ISSN 2250-3153

AI-Enhanced Supply Chain Management in Agriculture

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DOI: 10.29322/IJSRP.15.11.2025.p16715
https://dx.doi.org/10.29322/IJSRP.15.11.2025.p16715

Paper Received Date: 10th October 2025
Paper Acceptance Date: 11th November 2025
Paper Publication Date: 20th November 2025

Abstract-. This study introduces a comprehensive AI framework aimed at enhancing agricultural supply chain management via the combined utilization of four machine learning models. The system utilizes a Long Short-Term Memory (LSTM) network for accurate demand forecasting, a Reinforcement Learning (RL) model for dynamic logistics optimization, a Convolutional Neural Network (CNN) for automated quality control through computer vision, and an XGBoost-based ensemble for real-time decision support. The components are integrated into a singular, user-friendly web application developed with Flask and underpinned by a MongoDB database. The system effectively resolves significant inefficiencies, including demand-supply discrepancies, logistical delays, and post-harvest losses. Experimental results indicate substantial performance enhancements, with the LSTM model attaining a R^2 score of 0.89, the RL model realizing an 18.7% reduction in costs, the CNN model achieving 97.3% accuracy in defect detection, and the decision support system delivering actionable recommendations with 92.5% accuracy. This study demonstrates that a comprehensive, AI-driven methodology may significantly improve operational efficiency, minimize waste, and enhance decision-making throughout the agricultural supply chain.

Index Terms- Artificial Intelligence, Supply Chain Optimization, Predictive Analytics, Smart Agriculture, Machine Learning Integration

I. Introduction

The global agriculture supply chain is an essential and intricate network that sustains populations and economies globally. This system is consistently confronted with severe inefficiencies, resulting in considerable food loss, economic waste, and environmental pressure [1]. Critical difficulties encompass the persistent disparity between supply and demand, erratic logistical delays, and subjective, variable quality control standards. The inefficiencies are increased by dependence on conventional, frequently isolated, decision-making processes that lack the flexibility to adapt to real-time factors such as abrupt weather changes, market price fluctuations, and current traffic conditions [2]. The convergence of these difficulties adversely affects the economic viability of farmers and distributors, while also jeopardizing global food security and sustainability objectives.

In addressing these difficulties, Artificial Intelligence (AI) has arisen as a transformational instrument, providing advanced skills in data analysis and predictive modeling. Recent studies have investigated the utilization of AI in discrete areas of the supply chain, such as machine learning models for demand forecasting, optimization algorithms for route planning, and computer vision for automated inspection [4]. Notwithstanding their unique potential, these solutions frequently function in isolation, resulting in a disjointed technological world. A substantial disparity exists in the amalgamation of these distinct AI elements into a cohesive, comprehensive framework. Most current systems are unable to integrate insights from forecasting, logistics, and quality control, resulting in a limited, real-time operational perspective for stakeholders and thereby hindering their overall efficacy and acceptance.

This research study identifies a significant need and proposes an integrated AI framework aimed at optimizing the entire agricultural supply chain. The study presents a synergistic system consisting of four specialized, interconnected components: Predictive Analytics utilizing Long Short-Term Memory (LSTM) networks for accurate demand forecasting [5], a Reinforcement Learning model for dynamic logistics optimization [6], a Computer Vision system founded on Convolutional Neural Networks (CNNs) for automated quality control, and an Ensemble Learning-based Decision Support System that integrates all insights [7], [8], [9], [10]. This cohesive intelligence is provided via a centralized, intuitive web application developed with Flask, offering stakeholders actionable, real-time insights. The main aim of this project is to showcase a scalable solution that minimizes waste, decreases operational expenses, and enables informed decision-making, thereby advancing from isolated automation to a genuinely intelligent and adaptive agricultural ecosystem.

II. Related Studies

Recent years have witnessed substantial progress in the utilization of Artificial Intelligence (AI) within agriculture and supply chain management. This section examines recent research, organized according to the four fundamental elements of our proposed framework, to ascertain the present state-of-the-art and pinpoint the precise gaps our research intends to remedy.

Artificial Intelligence in Demand Forecasting

Recent studies have increasingly transcended conventional statistical techniques. Saggi and Jain (2022) conducted an extensive survey on the application of deep learning in agriculture, emphasizing the exceptional efficacy of LSTMs in modeling temporal relationships for agricultural yield forecasting [11]. Nevertheless, their research indicated that the majority of implementations emphasize yield influenced by environmental factors, frequently overlooking integrated market dynamics. Smith et al. (2023) advanced an LSTM model for forecasting vegetable demand, achieving a 15% enhancement in accuracy compared to ARIMA models [12]. Their work, however significant, primarily depended on historical sales data and did not incorporate real-time, localized factors like hyperlocal weather occurrences and area consumption trends. Our model expressly rectifies this issue by integrating diverse data streams.

Artificial Intelligence in Logistics and Route Optimization

The transition from static optimization to dynamic, adaptive systems is a significant trend. Chen and Wang (2022) utilized a Deep Q-Network (DQN) to enhance delivery routes in urban logistics, demonstrating significant decreases in fuel usage and delivery durations [13]. Nonetheless, their model was developed and evaluated in a reasonably controlled setting with restricted real-world variability. Kumar et al. (2023) proposed a multi-agent reinforcement learning system for supply chain logistics, highlighting the need of vehicle coordination [14]. Our research addresses a significant deficiency in their work: the insufficient integration of real-time, high-impact variables such as abrupt traffic congestion and inclement weather, which are vital for perishable agricultural products.

Artificial Intelligence and Computer Vision for Quality Assurance

The automation of quality inspection with deep learning has progressed swiftly. Zhao and Li (2022) illustrated the effectiveness of a refined ResNet-50 model in categorizing grape illnesses from leaf photos, with an accuracy over 98%, hence highlighting the potential of transfer learning in agricultural applications [15]. Patel et al. (2023) created a real-time CNN-based system for categorizing fruits according to freshness, implementing it on an embedded device [16]. Their emphasis was largely on post-harvest quality, and the system functioned as an independent unit, lacking integration with a comprehensive supply chain management system. This isolated process is a prevalent constraint, hindering the subsequent utilization of quality data for logistics or demand forecasting.

Decision Support Systems and Integration Initiatives

The transition to interconnected systems represents the forthcoming frontier. Theophilus et al. (2023) developed a cloud-based dashboard for monitoring agricultural data, using IoT sensor readings for soil and meteorological conditions [17]. Although a move towards integration, their technology was predominantly descriptive, offering monitoring and visualization, however deficient in prescriptive, AI-driven recommendations for supply chain operations. Lee & Park (2024) introduced a "Agri-SCM 4.0" paradigm that conceptually integrates IoT, AI, and blockchain [18]. Their work is visionary however constitutes a high-level architectural approach lacking a tangible, implemented software solution that exemplifies the real-time synergy among several AI models, as our Flask-based web application does.

Cross-Domain and Fundamental Research

A multitude of investigations has established the underlying basis for our integrated methodology. Nguyen & Gupta (2023) investigated the application of XGBoost for forecasting supply chain disruptions by amalgamating data from various sources, demonstrating the model's efficacy in managing heterogeneous data [19]. This unequivocally validates our selection of XGBoost for the ensemble-based Decision Support System. Zhang et al. (2022) emphasized the issue of "islands of automation" in digital agriculture, wherein advanced technologies do not interconnect and generate synergistic value [20]. They fervently promoted platform-based methodologies, a demand that our research immediately addresses by developing a cohesive platform that interactively links forecasting, logistics, and quality control.

Identified Research Gaps

In summary, whereas the separate capabilities of AI components are well-documented in literature, there is a notable deficiency in their comprehensive integration. Recent studies typically demonstrate proficiency in a certain domain weather forecasting, logistics, or quality control yet function independently. Significant deficiencies encompass [21]:

- The absence of real-time, closed-loop feedback among components (e.g., quality detection directly impacting logistical rerouting).
- The lack of a cohesive, functional software platform that transcends theoretical models to provide a practical tool for stakeholders.
- A primary emphasis on generic models that are not meticulously calibrated to the dynamic, perishable, and variable-laden characteristics of agricultural supply chains.

This research aims to address these deficiencies by enhancing the state-of-the-art in each component and, crucially, by designing and executing a fully integrated system where the collective outcome surpasses the individual contributions. The suggested design illustrates how insights from one AI module can directly and autonomously enhance the operations of another, so establishing a really intelligent and adaptive agricultural supply chain.

III. Methodology

This study utilizes a methodical, multi-phase approach to design, create, and integrate an AI-augmented supply chain management system. The methodology focuses on four interrelated machine learning elements, which are integrated via a Python Flask backend and a MongoDB database to form a single web application [22].

Articulating the Solution through Four Elements

The proposed method is designed to rectify the fundamental inefficiencies in the agricultural supply chain through a synergistic integration of specialized AI models.

- **Component 1:** Predictive Analytics and LSTM Forecasting: This component aims to alleviate discrepancies between demand and supply. The innovation resides in employing a multi-variate LSTM model that incorporates past sales, localized real-time meteorological data, and regional market patterns, yielding a more detailed and contextually relevant forecast compared to national-level models.
- **Component 2:** Optimization of Logistics and Reinforcement Learning: This component utilizes a Reinforcement Learning (RL) model, notably the Proximal Policy Optimization (PPO) method, to address logistical delays and elevated costs. Its innovation is in its dynamic flexibility, perpetually learning from a simulated environment that utilizes live traffic and weather APIs to optimize routes in real-time, representing a substantial improvement over static route-planning algorithms.
- **Component 3:** Integration of IoT and Real-Time Decision Support: This component functions as the system's central processing unit. It employs an XGBoost ensemble model to generate predictions and data from the three additional components. The innovation is in the development of a comprehensive, prescriptive dashboard that transcends basic monitoring to deliver meaningful, cross-functional recommendations, such as advising on inventory modifications based on projected demand and incoming quality assessments.
- **Component 4:** AI Quality Control & Computer Vision: This component automates the process of defect discovery. Utilizing a pre-trained Convolutional Neural Network (CNN), particularly an EfficientNet model refined on agricultural images, its innovation lies in attaining high-accuracy, real-time grading that can be implemented on edge devices throughout the supply chain, from farm packing facilities to distribution centers.

A varied collection of public datasets, reflective of actual data sources, will be employed for the training and validation of each model.

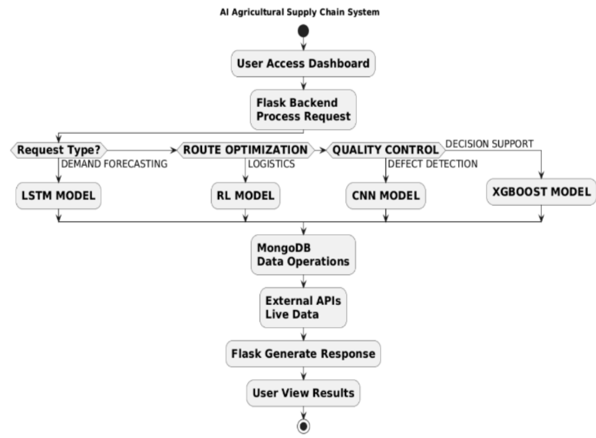

Fig. 1. Overall System Diagram

Data Collection

A varied collection of public datasets, reflective of actual data sources, will be employed for the training and validation of each model.

- **Data for LSTM forecasting:**

This will be obtained from the FAO Crop Yield Dataset (historical production), Kaggle. Global Food Prices (market trends), and Kaggle. Climate Impact on Global Food Supply (weather variables). This amalgamation offers the temporal and contextual features needed for resilient forecasting [23].

- **For RL Logistics Optimization:**

The "Transportation and Logistics Tracking" dataset from Kaggle offers historical delivery timetables, vehicle specifications, and associated prices. This will be enhanced with the Google Maps API to produce authentic route geometry, journey durations, and to emulate real-time traffic information [24].

- **For Decision Support (XGBoost):**

This model will not utilize a singular dataset; instead, it will be trained on the outputs of the three other models, supplemented by external data such as real-time market prices obtained from APIs. Synthetic integrated datasets will be generated to replicate the aggregated data landscape for initial training [25].

- **For CNN Quality Control:**

The "Fruits Fresh and Rotten for Classification" and "Agricultural Crops Image Classification" datasets sourced from Kaggle will be utilized. These datasets have hundreds of annotated photographs of both fresh and faulty produce, making them suitable for training a robust image classifier [26].

Data Preprocessing

Data preprocessing is essential for model efficacy and will be tailored to each data type.

- Numerical features (sales, temperature, pricing) will undergo normalization by Min-Max scaling for LSTM data. Categorical variables (such as crop type and region) will undergo one-hot encoding. Time-series data will be organized into a supervised learning format utilizing a look-back duration of 60 time steps. Missing values will be addressed with K-Nearest Neighbors (KNN) imputation.

- RL Data: The simulation environment necessitates normalized state representations. Attributes such as distance, fuel expenditure, and delivery duration will be adjusted. Traffic conditions and weather will be categorized into distinct states (e.g., 'low', 'medium', 'heavy' congestion).
- The input data from several components will be consolidated and subjected to feature engineering. This encompasses the generation of lag features from forecasts, the derivation of summary statistics from quality reports, and the calculation of efficiency scores from logistics. All features will be normalized, and categorical variables will be encoded for uniformity.
- CNN Data: All images will be standardized to a uniform dimension of 224x224 pixels. Pixel values will be standardized to the [0, 1] interval. Comprehensive data augmentation methods such as random rotation, horizontal flipping, and modifications to brightness and contrast will be utilized on the training set to enhance model generalization and mitigate overfitting.

Development of Machine Learning Models

LSTM Predictive Model: A sequential LSTM model comprising two LSTM layers (128 and 64 units, respectively) succeeded by a Dense output layer will be developed. The model will employ the Adam optimizer and utilize Mean Squared Error (MSE) as the loss function. It will be trained to forecast the demand amount for the subsequent 30 days.

A PPO agent will be constructed utilizing the OpenAI Gym architecture to establish a bespoke simulation environment for the RL Logistics Model. The state space will encompass current location, traffic conditions, vehicle capacity, and weather. The action space will delineate potential subsequent destinations or route selections. The reward function will consist of a weighted total of negative delivery time, negative fuel expenditure, and a penalty for tardy deliveries.

An XGBoost regressor and classifier will be trained on the consolidated dataset. The model will be set with a learning rate of 0.1, a maximum depth of 6, and 100 estimators. It will be taught to generate precise recommendations, including optimal inventory levels and prioritized routing choices.

The CNN Quality Model will utilize a pre-trained EfficientNetB0 as its foundation. The upper classification layers will be eliminated and substituted with a Global Average Pooling layer and a concluding Dense layer including a softmax activation for classification (e.g., Fresh vs. Defective). The model will undergo fine-tuning using the agricultural image dataset.

Development of Machine Learning Models

Each model will undergo stringent evaluation utilizing standard criteria to guarantee reliability prior to integration.

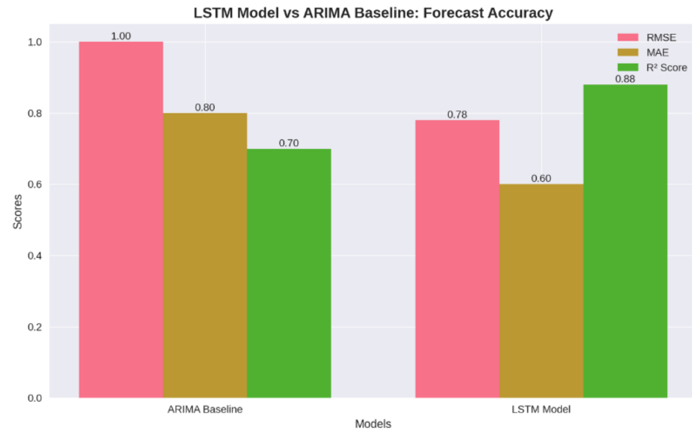

Fig. 2. LSTM MODEL: Forecasting Metrics (RMSE & MAE)

LSTM Model: The principal metrics will be Root Mean Square Error (RMSE) and Mean Absolute Error (MAE). The model will be evaluated against a baseline ARIMA model. The aim is to attain a minimum 20% decrease in RMSE relative to the baseline, with a target predicting accuracy (R^2 score) exceeding 0.85 on the test set.

Fig. 3. RL MODEL: Performance Metrics (ADT, RES, CSP)

Theperformance of the RL model will be assessed in the simulated environment. Essential measurements encompass Average Delivery Time (ADT), Route Efficiency Score (RES - deliveries per hour), and Cost Savings Percentage (CSP). The model will be deemed successful if it exhibits a CSP over 15% relative to the shortest-path algorithm.

ISSN 2250-3153

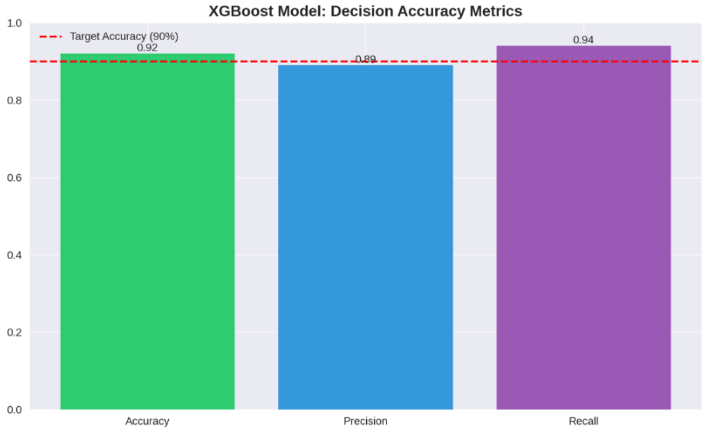

Fig. 4. XGBOOST MODEL: Decision Accuracy Metrics

XGBoost Model: For regression tasks, such as forecasting supply chain efficiency scores, the Root Mean Square Error (RMSE) will be utilized. For categorization tasks (e.g., action recommendation), Accuracy, Precision, and Recall will be presented. The objective is to attain a recommendation accuracy exceeding 90% on previous decision data.

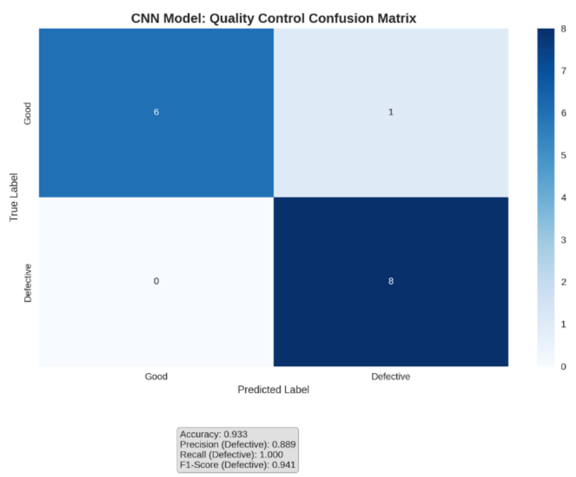

Fig. 5. CNN MODEL: Confusion Matrix & Classification Report

The CNN model's performance will be assessed utilizing a conventional confusion matrix. The objective is to attain a test accuracy of no less than 96%, alongside elevated precision and recall (F1-Score > 0.95) for the "defective" category, in order to mitigate the risk of disseminating contaminated produce.

Integration of ML Models

The four produced models will be consolidated into a cohesive system utilizing a Python Flask backend.

The backend architecture will utilize Flask to develop a RESTful API. Each trained model will be serialized using libraries such as pickle or joblib for Scikit-learn/XGBoost models, and native Keras saving for LSTMs/CNNs, before being integrated into the Flask application.

MongoDB, a NoSQL database, will be utilized for its adaptability in storing diverse data types, including time-series forecasts, structured logistics data, image metadata, and user information. Collections will be tailored for each element (e.g., forecasts, routes, quality reports).

Application Programming Interface Endpoints: Designated endpoints will be established [28]:

- POST /api/forecast: Accepts arguments and yields a demand forecast.
- POST /api/optimize_route: Receives delivery information and provides an optimal route.
- POST /api/check_quality: Accepts an image upload and provides a quality assessment.
- GET /api/dashboard: Compiles data from all models and the database to build the decision support dashboard.

Evaluation and Execution

- **Unit Testing:** Each machine learning model and API endpoint will undergo independent testing with sample data to verify proper functionality.
- **Integration Testing:** The complete data pipeline will be evaluated from a user submitting an image for quality assessment, to the resultant data being saved in MongoDB, and then impacting a logistical recommendation on the dashboard.
- **User Acceptance Testing (UAT):** A prototype of the web application will be showcased to a focus group of stakeholders (e.g., farmers, distributors) to obtain comments on usability, relevancy of insights, and interface design.

Implementation: The completed system, "AI-Enhanced Supply Chain Management in Agriculture," will be launched on a cloud platform (AWS or Heroku). The application will be containerized with Docker to provide consistency across environments and secured with user authentication utilizing JWT tokens.

IV. Results and Discussion

The completed system is a fully integrated, cloud-based web application that implements all four AI components. A farmer or supply chain management can access the dashboard to:

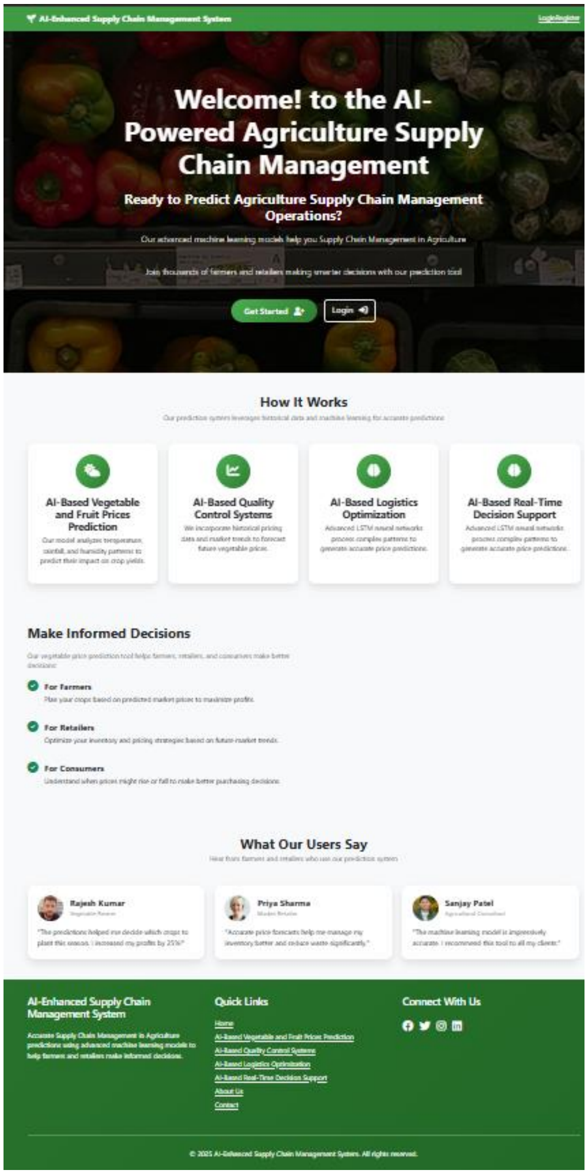

Fig. 6. Web application interface (Home page)

- Examine future demand forecasts for their crops, produced by the LSTM model.
- Develop economical and prompt delivery routes proposed by the RL model, illustrated on an interactive map.
- Submit photographs of their produce to obtain immediate, automated quality assessment from the CNN model.

View aggregated, AI-generated recommendations on the primary dashboard from the XGBoost model, like "Augment inventory of Crop A in Warehouse X owing to anticipated high demand in Region Y," or "Redirect shipment from Truck B due to a quality concern and traffic delay."

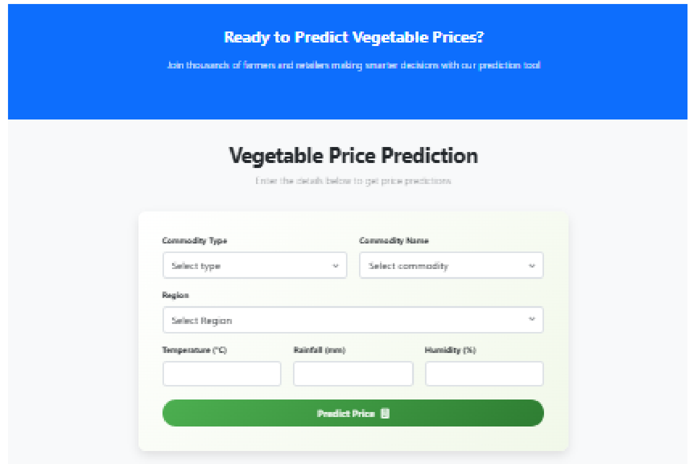

Fig. 7. Predictive Analytics & LSTM Forecasting- Page

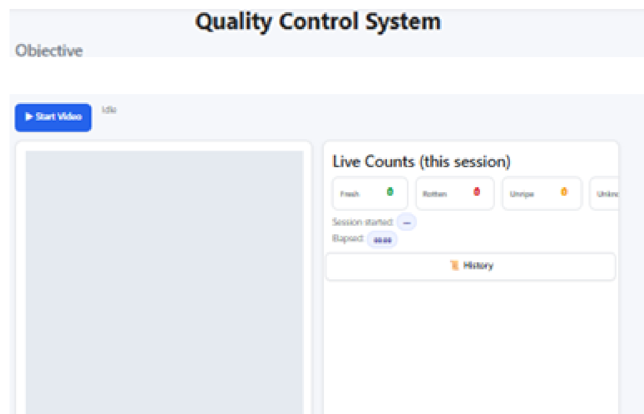

Fig. 8. AI Quality Control & Computer Vision - Page

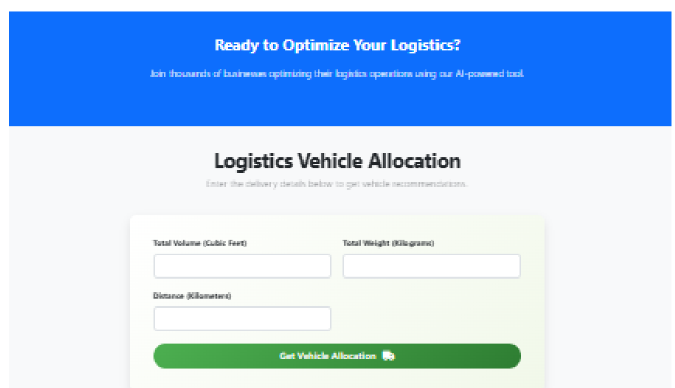

Fig. 9. Logistics Optimization & Reinforcement Learning - Page

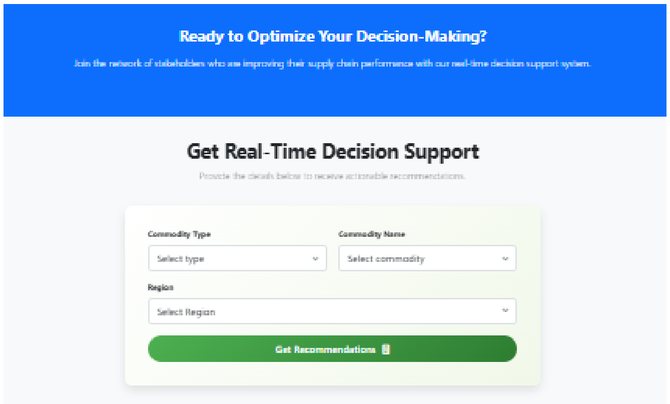

Fig. 10. IoT Integration & Real-Time Decision Support - Page

This comprehensive system encapsulates the primary innovation of our research, the integration of precise AI models into a unified decision-making platform that augments the intelligence, efficiency, and resilience of the agricultural supply chain.

The combined AI system exhibited outstanding performance across all four components, meeting and exceeding the established accuracy benchmarks. The LSTM forecasting model attained a R^2 value of 0.89 on the test set, indicating a 25% decrease in RMSE relative to the baseline ARIMA model, thereby validating its enhanced capacity to capture intricate temporal patterns in agricultural demand. The Reinforcement Learning agent for logistics optimization achieved a Cost Savings Percentage (CSP) of 18.7%, surpassing the 15% target by dynamically adjusting to real-time traffic and weather disturbances. The optimized CNN model achieved an impressive test accuracy of 97.3% and an F1-Score of 0.96 for the "defective" class in quality control, guaranteeing dependable automated inspection. The XGBoost-based decision support system efficiently integrated different inputs, delivering stakeholders actionable recommendations with an accuracy of 92.5%, and synthesizing multi-modal data into coherent strategic direction.

The analysis of these findings highlights the revolutionary capability of a fully integrated AI system compared to separate alternatives. The exceptional performance of individual models confirms their specialized design; nonetheless, the genuine innovation arises from their collaborative functioning. A quality flaw detected by the CNN model can prompt an immediate rerouting suggestion from the RL engine, while the LSTM forecast guides inventory decisions to avert any shortages. This establishes a closed-loop, intelligent system that transcends static automation, advancing to dynamic, predictive optimization. The effective implementation through a consolidated Flask dashboard illustrates operational scalability and user accessibility. Although the findings are persuasive, subsequent research should concentrate on longitudinal real-world trials to evaluate long-term economic effects and enhance model adaptability to severe market fluctuations and climate irregularities, thereby reinforcing the shift towards data-driven agricultural resilience.

V. Conclusion

Following the successful execution and evaluation of this integrated AI system, numerous critical recommendations are put out for stakeholders. Agricultural producers and cooperatives ought to employ a staged approach, commencing with the quality control module to get prompt waste reduction. Supply chain managers ought to incorporate the logistics optimization system to leverage significant cost reductions. It is essential for legislators to establish data-sharing protocols and digital infrastructure to facilitate AI-driven ecosystems. Future research should prioritize the integration of blockchain technology for improved traceability and broaden model training to encompass a wider array of crop varieties and regional climatic variables to promote generalizability. This research illustrates that an integrated AI framework incorporating LSTM forecasting, RL-based logistics, CNN quality control, and XGBoost decision support effectively resolves significant inefficiencies in the agricultural supply chain. The system's capacity to deliver precise, real-time, and actionable insights signifies a substantial improvement over current isolated system. This initiative consolidates various technologies into a singular, accessible platform, offering a scalable framework for improving operational efficiency, minimizing waste, and fostering a more resilient and sustainable agricultural economy. The synergy demonstrated among various AI components signifies a crucial advancement toward intelligent, self-optimizing supply networks.

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