024 13:16:51	Sanie danie	Cafe	Uttarahalli	Daily	1500	Yes	Yes	No Answer	No Answer	Very Good	No Answer
35	20-12-2024 13:18:31	Kabinet kabab	Food stall	Uttarahalli	Daily	1000	Yes	Yes	No Answer	No Answer	Very Good	No Answer
36	20-12-2024 13:19:43	Bihari mess	Cafe	Kengeri	Daily	1600	Yes	Yes	No Answer	No Answer	Very Good	No Answer
37	20-12-2024 13:19:57	The Plams	Cafe	Uttarahalli	Monthly	5000	Yes	Yes	1000	Delivery	Very Good	Good
38	20-12-2024 13:22:35	Idli point	Food stall	Kengeri	Daily	800	Yes	Yes	No Answer	No Answer	Very Good	No Answer
39	20-12-2024 13:22:48	Matha Sagar	Food Truck	Uttharahalli	Daily	1500	Yes	Yes	500	No Answer	Neutral	No Answer
40	20-12-2024 13:25:22	Sandwitch wala	Cafe	Kengeri	Weekly	3000	Yes	Yes	300	No Answer	Neutral	Nice project
41	20-12-2024 13:26:03	Mingos cafe	Cafe	Bengaluru	Weekly	1000	Yes	Yes	40%	No Answer	Very Good	No Answer
42	20-12-2024 13:27:16	Hotel kirshna	Food stall	Bengaluru	Weekly	1000	Yes	Yes	25%	No Answer	Very Good	No Answer
43	20-12-2024 13:27:17	Tees maar khan	Cafe	Kengeri,bengaluru	Weekly	5000	Yes	Yes	5000	No Answer	Neutral	No Answer
44	20-12-2024 13:29:23	Ganeshadharsha hotal	Food stall	Bengaluru	Weekly	700	Yes	Yes	30%	No Answer	Very Good	No Answer
45	20-12-2024 13:29:54	Swdha cafe	Cafe	Bengaluru	Weekly	800	Yes	Yes	30%	No Answer	Very Good	No Answer
46	20-12-2024 13:30:54	Colour cafe	Cafe	Bengaluru	Weekly	1200	Yes	Yes	30%	No Answer	Very Good	No Answer
47	20-12-2024 13:32:10	Bidhu	Food Truck	Bengaluru	Weekly	1200	Yes	Yes	30%	No Answer	Very Good	No Answer
48	20-12-2024 13:35:08	Pooja gobi	Food Truck	800	Weekly	800	Yes	Yes	30%	No Answer	Very Good	No Answer
49	20-12-2024 13:36:29	RNR food	Food Truck	Bengaluru	Weekly	1500	Yes	Yes	30%	No Answer	Very Good	No Answer
50	20-12-2024 13:37:57	Sri Basaveshwara kanavali	Food stall	Bengaluru	Weekly	1700	Yes	Yes	40%	No Answer	Very Good	No Answer

Powered by SurveyHeart

Figure 2.1 Real Time Survey of Food Business

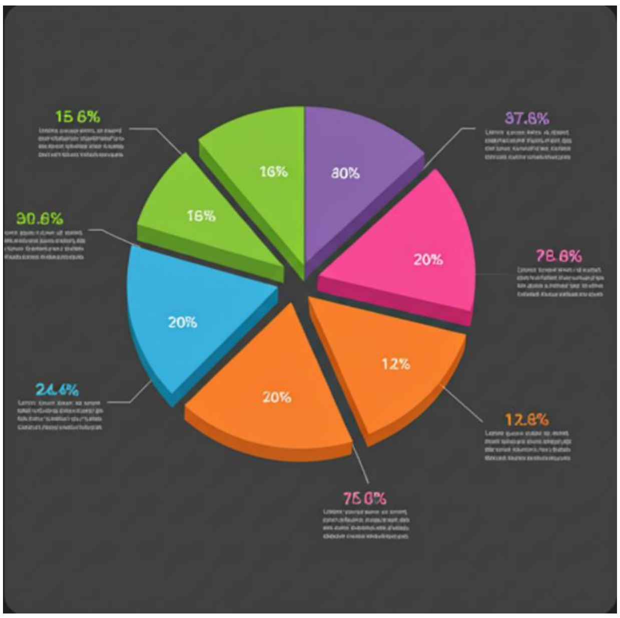

Figure 2.2 Price Variation

2.1.6. Conclusion

The real-time survey provided valuable insights into the dynamics of vegetable commodity pricing across a 10 km radius around RR Nagar. The data revealed significant regional variations influenced by shop type, location, and external factors such as seasonality and supply chain dynamics. These findings will serve as a critical input for designing a predictive model that accurately reflects the complexities of real-world pricing. By incorporating this diverse dataset, the commodity price predictor aims to enhance its adaptability and accuracy, making it a robust tool for stakeholders in the agricultural and retail sectors.

CHAPTER 3:

EXISTING SYSTEM

3.1 STOCK MARKET PREDICTION SYSTEMS

Stock market prediction systems are among the most sophisticated and well-established forecasting mechanisms. These systems analyze historical stock prices, trading volumes, and economic indicators using advanced algorithms to predict future trends. Predictive models, such as machine learning techniques and statistical methods, enable investors to make informed decisions by identifying patterns in stock performance. These systems are particularly effective in dealing with complex market dynamics and high-frequency data.

Over the years, the integration of artificial intelligence (AI) and deep learning techniques has further enhanced the capabilities of stock market prediction systems. These technologies process vast amounts of data, including social media sentiment and global economic indicators, to deliver real-time predictions.

3.2 COMMODITY MARKET PREDICTION SYSTEMS

Commodity market prediction systems focus on forecasting the prices of agricultural and industrial commodities such as crude oil, gold, and mustard seeds. These systems typically employ time-series analysis, econometric models, and machine learning algorithms to analyze historical data, market trends, and external factors like geopolitical events or weather conditions. The accuracy and reliability of these systems have been critical in enabling stakeholders to manage risks and optimize their investments.

Recent advancements in commodity price prediction include the use of advanced machine learning models like Random Forests, Support Vector Machines, and Long Short-Term Memory (LSTM) networks. These models not only handle temporal data effectively but also incorporate external variables such as currency fluctuations, transportation costs, and global trade policies.

3.3 LACK OF VEGETABLE COMMODITY PRICE PREDICTOR

Despite the advancements in commodity market prediction systems, specialized prediction systems for vegetables have yet to be developed. Vegetables pose unique challenges such as short shelf life, high sensitivity to climatic conditions, and localized demand-supply imbalances, which make standard prediction models inadequate. The absence of such systems highlights a significant gap in the market, necessitating the development of models tailored specifically to the complexities of vegetable price forecasting.

CHAPTER 4:

PROPOSED SYSTEM

4.1 PROBLEM STATEMENT

Small food businesses often face problems because vegetable prices keep changing unpredictably. Some of the main challenges include:

- Trouble with Budgeting: It’s hard to plan expenses when prices keep going up and down.
- Loss of Profits: Sudden price hikes cut into their earnings.
- No Prediction Tools: Small businesses don’t have the tools to predict prices like big companies do.

4.2 OUR SOLUTION

To address the lack of a vegetable commodity price predictor, we propose the development of a predictive system specifically designed to forecast vegetable price fluctuations. This system would leverage advanced machine learning techniques, such as Long Short-Term Memory (LSTM) networks, to analyze historical price data, supply-demand trends, and external factors such as transportation logistics.

Key Features of the Proposed System:

1. Real-Time Data Integration: The system will gather real-time market prices to provide accurate and timely predictions.
2. Localized Predictions: By focusing on hyper-local data, the system can address regional variations in supply and demand, offering tailored predictions for specific markets.
3. User-Friendly Interface: A simple and intuitive platform will enable users, including small-scale businesses and consumers, to access predictions easily and plan purchases accordingly.
4. Cost-Saving Insights: By predicting price fluctuations (e.g., identifying if a vegetable's price is high today but expected to drop tomorrow), the system will help users make informed purchasing decisions and reduce unnecessary expenses.
5. Scalability: The system will be designed to accommodate additional commodities, ensuring flexibility for future enhancements.

CHAPTER 5:

GOALS OF THE PROJECT

5.1 OBJECTIVES

- Develop an accurate model to predict vegetable prices based on historical data.
- Enable small-scale businesses to optimize inventory and budget decisions.
- Reduce food waste by improving inventory management through price forecasts.
- Promote market stability by providing actionable insights to stakeholders.
- Create a user-friendly system accessible to all stakeholders, regardless of technical expertise.

5.2 GOAL DESCRIPTION

The Commodity Price Predictor for Vegetables project is designed to address key challenges faced by small-scale businesses, farmers, and other stakeholders in the vegetable supply chain. The primary goal is to create a robust and reliable predictive system that can forecast future vegetable prices with a high degree of accuracy. This system will empower users to anticipate market trends, enabling them to make informed decisions regarding procurement, inventory, and sales strategies.

By leveraging historical data and other influencing factors, the predictive model aims to provide valuable insights that optimize resource allocation and budget management. For small scale food businesses, this means transforming limited profits into long-term financial gains by strategically timing purchases and sales based on accurate price predictions. This will ultimately lead to better decision-making processes, resulting in more stable and profitable operations.

Furthermore, the project aims to bring about market stability by providing key insights that help balance supply and demand. By mitigating the volatility of vegetable prices, the system will help reduce extreme price fluctuations, ensuring fair and predictable pricing for consumers and producers alike. This will foster trust among market participants and contribute to a more resilient vegetable market overall.

Overall, the Commodity Price Predictor for Vegetables project envisions a more efficient, stable, and sustainable vegetable market that empowers users, reduces waste, and contributes to the economic growth of the industry.

CHAPTER 6:

PROJECT DESIGN

6.1 VEGETABLES DATA EXTRACTION

The extraction of vegetable price data from the AGMARKNET website aligns with the industry's increasing reliance on digital platforms to gather accurate and timely information for agricultural market analysis. By using AGMARKNET, a trusted source for agricultural market data, the project ensures that the vegetable price data is comprehensive, reliable, and up-to-date, crucial for predicting market trends. The data extraction process involves collecting price information from multiple markets and regions in a structured format (CSV), which includes details such as commodity prices, supply, and demand.

This data extraction is fundamental for building the predictive models used in the Commodity Price Predictor for Vegetables project. The raw data will be cleaned, processed, and integrated into the forecasting system, enabling the model to generate accurate price predictions. By leveraging this information, the project aims to enhance the decision-making capabilities of stakeholders in the vegetable supply chain, optimizing inventory management, and minimizing risks associated with price fluctuations. The precise extraction of data from AGMARKNET ensures the accuracy and reliability of the predictive system, making it a key component in fostering market stability and improving operational efficiency.

6.2 USER-FRIENDLY INTERFACE

The Commodity Price Predictor for Vegetables will feature a user-friendly interface designed using Voila and ipywidgets, ensuring that even non-technical users can easily navigate and interact with the system. The interface will prioritize simplicity, clarity, and ease of use, enabling stakeholders like farmers, small businesses, and market analysts to input data, view predictions, and analyze trends without needing technical expertise. Interactive controls such as sliders, dropdowns, and buttons will allow users to customize inputs, while real-time visualizations like graphs and charts will present price trends and forecasts in an easily digestible format. The design will focus on logical organization and intuitive workflows, ensuring clear navigation and minimal confusion. By providing a visually appealing and intuitive user experience, the interface will enhance user satisfaction, reduce frustration, and improve overall usability, making the system accessible to a wide range of users in the vegetable supply chain.

6.3 DATA FLOW DIAGRAM

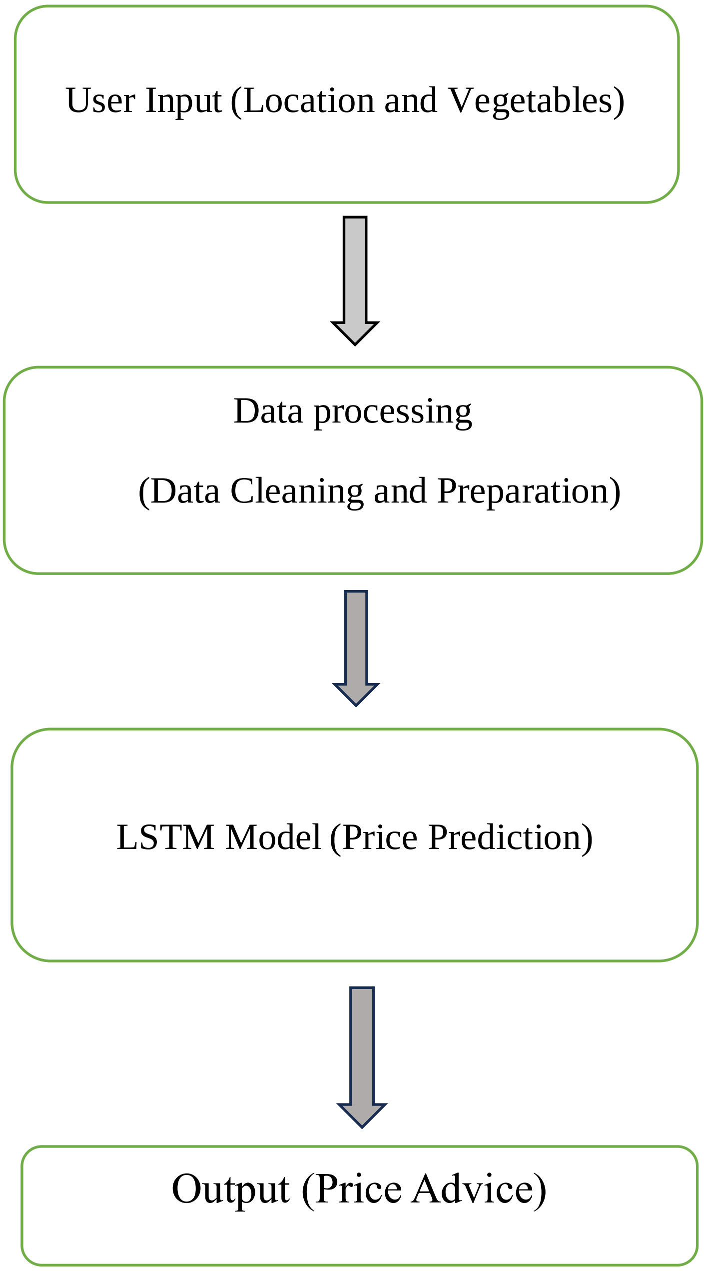

Figure 6.3 Data Flow Diagram

6.4 ALGORITHM FOR COMMODITY PRICE PREDICTION USING LSTM

The **Long Short-Term Memory (LSTM)** algorithm is a type of recurrent neural network (RNN) specifically designed to handle sequential data, making it ideal for predicting commodity prices over time. LSTM networks are well-suited for time series forecasting, as they can capture long-term dependencies and trends in historical price data, which is crucial for accurate price predictions in markets like vegetables.

LSTM works by using a series of memory cells that store information over time, allowing the model to learn from past price fluctuations and make informed predictions about future price trends. Unlike traditional neural networks, LSTM networks are equipped with gates that control the flow of information into, out of, and within the memory cells, helping to prevent the vanishing gradient problem and enabling the model to retain important long-term dependencies.

In the context of vegetable price prediction, LSTM can be trained on historical data, such as daily or weekly vegetable prices, weather patterns, market trends, and other relevant features. The algorithm processes this data in a sequential manner, learning to identify patterns and relationships that influence future prices. The output of the LSTM network is a forecast of future prices, which can be used to guide decision-making in the vegetable supply chain, such as inventory management, pricing strategies, and procurement planning.

The strength of the LSTM algorithm lies in its ability to handle large and complex datasets while providing accurate predictions. By learning from historical trends and incorporating external factors like seasonality or market conditions, LSTM can generate reliable price forecasts. Additionally, LSTM models can be fine-tuned for specific regions, vegetable types, or time frames, making them highly adaptable and effective in dynamic markets. This makes LSTM a powerful tool for improving the accuracy and efficiency of vegetable price prediction systems.

CHAPTER 7:

RESOURCE REQUIREMENTS

7.1 MINIMUM HARDWARE REQUIREMENTS

i. **Processor:** Intel i5 or AMD equivalent (multi-core)

ii. **RAM:** 8 GB

iii. **Storage:**256 GB SSD

iv. **Graphics Card (Optional):** If using GPU acceleration for training: NVIDIA GPU with CUDA support (e.g., NVIDIA GTX 1050 or higher)

v. **Peripherals:** Monitor, keyboard, and mouse (standard)

vi. **Network:** Stable internet connection for accessing cloud services, downloading datasets, or dependencies.

7.2 SOFTWARE REQUIREMENTS

i. **IDE/Code Editor:** Jupyter Notebook (for development, testing, and creating the Voila dashboard)

ii. **Programming Language:** Python 3.9 or later

iii. **Libraries and Frameworks:**

- For Data Handling & Analysis: Pandas, NumPy
- For Visualization: Matplotlib
- For Machine Learning/Deep Learning: TensorFlow/Keras, Scikit-learn
- For UI with Voila: ipywidgets

iv. **Frontend Technologies:**

- Voila (to render the Jupyter Notebook as an interactive dashboard)
- ipywidgets (used for interactive elements such as text inputs, dropdowns, buttons, and output display)

CHAPTER 8:
DESCRIPTION OF TOOLS AND TECHNOLOGIES

8.1 DESCRIPTION OF TOOLS

8.1.1 Jupyter Notebook

Jupyter Notebook is an open-source, web-based interactive development environment (IDE) widely used for data analysis, machine learning, scientific computing, and data visualization. It allows users to create and share documents that combine live code, equations, visualizations, and narrative text. Initially designed for Python, Jupyter also supports other programming languages like R, Julia, and Scala through its kernel system. It features a highly interactive environment, rich outputs including plots and visualizations, multi-language support, and seamless integration with libraries such as Pandas, NumPy, Matplotlib, and TensorFlow. Notebooks are saved in the portable .ipynb format, which can be easily shared or converted to formats like HTML, PDF, or slides.

One of the primary advantages of Jupyter Notebook is its ease of use, offering an intuitive, cell-based structure for running and testing code in segments. This makes it particularly suited for experimentation and prototyping. It excels in data visualization by directly embedding plots and graphs, and it enables users to combine code, results, and detailed documentation in a single document, making it ideal for research, tutorials, and teaching. With Markdown and LaTeX support, users can include mathematical expressions and narrative text alongside their code. Jupyter Notebook also provides real-time feedback during code execution, facilitating debugging and iterative development. Its versatility allows it to be used across various disciplines, while its extensibility supports plugins and extensions like Jupyter Lab, Voila for dashboards, and nbconvert for exporting notebooks.

In our project, Jupyter Notebook serves as the primary IDE for development, testing, and creating interactive dashboards. It is used to write and test scripts, preprocess data, and evaluate models. By leveraging the Voila extension, notebooks are transformed into user-friendly dashboards, enabling seamless sharing of results with stakeholders. The combination of interactive development, robust visualization, and extensive ecosystem support makes Jupyter Notebook an excellent choice for managing the end-to-end workflow in your project, from prototyping to deployment. This approach not only enhances collaboration but also accelerates the iterative development process by providing instant feedback. Additionally, the integration of widgets and interactive plots fosters better insights, enabling data-driven decision-making. The versatility of Jupyter Notebook ensures adaptability for diverse tasks, ranging from exploratory data analysis to full-scale production solutions.

8.2 DESCRIPTION OF TECHNOLOGIES

8.2.1 Python

Python is a high-level, versatile programming language known for its simplicity and readability. Created by Guido van Rossum in 1991, Python's clear syntax makes it accessible for beginners while offering powerful features for experienced developers. It supports multiple programming paradigms, including procedural, object-oriented, and functional programming, catering to diverse development needs. With a vast standard library and a thriving ecosystem of third-party libraries like NumPy, Pandas, TensorFlow, and Django, Python simplifies tasks ranging from data analysis and machine learning to web development and automation. Its cross-platform compatibility and interoperability with other languages further enhance its flexibility.

Widely adopted across domains like web development, data science, artificial intelligence, and scientific research, Python is celebrated for its adaptability and efficiency. Its active community ensures robust support, frequent updates, and abundant learning resources. Python's simplicity, combined with its powerful capabilities, makes it an ideal choice for creating anything from small scripts to complex applications, offering developers a streamlined and productive coding experience.

8.2.2 Voila

Voila is an open-source Python library that transforms Jupyter Notebooks into interactive web applications or dashboards. It allows users to showcase their data analysis, visualizations, and machine-learning models in a clean, user-friendly interface without requiring any coding knowledge from the end-user. Unlike traditional Jupyter Notebooks, Voila hides the code cells and displays only the outputs, making it ideal for presenting insights to non-technical stakeholders or building simple interactive tools. With Voila, users can seamlessly incorporate widgets and interactivity powered by libraries like ipywidgets, creating dynamic and engaging dashboards.

One of Voila's key advantages is its simplicity and integration within the Jupyter ecosystem. It requires minimal setup, and by leveraging the same environment as Jupyter Notebooks, it eliminates the need for additional frameworks or complex web development processes. Voila applications are rendered in real-time, meaning changes in the underlying data or models are immediately reflected in the interface. This makes it an excellent choice for projects involving live data or frequent updates. Additionally, Voila supports deployment to various platforms, including local servers, cloud services, and containerized environments, ensuring accessibility and scalability for a wide range of use cases.

8.2.3 Ipywidgets

Ipywidgets, or interactive widgets for Jupyter, is a powerful Python library that enables the creation of interactive and dynamic user interfaces within Jupyter Notebooks. These widgets allow users to interact with code and data in real-time by providing interactive controls like sliders, dropdowns, checkboxes, and buttons. By linking these controls to variables or functions, ipywidgets make it easy to build interactive visualizations, perform parameter tuning, or explore data without rewriting or rerunning code manually. They are particularly valuable in data analysis and machine learning workflows, where adjusting parameters and observing outcomes iteratively is crucial.

One of the major strengths of ipywidgets is its seamless integration with the Jupyter ecosystem and popular Python libraries such as Matplotlib, Pandas, and Plotly. This makes it straightforward to enhance notebooks with interactivity while keeping the development process simple and intuitive. The library also supports advanced customization and layouts, allowing users to create more complex interfaces by combining multiple widgets. With the ability to integrate with tools like Voila, ipywidgets can turn static notebooks into interactive dashboards and web applications, extending their use beyond data exploration to presentation and deployment.

CHAPTER 9:

IMPLEMENTATION OF CODE

9.1 LSTM MODEL CODE

```
from tensorflow import keras

from keras.layers import Dense, Dropout, LSTM

from keras.models import Sequential


model = Sequential()

model.add(LSTM(units=50, activation = 'relu', return_sequences=True, input_shape = (x.shape[1],1)))

model.add(Dropout(0.2))


model.add(LSTM(units=60, activation = 'relu', return_sequences=True, input_shape = (x.shape[1],1)))

model.add(Dropout(0.3))


model.add(LSTM(units=80, activation = 'relu', return_sequences=True, input_shape = (x.shape[1],1)))

model.add(Dropout(0.4))


model.add(LSTM(units=120, activation = 'relu'))

model.add(Dropout(0.5))

model.add(Dense(units=1))


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

model.fit(x,y, epochs = 35, batch_size=32, verbose=1)

past_10_days = train_data.tail(10)

test_data = pd.concat([past_10_days, test_data], ignore_index=True)

test_data_scale = scaler.fit_transform(test_data)

x = []

y = []

for i in range(10, test_data_scale.shape[0]):
```

```
  x.append(test_data_scale[i-10:i])
  y.append(test_data_scale[i,0])
x,y = np.array(x), np.array(y)
y_predict = model.predict(x)
y_predict
scale = 1/scaler.scale_
y_predict = y_predict*scale
y = y*scale
plt.figure(figsize=(8,6))
plt.plot(y_predict,'r', label = 'Predicted Price')
plt.plot(y,'g', label = 'Actual Price')
plt.xlabel('Time')
plt.ylabel('Price')
plt.legend()
plt.show()
model.save('Comodity Price Predictor.keras')
predictions = model.predict(x)
redictions

last_10_days = test_data_scale[-10:].reshape(-1, 1)
predicted_prices = []

for i in range(3):
    next_10_days_scaled = last_10_days.reshape(1, 10, 1)
    predicted_price_scaled = model.predict(next_10_days_scaled)

    predicted_price = scaler.inverse_transform(predicted_price_scaled)[0][0]
    predicted_prices.append(predicted_price)

    last_10_days = np.append(last_10_days[1:], predicted_price_scaled).reshape(-1, 1)

for i, price in enumerate(predicted_prices, 1):
    print(f"Predicted price for day {i} : {price:.2f}")
```

```
# Conversion factor: 1 quintal = 100 kilograms
predicted_prices_kg = [price / 100 for price in predicted_prices]

# Print the prices in kilograms
for i, price in enumerate(predicted_prices_kg, 1):
    print(f"Predicted price for day {i} in kg: {price:.2f}")
```

9.2 FRONTEND CODE

```
# Import required libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.preprocessing import MinMaxScaler
from tensorflow.keras.models import load_model
import ipywidgets as widgets
from IPython.display import display, HTML

# Load data
data = pd.read_csv("Vegetables.csv")

# Preprocess data
data = data.rename(columns={'Price (Rs./Quintal)': 'Price'})
data.dropna(inplace=True)

# Dropdown list for vegetables
vegetable_list = data['Commodity'].unique()

# Add CSS styling
style = """
<style>
    .widget-box {
        background-color: #f9f9f9;
        padding: 20px;
```

```
        border-radius: 10px;
        box-shadow: 0px 4px 8px rgba(0, 0, 0, 0.1);
        margin: auto;
        width: 60%;
        text-align: center;
    }
    .output-area {
        background-color: #e8f4fa;
        padding: 20px;
        border-radius: 10px;
        margin-top: 10px;
    }
</style>
"""
display(HTML(style))

# Create input widgets
location_input = widgets.Text(
    value='RR Nagar',
    description='Location:',
    placeholder='Enter your location',
    style={'description_width': 'initial'}
)

vegetable_input = widgets.Dropdown(
    options=vegetable_list,
    description='Vegetable:',
    style={'description_width': 'initial'}
)

# Button to trigger prediction
predict_button = widgets.Button(
    description="Predict Prices",
```

```
    button_style='primary'
)
output = widgets.Output()

# Align widgets in a VBox
input_widgets = widgets.VBox([location_input, vegetable_input, predict_button])
input_widgets.add_class("widget-box")

# Function to handle predictions
def predict_prices(b):
    with output:
        output.clear_output()  # Clear previous output

        # Get user inputs
        selected_location = location_input.value.strip().title()
        selected_vegetable = vegetable_input.value.strip().title()

        # Filter data for selected vegetable
        vegetable_data = data[data['Commodity'] == selected_vegetable]

        if vegetable_data.empty:
            print(f"No data available for {selected_vegetable}.")
            return

        # Preprocess data for model input
        scaler = MinMaxScaler(feature_range=(0, 1))
        vegetable_prices = vegetable_data.Price.values.reshape(-1, 1)
        scaled_prices = scaler.fit_transform(vegetable_prices)

        # Use the last 10 days of data for predictions
        last_10_days = scaled_prices[-10:]
        last_10_days = last_10_days.reshape(1, 10, 1)
```

```
    # Load pre-trained model and make predictions
    model = load_model('Comodity Price Predictor.keras')
    predicted_prices = []

    for _ in range(3):  # Predict for 3 days
        predicted_price_scaled = model.predict(last_10_days)
        predicted_price = scaler.inverse_transform(predicted_price_scaled)[0][0]
        predicted_prices.append(predicted_price)

        # Update the input with the latest prediction
        last_10_days = np.append(last_10_days[0, 1:], predicted_price_scaled).reshape(1, 10,
1)

    # Convert to price per kg
    predicted_prices_kg = [price / 100 for price in predicted_prices]

    # Display results
    print(f"Location: {selected_location}")
    print(f"Vegetable: {selected_vegetable}")
    for i, price in enumerate(predicted_prices_kg, 1):
        print(f"Predicted price for day {i} (per kg): ₹{price:.2f}")

    # Plot results

# Bind button click to prediction function
predict_button.on_click(predict_prices)

# Display styled widgets and output area
display(widgets.VBox([input_widgets, output]))
```

CHAPTER 10:

TEST CASES

Sl. No.	Input Description	Expected Output	Actual Output	Remarks
1	Entering the location in the input field and pressing "Enter".	The system should accept the location and update the interface with relevant dropdown options for vegetables.	The system accepts the location and displays the dropdown options correctly.	Pass
2	Selecting a vegetable (e.g., "Onion") from the dropdown.	The interface should highlight the selected vegetable and enable the "Predict Price" button.	The selected vegetable is highlighted, and the "Predict Price" button is enabled.	Pass
3	Pressing the "Predict Price" button after selecting a vegetable.	The system should predict and display the price for the next three days for the selected vegetable.	The system predicts and displays the prices for the next three days correctly.	Pass
4	Attempting to predict the price without selecting a vegetable.	The system should display an error message stating, "Please select a vegetable before predicting prices."	The system displays the correct error message.	Pass
5	Selecting multiple vegetables (e.g., "Onion" and "Beans") and pressing "Predict Price".	The system should predict and display prices for the next three days separately for each selected vegetable.	The system predicts and displays the prices for each selected vegetable correctly.	Pass
6	Providing an invalid location (e.g., a location not in the database).	The system should display a message stating, "Invalid location, please enter a valid location."	The system displays the correct error message.	Pass
7	Changing the location after already selecting a vegetable.	The system should reset the dropdown and disable the "Predict Price" button until a new vegetable is selected.	The system resets the dropdown and disables the "Predict Price" button as expected.	Pass
8	Exiting the application after performing predictions.	All temporary data, including selected location and vegetable history, should be cleared.	The system clears all temporary data as expected.	Pass

CHAPTER 11:

RESULTS

11.1 10 DAYS MOVING AVERAGE OF VEGETABLE: ONION

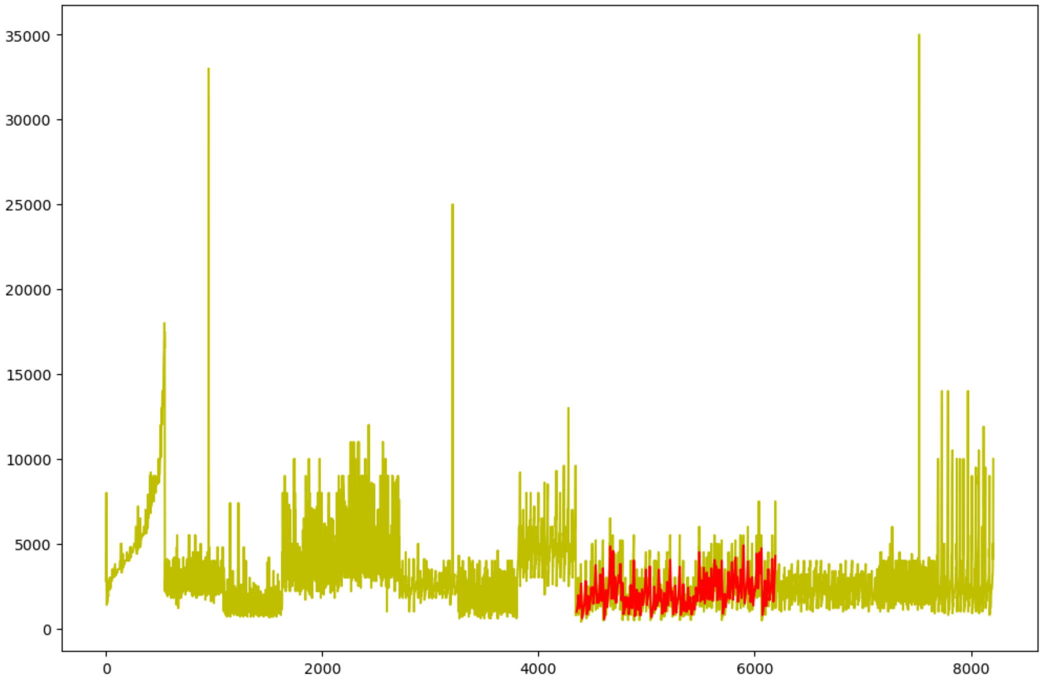

Figure 11.1 10 Days Moving Average of Onion

11.2 20 DAYS MOVING AVERAGE OF VEGETABLE: ONION

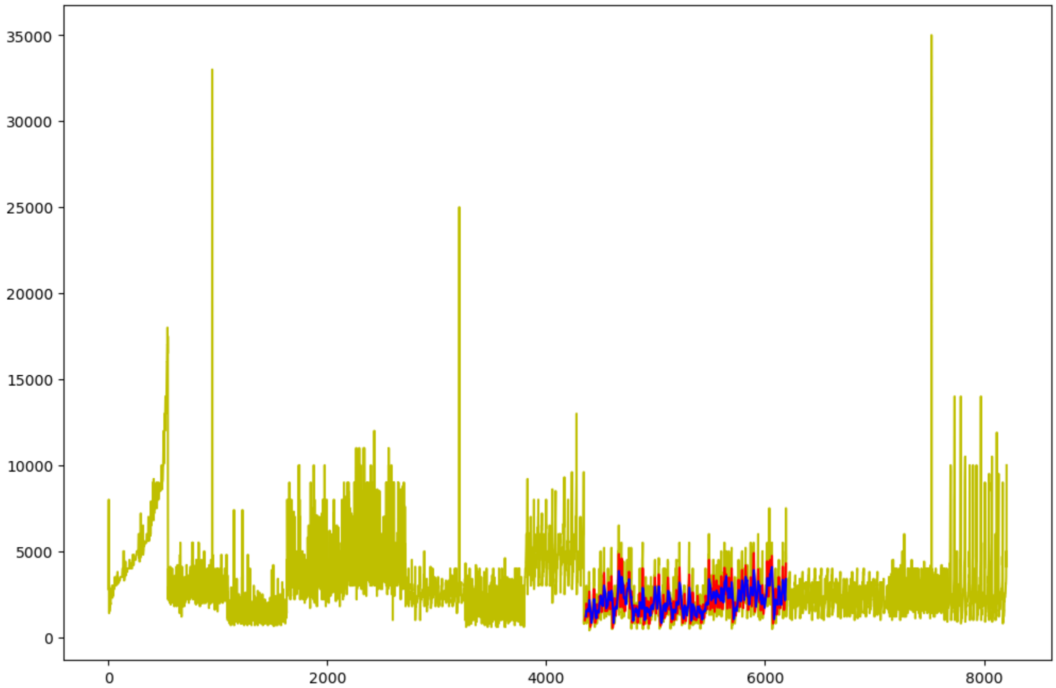

Figure 11.2 20 Days Moving Average of Onion

11.3 INPUTS GIVEN

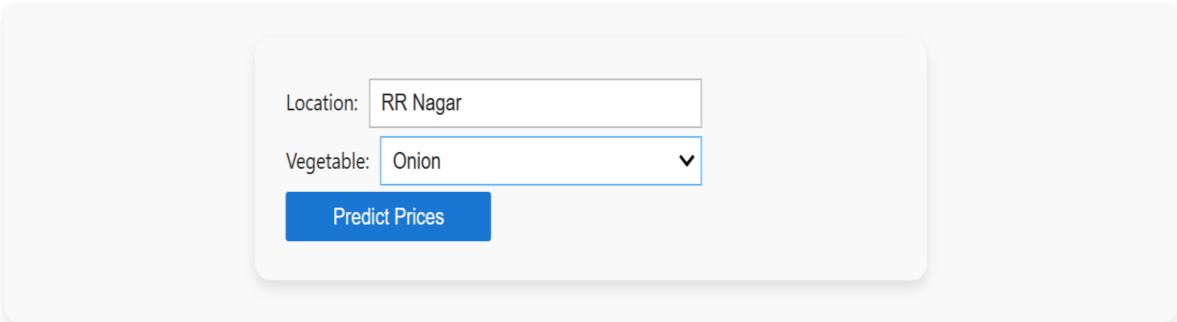

Figure 11.3 Inputs Given

11.4 OUTPUT

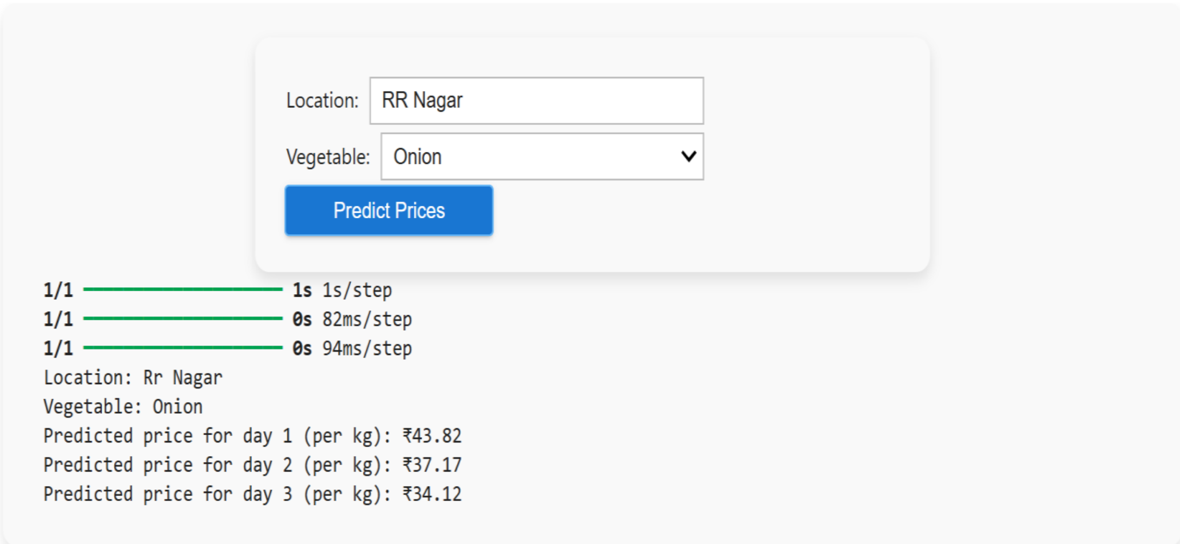

Figure 11.4 Output

11.5 PREDICTED PRICE VS ACTUAL PRICE GRAPH OF ONION

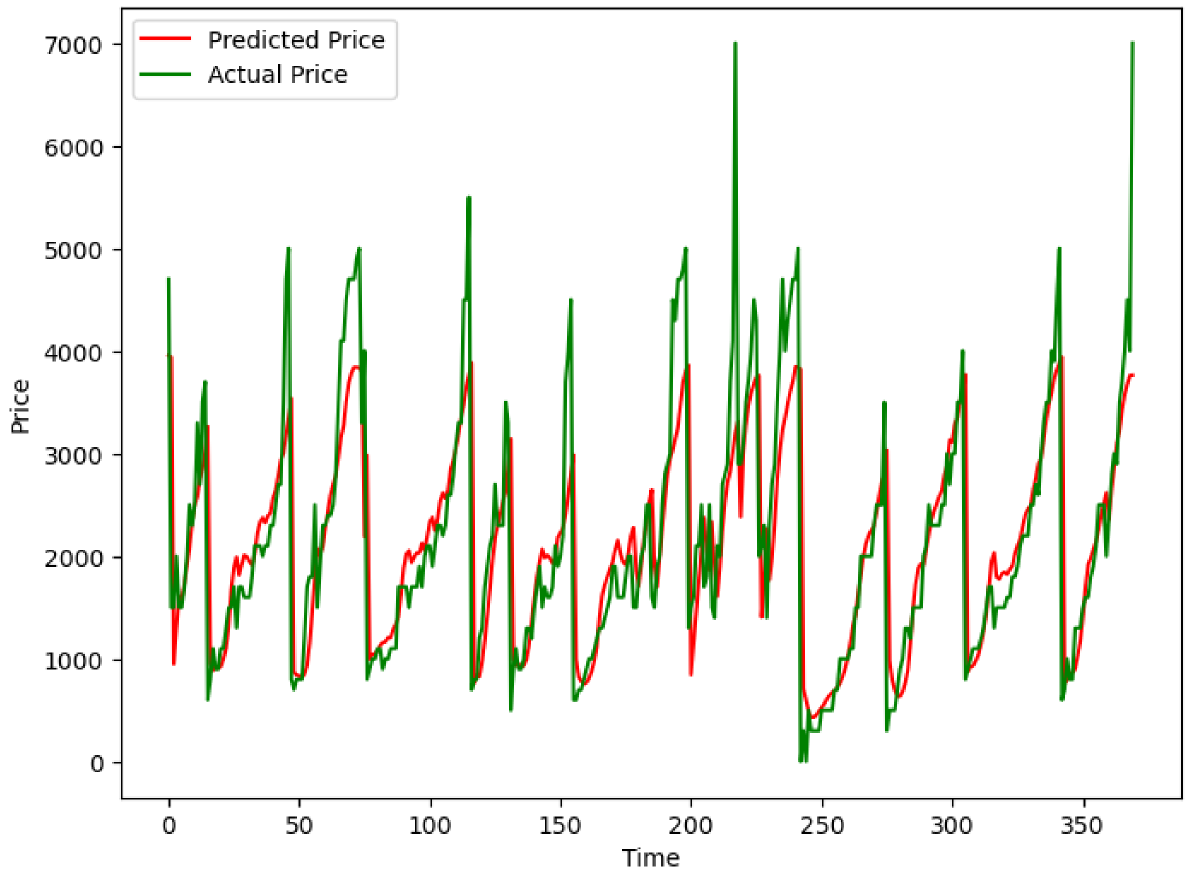

Figure 11.5 Predicted Price Vs Actual Price Graph of Onion

CONCLUSION

The commodity price predictor for vegetables marks a transformative advancement in utilizing machine learning to address the challenges of market volatility and price uncertainty in agricultural sectors. By implementing an LSTM model, the system capitalizes on its ability to process sequential data, capturing complex temporal dependencies and trends in historical price patterns to deliver highly accurate and timely predictions. This innovation is particularly valuable for stakeholders such as farmers, traders, policymakers, and consumers, offering a data-driven approach to optimize decision-making. Farmers can plan their cultivation cycles and harvesting strategies to align with anticipated price trends, thereby maximizing profits and minimizing losses. Traders benefit from enhanced inventory management, reducing the risks of overstocking or undersupply, while consumers gain insights into market trends, leading to more informed purchasing decisions.The model's ability to adapt to specific regional contexts, such as RR Nagar, further amplifies its practical utility, ensuring that predictions are tailored to localized market dynamics and conditions. Such regional specificity enhances accuracy and relevance, making it a powerful tool for bridging gaps in market information. Beyond economic advantages, this technology contributes to food security by minimizing waste, ensuring a steadier supply chain, and fostering greater transparency in pricing mechanisms.To fully realize its potential, the system must integrate real-time data streams from diverse sources, such as market databases, weather conditions, and socio-economic factors, which significantly influence price fluctuations. Continuous refinement of the model through robust validation, expansion to cover a broader range of crops and markets, and addressing challenges such as data quality and accessibility are essential steps. Moreover, efforts to democratize access to this technology through mobile applications, user-friendly interfaces, and outreach programs can help ensure its benefits are equitably distributed. Overall, the commodity price predictor is a promising innovation poised to revolutionize the agricultural economy by promoting efficiency, sustainability, and equity in food systems worldwide.

FUTURE ENHANCEMENT

To enhance the Commodity Price Predictor, the project can be extended to include a wider range of commodities such as fruits, flowers, grains, and spices, while integrating real-time data from market portals, weather APIs, and social media sentiment analysis to improve accuracy. Incorporating weather conditions like rainfall, temperature, and disaster alerts can provide insights into price fluctuations due to climate impacts. A farmer-centric mobile app or SMS-based service in regional languages can deliver daily price updates, weather forecasts, and customized selling recommendations. Advanced model enhancements like hybrid AI models, geospatial data integration, and blockchain for transparency can further refine predictions. Collaborations with local agricultural bodies and NGOs can ensure scalability, while workshops and chatbots can engage and educate farmers on leveraging the tool effectively, making it a powerful, sustainable solution for the agricultural ecosystem.

REFERENCE

- https://agmarknet.gov.in/
- https://www.geeksforgeeks.org/machine-learning-models/
- https://www.geeksforgeeks.org/deep-learning-introduction-to-long-short-term-memory/
- https://jupyter-tutorial.readthedocs.io/en/24.1.0/dashboards/voila/index.html
- https://en.wikipedia.org/wiki/Vegetable