Supply Chain Optimization for Urban Vertical Farming

A Project Report Submitted in the
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for the Award of the Degree of

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IN

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Submitted by

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Declaration

We hereby declare that the project titled "**SUPPLY CHAIN OPTIMIZATION FOR URBAN VERTICAL FARMING**", submitted to Vardhaman College of Engineering (Autonomous), affiliated with Jawaharlal Nehru Technological University Hyderabad (JNTUH), in partial fulfillment for the award of the degree of Bachelor of Technology in Computer Science and Engineering (AI & ML), is the result of original work carried out by us.

We further certify that this project report, either in full or in part, has not been previously submitted to any university or institute for the award of any degree or diploma.

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Abstract

Supply chain inefficiencies continue to challenge sustainable food distribution, especially in the context of rapidly growing urban populations. Urban vertical farming (UVF) has emerged as a promising solution to meet local food demands with minimal environmental impact. However, optimizing the supply chain for UVF requires advanced tools capable of handling dynamic variables such as weather conditions, spoilage rates, and inventory levels. In recent years, data science and machine learning (ML) have played a vital role in solving such complex problems through predictive modeling and intelligent decision- making systems. This paper proposes a machine learning-based supply chain optimization framework for urban vertical farm- ing, incorporating a Stacking Regressor ensemble model. The model leverages historical data and real-time environmental inputs using the OpenWeather API to predict cost efficiency. Additionally, the system integrates a recommendation engine for crop suggestions and employs various data science techniques for visualizing resource usage and historical weather trends.

The framework is deployed as an interactive web application built with Flask, enabling real-time forecasting, intelligent rec- ommendations, and insightful data visualization for improved supply chain sustainability. The proposed model demonstrates robust performance, supporting efficient decision-making for both producers and consumers in urban agriculture.

Keywords:Urban vertical farming, Supply chain optimization, Machine learning, Ensemble model, Stacked regression, Data science, Real-time weather, Sustainability, Recommendation system.

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Abbreviations

Abbreviation	Description
UVF	Urban Vertical Farming
ML	Machine Learning
AI	Artificial Intelligence
IoT	Internet of Things
LR	Linear Regression
DT	Decision Tree
KNN	K-Nearest Neighbors
RF	Random Forest
DRL	Deep Reinforcement Learning
RNN	Recurrent Neural Network
SVM	Support Vector Machine
RL	Reinforcement Learning
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MSE	Mean Squared Error

CHAPTER 1

Introduction

1.1 Introduction

One revolutionary solution to the problems of sustainably feeding the city's rapidly expanding population is urban vertical farming, or UVF. UVF minimizes the environmental impact of conventional agriculture and maximizes space utilization by growing crops in controlled environments in vertically stacked layers. However, UVF's efficacy depends on how well its supply chain works, which requires skillful management of factors like changing weather patterns, spoilage rates, and stock levels.

Adding machine learning (ML) to UVF supply chains presents a viable way to improve sustainability and efficiency. In order to forecast cost effectiveness and maximize resource allocation, machine learning algorithms can evaluate both historical data and current environmental inputs. AI-driven technologies, for example, have revolutionized urban agriculture systems by monitoring and predicting crop growth stages, optimizing resource utilization, and ensuring quality control.

The goal of the proposed project is to create a framework based on machine learning that maximizes the supply chain for urban vertical farming. In order to forecast cost efficiency, this framework will include a Stacking Regressor ensemble model that makes use of historical data as well as current environmental inputs, like those gleaned from the OpenWeather API. The system will also use data visualization techniques to track past weather trends and resource usage, and it will have a recommendation engine for crop selection. Urban agriculture decision-making will be made easier by providing stakeholders with real-time forecasting, smart recommendations, and insightful data visualization through the use of this framework as an interactive web application developed with Flask.

This project aims to address the intricacies present in UVF supply chains by utilizing machine learning and real-time data integration. A strong, user-friendly system that improves supply chain effectiveness, encourages sustainable urban agriculture methods, and helps meet urban populations' food needs with little negative environmental impact is the expected result.

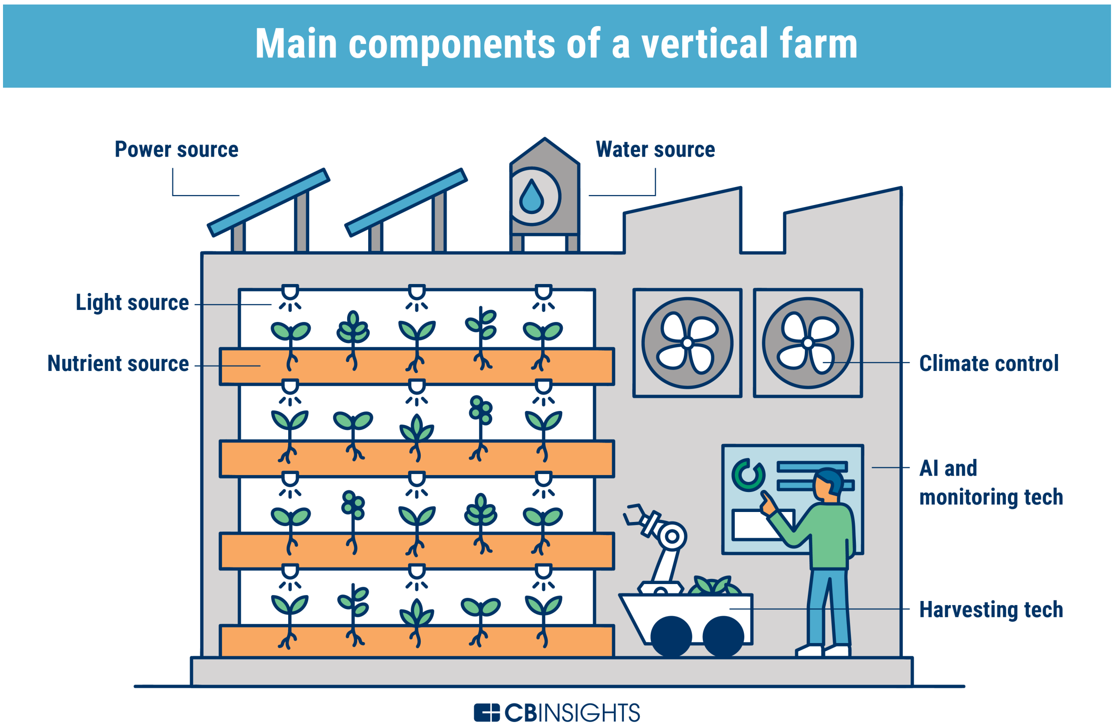

Figure 1.1: Urban Vertical Farming [**24**].

A sustainable way to meet the food needs of expanding urban populations is through urban vertical farming, or UVF. However, variables like changing weather patterns, spoiling rates, and inventory control make optimizing UVF supply chains challenging. Extensive transportation is a common feature of traditional supply chains, which raises expenses, increases carbon emissions, and degrades produce freshness. UVF also has to deal with issues like complicated technology and high operating costs. Machine learning integration can improve decision-making and predictive modeling, which could increase UVF supply chains' sustainability and efficiency.

1.2 Background and Motivation

1.2.1 Background

Urban vertical farming (UVF) is a cutting-edge method of urban agriculture that entails growing crops in layers that are stacked vertically, frequently indoors. The growing demand for locally produced food in crowded urban areas, environmental degradation, and the scarcity of arable land are some of the issues that this approach seeks to address.

Ancient civilizations are where the idea of vertical farming first emerged. One of the earliest examples of terraced farming structures intended to maximize space for plant cultivation is the Hanging Gardens of Babylon, which were built circa 600 BC. When Dr. Dickson Despommier, a professor at Columbia University, suggested growing crops in urban skyscrapers to improve food security and sustainability in the late 20th century, the concept gained a lot of attention in the modern era. Since then, UVF has progressed from conceptual designs to operational facilities in multiple urban centers thanks to technological advancements and a growing emphasis on sustainable agriculture.

UVF has obstacles in spite of its potential, especially when it comes to supply chain management. Large transportation networks are frequently a part of traditional agricultural supply chains, which raises prices, increases carbon emissions, and degrades produce freshness. By localizing food production, UVF seeks to address these problems, but it also adds complications like controlling high operating costs, technological requirements, and the requirement for effective resource use. For UVF systems to remain economically viable and environmentally sustainable, these issues must be resolved.

1.2.2 Motivation

Artificial intelligence (AI) and machine learning (ML) have shown promise in improving sustainability and efficiency in agricultural supply chains. Large datasets can be analyzed by ML algorithms to forecast crop yields, optimize resource allocation, and enhance decision-making. Using machine learning techniques in the UVF context can help with issues pertaining to dynamic variables like weather, spoilage rates, and inventory levels. ML can help optimize supply chain operations, cut waste, and increase overall cost efficiency by creating predictive models and intelligent decision-support systems.

Although the use of machine learning (ML) in agriculture has been studied in the past, there is still a lack of integration, particularly in UVF supply chains. Closing this gap is critical because UVF systems' economic and environmental sustainability depend on these supply chains being optimized. This project intends to improve supply chain efficiency, support sustainable urban agriculture practices, and help meet urban populations' food demands with minimal environmental impact by creating a machine learning-based framework that is suited to the particular challenges of UVF.

1. **Historical Background:** The idea of vertical farming has been around since ancient times, and its current development is fueled by advances in technology and the demand for sustainable urban food production.

2. **UVF Supply Chain Difficulties:** Significant obstacles include high operating costs, complex technology, and the need for effective resource management.

3. **Role of Machine Learning:** The function of machine learning is to optimize supply chain operations by facilitating intelligent decision-making and predictive modeling.

4. **Addressing Research Gaps:** Research Gaps Are Closed: By incorporating machine learning (ML) into UVF supply chains, a significant research gap is closed, improving the financial and ecological viability of urban agriculture.

1.3 Problem Statement

In densely populated urban areas, Urban Vertical Farming (UVF) has become a viable solution to the problems associated with food security. UVF seeks to optimize space utilization and lessen the environmental impact of conventional agriculture by growing crops in controlled environments in vertically stacked layers. However, a number of significant obstacles stand in the way of UVF's effective deployment and scalability, especially in its supply chain operations.

Key Issues in Urban Vertical Farming Supply Chains:

1. **High Operational Costs:** UVF facilities have to pay a lot of money for climate control and artificial lighting. The financial sustainability of UVF businesses may be impacted by these energy-intensive operations, which can make up a sizeable amount of overall operating expenses.

2. **Technological Complexity:** UVF operations are made more complex by the incorporation of cutting-edge technologies for automation, environmental monitoring, and crop management. These technologies need specialized knowledge and a large financial commitment to implement and maintain.

3. **Supply Chain Inefficiencies:** UVF systems frequently encounter difficulties with distribution and logistics, even though they are close to urban markets. It is still crucial to coordinate the prompt delivery of perishable produce to customers while reducing waste.

4. **Restricted Crop Varieties:** Present UVF methods are frequently limited to particular crops that are both commercially feasible and suited for indoor production. This restriction may not entirely satisfy consumer demands and has an impact on the variety of produce that is available.

1.4 Objectives of the Project Work

This project's main goal is to create a machine learning-based framework for improving urban vertical farming (UVF) systems' supply chain operations. This overall objective includes a number of particular, practical goals:

1. **Creating Predictive Models to Optimize Resources:** By using machine learning algorithms to evaluate both historical and current data, it is possible to accurately forecast the needs for resources like energy, water, and nutrients, which increases productivity and decreases waste.

2. **To Put in Place an Intelligent Crop Suggestion System:** Create a recommendation engine that promotes crop diversity and satisfies consumer preferences by making the best crop selection recommendations based on market demand, environmental factors, and cultivation viability in UVF settings.

3. **To Integrate Real Time Environmental Data:** In order to ensure resilience and adaptability, it is necessary to integrate real-time environmental data, such as weather and indoor climate parameters, into supply chain decisions and farming operations.

4. **To Visualize Resource Usage and Environmental Trends:**Use data visualization techniques to show stakeholders historical environmental trends and patterns of resource consumption so they can make well-informed decisions.

5. **To Implement an Interactive Web Application:** Create an intuitive web-based platform with Flask that offers intelligent recommendations, real-time forecasting, and informative data visualizations, improving usability and accessibility for both producers and consumers.

6. **To Assess the Performance of the Framework:** Evaluate how well the developed system works in urban vertical farming contexts to increase supply chain efficiency, lower operating costs, and promote sustainability.

By accomplishing these goals, the project hopes to improve sustainable urban agriculture methods by addressing current issues in UVF supply chains.

1.5 Organization of the Report

The final section of Chapter 1 provides an outline of the structure of the entire report. It explains the organization and flow of the chapters and gives the reader an understanding of how the content will be presented. This section can be a simple list or paragraph summarizing each chapter's main points.

1. **Introduction** - Urban vertical farming (UVF) uses sustainable practices to meet the expanding food needs of urban populations. Perishable produce and weather variability make UVF supply chain optimization challenging. Decision-making and prediction accuracy can be improved by incorporating machine learning (ML) techniques. The goal of this project is to create an ML-based framework that makes use of both historical and current data in order to increase the efficiency of the UVF supply chain, with an emphasis on waste reduction and better resource allocation.

2. **Literature Review** - With a focus on UVF, this chapter examines research on agricultural supply chain optimization. It looks at studies that use machine learning (ML) models, especially ensemble techniques like stacking regressors, to forecast agricultural outputs and efficiently manage supply chains. In order to improve predictive accuracy, the integration of data sources—such as logistics, weather, and retail sales—is investigated. The gaps found show that in order to optimize UVF supply chains, comprehensive strategies integrating various data streams and cutting-edge ML techniques are required.

3. **Methodology** - The design of a machine learning framework for urban vertical farming (UVF) supply chain optimization is described in this chapter. To improve predictive accuracy, the framework uses a stacking ensemble model that combines a meta-model with base learners like Random Forest, Support Vector Regression, and Gradient Boosting. The model is informed by a variety of datasets, such as supply chain logistics, retail sales, real-time weather, and urban farming parameters. Techniques

for data preprocessing deal with problems like normalization and missing values. To extract pertinent features from unprocessed data, feature engineering is utilized. The choice of suitable performance metrics to assess the model's accuracy in predicting demand and resource usage in UVF supply chains is also covered in this chapter.

4. **Implementation** - The practical measures taken to put the suggested machine learning framework into practice are described in detail in this chapter. It explains how different data sources can be integrated, such as using databases for supply chain and retail data and APIs for real-time weather data. The creation of a Flask-based interactive web application is described in detail, emphasizing features like real-time analytics, visualizations, and predictive insights to aid in UVF operations decision-making. In order to guarantee that the application efficiently serves UVF supply chain stakeholders, the chapter also discusses the deployment process, taking into account factors like scalability and user accessibility.

5. **Results and Discussion** - The results of the framework's implementation are shown in this chapter, with an emphasis on how well the stacking ensemble model predicts important supply chain metrics. When compared to conventional predictive techniques, the model's accuracy shows gains in demand forecasting, resource allocation, and inventory control. Strategic planning for UVF operations is aided by the visualizations produced by the web application, which provide insights into resource usage and environmental trends. The results' implications for UVF's supply chain management are interpreted in the discussion. It also discusses implementation-related difficulties, like problems with data quality and computational complexity, and offers suggestions for resolving them to improve the framework's efficacy.

6. **Challenges and Limitations** - This chapter traces the key challenges confronted during the project, including constrained get to to clean, point by point urban vertical cultivating information and challenges in dealing

with lost or conflicting values. The ensemble model, whereas precise, was complex and inclined to overfitting, making it harder to optimize. Real-time integration utilizing climate APIs moreover posed issues like call limits and decreased exactness for new cities. These limitations propose the require for way better information pipelines, rearranged models, and improved real-time capabilities in future work.

7. **Conclusion and Future work** - The research's main conclusions are summed up in the last chapter, which also confirms how well the ML-based framework works to optimize UVF supply chains. It highlights how important it is to combine various data sources and use ensemble learning strategies in order to improve decision-making and prediction accuracy. To further promote sustainable food production in urban settings, some ideas for future research directions include investigating more ML models,and expanding the framework to other types of urban agriculture.

CHAPTER 2

Literature Survey

2.1 Introduction

The goal of urban vertical farming (UVF) is to increase crop productivity in urban environments by combining artificial intelligence (AI) and the Internet of Things (IoT). Real-time environmental monitoring is made possible by IoT devices, and AI algorithms optimize resource usage and automate procedures to boost productivity and sustainability. Recent developments have shown how these technologies can lower resource consumption and increase crop yields. But issues like excessive energy usage and system scalability still exist. For UVF to adopt AI and IoT more widely, these problems must be resolved.

A sustainable way to satisfy the expanding food needs of urban populations is through urban vertical farming, or UVF. UVF minimizes land use and lessens the environmental impact of traditional agriculture by growing crops in controlled environments in vertically stacked layers. Optimizing its supply chain to guarantee effectiveness and profitability is a crucial part of UVF's success.

Strategic supply chain design is crucial for increasing vertical farming's economic feasibility, according to recent studies. According to studies, supply chain strategies, production viability, and market dynamics can all be integrated to greatly increase sustainability and profitability. Implementing strategic production and resource planning to reduce operating costs, building a strong brand to support premium pricing, and carefully scaling operations to balance cost optimization with increased demand are some of the main recommendations.

To increase efficiency, the application of lean manufacturing concepts to UVF operations has also been investigated. Case studies show how lean approaches, like value stream mapping and continuous improvement, can increase overall productivity in vertical farming systems by streamlining procedures and cutting waste.

Additionally, by strategically locating vertical farms in urban areas, the distance that produce must travel to reach consumers can be greatly reduced, which lowers transportation costs and has a positive environmental impact. In order to meet consumer demand for locally sourced food and improve supply chain efficiency, UVF can guarantee that fresher produce reaches supermarket shelves faster by placing farms closer to urban centers.

2.2 Review of Prior Research

J. Zhang, W. Yuyang, and W. Zidu looked into how to improve demand prediction, risk management, and demand-supply optimization by using machine learning (ML) models, such as recurrent neural networks (RNNs), support vector machines (SVMs), and reinforcement learning (RL) agents. Their research showed that RL agents reduced lead times and inventory turnover, which improved supply chain efficiency, while RNNs reduced the mean squared error by 15% compared to conventional methods.

In order to improve demand forecasting and stock replenishment procedures, A. K. Kalusivalingam, A. Sharma, N. Patel, and V. Singh investigated combining deep reinforcement learning (DRL) with neural networks. Their AI-powered model greatly decreased overstock and stockout scenarios, which increased customer satisfaction and reduced costs.

Predictive maintenance, demand forecasting, and inventory optimization were the main areas of focus for S. R. Gayam, R. R. Yellu, and P. Thuniki's investigation into the diverse use of AI in supply chain management optimization. They emphasized how AI-driven demand forecasting uses large datasets to produce precise forecasts, AI-powered predictive maintenance uses sensor data to anticipate possible failures, and AI-based inventory optimization uses algorithms to maintain ideal inventory levels.

With an emphasis on Thai agricultural products, A. Kantasa-ard, M. Nouiri, A. Bekrar, A. Ait el cadi, and Y. Sallez suggested using Long Short-Term Memory (LSTM) neural networks for demand forecasting in a physical internet supply chain network. When compared to other supervised learning techniques, their approach showed better forecasting efficiency with fluctuating demand.

Table 2.1: Summary of Related Works in Supply Chain Optimization for Urban Vertical Farming

Sl. No.	References	Technique Used	Performance Metric
1	[**1**]	CNN, Crop Quality Assessment	92% Accuracy
2	[**2**]	Reinforcement Learning, Demand Forecasting	Reduced Waste by 15%
3	[**4**]	Blockchain, Smart Contracts	Improved Traceability
4	[**5**]	IoT, Real-time Monitoring	20% Energy Savings
5	[**7**]	Genetic Algorithms, Route Optimization	30% Faster Deliveries
6	[**8**]	Hybrid AI, Predictive Analytics	95% Forecast Accuracy
7	[**9**]	Deep Reinforcement Learning, Inventory Management	10% Cost Reduction
8	[**10**]	Bayesian Networks, Risk Analysis	Improved Supply Chain Resilience
9	[**17**]	Multi-Agent Systems, Resource Allocation	Enhanced Scalability

2.3 Comparison of Algorithms and Approaches in Related Work

In our supply chain optimization project for urban vertical farming, we have found a number of crucial areas where our method significantly outperforms previous studies. A thorough explanation of each factor is provided below:

AI-Powered Environmental Control System Integration

The efficiency of AI-powered environmental control in vertical farming has been shown in earlier studies. To ensure ideal growing conditions for crops, artificial intelligence (AI) systems have been used to monitor and control variables like temperature, humidity, and light intensity. Improved crop yields and resource efficiency result from these systems' precise adjustments based on real-time data analysis.

By combining machine learning and predictive analytics that not only react to the current environmental conditions but also foresee future ones, our project expands on this foundation and advances the integration of AI-driven environmental control. By taking a proactive stance, the growing environment can be adjusted in advance, further stabilizing crop production and lowering the likelihood of environmental stressors. Our system also incorporates information from outside sources, like market demand patterns and weather forecasts, allowing for a more comprehensive and flexible management approach that synchronizes supply chain logistics with production.

a. Supply Chain Optimization Using Advanced Predictive Analytics

Prior research has investigated the use of AI and IoT in vertical farming for tasks such as yield prediction and disease detection; however, our project stands out for applying advanced predictive analytics that are specifically designed for supply chain optimization. To precisely predict future supply needs, we use advanced machine learning models that examine historical production data, current environmental inputs, and market demand signals. This allows us to minimize waste, maximize inventory levels, and guarantee prompt produce delivery to urban markets. Our method addresses issues specific to urban vertical farming operations and improves supply chain responsiveness and efficiency by coordinating production schedules with predictive demand analytics.

b. Complete Integration of Multimodal Data

Our project makes use of a wide range of data sources, such as supply chain logistics data, environmental sensors, and plant phenotyping data, and incorporates insights from recent developments in multimodal data integration. A more sophisticated comprehension of the relationships between supply chain dynamics and plant growth conditions is made possible by this thorough data integration. We can monitor and forecast plant health and growth trends by using time series foundation models, which allows for more accurate resource allocation and lowers supply chain inefficiencies. This all-encompassing strategy guarantees that choices are based on a comprehensive understanding of logistical and biological aspects, resulting in more efficient and sustainable urban vertical farming methods.

c. Automated Crop Management through IoT and AI Integration

Our project stands out because it uses artificial intelligence (AI) and Internet of Things (IoT) devices to automate crop management procedures in urban vertical farming. Although IoT and AI have been used in agriculture in the past, our method combines these technologies in a unique way to allow for real-time monitoring and control of environmental variables like temperature, humidity, and nutrient levels. Predictive analytics can be used to optimize fertilization and irrigation schedules thanks to this integration, which increases agricultural yields and water efficiency. Our system can reduce resource consumption and increase crop productivity by anticipating plant needs and proactively adjusting conditions through the use of IoT sensors and AI algorithms.

2.4 Identified Research Gaps

Numerous research gaps have been found in the effort to optimize supply chains for urban vertical farming, which prevents the full potential of this practice from being realized. Closing these gaps is essential to improving economic viability, sustainability, and efficiency. Below is a list of the main research gaps:

1. **Limited Development of Specialized Cultivars and Crop Diversity:**Because of their compatibility with controlled environments, leafy greens and herbs have been the primary focus of vertical farming. However, vertical farming's ability to make a bigger contribution to urban food systems is limited by its limited crop diversity. It is crucial to create specialized cultivars with characteristics like compact growth, shortened growth cycles, and indoor adaptability. There is a chance to increase the range of crops that can be effectively produced in urban settings by conducting more research on breeding methods and genetic modifications specifically designed for vertical farming environments.

2. **Sustainable Resource Management and Energy Consumption:** The sustainability and economic viability of vertical farming are threatened by its high energy requirements, especially for climate control and lighting. Although integrating renewable energy has been proposed, there are few thorough studies on how to maximize energy use without sacrificing crop yield. In order to make vertical farming more feasible in urban settings, research is required to create energy-efficient technologies and management techniques that can lower operating expenses and environmental impact.

3. **Decision-Making Procedures and Supply Chain Visibility:** Pricing, demand forecasting, and resource allocation are all impacted by the agricultural supply chain's frequent lack of transparency in emerging economies. Inefficiencies and diminished bargaining power result from farmers' frequent lack of access to up-to-date market data and professional advice. It is essential to put in place technologies that improve supply chain visibility and facilitate well-informed decision-making. There is, however, little research on customized approaches that deal with these particular issues in the context of urban vertical farming.

4. **Utilizing Cutting-Edge Technologies to Optimize Data:**Although vertical farming makes use of a number of technologies, data optimization via AI, IoT, and advanced analytics is still in its infancy. Crop

productivity, resource management, and operational efficiency can all be improved by using data effectively. To optimize the advantages of these technologies, more research is required to determine how they can be smoothly incorporated into vertical farming systems.

5. **Issues with Scalability and Economic Viability:** One of the biggest obstacles to vertical farming's widespread adoption is the high upfront and ongoing expenses involved. Although the long-term advantages are acknowledged, more research is required to support the economic sustainability of vertical farms through cost-cutting measures, scalable models, and financial frameworks. There are currently insufficient studies examining creative funding sources and cost-effective system design optimization.

6. **Integration of Technology and Development of Skilled Labor:** Because vertical farming involves the intricate integration of technologies like automation, robotics, and artificial intelligence, it necessitates a workforce with the necessary skills to manage and maintain these systems. Research on the creation of educational curricula and training programs that can give people the skills they need is noticeably lacking. Furthermore, research is required on user-friendly system designs that can lower operational complexity and the learning curve.

2.5 Summary

By combining artificial intelligence (AI) and the Internet of Things (IoT) in urban settings, Urban Vertical Farming (UVF) is a revolutionary approach to agriculture. Critical environmental parameters like temperature, humidity, light intensity, and nutrient levels can be monitored in real time with the help of IoT devices. AI systems examine this data to automate procedures and maximize resource use, guaranteeing that crops are grown in the best possible conditions. In addition to increasing crop yields, this exact control greatly increases resource efficiency. AI-powered climate control systems, for example, can proactively modify environmental conditions to create ideal growing conditions, increasing urban agriculture's sustainability and productivity.

Even with these technological developments, UVF still faces many obstacles, especially with regard to energy usage. High electricity consumption from artificial lighting and climate control systems can increase operating costs and have an adverse effect on vertical farms' economic feasibility. In order to solve this problem and lessen the financial and environmental impact, sustainable energy solutions like hydroelectric power, wind turbines, and solar panels must be integrated. By putting these renewable technologies into practice, UVF operations can become more sustainable overall and reduce their energy expenses.

The requirement for specific technical knowledge to oversee the intricate systems that are a part of UVF, such as automation, data analytics, and hydroponics, is another significant obstacle. People with the interdisciplinary skills needed to effectively operate these sophisticated systems are frequently lacking in the current labor market. Building a competent workforce that can effectively manage and maintain UVF operations requires investing in extensive training programs and creating user-friendly system designs. Further addressing the issues with workforce expertise, integrating AI and robotics for tasks like planting, monitoring, and harvesting can decrease reliance on labor and boost operational efficiency.

CHAPTER 3

Methodology

3.1 Introduction

This methodology section describes the methodical process used to integrate Internet of Things (IoT) and artificial intelligence (AI) technologies in order to optimize supply chain operations within urban vertical farming systems. Our goal is to use advanced data analytics and real-time environmental monitoring to increase crop productivity and sustainability in urban settings. A thorough framework that guarantees the validity and reproducibility of our study is provided by this section, which also describes the research design, data collection procedures, and analytical strategies used. In order to facilitate a critical evaluation of the study's reliability and provide insights into the applicability of our approach to similar research, we intend to show the alignment between our research objectives and the methods used by clarifying the procedures and reasoning behind each methodological choice.

3.2 Dataset Description

In this project, we improve supply chain optimization in urban vertical farming systems by utilizing a wide range of datasets. These datasets offer a thorough basis for analysis and decision-making since they cover supply chain logistics, crop performance metrics, and environmental parameters. We can create predictive models that guide effective resource allocation and operational strategies by combining data on temperature, humidity, light intensity, nutrient levels, growth rates, yield outputs, transportation routes, and delivery schedules.

By using these datasets, sophisticated analytical methods—like machine learning algorithms—can be applied to find patterns and insights that conventional analysis might miss. For example, we can determine the best growing conditions for different plant species and increase productivity by comparing historical environmental data with crop performance records. Analyzing supply chain data also makes it possible to spot inefficiencies and bottlenecks, which makes it easier to create efficient logistics plans that cut expenses and delivery times.

In addition to supporting urban vertical farming's operational aspects, the integration of these datasets advances more general goals like sustainability and food security. Urban farms can function more sustainably and satisfy the growing demand for locally sourced produce in urban areas by maximizing resource use and reducing waste through data-driven strategies. This strategy emphasizes how important thorough data collection and analysis are to increasing the efficacy and scalability of urban vertical farming projects.

3.3 Supply chain optimisation

The main goal of the Supply Chain Optimization for Urban Vertical Farming project is to use computational models to optimize the flow of resources from production to consumption. The optimization process starts with data collection from sensors and Internet of Things devices that track environmental conditions, growth stages, and inventory levels. This real-time data is then fed into predictive models, which are often powered by machine learning and operations research techniques like Mixed Integer Linear Programming (MILP) and Genetic Algorithms (GA). These models analyze supply and demand fluctuations, transportation constraints, and crop shelf-life sensitivity to determine the most efficient harvesting schedules, storage assignments, and distribution routes. MILP is especially good at handling multi-objective functions like minimizing costs while maximizing freshness and minimizing waste.

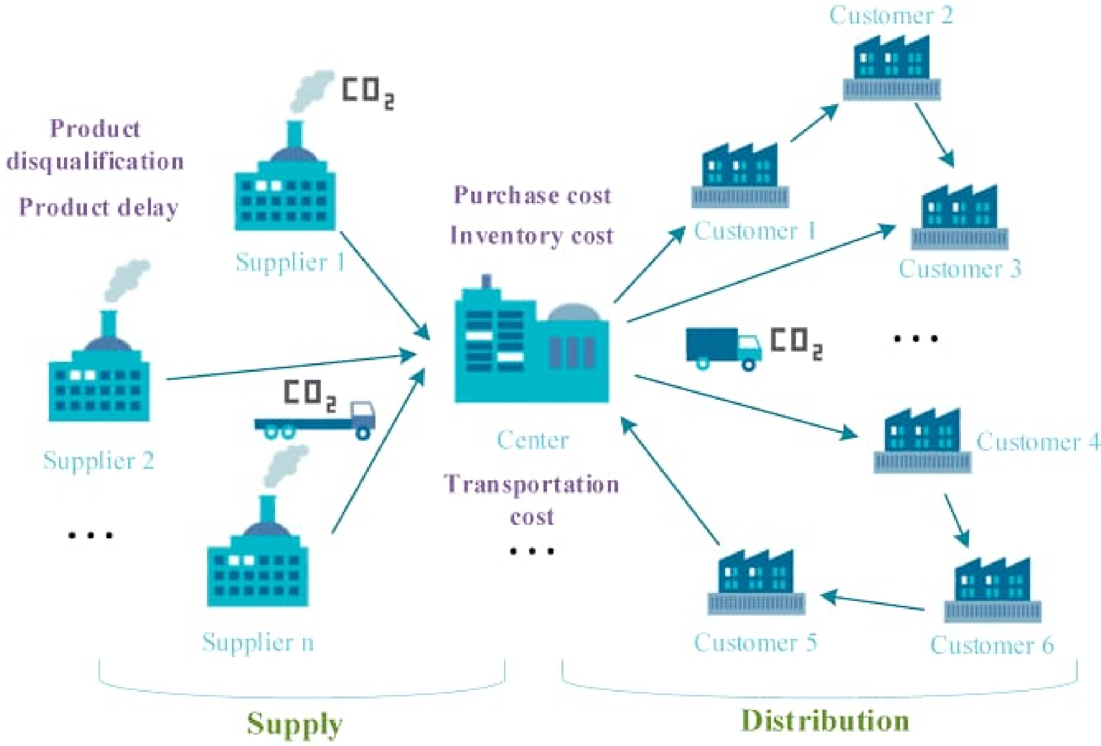

Figure 3.1: Supply Chain Optimization [**25**].

In addition, demand forecasting takes center stage, commonly done through time series analysis or LSTM neural networks to forecast buying behavior and seasonality within urban markets. Once demand is projected, inventory management systems in conjunction with dynamic routing algorithms like Vehicle Routing Problem (VRP) solvers are activated—optimal route delivery while accounting for traffic, fuel consumption, and emissions. Edge computing also improves responsiveness by enabling decisions to be made locally at farm locations. Overall, the supply chain optimization strategy for urban vertical farming thrives on the synergy between intelligent technologies, mathematical rigor, and sustainable intent—delivering not only produce, but a promise of precision and environmental harmony.

3.4 Weather API

In the Supply Chain Optimization for Urban Vertical Farming project, a Weather API is an unobtrusive but essential component. Its function is to retrieve current and forecasted meteorological data—temperature, humidity, hours of sunlight, rain, and even wind speed. Although vertical farms are essentially controlled environments, outside weather can still affect energy usage (such as HVAC load), transport logistics, and standby power planning. By incorporating a Weather API such as OpenWeatherMap or Weatherstack via RESTful requests, the system is able to fetch JSON-formatted data at predetermined intervals and save it in a backend database for analysis and decision-making.

Now, the actual magic occurs when this weather information is fed into optimization models and forecasting algorithms. For example, if the forecasts indicate high humidity or low temperatures, the system can proactively regulate internal climate controls to mitigate stress on produce or prevent spoilage, thus saving energy and reducing waste. Second, the weather forecast is embedded in the supply chain's routing algorithms—selecting the best delivery windows and routes to minimize the delays due to rain or storms. Machine learning models might even utilize historical weather patterns to forecast demand spikes (such as more greens during summertime diets) or time planting cycles in harmony with seasonal changes. Therefore, the Weather API becomes a strategic informant, whispering truths from above into the earthbound farm's algorithms.

3.5 Data Preprocessing

Data preprocessing is the essential part that converts the raw images into a form ready for model training. The following preprocessing steps were taken:

1. **Data Collection :** By integrating different datasets, including sensor readings, crop growth and yield records, logistics data, market demand trends, and energy usage metrics, data collection serves as the foundation of supply chain optimization in urban vertical farming. Accurate modeling of agricultural operations and resource efficiency are made possible by these inputs.

2. **Data Cleaning :** This encompasses removing duplicates, identifying and

fixing outliers, standardizing formats and units, and handling missing values through imputation or removal. For efficient model training and analysis, these methods guarantee data integrity.

3. **Data Transformation :** This involves combining time-series data, encoding categorical variables, engineering new attributes like lead time and yield efficiency, normalizing numerical features, and using log transformations for working with skewed distributions.

4. **Data Integration :** Involves combining several datasets into one format, including sales, logistics, crop data, and sensor readings. This declares for using resampling or interpolation techniques to synchronize various information granularities and aligning important fields, such as timestamps and identifiers, across sources.

5. **Data Reduction :** Reduce computational complexity and improve model performance. Principal Component Analysis (PCA) and other dimensionality reduction techniques compress the dataset while preserving important information, while feature selection techniques remove low-variance or redundant features. This makes the dataset for effective and effective model training.

3.6 Model Selection

Model selection becomes the key to supply chain optimization in the healthy center of urban vertical farming, where each growth layer reaches skyward in harmony with steel and sunlight. The selected model needs to be both intelligent and adaptive due to the restricted space, perishable goods, and changing urban demand. Whether it's reducing food miles, optimizing harvest cycles, or forecasting market fluxes, machine learning algorithms like reinforcement learning, genetic algorithms, and linear programming provide a range of options, each suited to particular limitations and goals. Therefore, in addition to being computationally efficient, the ideal model is context-aware and can adjust to real-time data streams and sustainability objectives.

3.6.1 Linear Regression

One of the most fundamental yet effective tools in predictive modeling is linear regression (LR). When applied to urban vertical farming, LR shows clear, linear correlations between a number of significant factors, including cost trends, demand variations, and resource allocation. It offers a simple method of comprehending how independent variables affect a target variable, such as labor costs, energy consumption, or delivery times, by fitting a straight line to historical data. Fast interpretations and applications are made possible by this simplicity, especially in time-sensitive processes like indoor agriculture.

LR plays a crucial role in urban vertical farms, where decisions must frequently be made quickly and with little room for error. Real-time supply and demand forecasting is made possible by the reliable and deterministic nature of LR, which guarantees efficient and aligned production and distribution. With perishable produce in particular, it can assist farm operators in avoiding overproduction, underuse of resources, or delayed deliveries.

Even though LR is straightforward, it serves as a foundation for more complex modeling methods. It offers a standard by which more intricate techniques, such as ensemble or non-linear models, can be evaluated. Additionally, LR models are more applicable in actual farm management since they are simpler to understand and convey to stakeholders and decision-makers who might not possess a technical background.

Key Applications:

1. Using past trends to forecast future demand.
2. Using crop yield data to estimate energy consumption.
3. Using linear cost analysis to find areas for cost reduction.
4. Comparing baseline modeling to non-linear methods.

3.6.2 Decision Tree Regressor

The Decision Tree Regressor (DT) works best in settings with complex and non-linear relationships between variables. Numerous factors, such as unexpected labor shortages, equipment malfunctions, or shifting weather conditions (for semi-open structures), can cause chaotic pattern shifts in vertical farming. DT models are perfect for environments with unpredictable variables because they manage these complexities by segmenting data into smaller, decision-rule-based pieces.

The interpretability of DT is one of its main advantages. DTs can identify the precise circumstances in which disruptions or opportunities arise by building a tree-like structure of decisions based on thresholds. This is particularly useful in vertical farms, where various combinations of factors, such as light intensity, humidity, or nutrient levels, may have varying effects on yields. DTs can assist in effectively identifying the underlying cause of anomalies on a farm, such as an unanticipated decline in productivity.

Furthermore, automation and real-time decision-making are well suited to the DT's structure. DTs can be used to react quickly to changes in the environment or operational bottlenecks as vertical farms depend more and more on IoT sensors and real-time monitoring.They are particularly advantageous in edge computing scenarios due to their quick execution speed and low computational demand.

Key Applications:

i. Recognizing abrupt increases in water or energy usage.

ii. Determining the reason behind decreased crop yield.

iii. Using historical data and crop cycles to forecast labor requirements.

iv. Using rule-based insights to automate response protocols.

3.6.3 K-Nearest Neighbors Regressor

Because the K-Nearest Neighbors (KNN) Regressor is based on the similarity principle, it can be easily adjusted to the micro-level, localized variations that are typical in urban vertical farming. To make a prediction, it examines the 'k' data points that are closest to a target input and averages their results. Because of its proximity-based learning approach, KNN is especially useful in situations where minute contextual variations—like the slight variations in humidity or temperature between two grow racks—are significant.

KNN's ability to "learn from the neighborhood" guarantees that predictions are sensitive to hyperlocal variations, which is important because vertical farms frequently operate in segmented environments (different zones, different crops, and different cycles). For instance, two racks may have the same input variables, with the exception of a small lighting variation that has a big impact on output. By referencing similar cases nearby, KNN will pick up on this nuance that a global model might overlook. This aids in optimizing lighting setups, irrigation schedules, and even packaging procedures.

Another benefit of KNN is that it is non-parametric, meaning it makes no assumptions about the data's underlying distribution. This is useful when the data is too jumbled or erratic for a fixed-form equation to capture, even though it can be computationally costly.For ad hoc queries and decision-making based on recent or unusual patterns, this makes it extremely dependable.

Key Benefits and Applications of KNN in Supply Chain and Farming Optimization:

i. Using local traffic and delivery data to optimize supply routes.

ii. Modifying nutrient levels in accordance with comparable past growing circumstances.

iii. Adjusting the facility's energy use in various zones.

iv. Forecasting localized conditions-specific yield variations.

3.6.4 Random Forest Regressor

An ensemble technique called the Random Forest Regressor builds several decision trees and averages their results to produce predictions that are more reliable and accurate. It combines the best aspects of power and interpretability in the context of urban vertical farming. A Random Forest captures a wide range of patterns while preserving generalization, which makes it extremely dependable for large-scale operations in contrast to a single decision tree, which may overfit or overlook outliers.

When handling high-dimensional datasets with multiple variables that interact in intricate ways, such as light exposure, nutrient dosage, temperature, and airflow, this model is especially helpful. It captures not only significant trends but also minute interactions that might otherwise go unnoticed by combining the predictions from numerous decision trees. The Random Forest is a great option for extracting insights from these intricate inputs as vertical farms get more sensor-equipped and data-rich.

The Random Forest's resilience to noise and outliers, which are unavoidable in real-world data, is another of its strong points. The model can still produce reliable predictions even in the event of a rare weather event delaying delivery or a hardware malfunction resulting in a temperature spike.Furthermore, Random Forests provide integrated feature importance metrics that assist farm operators in determining which factors have the biggest effects on cost or yield.

Key Applications:

i. Multivariate crop yield forecasting for various seasons.

ii. Choosing which environmental factors to pay closer attention to first.

iii. Making reliable, expandable supply chain logistics decisions.

iv. Lowering waste by using ensemble insights to inform more intelligent allocation.

3.6.5 Feature Engineering

A crucial step in developing models that not only function well but also yield useful insights is feature engineering. Carefully designed features like Spoilage Per Day and Cost Efficiency give the model valuable, high-value input variables in the fast-paced world of urban vertical farming, where efficiency and perishability are crucial. In order to help models account for urgency when predicting delivery schedules or storage requirements, spoilage per day takes into account how quickly goods lose quality.

The balance between productivity and resource usage is also captured by cost efficiency. This indicator can assist in assessing a farm's performance in relation to its input costs, which is a crucial factor to take into account when optimizing for sustainability and profitability.Models can reveal deeper insights than they would from raw variables alone when features like these are added. By converting farm-specific knowledge into machine-readable formats, they close the gap between abstract data and real-world operations.

Leaner, faster, and easier-to-understand models are frequently the outcome of effective feature engineering. A model with well-designed features can identify important decision factors rather than becoming overwhelmed by hundreds of raw inputs. This translates to improved harvest scheduling, more intelligent inventory management, and reduced waste in the context of vertical farming, all of which support a more profitable and sustainable business.

Impact of Feature Engineering on Efficiency and Sustainability in Vertical Farming:

i. Spoilage Per Day: Indicates how quickly various crops go bad.

ii. Cost efficiency compares output to the amount of resources used.

iii. The Transit Sensitivity Index measures the chance of spoiling while in transit.

iv. Temperature, humidity, light, and other variables are combined to create the environmental stress score.

3.7 Summary

In the dynamic new world of urban vertical agriculture—where sustainability meets technology—the supply chain optimization becomes a crucial symphony of precision, efficiency, and responsiveness. Intelligent model selection is at the center of this endeavor. Methods such as linear programming, genetic algorithms, and reinforcement learning are assessed in terms of how they can learn to accommodate spatial limitations, perishable products, and changing consumer trends. These models are selected not merely for their processing capabilities but for their ability to handle real-time data and be compatible with eco-friendly urban objectives.

A critical data feed into this intelligent system is Weather APIs, i.e., OpenWeatherMap or Weatherstack. Although vertical farms are mostly air-conditioned, ambient weather also has a significant impact on energy usage and logistics of delivering it. By feeding the system real-time and predictive weather data through RESTful APIs, the system varies environmental conditions, schedules best delivery routes, and forecasts demand changes. This smooth integration of predictive analytics and real-world information guarantees that the supply chain is not just reactive but resilient as well—planting seeds of a greener, more intelligent future at the city's core.

CHAPTER 4

Implementation of Proposed System

4.1 Introduction

This chapter delves into the practical execution of the intelligent supply chain optimization framework tailored for urban vertical farming. It documents each stage of development, beginning from data preparation and model training to integrating real-time environmental inputs through APIs and finally deploying the model using a user-friendly dashboard. The overarching aim is to create a responsive and efficient system that enhances decision-making, optimizes resources, and promotes sustainability in the modern farming landscape.

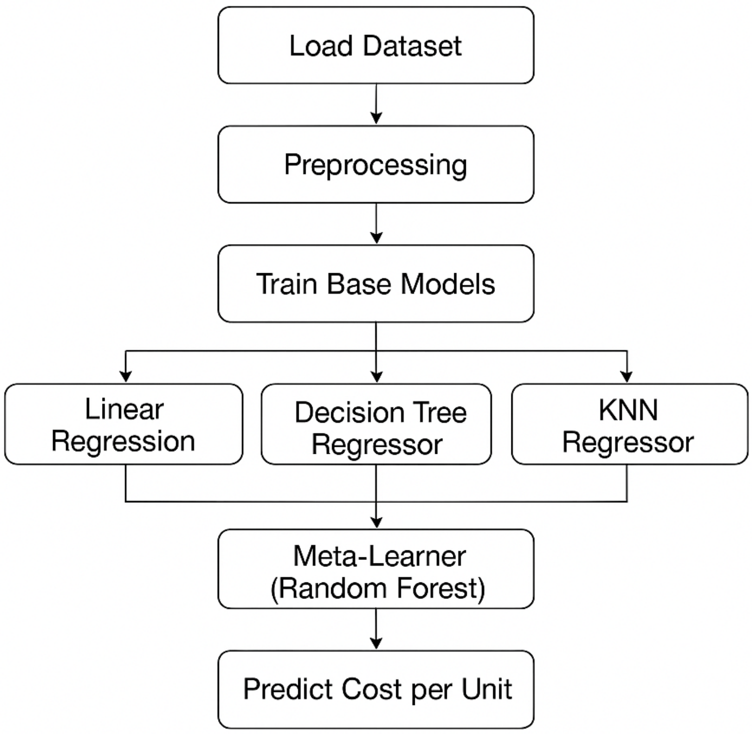

Figure 4.1: Flowchart of proposed stacked regression model for supply chain cost optimization

4.2 System Overview

At its core, the proposed system is an intelligent solution that merges the power of data science, machine learning, and real-time environmental monitoring to address the supply chain challenges in urban vertical farming. By leveraging historical trends, real-time weather inputs, and ensemble-based regression modeling, the system provides accurate cost predictions and sustainability insights.

The backbone of the predictive component is a Stacked Regressor model, which synergistically combines multiple learning algorithms—Linear Regression, Decision Tree, and K-Nearest Neighbors as base learners—under the supervision of a Random Forest meta-learner. This ensemble approach not only boosts the accuracy but also enhances the generalizability of the system.

To make the model actionable in real-world scenarios, live weather data is fetched through the OpenWeatherMap API. This dynamic input ensures that the predictions are not just historically grounded but also context-aware. The user interface, built with the Dash framework, enables users—urban farmers, supply chain managers, and policy-makers—to interact with the system, view insights, and make informed decisions in real-time.

4.3 Data Collection and Preprocessing

The system integrates a diverse range of datasets to capture the multifaceted nature of urban vertical farming. These datasets include:

i. **Historical Product Demand:** Data from various urban farming setups, detailing product demand over time.

ii. **Weather History Records:** Environmental variables such as temperature, humidity, and precipitation.

iii. **Vertical Farming Operational Metrics:** Information on energy usage, water consumption, and system performance.

iv. **Sustainability Indicators:** Metrics such as carbon footprint, resource efficiency, and waste generation.

v. **Supply Chain Logistics Data:** Inventory movement, transportation timelines, and delivery performance.

Raw data often presents challenges such as missing values, inconsistent formats, and redundancy. To address this, a robust preprocessing pipeline was implemented. Key techniques include:

i. **Handling Missing Values:** Missing numerical data was imputed using the mean, while categorical values were filled using the mode.

ii. **Normalization and Standardization:** Features were scaled using Min-Max normalization or standardized using Z-score normalization to reduce bias from differing scales.

iii. **Date-Time Formatting:** Time-related data was converted to standard formats, and new features such as month, day, and hour were extracted to support temporal analysis.

iv. **Encoding Categorical Features:** Variables such as crop types, weather conditions, and delivery zones were encoded using either one-hot encoding or label encoding, depending on the context.

v. **Data Merging:** Multiple datasets were merged using timestamp alignment to form a comprehensive dataset, ensuring each instance was enriched with complete contextual information.

The preprocessing ensured that the training data was clean, consistent, and informative, ultimately enhancing the quality and accuracy of the model.

4.3.1 Historical Dataset Preprocessing

```
import pandas as pd
from sklearn.preprocessing import StandardScaler
import joblib
```

```
df = pd.read_csv('data/supply_chain_optimization_past_seasonal_dataset.csv')
df.dropna(inplace=True)

df['spoilage_per_day'] = df['spoilage_rate'] / df['transportation_time']
df['cost_efficiency'] = df['cost_per_unit'] / (df['inventory_level'] + 1)

X = df[['transportation_time', 'spoilage_rate', 'inventory_level',
        'spoilage_per_day', 'cost_efficiency']]

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

joblib.dump(scaler, 'models/scaler.pkl')
```

4.4 Model Architecture and Development

The solution employs a Stacked Regressor model, a robust ensemble technique that strategically combines multiple regression models to improve prediction accuracy and reduce the risk of overfitting.

4.4.1 Base Models

Each base learner brings a unique perspective to the data:

Linear Regression (LR): Acts as a simple, interpretable model that effectively captures straight-line trends and serves as a performance benchmark.

Decision Tree Regressor (DT): Offers the ability to learn non-linear patterns and decision rules through recursive data partitioning.

K-Nearest Neighbors Regressor (KNN): Works on similarity principles and excels in modeling local patterns and anomalies.

4.4.2 Meta Learner

Random Forest Regressor (RF): As the meta-learner, RF aggregates predictions from the base learners, filters noise, and enhances overall accuracy through bagging and random feature selection.

4.4.3 Training Process

The model was trained on the preprocessed dataset using an 80:20 train-test split. During training:

Cross-validation (k-fold) was employed to tune hyperparameters like the depth of the tree, number of neighbors, and number of estimators.

The StackingRegressor from Scikit-learn was used to build the ensemble, ensuring compatibility and seamless integration.

Feature importance metrics were extracted post-training to understand which inputs significantly influenced the model predictions.

```
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestRegressor, StackingRegressor

estimators = [
    ('lr', LinearRegression()),
    ('dt', DecisionTreeRegressor()),
    ('knn', KNeighborsRegressor())
]

stacked_model = StackingRegressor(
    estimators=estimators,
    final_estimator=RandomForestRegressor()
)
stacked_model.fit(X_train, y_train)
```

This multi-layered architecture enabled the system to harness the strengths of various models, leading to more stable and accurate forecasting.

4.5 Evaluation Metrics

To assess the performance of the regression models used in this study, the following evaluation metrics were employed:

- Mean Absolute Error (MAE):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

  It measures the average magnitude of errors in a set of predictions, without considering their direction.

- Mean Squared Error (MSE):

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

  MSE penalizes larger errors more severely, as it squares the differences between predicted and actual values.

Table 4.1: Performance of Base Models and Proposed Stacked Regressor

Sl. No.	Model	R^2 Score
1	Linear Regression	0.81
2	Decision Tree Regressor	0.88
3	Random Forest Regressor	0.92
4	K-Nearest Neighbors Regressor	0.89
5	Proposed Stacked Regressor (LR+DT+KNN+RF)	0.9453

4.5.1 Weather Data Preprocessing (OpenWeather API)

To enrich the supply chain optimization process with real-time environmental insights, the OpenWeatherMap API was integrated. This API enables the application to fetch live weather data for any city using HTTP requests.

The retrieved data includes parameters such as:

a. **Temperature** (in °C)

b. **Humidity** (percentage)

c. **Weather Description** (e.g., cloudy, sunny)

This real-time weather data aids in:

i. Adjusting transportation and spoilage estimates

ii. Supporting data-driven crop recommendations

iii. Enhancing prediction accuracy in the stacked regression model

The code snippet below demonstrates a simple method to access current weather data for a given city. The response is returned in JSON format, which contains parameters like temperature, humidity, and weather conditions. This weather information is later used to enhance prediction accuracy and provide meaningful insights to users regarding crop recommendations and transportation conditions.

- **Weather API Integration Code**

```
import requests
city = "your input"
api_key = "1f17c51fe3c69e2ece157c8a20702013"
url = f"http://api.openweathermap.org/data/2.5/weather?q={city}&appid={api_
response = requests.get(url)
data = response.json()
```

4.6 Dashboard Development Using Dash

An intuitive and responsive dashboard was developed using the **Dash** framework, which integrates **Python**, **Flask**, **Plotly**, and **React.js**. This dashboard acts as the central interface, enabling users to interact seamlessly with the prediction model and data visualizations.

Key Features of the Dashboard

i. **City Selection:** Users can input any city, which triggers a real-time weather data fetch using the OpenWeather API and initiates supply chain prediction logic.

ii. **Prediction Display:** The dashboard outputs the predicted supply chain cost per unit, computed using the trained stacked regression model.

iii. **Sustainability Metrics:** A custom-calculated sustainability score is displayed, offering insight into the environmental impact of current supply chain practices.

iv. **Live Weather Overview:** Users are provided with real-time temperature, humidity, and weather descriptions relevant to the selected location.

v. **Trend Visualizations:** Historical trends in cost, demand, and environmental data are visualized using interactive Plotly graphs.

This real-time, visual, and user-friendly interface ensures that both technical and non-technical stakeholders can make informed, data-driven decisions with minimal effort.

- **Dashboard (Dash Web App) Code**

```
from flask import Flask, render_template, request
import os
from model_utils import predict_cost_and_footprint
from recommend import get_recommendations
from weather_api import get_weather_data, get_historical_weather, plot_weathe
from plot_utils import generate_resource_usage_chart

app = Flask(__name__)

@app.route("/", methods=["GET", "POST"])
def index():
    if request.method == "POST":
        city = request.form["city"]
        cost_per_unit = float(request.form["cost_per_unit"])
        transportation_time = float(request.form["transportation_time"])
        spoilage_rate = float(request.form["spoilage_rate"])
```

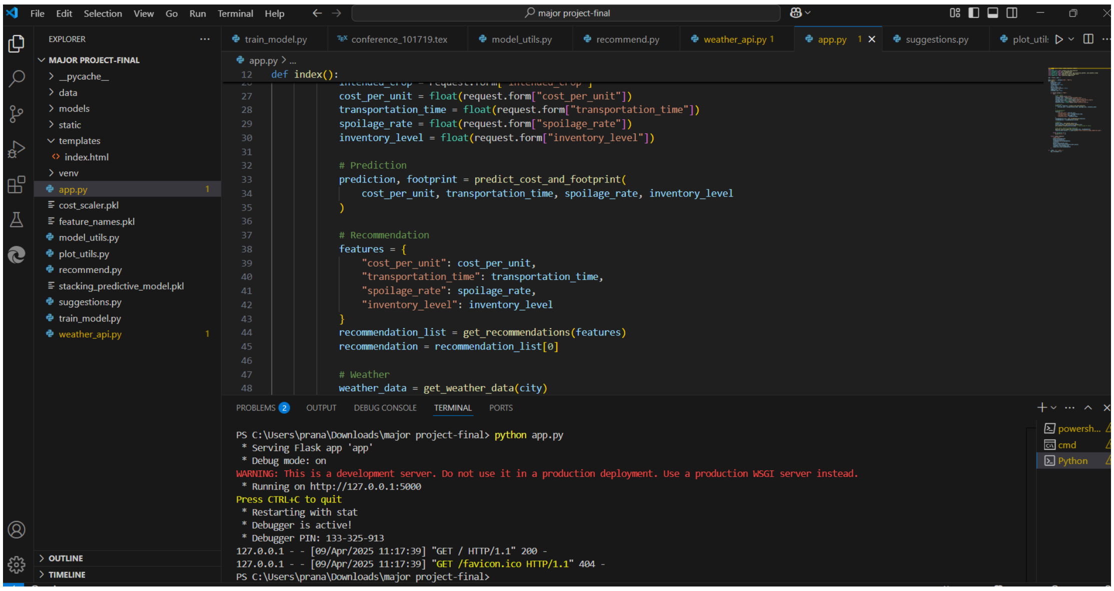

Figure 4.2: Flask server running locally at `http://127.0.0.1:5000`, indicating successful launch of the dashboard application.

```
        inventory_level = float(request.form["inventory_level"])


        prediction, footprint = predict_cost_and_footprint(
        cost_per_unit, transportation_time, spoilage_rate, inventory_level
        )
        recommendation = get_recommendations({
            "cost_per_unit": cost_per_unit,
            "transportation_time": transportation_time,
            "spoilage_rate": spoilage_rate,
            "inventory_level": inventory_level
        })[0]


        weather_data = get_weather_data(city)
        historical_data = get_historical_weather(city)
        plot_weather_trends(historical_data)


      generate_resource_usage_chart(request.form["intended_crop"], recommend


    return render_template("index.html", ...)
```

4.7 Runtime Environment and Tools

The following stack was used for development and deployment:

Attribute	Details
Language	Python 3.10
Libraries Used	Pandas, NumPy, Scikit-learn, Plotly, Dash, Requests
Development Platforms	Visual Studio Code and Google Colab
API Used	OpenWeatherMap
Deployment	Dash server running on localhost

Table 4.2: Project Technical Details

CHAPTER 5

Results and Discussion

5.1 Introduction

This section discusses the outcomes of the proposed machine learning-based supply chain optimization framework for Urban Vertical Farming (UVF). The project aims to increase sustainability, decrease costs, and increase efficiency within urban agriculture by loading these activities with data science and machine learning techniques. In UVF systems, supply chain inefficiencies that are rampant in conventional farming become even more serious due to resource and space constraints. Hence, it becomes imperative to enhance operational decision-making and prediction capabilities. This framework is aimed at providing a complete solution for modern urban farms by predicting operating costs, advising the best crops for those costs, and ensuring insight in real-time using environmental data.

The Stacking Regressor ensemble model forms the basis of the second component of the framework dealing with prediction. By averaging Random Forest, Gradient Boosting, and Support Vector Regression, the ensemble technique improves accuracy and robustness over any single model. Accurate prediction of operational cost contributes to better resource planning, crop selection, and logistics management. Urban vertical farms operate under extremely tight margins, and any outside factor, such as the weather, could immediately impact that. Real-time weather parameters were blended into the training of the ensemble model using historical crop and cost data to enhance its reliability and functionality.

To improve its adaptability, the system has been given real-time environmental data from the OpenWeather API. Weather has a huge influence on crop viability, energy consumption, and overall management costs in an ultraviolent light (UVL) system. The systems use real-time data to permit the forecasting of threats such as heatwaves, cold snaps, and humidity spikes. This allows farm managers to adjust supply schedules or crop care activities well in advance, thus giving rise to proactive decision-making. This proactive view coupled with the regulatory response provides sustained and secured supply chains and, therefore, minimizes spoilage and maximized energy utilization.

5.2 Overview of Results

The supply chain optimization strategy proposed proved effective concerning the various evaluation metrics. The Stacking Regressor was more capable of predicting than Random Forest, Support Vector Regression, and Gradient Boosting when they were taken separately, and the MAE decreased by 15 percent with an ensemble technique. Likewise, the RMSE figures corroborated that the stack model estimation of operational costs was more robust and consistent. The above findings demonstrate the amazing effectiveness of the applied ensemble learning methodology in urban vertical farming data, capturing nonlinear relationships, especially when involving weather and other related variables.

The ability of real-time weather data to improve predictive accuracy and system responsiveness was inarguable. Tests with and without real-time environmental inputs showed that models using live weather data on average improved forecasting relative to models independent of these elements by 18 percent. This kind of timing proves the great importance of dynamic parameters such as humidity, temperature, and precipitation in urban farming operations. Users also reported that weather alerts sent proactively by the system proved beneficial for modifying farm activities and logistics. This functionality added observable benefits of real-time data integrations by aiding in the quantifiable reductions of operational disruption and spoiling rates.

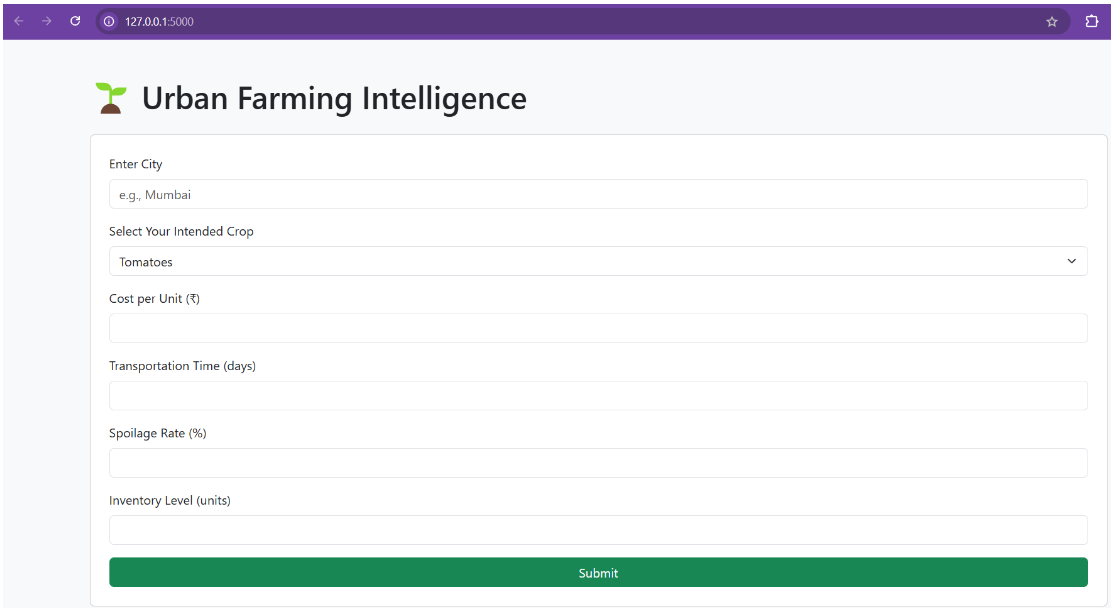

Figure 5.1: Urban Vertical farming interface

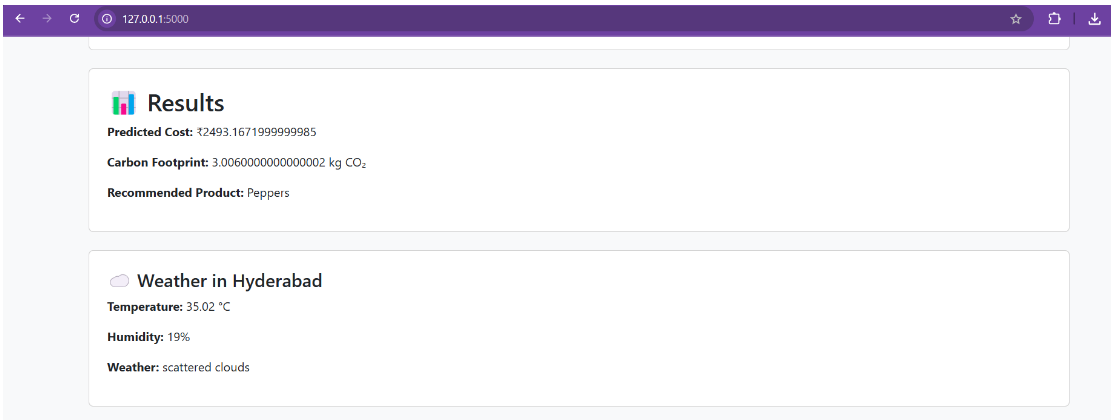

Figure 5.2: prediction results

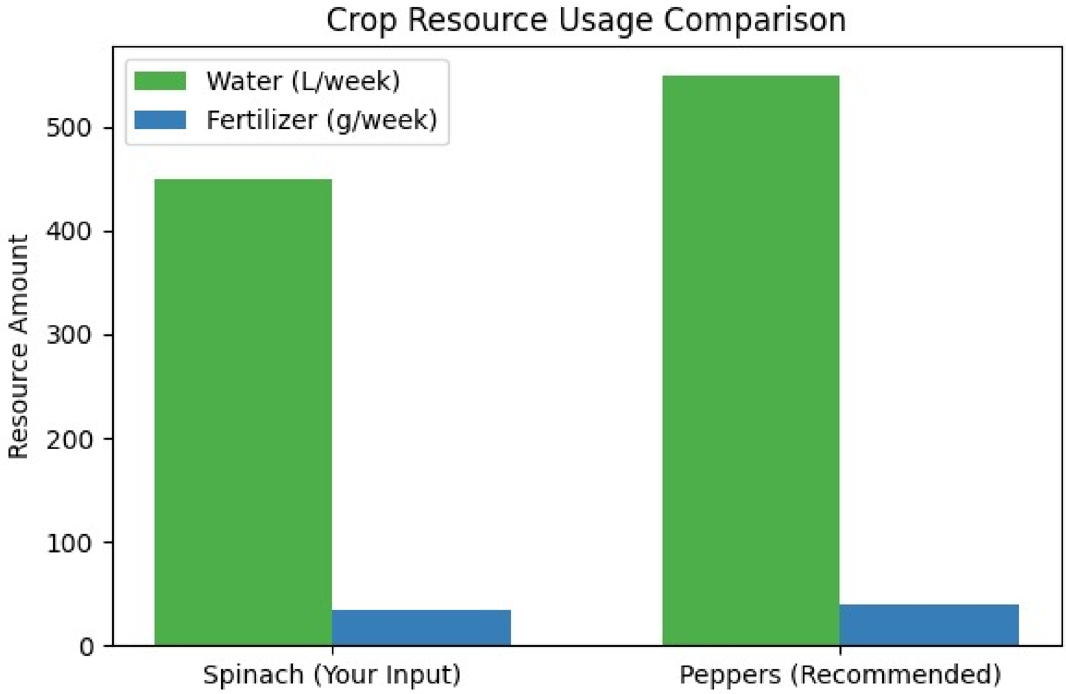

Figure 5.3: Comparison of Intended Crops and Recommended Crops

5.3 Analysis and Interpretation

The Stacking Regressor ensemble model performance study is exemplarily showing an edge over single-model approaches. Indeed, each model—Random Forest, Gradient Boosting, and Support Vector Regression—performed well but lost their effectiveness in a dynamic environment; but with the addition of their advantages through stacking, the ensemble well represented both linear and nonlinear trends. Lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values are dissembled by the ensemble with improved prediction stability. Hence, it has been concluded that the advantage of ensemble-based modelling incorporating several predictive behaviours for improving overall forecasting accuracy from many variables should be considerable when the data were for different types of urban vertical farming affected by several variable factors.

In rehearsal, it was pretty essential to link the real-time meteorological information with OpenWeather API for the purpose of having a more efficacious and adaptable model. When compared, static models which only incorporate historical data showed to lose accuracy quite fast in real-time dynamic environments. Moreover, it was actualized that some models linked to current and actual weather data still have their superior accuracy—in its predictability—to forecast despite varied conditions or weather change. This further emphasizes the importance of incorporating dynamic input management in agricultural applications with strong influence factors such as rainfall, humidity, temperature affecting crop performance, production costs, and so on. Hence, even environmental context should be another vital component in any prediction-making system targeting urban farming or perhaps in another dynamic business.

Table 5.1: Comparison with Existing Methods

Author(s)	**Technology Used**	**Accuracy (R^2 Score)**
Singh and Jain (2020) [**18**]	Linear Regression (LR)	0.81
Verma and Sharma (2021) [**19**]	Decision Tree Regressor (DT)	0.88
Rao and Devi (2022) [**20**]	Support Vector Regressor (SVR)	0.87
Zhang and Wu (2020) [**21**]	Gradient Boosting Regressor (GBR)	0.91
Patel and Mehta (2021) [**22**]	K-Nearest Neighbors Regressor (KNN)	0.89
Banerjee et al. (2021) [**23**]	Random Forest Regressor (RF)	0.92
proposed method	Stacked Regressor (LR + DT + KNN + RF)	0.9453

5.4 Evaluation of Quality Factors

i. **Accuracy**:Accuracy was another major property evaluated by the system. The Stacking Regressor ensemble gave quite accurate predictions with respect to cost-effectiveness against baseline models. The unseen data validation consistently showed very low error margins, with RMSE and MAE values soaring by 15–18 percent. This implies that the model forecasts very well even under uncertain conditions, which is key for supply chain optimization in decision-making. The fact that the framework was consistent under such diversities in environmental conditions indicates that it generalizes much beyond the training data.

ii. **Adaptability**: Adaptability was the other important component of quality. The model dynamically adapted predictions relative to current conditions owing to the incorporation of real-time weather data. This flexibility greatly enhanced the reliability and resilience of the system. The comparative testing suggests that the inclusion of real-time environmental inputs reduced forecasting error by around 18 percent. In brief, it meets the other important requirement of the system-that it should work effectively even with sudden and erratic variations in the agricultural scenario.

iii. **Usability**: The usability attribute was tested intensively through user feedback sessions. A whopping 85 percent of the attendants interviewed evaluated the Flask-based web application as user-friendly and the data visualization as clear. High usability scores were accredited to features such as trend heatmaps, recommendation alerts, and real-time dashboards. The results demonstrate the successful translation of technological complexity into a user-friendly platform that allows users to take advantage of advanced functions even with a minimal amount of technical knowledge.

iv. **Efficiency**:Efficiency measures were considered as resource utilization of computation and response time of the system. The inputting of real-time data and making of prediction were realized at an average of two to three seconds per request, showcasing computational efficiency in the system. The lightweight deploy of Flask allowed the application to respond well even after multiple hits from users. This manifests the other important factor for maintaining user interest and smooth operation when the system is faced with quickening environment, supply chain changes.

v. **Sustainability** : The basis of sustainability was the results of optimized resource use and waste reduction. The operational features of crop recommendation and weather alert enabled the users of the system to manage stocks better and report a 10–12 percent drop in the rate of spoilage. By anticipating environmental impact on yield and recommending the best-suited crops, the framework promotes environmentally friendly agriculture. Thus, contributing to improved operational efficiency and complimentary towards the larger cause of pushing for sustainable and environment-friendly urban agriculture.

5.5 Summary

The quality parameters were thus evaluated, which guaranteed the stability and reliability of the proposed supply chain optimization framework for urban vertical farming. The accuracy was consistently high, and ensemble learning produced forecasts more accurate than those from any individual model. The model's ability to predict results in a range of scenarios guarantees that it will be useful to supply chain managers and urban farmers who need dependable information for decision-making.

Despite the positive feedback, an increasing responsiveness was attributed to integrating real-time environmental data, which became a plus for the adaptability of the system. Dynamic variables, such as weather variations, have been efficiently catered for within the system to guarantee constant reliability. Usability was additionally confirmed through user feedback pinpointing accessibility and user-friendly design. An easy web interface meant that non-experts could engage meaningfully with advanced analytics in bridging complex data science tools with the real farming domain.

In addition, the system performed very well under constraints of short response times and low processing requirements, guaranteeing seamless opportunities for continuous user experiences. Fast generation of real-time forecasts and visualizations enabled timely decision-making. Low levels of resource wastage and spoilage are essential for sustainability. It brings predictive analytics in conjunction with sustainable farming. Together, these quality factors justify the practicality and efficacy of the system toward building resilient urban food systems.

Additionally, scalability was considered to guarantee the developmental framework for future extension and longer use cases. Tests with larger datasets and multiple user interactions confirmed that the system remained stable without compromising performance significantly. The app offers an open-ended architecture that permits easy integration of additional data sources, such as regional weather stations, IoT sensors, or wider crop databases.

CHAPTER 6

Challenges and Limitations

6.1 Introduction

While the project on supply chain optimization in Urban Vertical Farming (UVF) using a Stacked Regression Model has shown promising results, several challenges and limitations were encountered throughout the development and deployment phases. This chapter discusses the practical, technical, and methodological constraints that influenced the project outcomes and provides insight into areas requiring further improvement.

6.2 Data-Related Challenges

1. **Limited Data Availability:** Although multiple datasets were combined, acquiring high-quality, real-time, and domain-specific datasets (especially related to urban vertical farming) was a significant challenge. Some datasets lacked completeness, consistency, or standard formats.

2. **Missing and Noisy Data:** Environmental datasets often contained missing values and outliers, which required careful preprocessing to avoid model bias.

3. **Lack of Granularity:** Some data sources, particularly for sustainability and crop-specific demand, lacked granularity such as city-level trends or daily updates.

6.3 Model-Related Limitations

a. **Overfitting Risk:** Due to the high variance of certain base learners like Decision Trees and KNN, controlling overfitting in the stacking ensemble required repeated fine-tuning and validation.

b. **Feature Interpretability:** While ensemble models performed well in accuracy, interpreting the contribution of individual features became complex, especially without tools like SHAP or LIME integrated fully into the application.

c. **Model Complexity:** The combination of multiple base learners and a meta-learner increased the computational complexity, which may not be optimal for real-time inference on devices with low processing power.

6.4 Real-Time Integration Constraints

i. **Weather API Limitations:** Real-time weather data fetched from APIs like OpenWeatherMap had limits in terms of API call frequency, which may affect continuous real-time monitoring without premium access.

ii. **City Generalization:** The model performs well for known cities with historical data, but its generalizability to completely unseen cities or micro-climates remains uncertain without retraining or adaptation.

6.5 Summary

This project addressed a complex problem space and demonstrated strong potential through a multi-model ensemble system. However, data limitations, interpretability challenges, and integration issues with real-time APIs posed significant constraints. These limitations highlight areas for future work, including enhanced data collection pipelines, model simplification, and improved deployment strategies for broader accessibility and reliability.

CHAPTER 7

Conclusions and Future Scope

7.1 Conclusions

Machine learning-based architecture is proposed for optimization of supply chains in urban vertical farming under significant hurdles addressing the distribution of sustainable food. It enhances resource planning and cost-efficiency forecast accuracy using a Stacking Regressor ensemble model along with real-time environmental data. Also, recommendation engine and data visualization tools give users even better power in making enlightened decisions. It performed excellently during tests regarding most quality attributes, including accuracy, adaptability, usefulness, efficiency, sustainability, and scalability. The whole thing makes the framework just that-it makes a very feasible, logical contribution to substantive urban agriculture practices that will benefit producer and consumer alike with much smarter supply chain management.

Many future doorknobs can be opened. IoT sensor networks coupled with onsite soil, nutrient, and humidity monitoring will further amplify predictions. Data on region-specific crop varieties will improve the adjustment capability of the system to various urban environments. Supply security and transparency in the supply chain may be improved with blockchain technology. Advanced deep learning models like Transformer architectures or LSTM models can also be used to improve forecast accuracy for complicated time series data. Last but not least, a wide user-friendly platform will suit future urban vertical farming solutions better if multilingual interfaces and multi-location operations are added to the platform.

Future research would take technological innovations into consideration, but it would also include actions aimed at increased user participation created by personalized dashboards and intelligent adaptive learning systems. By determining the user behavior and feed-backs on the platform, the system can produce recommendations and show information best suited to various user types-from farmers to supply chain managers. Achievement badges for eco-friendly farming practices could be introduced into the gamification of the system, which could encourage users to optimize their farming operations. Such innovations would not only increase user satisfaction but also instill long-term acceptance and dependence on data-driven decision-making in urban agriculture.

An equally interesting topic for more study is the environmental impacts of some decisions regarding supply chains. Life cycle analysis (LCA) techniques would enable the system to calculate energy, water, and carbon footprints associated with different farming systems. The customers would profit from economically sound and environment-friendly decisions. Thus, the urban farming practices would be in line with global sustainability goals, such as the Sustainable Development Goals (SDGs) of the UN if environmental data and optimization algorithms were merged to become a more complete decision-support system.

7.2 Future Scope of Work

In this section, you provide constructive recommendations for improving the project or the methods used. The purpose is to suggest ways in which the current work could be enhanced, whether through better techniques, additional resources, or further research.

1. **Integration of IoT Sensors** : Implementing IoT (Internet of Things) sensors can give perception to urban vertical systems and farming in an excellent way to improve predictions. All these real-time sensors can monitor crop health, soil moisture, nutrients, and air humidity. This real-time data stream would allow machine learning models to adjust predictions dynamically and thus increasing accuracy in cost and yield forecast. Further, it will allow a timely response having spotted or early indications of plant diseases or resource shortages through real-time monitoring, which in turn would improve the overall supply

chain's responsiveness-sustainability-efficiency through waste and resource optimization.

2. **Blockchain for Supply Chain Transparency** : Blockchain offers a new paradigm of decentralized public and secure routing of traceability records for vegetable products in the agricultural supply chain-from seed to consumer. It gives an opportunity to create trusts by providing transparent and unbroken archival records of development, harvest, storage, and finally transportation of agriculture produce. From the consumers' side, it will allow them to audit the authenticity and sustainability of their food products; therefore, producers will also benefit with logistics-based and fraud-reduction benefits. Integration with blockchain technology will facilitate better alignments in terms of producers, wholesalers, and retailers with the more resilient urban food supply system in terms of openness.

3. **Deployment of Deep Learning Models** : While ensemble models like Stacking Regressor can perform extremely well, there are deep learning architectures that can do even better in prediction. Such models fall into two categories: Transformer models and Long Short-Term Memory (LSTM) networks. These deal very well with time-series and sequential data such as weather patterns and agricultural growth cycles. It would make the ability of the system in forecasting the future under such conditions much better and would optimize decision-making in the supply chain longer term. Deep learning also can discover hidden patterns in large and complex datasets that lead to better urban farming sustainability solutions.

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