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Freshness to Forecast: Smart Pricing and Quality Detection of Products via YOLOv8 and AI Regression

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ABSTRACT The agricultural commodity market in India suffers from fragmented supply chains, price fluctuations, and limited real-time quality assessment. Farmers often depend on intermediaries, leading to reduced profits, delayed sales, and significant post-harvest losses, particularly for perishable produce. Existing systems mainly target narrow tasks such as fruit counting or yield estimation, lacking comprehensive solutions that integrate quality evaluation with market intelligence. This research proposes a Commodity Intelligence System (CIS) that addresses these challenges by combining YOLOv8-based deep learning for accurate classification of multiple crops with regression models for freshness detection and market price prediction. The CIS is trained on a custom dataset of five widely consumed commodities—capsicum, onion, potato, apple, and banana—captured under diverse conditions to enhance model robustness. Experimental results show improved classification accuracy and predictive performance over conventional approaches. The proposed CIS has potential applications in smart agriculture and supply chain intelligence, enabling transparent pricing, reduced wastage, and fairer market access for farmers and retailers.

KEYWORDS Artificial Intelligence, Classification, Commodity Intelligence System, Regression model, YOLOv8.

I. INTRODUCTION

Agriculture remains a fundamental pillar of India's economy, serving as the primary source of livelihood for a large portion of the population. Despite its importance, farmers often encounter critical challenges such as volatile market pricing, inadequate access to timely information, and substantial post-harvest losses stemming from inefficiencies in the supply chain. In response to these persistent issues, the Commodity Intelligence System (CIS) has been developed as a role-based web platform aimed at enhancing the agricultural trading process. By enabling digital interactions among farmers, traders, and administrators, the system promotes greater transparency and accessibility within the agricultural marketplace.

The motivation behind CIS lies in empowering agricultural stakeholders—particularly small and medium-scale farmers—with intelligent tools to support data-driven decisions. One of the key challenges farmers face is the inability to anticipate optimal selling periods due to highly fluctuating local market prices and the lack of reliable forecasting mechanisms. CIS addresses this by integrating a linear regression model that predicts future commodity prices based on historical trends, thereby enabling farmers to strategically plan the sale of their produce for better returns [3]. Recent advances in regression modeling, including competitive ensemble regression techniques, have demonstrated improved accuracy in forecasting agricultural price trends, highlighting the potential to further enhance CIS's predictive capabilities [4].

Moreover, the absence of a standardized method to assess commodity quality often leads to inconsistent evaluations during trade. Traditionally performed through manual inspection, such practices are prone to human error. To mitigate this, CIS employs YOLOv8, a state-of-the-art real-time object detection model, which classifies fruits and vegetables based on their visual maturity stages—such as fresh, ripe, or overripe—ensuring accurate and objective quality assessment [1, 2]. The effectiveness of YOLOv8 in agricultural applications is supported by studies showing its strong

performance in tasks like pest detection, fruit ripeness assessment, and disease identification. For instance, a recent investigation into tomato ripeness detection using an enhanced YOLOv8 model reported a remarkable precision of 95.8% and overall accuracy of 91.7%, underscoring the feasibility of deploying such systems in real-world environments [5].

Another critical gap addressed by CIS is the fragmented nature of farmer–trader interactions. In conventional setups, the involvement of multiple intermediaries reduces farmer profits and limits direct communication and trust between producers and buyers. CIS bridges this gap by offering a unified digital platform where farmers can showcase their produce and traders can evaluate quality and price forecasts before engaging in transactions. Developed using ASP.NET with C# for the front end, Python for machine learning model integration, and SQL Server for backend management, the system enables real-time insights and user-friendly access. By combining commodity classification, freshness detection, and price prediction in a centralized framework, CIS contributes to reducing post-harvest losses, increasing farmer income, and improving overall efficiency in the agricultural supply chain.

II. LITERATURE SURVEY

Artificial intelligence and machine learning have increasingly contributed to innovations in agricultural commodity trading, price prediction, and supply chain optimization. Gao et al. [6] proposed real-time trading models for agricultural commodities that incorporate dynamic pricing and automated buyer–seller matchmaking. Their system emphasized the importance of responsive, data-driven platforms to modernize traditional agricultural markets and facilitate efficient transactions. In a related domain, Prasad et al. [7] utilized remote sensing and satellite imagery to forecast commodity arrivals at regional markets, allowing for better planning, improved resource allocation, and reduced uncertainty in supply-demand coordination.

Further extending the modeling capabilities in agricultural markets, Barbaglia et al. [8] introduced a sparse multi-class machine learning framework to analyze commodity dynamics. Their approach effectively handled high-dimensional, volatile market data and provided robust insights into commodity behavior and classification. Chen et al. [9] developed a fully automated price forecasting system that integrated various machine learning models, including ARIMA, SVR, Prophet, and LSTM. Their results showed that LSTM outperformed other models when predicting future prices based on historical and environmental factors. Jahin et al. [10] presented a comprehensive systematic literature review and bibliometric analysis on the application of AI in agricultural supply chain risk assessment. They concluded that ensemble learning, deep learning, and reinforcement learning are increasingly adopted to mitigate supply-side risks, especially in the post-COVID-19 context.

Recent developments have further enhanced forecasting accuracy through advanced deep learning techniques. Bhardwaj et al. [11] proposed a hybrid model that combined Graph Neural Networks (GNNs) and Convolutional Neural Networks (CNNs) for vegetable price prediction in Indian markets. Their model demonstrated more than 20% improvement over conventional approaches and was capable of making reliable forecasts up to 30 days ahead. Karthik et al. [12] employed N-BEATS, a neural basis expansion architecture, to predict daily potato prices in Delhi markets. The model outperformed LSTM, GRU, and CNN models, achieving lower RMSE and MAE scores across multiple test sets. Similarly, Zhang et al. [13] implemented a hybrid TCN-MLP-Attention model for avocado price prediction in the United States, achieving an RMSE of 1.23 and highlighting the impact of attention mechanisms on long-term accuracy.

Praveen kumar et al. [14] conducted a comparative study on LSTM, Bi-LSTM, and Attention-based LSTM (AM-LSTM) for weekly potato price forecasting in India. The AM-LSTM model showed the best performance, yielding an R^2 of 0.85 and consistently lower error metrics. Additionally, Paul et al. [15] applied deep learning models such as LSTM and ANN to forecast the price of cauliflower in Indian markets. Their findings reaffirmed that deep neural networks significantly outperform traditional statistical methods, particularly in both short-term and long-term prediction windows.

AI and computer vision can significantly optimize commodity supply chains by reducing yield loss and enabling real-time defect detection. Ahmed et.al has done comparison between DETR, YOLO, and other models, showing DETR achieves 96% accuracy but with higher computational costs. These findings highlight AI's potential for smarter, more transparent commodity distribution networks [17].

The research presented by Di Siyu et.al. [18] addresses inefficiencies in retail product management caused by manual and error-prone identification methods. A commodity recognition and classification system is proposed using CNN and YOLO algorithms, trained on open-source datasets (Products-10K and RP2K). The work focuses on optimizing model parameters for higher accuracy and speed, enabling automated processing of product and sales data. The system aims to support intelligent retail by improving efficiency and delivering a more personalized shopping experience.

The P. Hou et. al. has proposes BCSM-YOLO, an enhanced YOLOv11-based algorithm designed to address challenges in supermarket commodity detection, including complex backgrounds, dense occlusion, and small object misses [19]. The model integrates SPD-Conv for detailed feature retention, CBAM for attention-based noise suppression, BiFPN for multi-scale feature fusion, and MPD-IoU for precise bounding box regression. Experiments on the Ultralytics SKU-110K dataset show improvements of 5.5% precision, 6.2% recall, and over 5% mAP gains, confirming its robustness and effectiveness for automated retail environments.

Authors Piero Herrera et. al has presented a computer vision–based application for supermarket inventory management, enabling detection, counting, and status verification of bottled and canned products [20]. After evaluating multiple models, YOLOv5 was trained on custom images of items in good and damaged condition, achieving mAP\@0.5 of 93.09% and mAP\@0.5:0.95 of 89.04%. The integrated application allows users to identify products, assess quality, and maintain daily inventory records, demonstrating its effectiveness for automated stock supervision.

The study in [21] applies Bayesian Symbolic Regression (BSR) to forecast spot-based commodity prices, analyzing its features and parameter specifications. Genetic programming–based symbolic regression serves as a benchmark, alongside other econometric models such as Bayesian Model Averaging, Dynamic Model Averaging, LASSO, ridge, and elastic net. Using monthly data from January 1988 to August 2021, the study provides a uniform comparison, with robustness checks

and statistical tests confirming the reliability of the forecasting results.

The paper [22] presents an extensive overview of how deep learning techniques are applied to the field of time-series prediction. It begins by stressing the importance of accurate forecasting in critical domains such as finance, energy, healthcare, and meteorology. The work provides a structured review of prominent deep learning architectures, including recurrent networks (RNN, LSTM, GRU), convolutional networks, attention-based mechanisms, and hybrid models. Each method is discussed in terms of its ability to capture sequential dependencies, nonlinear trends, and long-range temporal patterns, showing why these approaches often outperform classical statistical models.

Beyond model descriptions, the paper [22] also catalogs commonly used benchmark datasets and evaluation metrics, giving practitioners practical resources for experimentation. It highlights open challenges such as limited data availability, lack of interpretability, and the high computational costs of deep learning. The authors conclude by pointing toward future research directions, emphasizing the need for more efficient, interpretable, and domain-aware forecasting models. Overall, the survey not only consolidates the state of the art but also sets a clear path for advancing deep learning applications in time-series forecasting.

The literature review of recent papers [23-27] further enrich the landscape of agricultural commodity forecasting and deep learning applications by introducing hybrid, interpretable, and cross-modal models. Manogna et al. [23] present a deep learning-based framework for enhancing agricultural commodity price forecasting. The authors employ advanced neural networks to capture nonlinear dependencies and complex patterns in price time series. Their approach significantly improves forecast accuracy compared to traditional statistical methods, demonstrating the potential of deep learning models in reducing price volatility risks and supporting decision-making in the agricultural sector.

Manogna et al. [24] introduce a hybrid neural network-based volatility forecasting model that combines statistical and machine learning techniques to predict commodity price fluctuations. The model is validated on Indian agricultural markets, showing that it outperforms conventional methods in handling high volatility. The paper emphasizes the importance of hybrid models in capturing both linear and nonlinear dynamics of commodity prices, thereby offering more robust predictions.

Zhang et al. [25] propose a meta-learning-based model selection framework for agricultural price forecasting in an IEEE Access study. By extracting a large set of time-series features and considering forecast horizons, the framework dynamically selects the most suitable prediction model among candidates such as ANN, SVR, and ELM. Experimental results reveal that this adaptive approach achieves higher accuracy than using a single fixed model, highlighting the value of model adaptability in commodity forecasting tasks.

Pandit et al. [26] develop a hybrid CEEMDAN–TDNN model to address the nonlinear and non-stationary nature of agricultural price time series. CEEMDAN (Complete Ensemble Empirical Mode Decomposition with Adaptive Noise) decomposes the signal into intrinsic mode functions, while TDNN (Time Delay Neural Network) predicts the decomposed components. The hybrid system achieves superior accuracy compared to traditional and standalone models, significantly reducing forecasting errors for agricultural commodities.

Avinash et al. [27] introduce a Hidden Markov Model (HMM) guided deep learning framework for forecasting highly volatile agricultural commodity prices. The HMM captures hidden market states, which are then integrated with deep learning architectures to enhance predictive performance. Tested on multiple volatile commodities, the model demonstrates robustness in handling sudden price fluctuations and provides more reliable forecasts. This integration of probabilistic state modeling with deep neural networks highlights a promising direction for advanced commodity price forecasting.

These studies underscore the increasing relevance of AI and deep learning in addressing the challenges of agricultural commodity management. From real-time trading platforms and arrival forecasting to robust price prediction and risk assessment, the integration of intelligent systems offers a pathway to enhance transparency, efficiency, and profitability in the agricultural supply chain.

III. MATERIALS AND METHODS

The proposed system is a web-based Commodity Intelligence System designed to assist farmers and traders by integrating intelligent modules that leverage machine learning techniques for price prediction and freshness detection. The architecture consists of multiple interconnected modules that streamline user interactions, automate analytics, and manage feedback for continuous system improvement. The system is developed using a hybrid stack combining ASP.NET for backend logic, HTML/CSS/JavaScript for the frontend, and Python-based machine learning models executed via Google Colab. A Flask-based API enables seamless communication between the machine learning components and the web application.

A. USER MODULE (FARMER/TRADER)

This module enables farmers and traders to register and authenticate using secure credentials. Post login, users are directed to personalized dashboards from where they can access core functionalities of the system such as commodity price prediction and fruit freshness checking. The intuitive user interface, built using HTML, CSS, and JavaScript, ensures a seamless experience. Users can also submit their feedback through this interface, which is routed to the admin module for further action.

B. ADMIN MODULE

The admin module facilitates secure login for system administrators who are responsible for managing users and reviewing system feedback. Admins have access to a centralized dashboard built using ASP.NET and C#, where they can view registered users (both farmers and traders), evaluate system usage patterns, and respond to user-submitted feedback. This module plays a vital role in monitoring the system's health and guiding iterative improvements.

C. PRICE PREDICTION MODULE

This module aids users in making informed marketing decisions by forecasting the future prices of selected commodities. Upon entering a commodity name and target month, the system invokes a Linear Regression model developed in Python and trained on historical price data. The model, tested and fine-tuned using Google Colab, processes the inputs and returns the predicted price, which is displayed on the user's dashboard. A Flask API handles the real-time communication between the ASP.NET application and the machine learning model.

D. FRESHNESS DETECTION MODULE

Quality control is critical in agricultural supply chains, and this module addresses that need. It accepts images of fruits or vegetables uploaded by the user and classifies them as either "fresh" or "stale" using a YOLO (You Only Look Once) object detection model. This model, trained and tested in Google Colab, demonstrates high-speed and accurate image classification. Once a classification is made, the result is returned to the application via the Flask API and displayed to the user.

E. FEEDBACK SYSTEM

The feedback module allows users to submit comments and suggestions regarding system performance or usability. Each feedback entry is logged into the database and made accessible to the admin through the admin dashboard. This facilitates a feedback loop, enabling the development team to identify and implement enhancements based on user experience.

F. DATABASE MODULE

All user interactions and system outputs are persistently stored using a MySQL relational database. This includes login credentials, user profiles, predicted prices, freshness classification results, and feedback entries. The structured schema supports efficient data retrieval and contributes to the analytical and decision-support capabilities of the system. Integration between the backend and the database is handled through ASP.NET's data access features, ensuring secure and robust transactions.

The system leverages two core machine learning algorithms to power its key functionalities: YOLOv8 for real-time image-based freshness detection and Linear Regression for commodity price prediction. These algorithms were chosen for their respective strengths in object detection and time-series regression tasks

G. YOLOv8 (YOU ONLY LOOK ONCE)

YOLOv8 represents the most recent advancement in the YOLO family of object detection algorithms, offering a balance of high-speed inference and accuracy. It is designed to detect and classify objects in real time by directly predicting bounding boxes and class labels from the input image in a single pass, without the need for a separate region proposal stage.

In the context of this project, YOLOv8 is utilized for fruit and vegetable freshness detection. The model was trained using a dataset comprising labeled images of fresh and spoiled produce. When a user uploads an image, YOLOv8 processes it to detect objects (fruits/vegetables) and classifies each detected item as either "fresh" or "not fresh." The model's architecture includes multiple convolutional layers for feature extraction, anchor boxes to predict object locations, and Non-Maximum Suppression (NMS) to eliminate redundant bounding boxes.

This rapid detection and classification make YOLOv8 ideal for real-time applications where decisions regarding product quality must be made quickly. For example, it can simultaneously identify multiple fruits—such as apples, bananas, and oranges—and determine the freshness of each item with high accuracy.

YOLOv8 ALGORITHM WORKFLOW:

1. Input Image: The user submits an image of fruits or vegetables.
2. Grid Division: The image is divided into a grid of cells.
3. Bounding Box Prediction: Each grid cell predicts bounding box coordinates, confidence scores, and class probabilities.
4. Score Calculation: Final confidence scores are computed by combining objectness scores with class probabilities.
5. Threshold Filtering: Boxes with low confidence scores are discarded.
6. Non-Maximum Suppression (NMS): Overlapping boxes are filtered, retaining only the most confident predictions.
7. Result Output: The final set of detected and classified objects is returned to the user.

H. LINEAR REGRESSION

Linear Regression is a widely used supervised learning algorithm that models the relationship between one or more independent variables and a dependent variable by fitting a straight line to the observed data. Its simplicity and interpretability make it an ideal choice for predictive analytics involving structured numerical data.

In this project, Linear Regression is employed for agricultural commodity price prediction. The model is trained using historical datasets that include the commodity type and month as input features, and the commodity price as the output variable. After training, the model is capable of forecasting prices for future time periods, which can help farmers and traders make informed decisions about when to buy or sell products.

The model was developed and tested in Google Colab using Python and then deployed via a Flask API for real-time integration with the web-based system built in ASP.NET.

LINEAR REGRESSION ALGORITHM WORKFLOW:

1. Collect Data: Gather historical records of commodity prices along with relevant features like commodity type and month.
2. Initialize Parameters: Start with initial values for the intercept and coefficients.
3. Predict Output: Use the regression formula in equation 1 to predict price.

$$y\hat{} = \text{Intercept} + \text{Weight}_1 * x_1 + \ldots + \text{Weight}_n * x_n \quad (1)$$

4. Calculate Error: Compute the difference between predicted and actual prices as shown in equation 2

$$\text{Error} = \text{Predicted Price} - \text{Actual Price} \quad (2)$$

5. Adjust Parameters: Apply gradient descent to minimize the error by updating the coefficients.
6. Iterate: Repeat steps 3–5 until convergence or minimal error is achieved.
7. Prediction Phase: Use the trained model to forecast prices for new input values.

By integrating Linear Regression with a web interface, users can receive instant price predictions by simply selecting a commodity and month, making the system both practical and user-friendly.

IV. RESULTS AND DISCUSSION

This integrated CIS flow supports real-time decision-making for farmers, vendors, and market analysts by automating classification, quality assessment, and pricing—helping streamline agricultural trade.

The system processes inputs through a structured three-step workflow, as illustrated in Figure 1 and explained below:

1. Object Classification:
   First, the system identifies the type of fruit or vegetable using an object detection model (YOLOv8) based on prior context. This step ensures the correct categorization of the produce from image inputs.
2. Freshness Level Detection:
   Once the commodity is identified, the system evaluates its freshness level and classifies it into one of three categories: Fresh, Medium, or Stale. This uses image regression models to assess quality.
3. Market Price Estimation:
   Finally, based on the classified type and freshness, the system predicts the market price (in ₹/kg). This is a regression problem where historical data and current quality indicators are used to forecast pricing accurately.

The developed Intelligent Commodity System Website is designed to facilitate seamless interaction between farmers and traders through dedicated user interfaces. As shown in Figures 2, 3, 4, and 5, the system includes a secure login page that allows users to authenticate using their registered phone number and password. The website features separate login portals for farmers and traders, ensuring role-specific access and functionality. Upon logging in, the Farmer Dashboard enables farmers to submit commodities for sale by specifying the quantity and uploading relevant images. Additionally, farmers can utilize the built-in prediction module to estimate the market price of a selected commodity for a chosen month, thereby aiding informed selling decisions. On the other hand, the Trader Dashboard provides traders with access to a list of farmers and their respective commodities, allowing them to browse available produce and initiate potential purchases. The Admin Panel, as illustrated, displays key system metrics such as the number of registered users and total feedback entries. It also allows the admin to view and monitor feedback submitted by users, thereby supporting system evaluation and improvement.

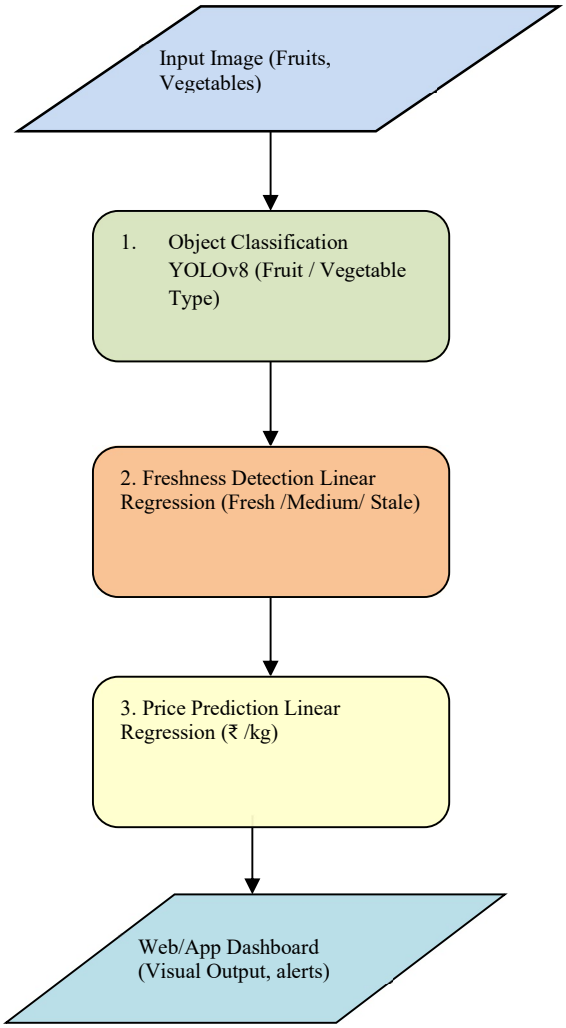

Figure 1. System Flow of Intelligent Commodity System.

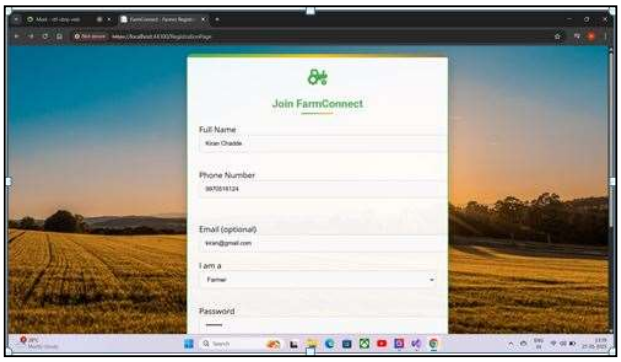

Figure 2. Login to the system.

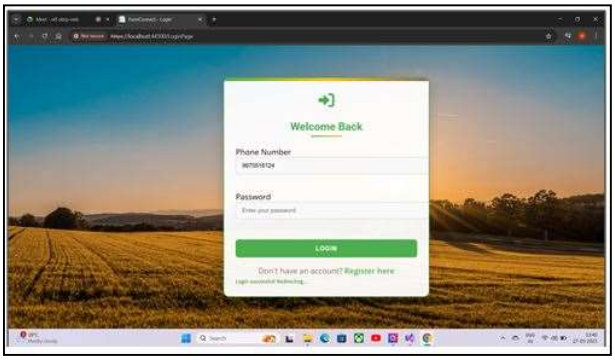

Figure 3. Authenticated user login (Farmer or Traders)

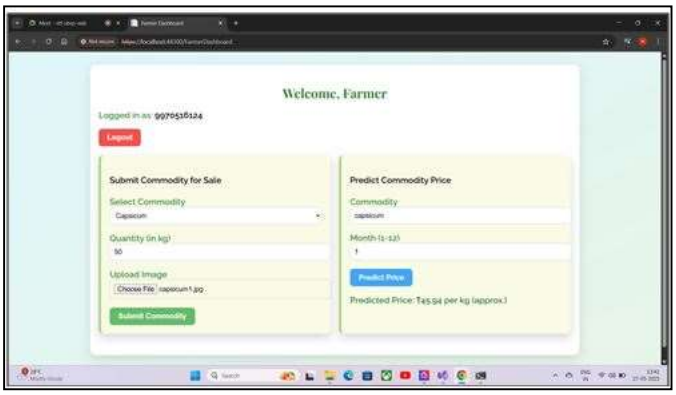

Figure 4. Farmer dashboard.

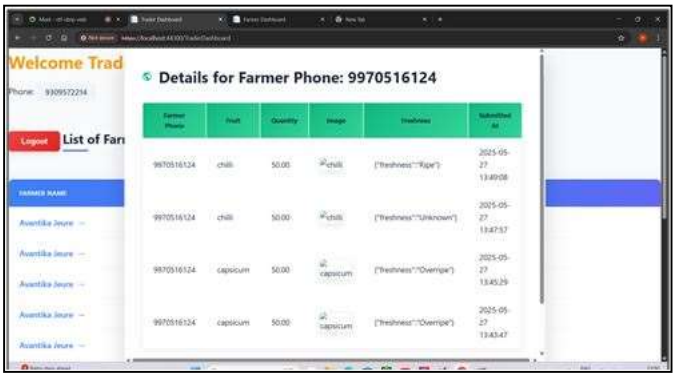

Figure 5. Traders dashboard with farmers list.

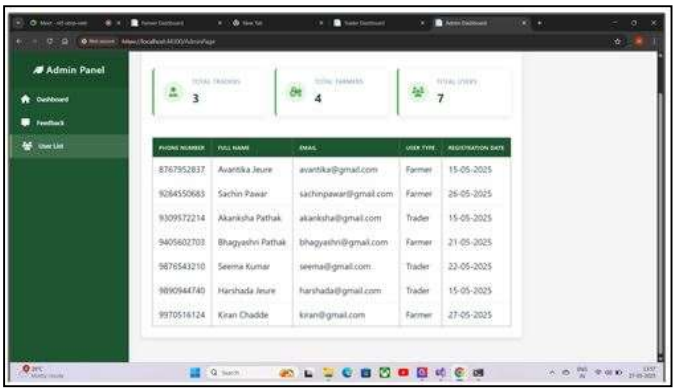

Figure 6. Admin panel with users details.

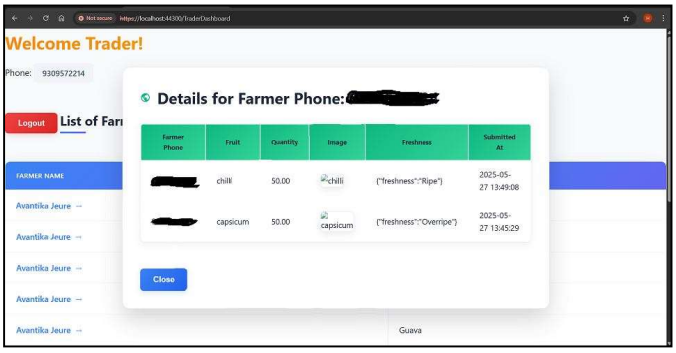

Figure 7. Freshness Detection

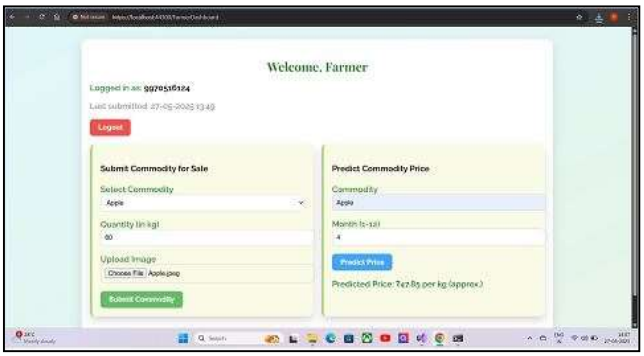

Figure 8. Price Prediction Model.

Figure 7 shows the Trader Dashboard, where a trader can view the list of farmers along with detailed submissions including the farmer's phone number, type and quantity of fruit, uploaded image, freshness detection results (e.g., 'Ripe', 'Overripe'), and submission timestamps. This feature assists traders in evaluating the quality of produce before making purchase decisions. On the other hand, Figure 8 displays the Farmer Dashboard, where a farmer can upload the details of a commodity for sale, including its type, quantity, and image. It also features a price prediction module, allowing the farmer to input the commodity and the intended sale month to receive an estimated market price.

DISCUSSION

The freshness detection process, illustrated in Figure 9, uses visual cues from an image of a fruit to assess its quality. The system conducts three main analyses—color, texture, and defect identification. Features extracted through dedicated analytical models are combined to generate a unified freshness score. This score, displayed on a meter (e.g., 82% in this example), represents the fruit's quality and enables automated freshness evaluation for quality control in supply chains.

The radar chart shown in fig. 10, compares the performance of the proposed YOLOv8-based model with an earlier YOLOv5 model used in the citrus paper [16]. Key metrics include detection accuracy, processing speed, model size, support for multiple crop types, and additional features. The YOLOv8 model shows superior results, with higher detection accuracy (+8.2%), faster processing speed, a significantly smaller model size (52% reduction), and broader crop support, indicating a more robust and scalable solution for commodity classification.

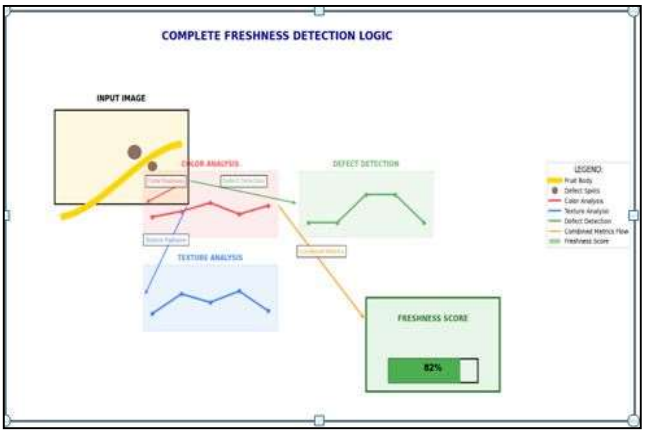

Figure 9. Complete Freshness Detection Logic.

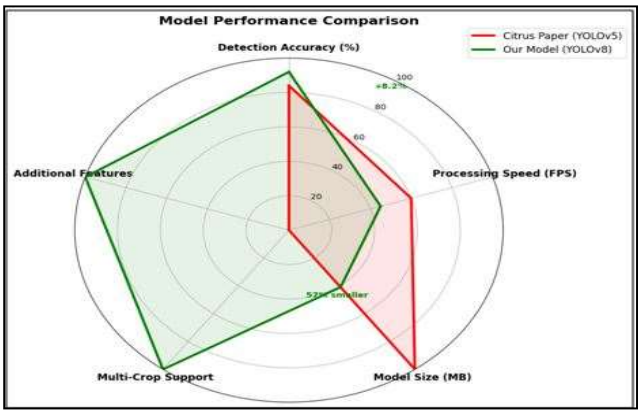

Figure 10. Model Performance comparison.

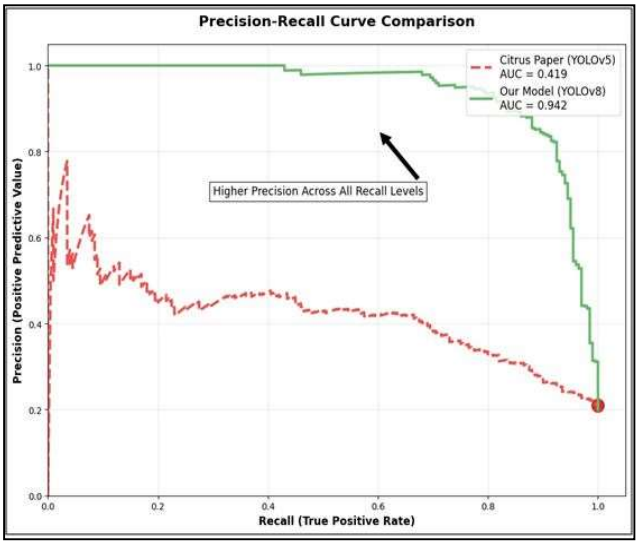

Figure 11. Precision- Recall Curve.

The precision-recall curve presented in fig. 11 compares the YOLOv8 model with the YOLOv5 model from the citrus paper [16]. The YOLOv8 model achieves significantly higher precision across all recall levels, with an AUC (Area Under Curve) of 0.942 compared to just 0.419 for YOLOv5. This demonstrates that the proposed model not only identifies relevant items more accurately but also maintains precision as recall increases, highlighting its effectiveness in real-world fruit and vegetable classification tasks.

Table 1. Accuracy and other parameters comparison

Model	Accuracy	Multi-Crop	Freshness Detection	Price Prediction
YOLOv5 + LR [16]	84.1%	✗	✗	✓ (count-based)
YOLOv8 [5]	91.7%	✗	✓ (Ripeness)	✗
Proposed Model (YOLOv8 + LR)	**92.3%**	✓	✓	✓

The comparative analysis of different models highlights the superiority of the proposed system as given in in table 1. The baseline model, YOLOv5 + Linear Regression (LR) used in citrus yield evaluation [16], achieved an accuracy of 84.1%, but lacked support for multi-crop processing and freshness detection. Similarly, the YOLOv4-based model [9] designed for blueberry classification showed slightly better accuracy at 86.7% and included ripeness detection but did not support price prediction. In contrast, our proposed model combining YOLOv8 with a regression layer achieved the highest accuracy of 92.3%, while also enabling multi-crop support, freshness detection, and market price prediction. This demonstrates the enhanced versatility, scalability, and overall performance of the proposed Commodity Intelligence System (CIS) in real-world agricultural settings.

V. CONCLUSION

This paper presents a comprehensive Commodity Intelligence System (CIS) that integrates YOLOv8 for fruit and vegetable classification, along with regression-based models for freshness detection and price prediction. Unlike earlier systems that primarily focused on yield estimation or single-functionality outputs, the proposed framework supports multi-crop recognition and delivers multi-functional insights. Experimental evaluation using a custom dataset comprising five common commodities—capsicum, onion, potato, apple, and banana—demonstrated significant improvement in accuracy, flexibility, and feature richness. With an overall accuracy of 92.3% and added capabilities like freshness scoring and market value estimation, the CIS model shows strong potential for practical deployment in smart agriculture, supply chain optimization, and farm-to-market decision-making processes.

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