Mr Amol Vishnu Sawant, 2026, 14:2
ISSN (Online): 2348-4098
ISSN (Print): 2395-4752

International Journal of Science, Engineering and Technology

An Open Access Journal

Seasonal Crop Supply Chain Planner with Local Demand Forecasting

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Abstract- The Indian agricultural sector continues to face major inefficiencies due to the persistent mismatch between crop production and localized market demand. Farmers often cultivate crops without accurate insights into city-level requirements, resulting in oversupply, wastage, reduced profits, or undersupply leading to scarcity and inflation. To address this issue, the proposed system "Seasonal Crop Supply Chain Planner with Local Demand Forecasting" integrates artificial intelligence and web technologies to provide actionable demand forecasts for farmers. The system is designed as a web application where farmers can register with basic profile details. Upon login, farmers gain access to localized demand forecasts for key seasonal crops. Dataset downloaded from internet serve as the basis for model training. The forecasting module employs a Long Short-Term Memory (LSTM) network, which is capable of capturing complex temporal dependencies, seasonal variations, and non-linear patterns in agricultural demand data. The expected outcome of this system is to minimize post-harvest losses, improve decision-making for crop cultivation and supply, stabilize farmer incomes, and enhance food availability for consumers. Performance of the forecasting model will be evaluated using statistical measures such as Root Mean Square Error (RMSE). The system has the potential to serve as a decision-support tool for small and medium-scale farmers, contributing toward a more efficient and sustainable agricultural supply chain in India.

Keywords- Key concepts of this system include AI-driven demand forecasting, seasonal crop planning, and localized market intelligence. It leverages Long Short-Term Memory (LSTM) models to analyze historical agricultural data and predict city-level crop demand, helping farmers make informed cultivation decisions. The platform integrates web-based access, farmer registration, and real-time insights to reduce supply-demand mismatch, minimize wastage, stabilize prices, and improve farm profitability. Evaluation metrics like RMSE ensure model accuracy, making it a reliable decision-support tool for sustainable agricultural supply chain management.

I. INTRODUCTION

Agriculture is the backbone of the Indian economy, contributing nearly 18% to the national Gross Domestic Product (GDP) and employing more than 40% of the workforce. Despite this crucial role, the agricultural supply chain in India remains fragmented and inefficient, often resulting in severe post-harvest losses, price volatility, and income instability for farmers. One of the major causes of these challenges is the mismatch between crop production and localized market demand. Farmers typically make decisions about crop selection and distribution without accurate insights into city-level demand patterns, leading to either oversupply (which drives down prices and increases wastage) or undersupply (which causes scarcity and higher consumer prices).

To address this challenge, modern data-driven forecasting methods can play a transformative role. With the rapid availability of open datasets from government bodies such as the Ministry of Agriculture & Farmers' Welfare, Directorate of Economics and Statistics (DES), and Agmarknet, as well as market arrival and price records from Agricultural Produce Market Committees (APMCs), it has become feasible to apply machine learning algorithms for demand forecasting at city or regional level. Unlike traditional models such as ARIMA, which are limited in handling non-linear and highly seasonal demand patterns, Long Short-Term Memory (LSTM) networks are capable of capturing long-term dependencies and irregular temporal fluctuations in agricultural demand data.

The proposed project, Seasonal Crop Supply Chain Planner with Local Demand Forecasting, aims to develop a web application that integrates farmer profiles and demand data to generate localized forecasts for seasonal crops. Farmers will log into the system, and based on their registered city, the system will provide AI-powered demand predictions for major crops. These insights can assist farmers in making informed planting and supply decisions, reducing losses, and improving profitability.

By leveraging deep learning-based forecasting and an accessible web interface, this system seeks to empower farmers with actionable information, enhance supply chain coordination, and contribute toward the larger goals of food security, reduced wastage, and sustainable agriculture in India.

II. LITERATURE SURVEY

A number of studies have explored crop forecasting, supply chain planning, and demand prediction in India using AI and statistical techniques. These works provide a foundation for developing localized demand forecasting systems for farmers.

Title	Authors / Year	Methods Used	Key Findings	Publisher
Crop recommendation and forecasting system for Maharashtra using machine learning with	2024	ML + LSTM + EM	Forecasted crop demand and suitability in Maharashtra using weather and historical crop data.	Springer – Discover Sustainability

LSTM: a novel expectation-maximization technique			LSTM effectively captured temporal variations.	
Classification and Estimation of Crop Yield Prediction in Karnataka using LSTM with Attention	2023	LSTM + Attention + Feature Selection	Applied LSTM with attention for crop yield prediction; high accuracy (~98%)	IJISAE
Mechanism			. Demonstrates handling of seasonal and city-level variation.	
Crop Yield Prediction using Deep Learning Algorithm based on CNN-LSTM with	2024	CNN - LSTM + Attention	Hybrid CNN-LSTM architecture for wheat and rice; useful reference for	Indian Journal of Agricultural Research

Attention Layer and Skip Connection			combining temporal and spatial patterns.	
ARIMA models to forecast demand in fresh supply chains	2011	ARIMA	Applied ARIMA to onion sales in Ahmedabad market; achieved MAPE of 43.14%. Shows volatility in perishable goods demand.	Int. Journal of Operational Research, Inderscience Publishers
Forecasting wheat prices in India	2018	ARIMA	Modeled monthly wheat price trends (2006–2017). Useful for understanding seasonal price variations.	Journal of Wheat Research, ICAR

Summary of Insights for Proposed Work:

- LSTM networks are effective in capturing temporal and seasonal patterns, outperforming ARIMA in volatile or non-linear demand scenarios.
- Attention mechanisms further enhance prediction by focusing on important time steps, improving city-level accuracy.
- Hybrid approaches (ARIMA + ANN, CNN-LSTM) can be adapted in future work for combining temporal and spatial patterns.
- Government datasets (Agmarknet, DES) are reliable sources for training AI models in Indian local markets.

III. PROPOSED WORK

3.1 Problem Definition

Agricultural supply chains in India face significant inefficiencies due to the mismatch between crop production and localized market demand. Farmers usually make cultivation and distribution decisions without reliable forecasting, leading to either surplus (causing wastage and reduced farmer income) or shortage (causing higher consumer prices and unmet demand). While government agencies and private players collect data on crop production and prices, localized city-level demand forecasting is still missing in most systems. Hence, there is a pressing need for an intelligent system that can analyze historical demand patterns, seasonal variations, and weather conditions to generate accurate demand forecasts for farmers, enabling them to plan crop supply more efficiently.

3.2 Scope of Project

The proposed system will focus on providing city-specific local demand forecasts for major crops using AI techniques, primarily Long Short-Term Memory (LSTM) networks for time-series prediction. The system will be developed as a web application with functionalities for managing farmer profiles and demand data. Key stakeholders include:

- Farmers: who will log in to the system, view demand forecasts for their respective city, and plan their cultivation and supply accordingly.
- Researchers and Policymakers: who may use aggregated demand insights to plan procurement and distribution policies.
- The scope is limited to:
- Demand forecasting at the city level (not at state or national aggregation).
- Crops with sufficient historical data available (such as wheat, rice, onions, and tomatoes).
- Integration of historical demand data from government/market sources and farmer profiles.

3.3 Project Objectives

The major objectives of the project are:

- To design a web-based platform that allows farmers to register and access local demand forecasts.
- To implement forecasting using LSTM for predicting future demand of seasonal crops in a given city.
- To provide a user-friendly dashboard that displays forecasted demand, historical trends, and seasonal variations.
- To support data-driven decision making in the agricultural supply chain, thereby reducing waste, stabilizing farmer incomes, and improving food availability.
- To evaluate the performance of the forecasting model using statistical metrics such as RMSE.

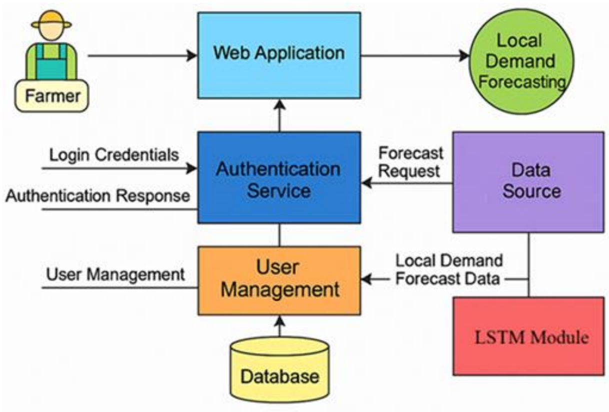
3.4 Project Constraints

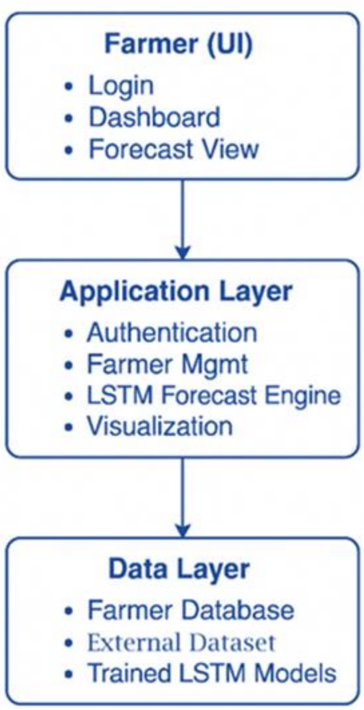
- Data Availability: Reliable city-level demand datasets may be limited or incomplete; system performance will depend on the quality of available data.
- Computational Resources: Training LSTM models may require significant computational power, and in the absence of high-performance hardware, training time may be long.
- Scalability: Initially designed for selected cities and crops; scaling the system to pan-India coverage may require additional datasets and infrastructure.
- User Accessibility: Many farmers may have limited digital literacy and may rely on

simplified interfaces or assistance to use the system.

- External Factors: Sudden market shocks due to pandemics, policy changes, or extreme weather events may not be fully captured by the model.

IV. SYSTEMS ARCHITECTURE





V. PROJECT REQUIREMENT SPECIFICATION

5.1 Performance Requirements

- The system must generate localized demand forecasts for major crops with an accuracy of at least 80–85%, measured using RMSE.
- Forecast generation for a single city dataset should complete within 20–30 seconds for small datasets (≤ 5 years of records) and within 60 seconds for larger datasets (> 10 years).
- The web application must support concurrent access of at least 10 farmers without significant degradation in response time.
- Operations (farmer registration, login, profile management) should complete within 20 seconds under normal load.

5.2 Software Quality Attributes / Requirements

- Usability: Interface must be farmer-friendly, using simple dashboards.
- Reliability: The system should achieve 99% uptime during deployment.
- Maintainability: The codebase must follow modular design principles (separate modules for data preprocessing, forecasting, and user management).
- Scalability: The system should support extension from a few cities to nationwide coverage with minimal changes.
- Portability: The application should run smoothly on Linux and Windows servers without major modifications.

5.3 Safety Requirements

- The system must not suggest harmful or misleading forecasts that could cause farmers to incur severe financial loss.
- Backup and recovery procedures must be implemented to prevent loss of critical farmer data and forecasting history.
- The application must handle incorrect or missing data gracefully, ensuring system crashes are avoided.

5.4 Security Requirements

- Farmers must authenticate with username and password; credentials will be encrypted.

- All sensitive data (including farmer profiles and demand records) should be stored in proper way.
- The system must use CSRF protection in website to prevent unauthorized form submissions.
- Role-based access: Only registered farmers can log in.
- HTTPS must be used in production deployment to prevent data interception.

5.5 Hardware Requirements

- Server:
- Processor: Intel i5 or above (quad-core)
- RAM: Minimum 8 GB (16 GB recommended for LSTM model training)
- Storage: 250 GB SSD
- Client (Farmer device):
- Any smartphone or desktop with an internet browser
- Minimum 2 GB RAM and 4 GB storage for mobile devices

5.6 Software Requirements

- Operating System (Server): Ubuntu 20.04 LTS / Windows Server 2019
- Framework: Python 3.10 or above
- Database: SQLite (for local development), MySQL (for production deployment)
- Machine Learning Libraries: TensorFlow/Keras, Scikit-learn, Pandas, NumPy, Matplotlib

5.7 Other Requirements

- Dataset Sources: Agmarknet, APMC market arrivals and prices, Ministry of Agriculture & Farmers' Welfare datasets.
- Training Frequency: The LSTM forecasting model should be retrained monthly as new demand data becomes available.
- Documentation: Technical documentation for system administrators must be provided.

VI. PROJECT PLANNING

6.1 Project Estimates

a) Effort Estimates

- Requirement Analysis & Dataset Collection: ~3 weeks (including Agmarknet/APMC data cleaning).
- Model Development (LSTM Forecasting): ~5 weeks (data preprocessing, model building, training, evaluation).
- Web Application Development: ~4 weeks.
- Integration & Testing: ~3 weeks.
- Documentation & Deployment: ~2 weeks.

Total Estimated Effort: ~17 weeks (≈ 4 months).

b) Cost Estimates

- Human Resources:
- AI/ML Engineer (1 person × 4 months) ≈ ₹2,00,000
- Web Developer (1 person × 3 months) ≈ ₹1,50,000
- Data Analyst (1 person × 2 months) ≈ ₹80,000
- Project Manager (part-time, 4 months) ≈ ₹1,00,000
- Subtotal: ≈ ₹5,30,000
- Infrastructure & Tools:
- Cloud server (AWS / GCP for training & deployment): ≈ ₹15,000/month × 4 = ₹60,000
- Software licenses & domain/hosting = ₹20,000
- Subtotal: ≈ ₹80,000
- Estimated Total Project Cost: ≈ ₹6,10,000 (excluding contingency).

c) Time Estimates (PERT / Gantt chart style)

- Total timeline: 4 months
- Critical tasks: Data preparation, LSTM training, Web integration.

6.2 Team Structure

To ensure efficient execution, the project will be developed by a small but specialized team:

1. **Project Manager**
   - Oversees project milestones, schedules, and deliverables.
   - Coordinates communication between technical and non-technical stakeholders.

2. **AI/ML Engineer**
   - Responsible for designing and implementing the LSTM forecasting model.
   - Handles feature engineering, preprocessing, and model evaluation.

3. Web Application Developer (Python Specialist)

- Builds web system, dashboards, and integration with forecasting module.
- Ensures usability and responsive design.

4. Data Analyst

- Collects and preprocesses demand data from sources like Agmarknet and APMC.
- Validates datasets and prepares reports for training and evaluation.

5. Quality Assurance (QA) Engineer (part-time role)

- Conducts unit testing, integration testing, and system validation.
- Ensures system performance, security, and user-friendliness.

6. System Administrator / DevOps (part-time role)

- Deploys system on cloud/servers.
- Handles backups, monitoring, and maintenance.

VII. PROJECT SCHEDULE

A well-defined project schedule ensures timely execution, resource allocation, and monitoring of milestones. The schedule for this project is divided into multiple phases, each with its own deliverables and dependencies.

7.1 Project Breakdown Structure (PBS)

The Project Breakdown Structure (PBS) is shown below:

1. Phase 1: Requirement Analysis

o Collect datasets.
o Define system objectives and constraints.
o Identify input/output variables for LSTM.

2. Phase 2: System Design

o Design database schema.
o UML diagrams and data flow diagrams.
o LSTM model design architecture.

3. Phase 3: System Development

o Backend: Python with SQLite integration.
o Frontend: HTML, CSS, Bootstrap for UI.
o LSTM model development in Python (TensorFlow/Keras).

4. Phase 4: Model Training & Testing

- Preprocess datasets (normalization, feature engineering).
- Train LSTM model with historical data.
- Evaluate accuracy with test datasets.

5. Phase 5: Integration

o Integrate LSTM predictions into web system.
o Create farmer profile module.
o Generate prediction reports.

6. Phase 6: Validation & Deployment

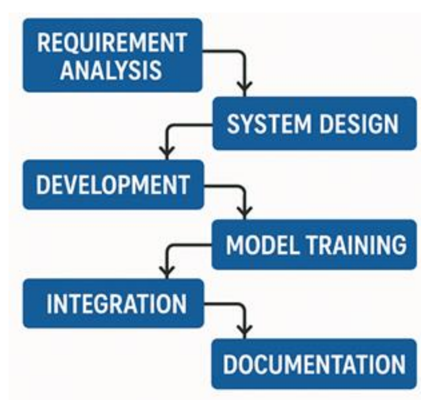
o Test GUI with real users (farmers).
o Debugging and error handling.
o Deployment on localhost/server.

7. Phase 7: Documentation & Reporting

o Prepare project report.
o Final presentation.

7.2 Task Network (Dependency Chart)

The task dependency chart can be represented as:



7.3 Time-line Charts (Gantt Chart)

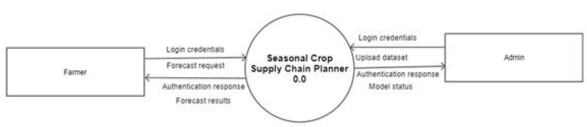
Task	Duration	Week 1	Week 2	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	Week 10	Week 11	Week 12	Week 13	Week 14	Week 15	Week 16	Week 17
Requirement Analysis & Dataset Collection	3 weeks																	
Model Development (LSTM Forecasting)	5 weeks																	
Web Application Development	4 weeks																	
Integration & Testing	3 weeks																	
Documentation & Deployment	2 weeks																	

Total Project Duration: 17 weeks (~4 months)

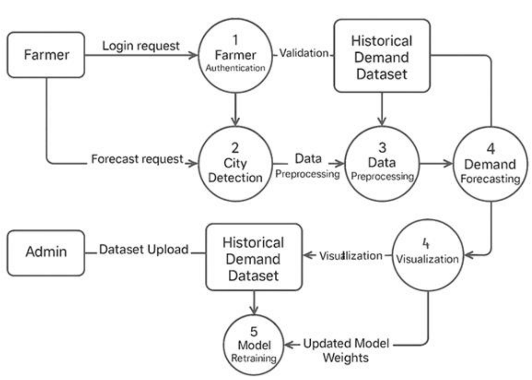
VIII. PROJECT DESIGN

DFD

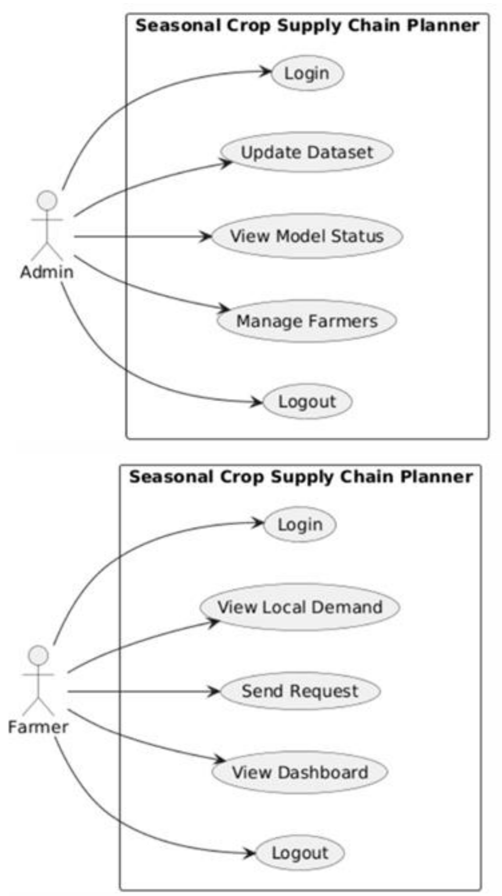
Context-Level DFD (Level-0)



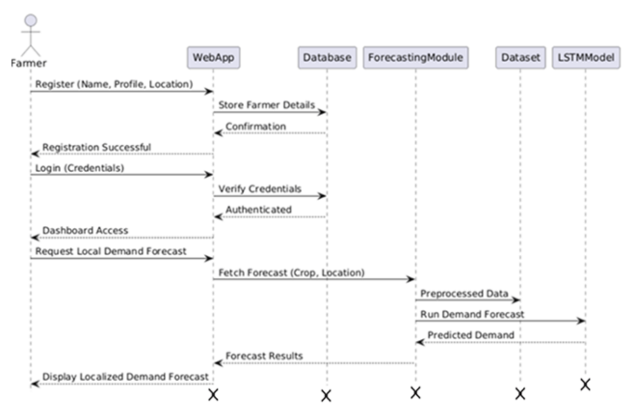
First-Level DFD (Level-1)

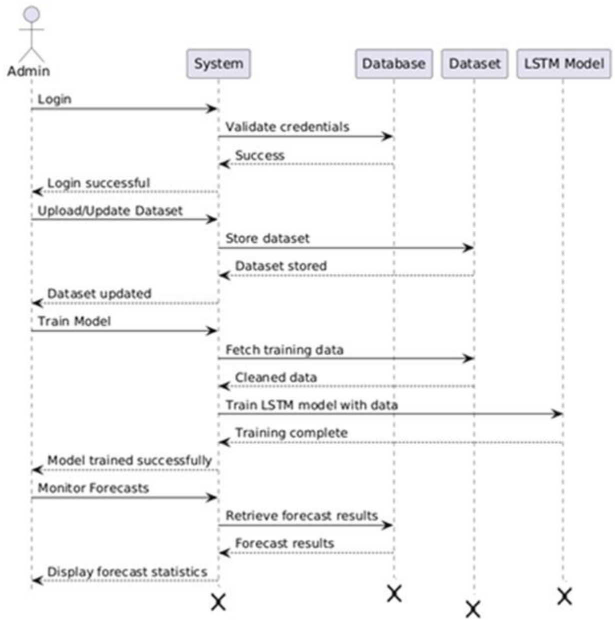


USE Case

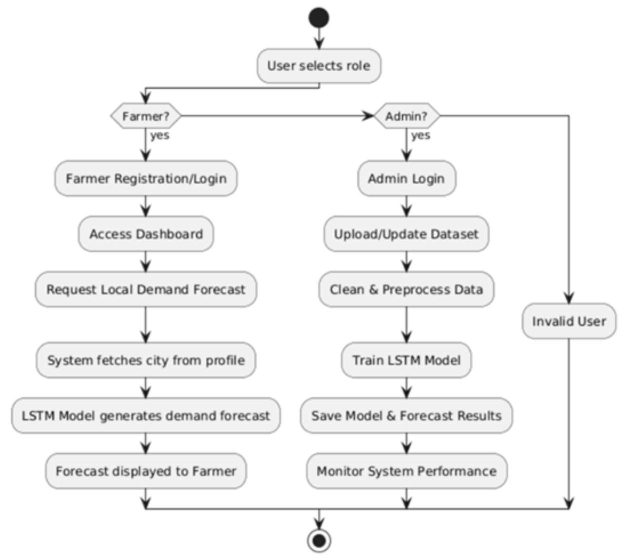


Sequence Diagram

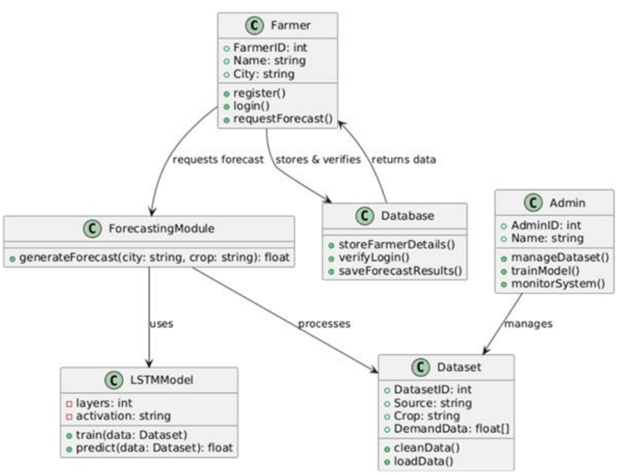




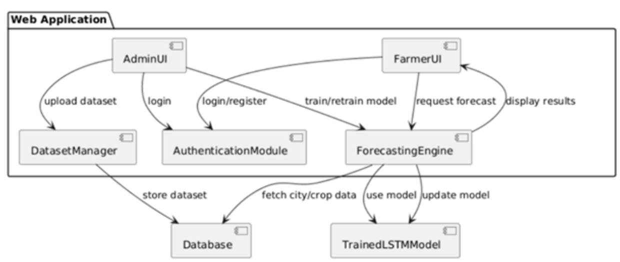
Activity Diagram



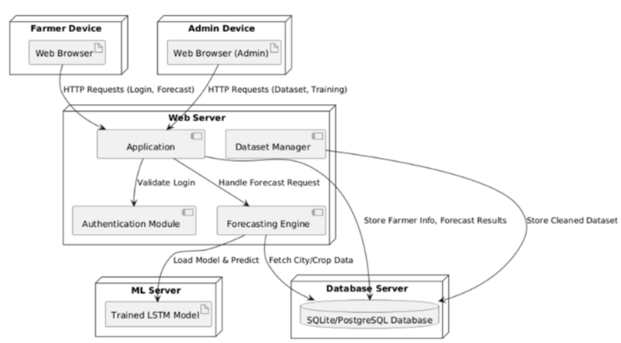
Class Diagram



Component Diagram



Deployment Diagram



IX. SYSTEM IMPLEMENTATION

The System Implementation phase involves turning the design and planned modules into a fully functional system that can be tested and deployed. For the proposed project, the implementation is divided into two main components: the AI-based forecasting module and the python-based web application for farmer interaction.

9.1 AI-Based Forecasting Module (LSTM)
- Dataset Preparation
- Model Development
- Evaluation

9.2 Python-Based Web Application
- UI/UX Design
- Integration of AI Module
- Security and Error Handling

Implementation Outcome
- Farmers can log in and immediately view localized demand forecasts.
- Admin can upload new market data, retrain the model, and monitor forecast performance.
- The system provides an integrated AI + web interface solution for improving decision-making in the seasonal crop supply chain.

X. EXPERIMENTAL RESULTS

10.1 GUI
10.2 Working Modules
10.3 Experimental Results

XI. CONCLUSIONS

The Seasonal Crop Supply Chain Planner with Local Demand Forecasting successfully demonstrates the application of AI for city-level crop demand prediction in India. By integrating historical data with a web-based farmer interface, the system provides actionable insights to optimize crop supply and minimize economic losses.

Key outcomes:
- Accurate Local Demand Forecasts
- Farmer-Centric Platform
- Reduced Wastage & Market Inefficiency
- Economic Impact
- Future Extensions

In conclusion, the project highlights the critical role of AI in local demand forecasting, demonstrating a practical solution to enhance agricultural supply chain planning for small and medium-scale farmers.

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