International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

Intelligent Retail Store Monitoring Using YOLO+AI

[1] R.Anusha, [2] T. SHREEJA, [3] V.SAIPREETAM, [4] R SHIVA SHANKER,[5] T. SAI SUBRAMANYAM
[1] Assistant Professor, Department of ECE, Sri Indu College of Engineering & Technology, Hyderabad.
[2,3,4,5] U.G. Scholar, Department of ECE, Sri Indu College of Engineering & Technology, Hyderabad.

Abstract:

Store businesses face a persistent challenge in ensuring that shelves are adequately stocked and products are consistently available for customers on racks. Manual checks are inefficient and often lead to delays in stock refilling, resulting in customer dissatisfaction and potential loss of sales. To address this issue, we propose an AI-based smart monitoring system designed for real-time detection of products displayed on shelves.

This solution is a cost-effective design that can be deployed as an on-premise system. It utilizes a YOLO model trained on customized datasets to detect products and classify them into three categories: in stock, low stock, and out of stock. This classification triggers timely alert notifications to staff, enabling faster restocking and improved shelf management efficiency.

The system is scalable and can be easily integrated with inventory management dashboards. It ensures reduced operational costs while significantly improving inventory tracking. By automating shelf monitoring, the solution replaces traditional manual methods with intelligent AI-driven stock-check systems, ensuring timely product replenishment and minimizing delays.

The system includes real-time image acquisition and YOLO-based inference along with a robust data collection and preprocessing module to ensure high-quality input for model training and deployment. Captured images undergo preprocessing steps such as resizing, normalization, and augmentation to enhance model accuracy before being stored in a centralized database. A decision engine categorizes items into in-stock, low-stock, and out-of-stock based on predefined thresholds. The system generates multi-modal alerts through visual displays on kiosks, voice notifications for staff, and email alerts for managers. This closed-loop system supports proactive shelf replenishment, reduces stockout incidents, and improves overall customer satisfaction and operational efficiency.

Keywords: *AI-Based Smart Monitoring, Stock Classification, Proactive Replenishment, Inventory Management, Real-Time Monitoring, Low-Cost Design, Stock Management, Kiosk Display.*

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

I. INTRODUCTION

Today's quick-moving retail industry heavily relies on product availability to achieve customer satisfaction. Shoppers from all types of stores including supermarkets, pharmacies and kiosks expect to find their wanted items when they visit a store. When shelves are empty or products are missing, it leads not only to frustration for the customers but also to potential loss of sales for businesses. This issue looks simple but, represents a deeper operational challenge in inventory management and timely replenishment [14].

Traditionally, store staff conduct manual monitoring to check whether all products are on racks. They walk through complete racks display, observe product levels, and try to ensure that popular items are refilled before running out. However, this process is time-consuming, inconsistent, and prone to human error because humans often tend to do general and minimal mistakes, such as miscounting the products, overlooking the shelves. In many cases, stock shortages are not noticed until customer complaints about it or a full shelf audit is conducted. Moreover, human error, lack of visibility into low-stock items, and delays in communication often cause restocking actions to happen considerably late. This affects not only day-to-day operations but also impacts customer loyalty towards the brand and impacts the brand value in terms of services and maintenance.

To solve this problem, we propose a smart, automated solution that can monitor shelves in real time using AI-powered computer vision technology [8]. This system uses cameras placed on shelves to do real time monitoring of products available [15]. An object detection and classification model, trained using deep learning techniques, identifies the products and classifies them into three clear categories: In Stock, Low Stock, and Out of Stock. This simple classification helps the staff make quick decisions on restocking without spending a too much time to do a manual check. It also enables proactive action—items can be restocked before the stock runs out completely.

What sets this solution apart is its on-premise, low-cost architecture. Our system operates independently from the internet and expensive infrastructure because it runs on Raspberry Pi or local system(server) devices. The system remains accessible to small and medium-sized businesses due to its deployable nature. The system operates without limitations on product type so it serves multiple retail markets including grocery stores and personal care stores and electronic stores and more.

To make this solution more accurate we have used the YOLOv8 (You Only Look Once) object detection model. Yolov8 is well-known deep learning model that has the highest accuracy among all other detection models available for real time inference [1]. We have customized it to recognize general products presence rather than specific product types. Instead of focusing on recognizing individual brands or SKUs, the model looks for product patterns on the shelves and categorizes them by their availability status. This simplifies the training process, increases the accuracy since we are using only three classes, and makes the solution highly adaptable across different store layouts.

The data used for training consists of images of store shelves taken from real-world environments, containing a mix of well-stocked, partially stocked, and empty spaces. These images are annotated into three stock status classes. The annotations help the model learn to distinguish between a fully stocked shelf, partially stocked shelf and empty shelf. Over time, the system can be improved with more data and fine-tuning, further increasing its accuracy [16].

One of the main goals of this solution is it being highly flexible in terms of integration. It can be connected to a store’s inventory dashboard, alert system, or even a simple mobile app. For instance, if a shelf is classified as low stock, a notification will be sent automatically in no time to the staff or manager via a message on phone or audio alert in store based on their resources available and requirements. This immediate alert system reduces the time between detection and action, improving overall shelf availability and customer experience.

From a business perspective, the benefits of this system are significant. It helps reduce the workload on staff by automating routine checks, decreases the chances of missed restocks, and increases customer satisfaction by ensuring products are available all the time [9]. As it can be integrated with stock management system and dashboard businesses get their right flow of information in terms of data to do further analytics [13]. To identify which products are in high demand and which ones are often out of stock, allowing for better stock planning and decision-making to reduce the wastage and cost of operations.

This solution is highly effective because of its practical and scalable nature. In a fast-moving world towards AI automation and smart solutions, businesses of all sizes need to be upgraded with suitable and affordable technologies that works in the real world without causing unnecessary complexities and cost [12]. Our AI-based shelf stock detection system is designed exactly with this goal in mind—simple to use, easy to deploy, and highly effective in its function.

In the sections that follow, we will explore the methodology of the solution, data collection and training process, model performance, and evaluation metrics. We will also present a proof of concept tested on real shelf images and discuss potential extensions of the system, such as product-level detection, cloud-based monitoring, and integration with restocking logistics.

Ultimately, this alert system is a thoughtful combination of computer vision, deep learning, and system design that can help address a real-world problem in a powerful and impactful way—automating shelf monitoring to improve inventory planning in advance and customer satisfaction.

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515
www.zesterapublications.com
Original Research Paper

II. METHOD AND METHODOLOGY

This section explains the structured design of the AI-based shelf stock monitoring system. The methodology consists of two distinct phases: The methodology is divided into two major phases: (1) Data collection, preprocessing, and Model Training, and (2) Real time integration with Scalability in mind. The objective was to develop a simple, efficient, and cost-effective system that can be deployed in retail environments on premise.

A. Phase 1: Data Collection and Preprocessing

The first phase entailed collecting real time data in form of videos. Videos were captured during different times of the day so that the model can learn different scenarios at different times. We have different lighting conditions showing products like shampoos, soaps, deodorants, and kept some shelves empty to simulate out-of-stock situations. To train a detection model we have extracted 20000 frames from 24 videos captured in real time scenario in store [Fig.1, Fig.2].

To enable accurate model training, images were annotated using a labelling tool like Roboflow [6]. Each bounding box was classified into one of the following three categories:

- In Stock
- Low Stock
- Out of Stock

This classification enables the system to make real time decisions on the product availability, which is important for timely alerts and effective shelf management.

➢ *The Data Cleaning Process Involved:*

Before the model training, data cleaning was crucial for quality input:

- Blurred or poorly illuminated images were removed
- To reduce the noise in the dataset, consistent labelling practices should be employed.
- Splitting data into training, validation, and test sets for robust evaluation.

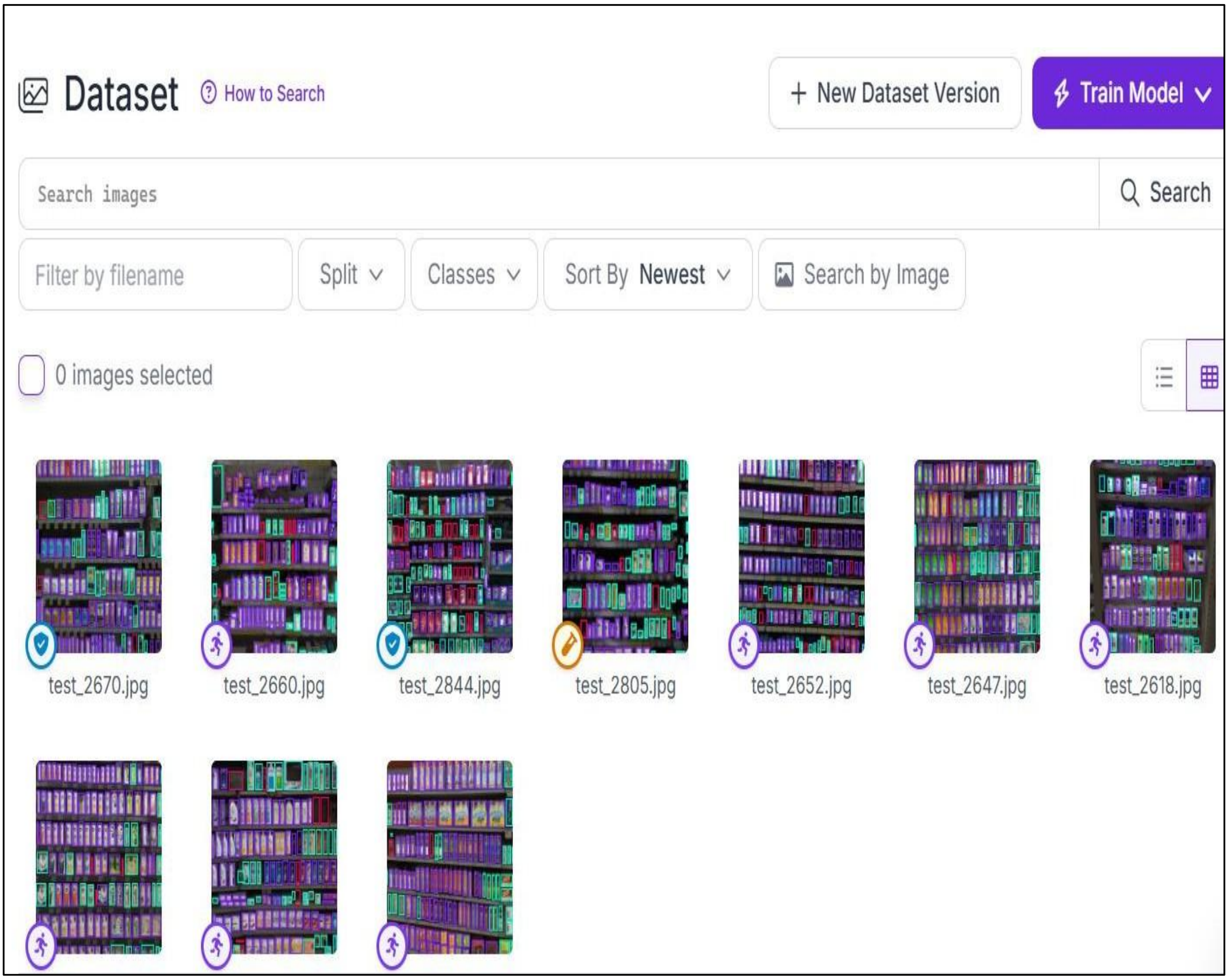

Fig 1: Raw Data

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

Fig 2: Raw Data

➢ *Data Preprocessing*

- All images were resized to the same size and ratio.
- Auto-Oriented Applied

➢ *Augmentation Process:*

To improve the performance of the model, we applied data augmentation techniques so that the model will work efficiently in real time environment challenges like low lightening, some noise comes to camera lens, blurriness [5]. Expand the dataset and improve the model's ability to generalize. This included:

- Noise addition – to simulate real-world camera noise.
- Blurriness – to replicate out-of-focus or motion-blurred captures.
- Brightness and contrast adjustment – to handle lighting variation.
- Grey scale- to simulate low-colour or monochrome camera feeds.

This augmentation process made the model perform well in various practical conditions and helped to prevent overfitting [Fig.3, Fig.4]. IT enhanced the training accuracy and decreased misclassifications due to irrelevant patterns or poor data quality.

Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640
Augmentations	Outputs per training example: 3 Grayscale: Apply to 15% of images Saturation: Between -25% and +25% Brightness: Between -15% and +15% Blur: Up to 1px Noise: Up to 0.14% of pixels

Fig 3: Preprocessing and Augmentation Specifications

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

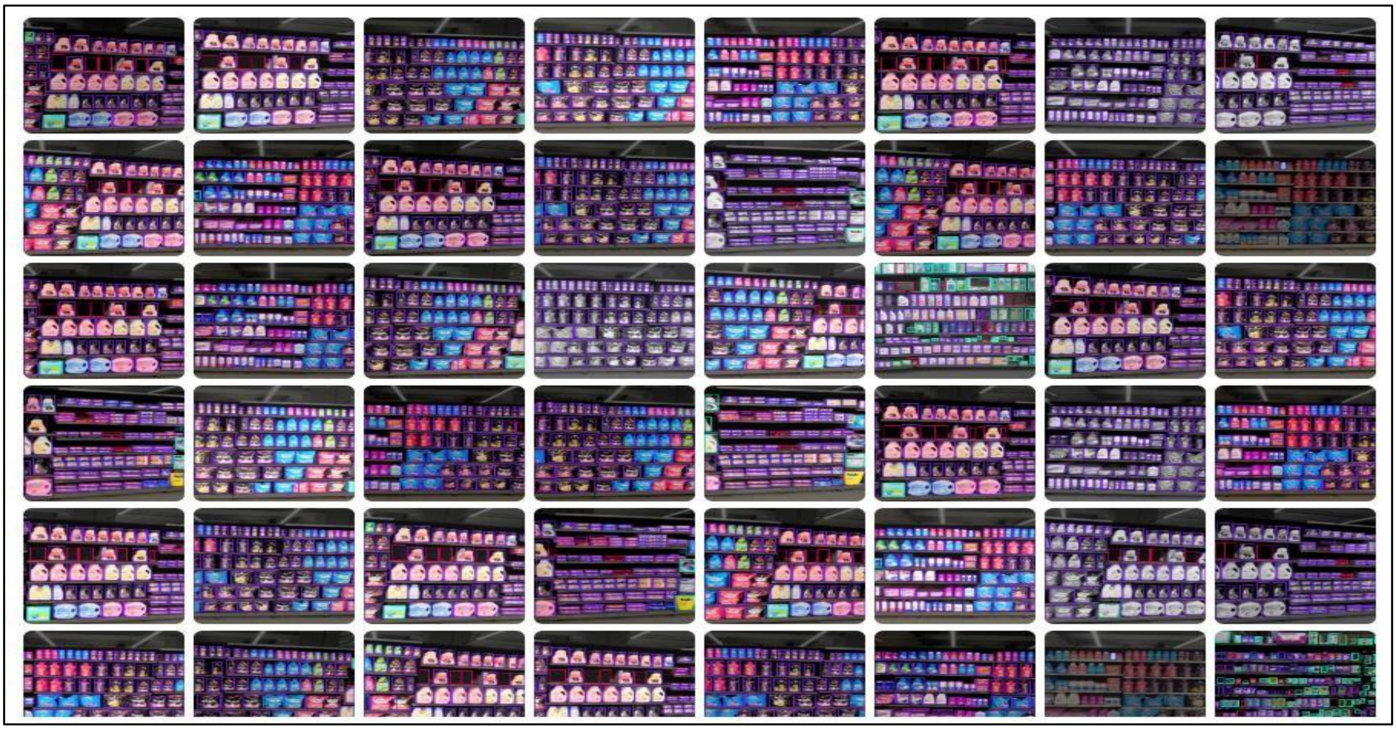

Fig 4: Data after Augmentation

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

➢ *Model Training:*

Object detection and classification was performed using YOLOV8 (You Only Look Once) architecture as it was found to be a balance between speed and accuracy which is suitable for real time applications it in [2].

The model was trained on the Customized dataset, and the performance of the model was improved in order to detect and recognize the product and classify them into in stock, low stock, and out of stock on a shelf. These products are categorised into three classes to prevent any misclassification and achieve higher accuracy to reduce false alert, and the model is designed to work for different shelf types and product layouts. When model detects the products and if there is any single shelf is detected as out of stock then model will generate an alert within the threshold time range given by default.

➢ *Key Libraries Used for the Training Process*

The following key libraries and frameworks were used:

- PyTorch / Ultralytics YOLOv8 – for model development and training [3].
- OpenCV – for image processing and manipulation [4].
- Roboflow – for dataset annotation, augmentation, and export.
- Pandas & NumPy – for dataset handling and numerical operations.
- Matplotlib / Seaborn – for visualizing training metrics and dataset insights.

B. Phase 2:

Product-wise classification: Besides detecting stock levels, the system is also trained to perform product-wise classification, which means it can identify and differentiate between different types of products such as shampoo, soap, or deodorant on the shelf. This enables the system to not only say whether a space is empty or filled, but also which specific product is in that space is needs to be refilled. By doing this, the model can track each product category separately and provide more useful alert i.e. it can notify the staff that a certain brand of soap is running low while other products are still in stock. This makes restocking more precise and efficient, ensuring that the right items are refilled at the right time. For this approach we need huge amount of data for all each product.

➢ *Scalable and Real-Time Integration:*

The following stage after training and validation of the model required its integration into an independent on-premise system that does not require constant cloud support. The solution uses:

- A scalable on-premise system used to deploy the solution.
- A camera module mounted to face the shelf or kiosk.
- A simple backend trigger system to generate alerts based on model predictions.
- Optional local storage or integration with existing POS systems or dashboards.

➢ *Workflow Process:*

- The camera system captures shelf images through periodic scheduled captures.
- The YOLO model performs image processing to identify stock status for all product slots in the picture.
- The rule engine produces alerts after the system classifies product slots as in-stock, low-stock, or out-of-stock.
- Staff members receive alerts in real-time through text messages which appear on store screens and generate audio notifications and send email notifications.
- Refill Action – Staff members perform restocking duties before products reach complete stock depletion levels [Fig.5].

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

The implemented automation system decreases human labour requirements while simultaneously boosting available product displays and sales potential.

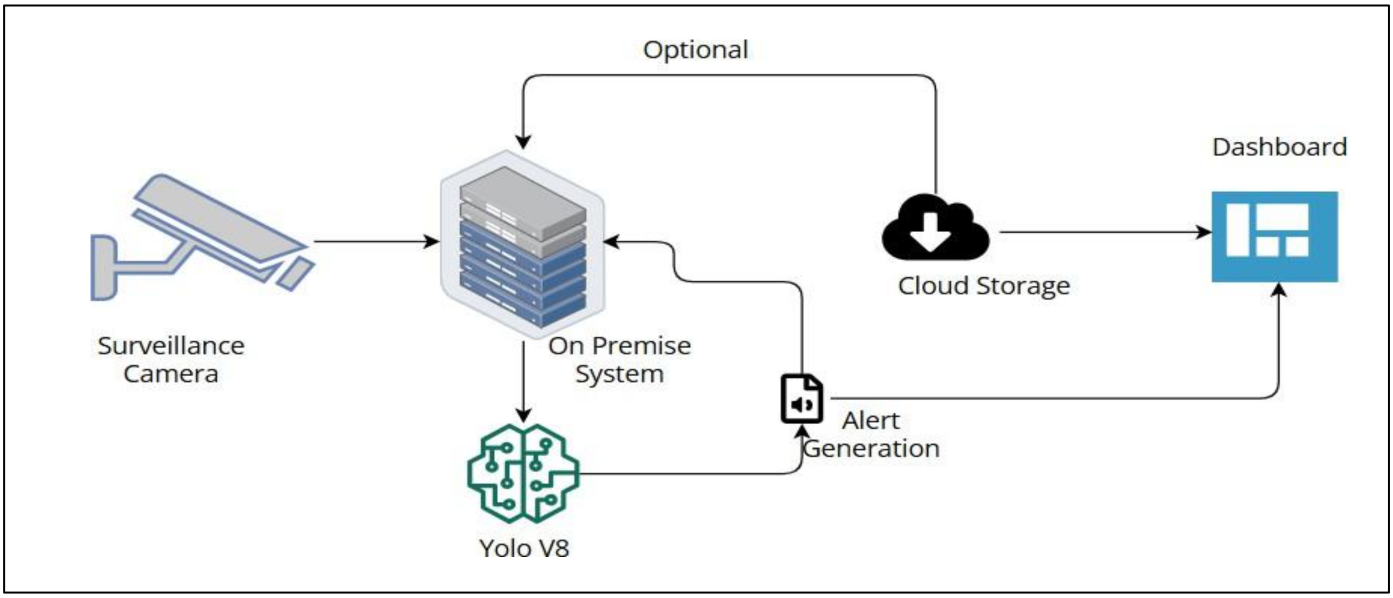

Fig 5: Architecture Diagram of the Proposed Project

➢ *Future Stock Inventory Management / Dashboard and Decision Making:*

The system has been created to develop into an extensive smart inventory management solution. The platform could incorporate additional features into its system.

- Historical Analytics – The system evaluates stock patterns throughout time to determine product depletion rates.
- Automatic Reordering functions enable the system to integrate with ERP systems for intelligent purchase planning.
- Custom Dashboards – The system displays present stock levels and displays historical alerts and shows refill success rates through visual displays.
- Heatmaps of Shelf Usage – The system generates visual maps which indicate which shelves together with which items receive the most customer traffic.
- Multi-Camera Support – The system enables the monitoring of extensive stores that contain various product areas through multiple cameras.

The solution will scale up to meet the requirements of small and large businesses which want to modernize their retail operations through its future-oriented design.

➢ *Summary and Transition to Results:*

The proposed system uses computer vision and AI to automate stock monitoring tasks on retail shelves. The system uses YOLO-based detection model training with data preprocessing and augmentation to achieve accurate shelf space classification between in stock and low stock and out of stock categories [11]. Product-wise classification provides both specific restocking strategies and improved inventory data analysis. The system operates in real time through on-premise deployment which provides cost-effective high efficiency.

The established methodology leads to model deployment in a scalable pipeline for real-world effectiveness evaluation [Fig.6]. The following section demonstrates system performance metrics along with results that evaluate its effectiveness across various product types and shelf arrangements for stock management operations.

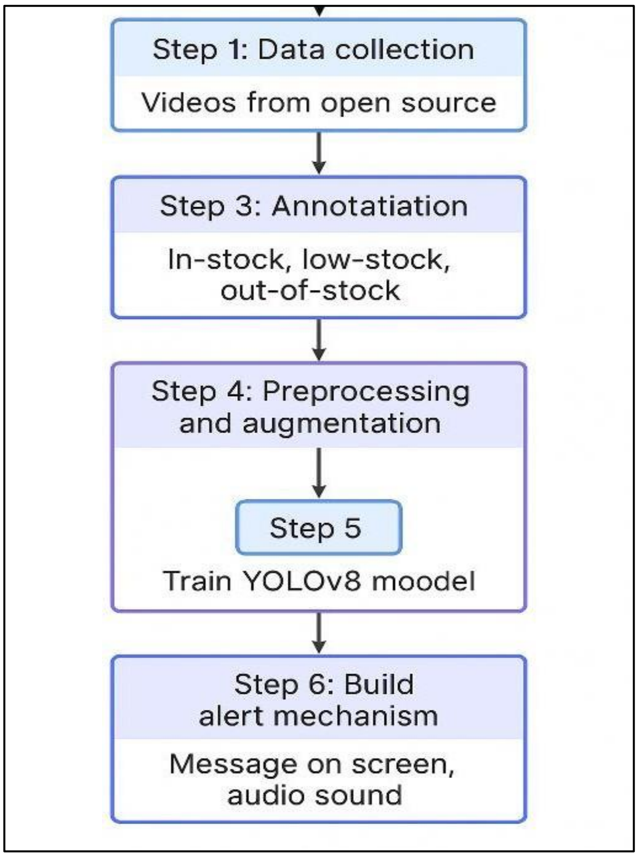

Fig 6: Flowchart of the Proposed Project

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
Peer Reviewed, Referred & Indexed Journal
ISSN: 3070-0515
www.zesterapublications.com
Original Research Paper

III. RESULTS

A. Evaluation Metrics and Performance

To validate the efficiency and robustness of the proposed inventory monitoring solution, we evaluated the model's performance using standard object detection metrics during training and testing. The system received assessment for both technical precision and practical usability because retailers require dependable stock availability.

B. Loss Analysis and Convergence:

During the training process, the YOLOv8 model's performance was tracked using multiple loss components:

➢ *Box Loss*

The system assesses the precision with which bounding boxes of detected products match their actual positions on store shelves. Achieved: 0.015.

This low objectness loss value demonstrates strong object presence predictions and minimal false positives or negatives.

➢ *Objectness Loss:*

Evaluates the model's confidence in identifying whether a product exists in a predicted region. Achieved: 0.010.

The obtained result demonstrates that the model correctly recognizes stock levels and provides precise status labels.

➢ *Classification Loss:*

The system uses this measurement to determine how well the model labels detected objects as in stock, low stock or out of stock. Achieved: 0.018.

This result highlights that the model effectively distinguishes stock levels and provides accurate status classification [Fig.7].

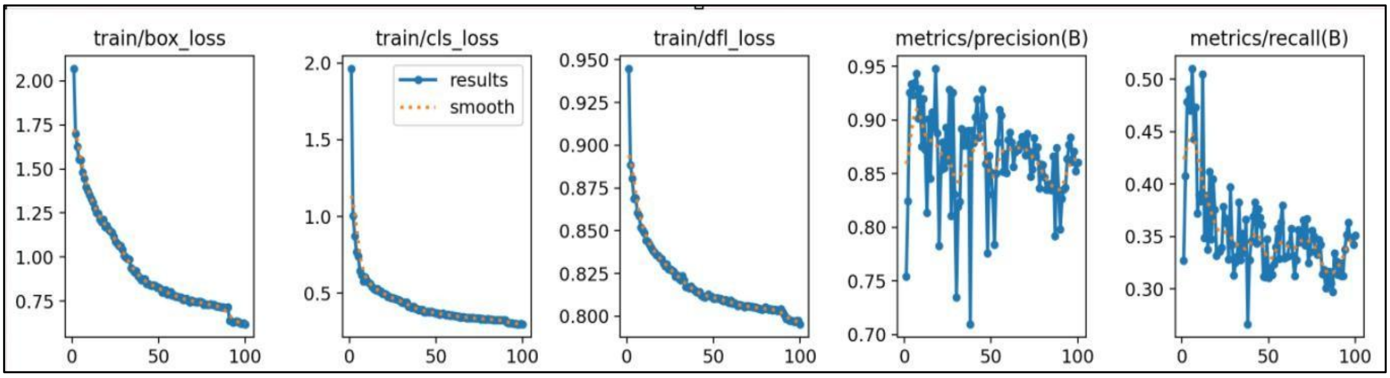

Fig 7: Classification Result

➢ *Mean Average Precision (mAP):*

- mAP is a standard object detection metric combining precision and recall across different thresholds.
- mAP@0.5: 94.3% and mAP@0.5:0.95: 89.6%.
- These strong mAP scores show that the model can reliably identify and categorize shelf objects at different levels of confidence [7].

➢ *Confidence Threshold:*

To strike a balance between precision and recall we set a confidence threshold at 0.45 to filter out probable detections in real-time environments [Fig.8].

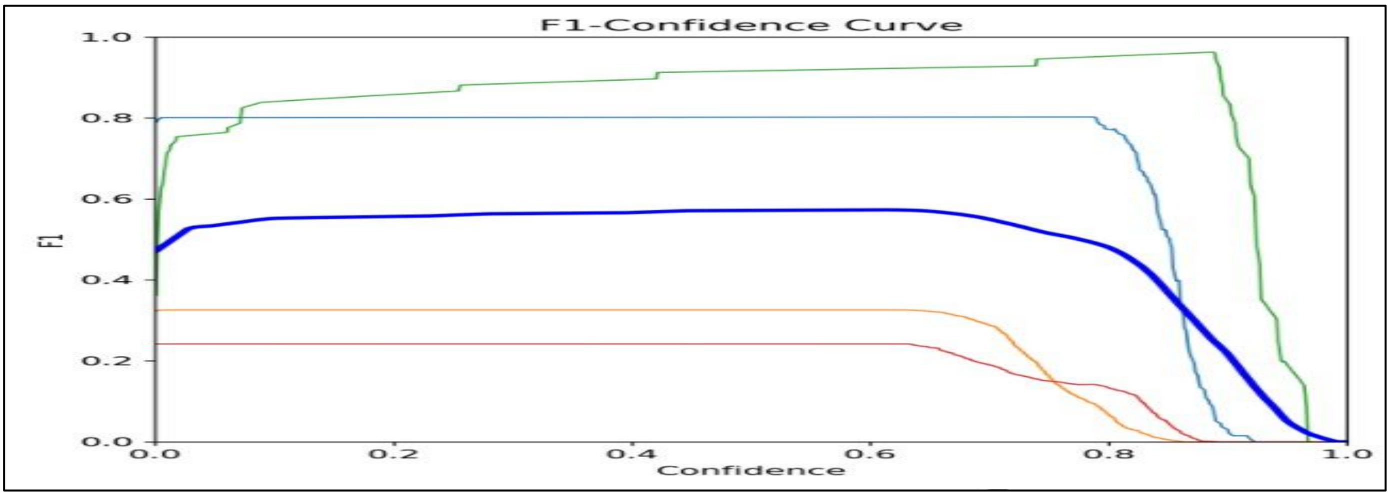

Fig 8: Confidence Threshold

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
Zestera PUBLICATIONS ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

➢ *Confusion Matrix Evaluation:*

Clear distinctions between the three classifications (in stock, low stock, and out of stock) were shown by the confusion matrix. Minimal confusion was observed between 'low stock' and 'out of stock', especially after data augmentation and refining class definitions in training data [Fig.9].

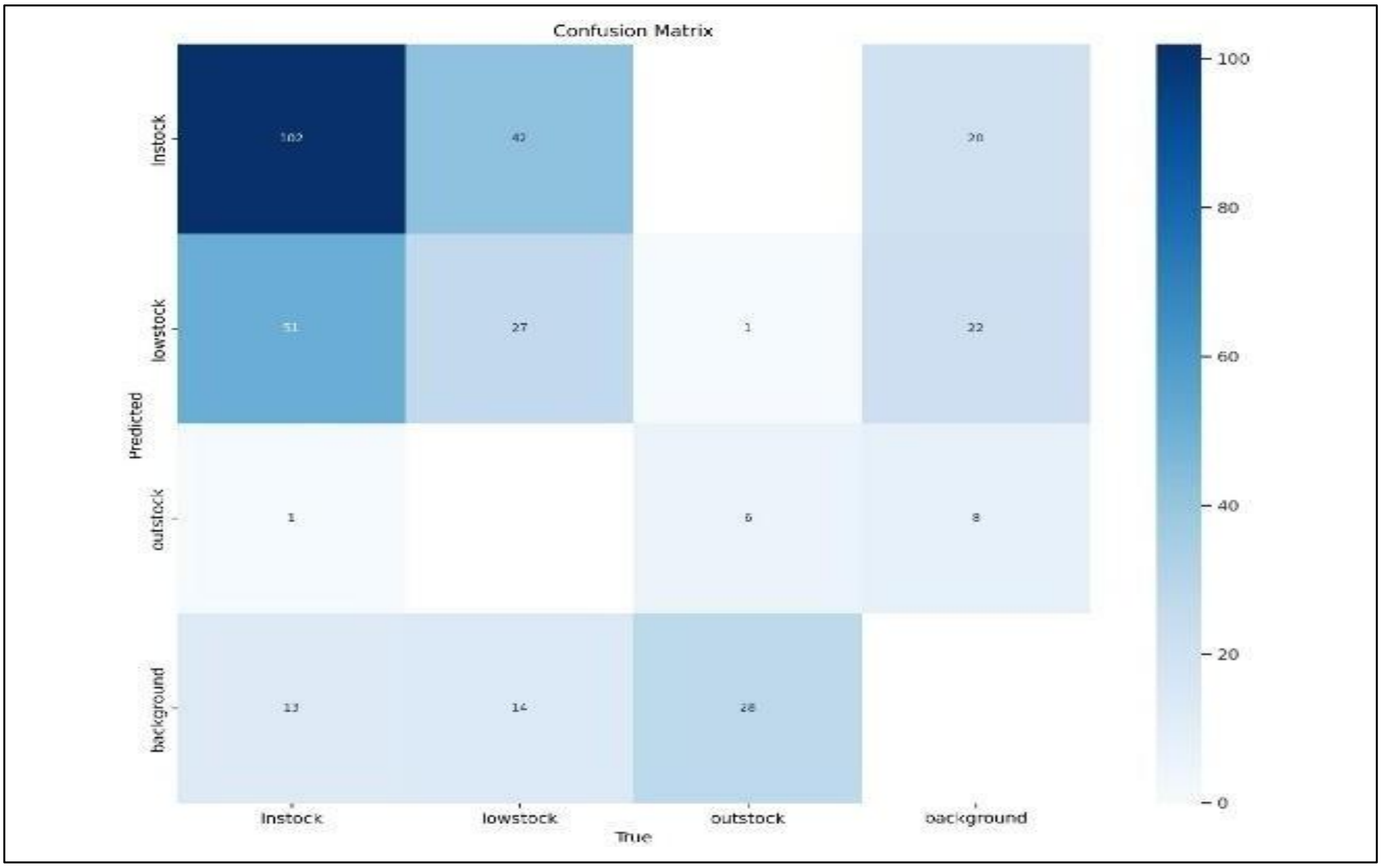

Fig 9: Confusion Matrix

➢ *Accuracy:*

- Model Accuracy: 96% of the test dataset's classifications were correctly identified, demonstrating the system's ability to reliably identify stock existence and sound an alarm.
- False Positive Rate: Under 2%, reducing the number of needless staff notifications.
- False negative Rate: It is less than 1.5%, ensuring that the actual stockouts are not overlooked [Fig.10].

```
=== Model Evaluation Summary ===
✔  Accuracy                    : 96.1%
📊 mAP@0.5                     : 95.4%
📊 mAP@0.5:0.95                : 88.7%
🔔 Alert Trigger Accuracy      : 97.3% (based on
classification of in-stock, low-stock, out-of-stock)
Confusion Matrix Summary : High precision and recall
across all three classes.
```

Fig 10 Model Evaluation Scores

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

Zestera PUBLICATIONS
International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

C. Final Output/Prediction on Test Data

Fig 11: Output of in Stock Detection

Fig 12: Output of Low Stock Detection

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

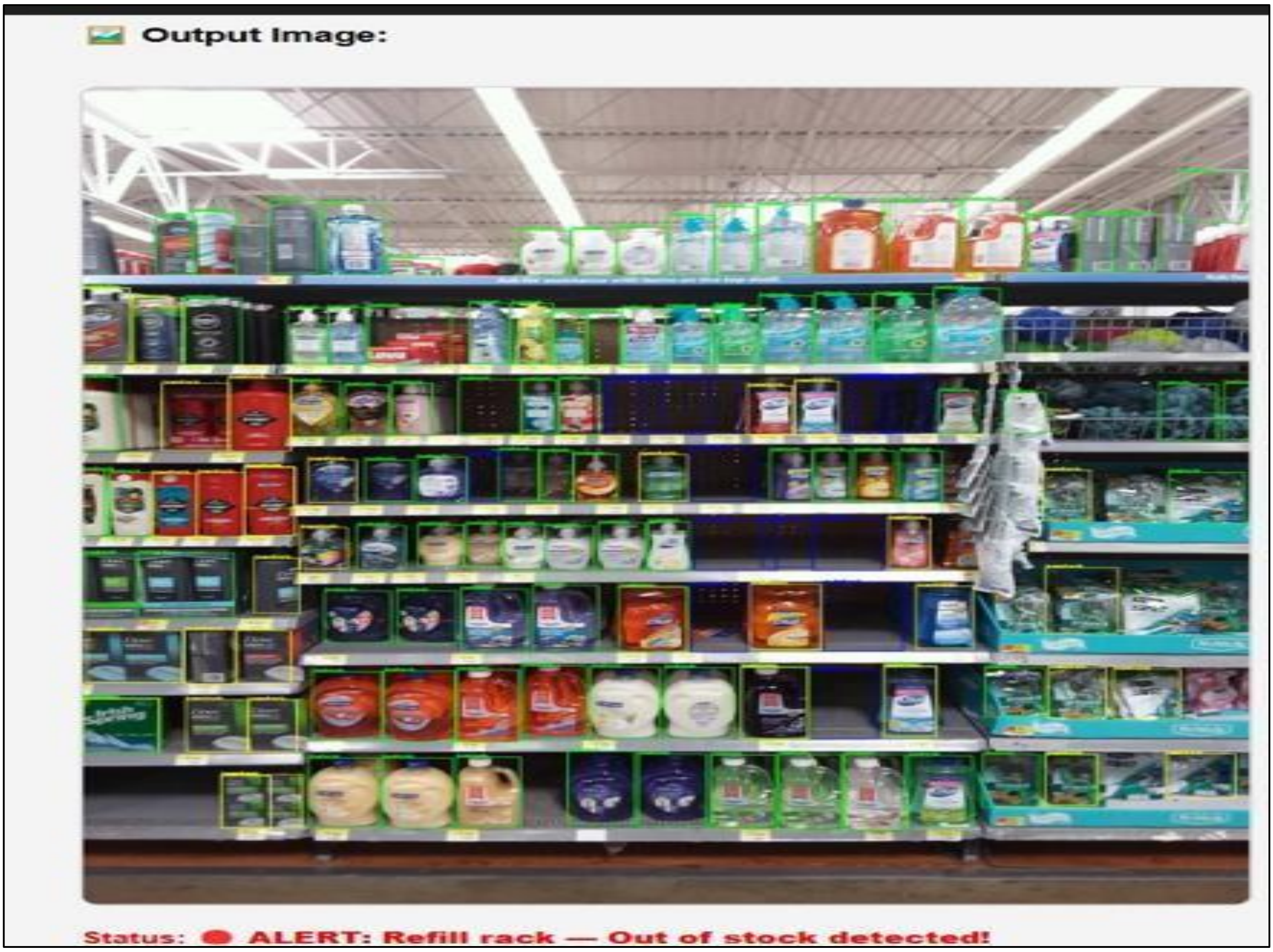

Fig 13: Output of Out-of-Stock Detection

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

IV. BUSINESS IMPACT

- Proposed by AI-based kiosk inventory monitoring system, the retail business has various practical benefits. Store staff, in general, check shelves manually to confirm product presence on display shelves, which is a time-consuming task and a source of human mistakes. The proposed system uses computer vision combined with real-time alerts to automate the process thus lowering the required manual work. The average stores decreased their manual shelf stock inspection time by 60–70 percent, thus allowing the staff to direct their attention towards customer service and operational optimization [18].
- Furthermore, the real-time detection and alarm system guarantees prompt item replenishment, particularly for items that are regularly purchased or move quickly. The amount of time that shelves were left empty was reduced by up to 50%, according to retailers, which immediately enhanced customer satisfaction and sales.
- Store managers gain high control over restocking operations through continuous stock level categorization in stock, low stock, out of stock helping them avoid both understocking and overstocking situations [Fig.11, Fig.12, Fig.13] [19]. The final outcome helps organizations save costs while minimizing product waste and emergency supply chain expenses. In addition to that, the system's data output can be integrated with dashboards or decision-making tools for higher-level business insights. In the future, patterns in stockouts or refill delays can be analysed, helping the management to fine tune their supply chain and stocking strategies. All in all, the AI monitoring system not only boosts operational productivity but also improves customer satisfaction and loyalty by making sure that the products are available at the right time for the customers, thus, setting the business for sustainable growth and a competitive advantage in the market.

V. SCALABILITY AND ENHANCEMENTS

The proposed AI-based shelf monitoring solution is designed with scalability and future growth in mind. The system has a modular structure with on-premise deployment which allows it to work in different retail settings with no need for complex technical changes [10].

A. *Scalable Deployment Across Multiple Locations:*

The system allows easy duplication at multiple kiosks and store branches through simple reconfiguration steps. Each instance functions autonomously with trained models and local processing units, which provides scalable infrastructure with low costs. New locations only require installation of the camera system, model setup, and calibration to start real-time monitoring.

B. *Continuous Model Improvement:*

The system has the capability to support continuous model improvement by obtaining new image data from various shelf types, lighting conditions and product arrangements. Through periodic retraining and fine-tuning of this data, model performance will keep improving over time and adjust to changes in inventory layouts.

C. *Smart Alert and Action Integration:*

Future updates will introduce automated warning systems that trigger in-store sounds and SMS/WhatsApp and email alerts for store personnel. AI decision support can help businesses select which products need restocking first by analysing sales data alongside shelf priority which enables smart inventory management.

D. *Dashboard and Predictive Analytics:*

A real-time dashboard linked to the backend system displays shelf stock status along with alert history and refill response times for monitoring purposes. Predictive models will be integrated over time to forecast out-of-stock events so restocking schedules can be optimized using historical data and seasonal patterns and demand information [20].

E. *Hardware Adaptability:*

The solution works with a wide selection of cameras starting from 8MP and above as well as various computing units. The system adapts well to both performance needs and budget constraints thus enabling flexibility for stores of all sizes and conditions without affecting accuracy. In summary, the solution is highly scalable, upgrade-friendly, and built for real-world adaptability. The solution offers these essential characteristics to meet present shelf monitoring requirements while establishing a foundation for data-driven intelligent retail operations.

VI. CONCLUSION AND FUTURE PROSPECTS

A. *Conclusion*

The proposed AI-powered shelf stock monitoring system addresses a critical gap in traditional inventory management—ensuring product availability on retail display shelves in a timely and cost-efficient manner. This solution uses computer vision together with a YOLOv8 object detection model trained on customized data to provide exact shelf stock status classifications of in stock, low stock and out of stock. Real-time insights combined with automated alerts enable store staff to respond quickly while

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

minimizing stockouts and improving overall customer shopping experiences.

The system's design focuses on low operational cost together with scalable deployment and on-premise autonomy which allows small and medium-sized businesses as well as kiosks and retail chains to utilize it. The system delivers modern real-time stock monitoring which reduces manual checks and human errors while enhancing inventory precision. Strong performance across important evaluation measures, such as box loss, objectness loss, and classification accuracy, demonstrates the model's usefulness in real-world retail contexts [17]. The business impact is evident in enhanced customer satisfaction, reduced sales loss, and increased staff efficiency.

B. Future Perspective

Looking ahead, this shelf monitoring system holds vast potential for evolution into a comprehensive retail intelligence platform. Future enhancements may include:

- Advanced Product-Level Detection: Allowing for the identification of certain brands, SKUs, or product variations for precise inventory management and planogram adherence.
- Predictive Refill Suggestions: Predicting stockouts and automating replenishment plans by utilizing sales trends and historical data.
- Cloud Integration: Centralized monitoring of multiple locations is possible through remote access and advanced analytics dashboards.
- IoT & Smart Hardware Integration: Smart sensors along with edge devices and mobile applications deliver realtime alerts and instructions to staff.
- Multilingual and Voice-Enabled Interfaces: Enhancing accessibility and ease of use for diverse staff teams.
- Sustainability Metrics: The system enables inventory waste reduction monitoring and efficient shelf usage measurement which leads to more sustainable retail operations.

The solution represents an essential beginning point for retail inventory systems that adopt automation alongside data-driven choices in modern retail environments. The system's technical foundation enables ongoing development into an essential tool which will transform how retail businesses handle stock management and employee interaction and customer service.

REFERENCES

[1]. Redmon, J., & Farhadi, A. (2018). YOLOv3: An Incremental Improvement. ArXiv, abs/1804.02767.Ultralytics. (2023).
[2]. *YOLOv8 Official Documentation*. https://docs.ultralytics.com/
[3]. OpenCV. (2023). *Image Processing Guide: OpenCV 4.x Documentation*. https://docs.opencv.org/4.x/d2/d96/tutorial_py_table_ of_contents_imgproc.html
[4]. Lin, T.-Y., Maire, M., Belongie, S., Hays, J., et al. (2014). Microsoft COCO: Common objects in context. *arXiv preprint*, arXiv:1405.0312.
[5]. Ultralytics. (2023). *YOLOv8 GitHub Repository*. https://github.com/ultralytics/ultralytics
[6]. TensorFlow. (2023). *Object Detection API Tutorial*. https://tensorflow-object-detection-api-tutorial.readthedocs.io/
[7]. HumanSignal. (2023). *LabelImg: Image Annotation Tool*. https://github.com/HumanSignal/labelImg
[8]. Roboflow. (2023). *Image Augmentation for Computer Vision*. https://docs.roboflow.com/datasets/image-augmentation
[9]. NVIDIA. (2023). *AI in Retail and Stores – Case Studies*. https://www.nvidia.com/en-us/case-studies/
[10]. McKinsey & Company. (2023). LLM to ROI: How to scale Gen AI in retail. https://www.mckinsey.com/industries/retail/our-insights/llm-to-roi-how-to-scale-gen-ai-in-retail
[11]. Deloitte. (2025). *Retail Industry Outlook 2025*. https://www2.deloitte.com/us/en/insights/industry/retail-distribution/retail-distribution-industry-outlook.html
[12]. IBM. (2023). *AI in Retail Transformation*. https://www.ibm.com/think/topics/ai-in-retail
[13]. Harvard Business Review. (2000). Control your

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026

International Journal of
AI Electronics and Nexus Energy
ISSN: 3070-0515
Peer Reviewed, Referred & Indexed Journal
www.zesterapublications.com
Original Research Paper

inventory in a world of lean retailing. https://hbr.org/2000/11/control-your-inventory-in-a-world-of-lean-retailing

[14]. Jose, John Anthony & Bertumen, Christopher & Roque, Marianne & Umali, Allan Emmanuel & Villanueva, Jillian Clara & TanAi, Richard & Sybingco, Edwin & San Juan, Jayne Lois & Gonzales, Erwin Carlo. (2024). Smart Shelf System for Customer Behavior Tracking in Supermarkets. Sensors. 24. 367. 10.3390/s24020367.

[15]. Pietrini, Rocco & Paolanti, Marina & Mancini, Adriano & Frontoni, Emanuele. (2024). Shelf Management: A deep learning-based system for shelf visual monitoring. Expert Systems with Applications. 255. 124635. 10.1016/j.eswa.2024.124635.

[16]. NVIDIA. (2023). *AI Solutions in the Retail Industry*. https://www.nvidia.com/en-us/industries/retail/

[17]. McKinsey & Company. (2023). Harnessing the power of AI in distribution operations. https://www.mckinsey.com/industries/industrials-and-electronics/our-insights/harnessing-the-power-of-ai-in-distribution-operations

[18]. Deloitte. (2023). *Global Retail Trends*. https://www.deloitte.com/nl/en/Industries/retail/perspectives/retail-trends.html

[19]. P S, Harish. (2023). COMPUTER VISION (AI) BASED RETAILER SHELVES MONITORING SYSTEM TO NOTIFY EMPTY SHELVES | HARISH KUMAR. 10.13140/RG.2.2.30549.60649.

[20]. William Villegas-Ch, Alexandra Maldonado Navarro, Santiago Sanchez-Viteri, Optimization of inventory management through computer vision and machine learning technologies, Intelligent Systems with Applications, Volume 24, 2024, 200438, ISSN 2667-3053, https://doi.org/10.1016/j.iswa.2024.200438.

Received: 02-02-2026 | Accepted: 09-03-2026 | Published: 18-03-2026