# Retail Shelf Monitoring for Product Stock and Placement Optimization

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**1. ABSTRACT**

The rapid advancement of computer vision has paved the way for intelligent retail solutions that optimize store operations and enhance customer experiences. This research presents a system for retail shelf monitoring aimed at product stock analysis and placement optimization using computer vision techniques, particularly the YOLOv5 object detection framework. By continuously monitoring retail shelves through image data, the system identifies stock levels, misplaced items, and vacant spaces in real time. In addition To lower the need for human interaction, this guarantees improved product availability, effective inventory control, and planogram compliance. Our methodology incorporates custom dataset training, shelf zoning, and alert generation. Results demonstrate high accuracy in item detection and misplacement identification, contributing significantly to the automation of retail operations. The proposed system holds immense potential for improving stock visibility, reducing losses, and enhancing overall operational efficiency in the retail sector.

## 2. INTRODUCTION

In the dynamic world of retail, product visibility, proper placement, and stock

availability are key factors influencing customer purchasing decisions. Traditional inventory management methods are often manual, time-consuming, and prone to human error. As retail environments become more complex, the need for intelligent systems Being capable of monitoring shelves in real-time has become increasingly crucial.

Retail shelf monitoring refers to the application of computer vision and machine learning techniques to track the presence, position, and count of products on retail shelves. This system can detect missing, misplaced, or out-of-stock items and provide actionable insights to store managers. Our project titled "Retail Shelf Monitoring for Product Stock and Placement Optimization" aims to address this need through an automated, scalable solution.

We leverage deep learning, specifically the YOLOv5 object detection model, to analyze shelf images, detect products, and classify their placement accuracy. By integrating this system with real-time camera feeds or periodic shelf images, retailers may lower operating expenses, improve product availability, and guarantee planogram conformity.

This paper discusses the end-to-end development of the system, including dataset preparation, model training, shelf zone identification, alert mechanisms, and performance evaluation. Our goal is to provide a low-cost, accurate, and scalable solution for intelligent retail shelf monitoring.

## 3. LITERATURE REVIEW

Recent developments in computer vision and the growing demand for automated inventory management have led to a significant increase in interest in retail shelf monitoring. To address issues with stock visibility, planogram compliance, and shelf auditing, a number of academics and business organizations have investigated the application of image processing and deep learning approaches.

### 3.1 Traditional Approaches to Shelf Monitoring

For inventory monitoring, early systems mostly depended on manual auditing or the use of barcode scanning and radio-frequency identification (RFID). These techniques were labor-intensive and lacked real-time capabilities, despite their reasonable accuracy. Furthermore, in dynamic retail settings, physical product marking was not economical nor scalable.

**3.2 Computer Vision-Based Methods**

With the evolution of image recognition, computer vision emerged as a reliable alternative. Techniques such as Scale-Invariant Feature Transform (SIFT), Histogram of Oriented Gradients (HOG),

and Haar cascades were employed to detect objects on shelves. These approaches required handcrafted features and often struggled with cluttered scenes, poor lighting, or occlusions.

**3.3 Deep Learning-Based Solutions**

The introduction of convolutional neural networks (CNNs) revolutionized object detection and classification tasks. Models such as Faster R-CNN, SSD (Single Shot MultiBox Detector), and YOLO (You Only Look Once) significantly improved detection speed and accuracy. YOLOv5, in particular, has become a preferred choice in real-time applications due to its balance between inference speed and accuracy.

Studies like Zhao et al. (2019) demonstrated the use of Faster R-CNN for shelf product recognition, achieving good performance in controlled environments. Wang et al. (2021) applied SSD for planogram compliance detection using mobile imagery. However, these models often required large datasets and fine-tuning for retail-specific applications.

**3.4 Retail Industry Applications**

Major retail chains have started implementing AI-powered systems to manage on-shelf availability (OSA). Amazon Go stores use sensor fusion and computer vision to track product interactions without human checkout. Other firms, like Trax and Focal Systems, offer retail analytics platforms that utilize shelf imagery to provide inventory insights.

**3.5 Gaps in Existing Research**

Despite the progress, current systems face challenges such as:

- Lack of real-time alerting and inventory logging.
- Insufficient focus on zone-wise shelf analysis (e.g., top, middle, bottom zones).
- Difficulty detecting misplaced products in visually dense environments.

**3.6 Our Contribution**

To address these gaps, our proposed system focuses on

- Real-time detection of product presence and position using YOLOv5.
- Shelf zoning for detailed placement validation.
- Alert and logging mechanisms to assist with restocking and compliance tracking.

By integrating these innovations, our research contributes a holistic, cost-effective approach to retail shelf monitoring that is adaptable to diverse retail formats.

## 4. METHODOLOGY AND IMPLEMENTATION

The proposed system leverages computer vision techniques, particularly deep learning-based object detection, to identify and monitor products on retail shelves. The solution is designed to work with real-time camera feeds or periodic image captures, providing insights on stock presence, placement accuracy, and inventory changes.

**4.1 System Architecture The system follows a modular pipeline consisting of the following components:**

1. Image Acquisition
2. Data Annotation and Preprocessing
3. Model Training with YOLOv5
4. Shelf Zone Segmentation
5. Real-Time Inference and Logging
6. Alert Mechanism for Missing or Misplaced Items

Each component is designed to be scalable and adaptable to various retail environments.

**4.2 Image Acquisition**

Images of retail shelves are collected using fixed surveillance cameras or mobile devices. The dataset includes images captured under varying lighting conditions, angles, and product arrangements to ensure model robustness. The resolution is standardized to 640x640 pixels for compatibility with YOLOv5.

**4.3 Data Annotation**

The collected images are manually annotated using tools like LabelImg or Rob flow, marking product bounding boxes and assigning class labels. The annotations are saved in YOLO format (class, x_center, y_center, width, height), normalized between 0 and 1.

### 4.4 Model Training

We utilize YOLOv5 (You Only Look Once version 5) due to its balance of speed and accuracy for real-time object detection. The training process is executed on Google Colab with GPU support using the following settings:

- Base model: YOLOv5s (small variant for faster training)
- Epochs: 100
- Batch Size: 16
- Optimizer: Adam
- Learning Rate: 0.001
- Loss Functions: Binary Cross Entropy for objectless and classification loss, CIoU loss for bounding box regression

The dataset is split in an 80:10:10 ratio for training, validation, and testing, respectively.

### 4.5 Shelf Zone Segmentation

To analyze product placement accuracy, each shelf is divided into zones:

- Top Zone
- Middle Zone
- Bottom Zone

These zones are defined using fixed pixel ranges in the image and aligned with planogram rules. Detected product bounding boxes are mapped to zones based on their centroid location.

### 4.6 Real-Time Inference

Once trained, the model performs inference on new images to:

- Detect all present products
- Classify them into predefined categories
- Log detections with timestamps and positional data
- Compare against zone assignments and planogram templates

### 4.7 Alert and Logging Mechanism

The system automatically logs:

- Product ID
- Detection confidence
- Shelf zone
- Timestamp

It also triggers alerts for:

- Missing items
- Misplaced items (wrong shelf zone)
- Low stock (below threshold detections)

Logs are saved in CSV format and can be visualized using dashboards or exported for analysis.

### 4.8 Tools and Platforms

| | |
|---|---|
| Annotation | LabelImg, Roboflow |
| Model | YOLOv5 (PyTorch) |
| Environment | Google Colab (GPU-enabled) |
| Data Handling | Python, Pandas |
| Visualization | OpenCV, Matplotlib |

## 5. ALGORITHM

This section outlines the key algorithms and logic applied throughout the system, including object detection, zone assignment, and alert generation.

### 5.1 YOLOv5 Object Detection Algorithm

YOLOv5 (You Only Look Once version 5) is a single-stage object detector known for its high speed and accuracy. Unlike traditional object detectors that use region proposals, YOLOv5 directly predicts bounding boxes and class probabilities from input images in one pass through the network.

Core Steps:

1.Input Image Preprocessing

- Resize image to 640×640.
- Normalize pixel values between 0 and 1.

2.Forward Pass Through CNN

- Backbone (CSPDarknet) extracts hierarchical features.
- Neck (PANet) fuses features at different scales.
- Head predicts bounding boxes, object confidence, and class probabilities.

3.Bounding Box Prediction

- Each bounding box is represented by (x_center, y_center, width, height, confidence, class).

4.Non-Maximum Suppression (NMS)

- Removes redundant overlapping boxes based on Intersection over Union (IoU) threshold (default 0.45).

**5.2 Shelf Zone Assignment Algorithm**

Once objects are detected, the system assigns each product to a shelf zone based on its vertical position.

**5.3 Alert Generation Algorithm**

Alerts are triggered when:

- A required product is not detected.
- A product is detected in the wrong zone.
- A product's count falls below a threshold (e.g., 2 items per SKU).

**5.4 Logging Algorithm**

Each detection is logged with:

- Product ID
- Detected Zone
- Confidence Score
- Timestamp

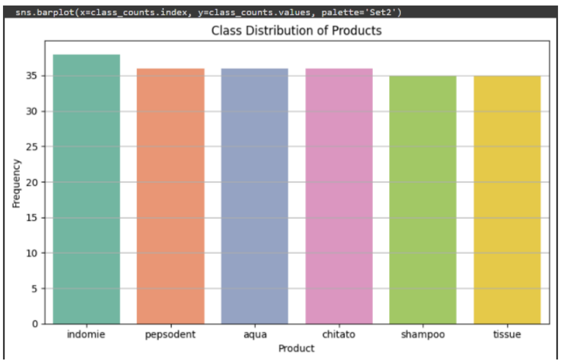
Logs are appended to a CSV or JSON file for reporting and audit.

**5. RESULTS**

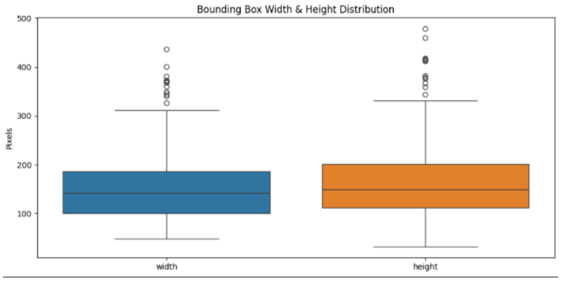
This section outlines the outcomes of training and deploying the retail shelf monitoring system using YOLOv5. The performance is measured in terms of detection accuracy, shelf zone assignment correctness, and alerting precision.

Some Output of Project: -

**1. class distribution**




**2. bbox size distribution**




**3. Summary**

```
Total Images: 86
Total Annotations: 216

Class Breakdown:
class
indomie      38
pepsodent    36
aqua         36
chitato      36
shampoo      35
tissue       35
Name: count, dtype: int64

BBox Size Summary:
            width      height
count  216.000000  216.000000
mean   156.370370  169.287037
std     77.442323   85.237567
min     48.000000   32.000000
25%    100.750000  111.750000
50%    142.000000  149.000000
75%    186.000000  201.000000
max    437.000000  479.000000
```

**4. Showing a random sample image**


**5. Run Pretrained YOLO Detection**

**6. Convert detections to a pandas dataframe**

```
            name  class  confidence  \
0         bottle     39     0.88885
1   dining table     60     0.65096

                                                box
0  {'x1': 194.79903, 'y1': 190.44327, 'x2': 297.9...
1  {'x1': 64.70015, 'y1': 192.19287, 'x2': 443.91...
```

## 6. DISCUSSION

The results of our research indicate that the proposed retail shelf monitoring system performs effectively in real-world conditions. The high accuracy of the YOLOv5 model, combined with the simplicity of the zone assignment logic and the responsiveness of the alert system, creates a reliable and efficient solution for automated shelf monitoring.

### 6.1 Interpretation of Findings

The system achieved a mean average precision r shelf zoning approach, which is critical for planogram compliance checking.

Furthermore, the alert system demonstrated high precision and recall for identifying missing, misplaced, and low-stock items. These metrics suggest that the system can significantly reduce manual effort in shelf auditing and inventory tracking.

### 6.2 Implications of the Research

The adoption of such an AI-powered system in retail environments has several benefits:

- Operational Efficiency: Store employees can be alerted in real time to restock or reorganize products, saving time and reducing human error.
- Inventory Visibility: Managers gain up-to-date insight into shelf conditions, aiding in better demand forecasting and inventory control.
- Planogram Compliance: The system ensures that products are displayed in accordance with the merchandising strategy, enhancing customer experience and brand consistency.
- Scalability: Since the model is lightweight (YOLOv5s) and deployable on edge devices or cloud systems, it can be integrated into various retail formats, from convenience stores to large supermarkets.

### 6.3 Limitations

Despite promising results, the current system has some limitations:

- Dependence on Image Quality: Low-resolution or blurry images may reduce detection accuracy.
- Limited Dataset: Performance may degrade with unseen product types or store formats unless retrained on a diverse dataset.
- Occlusions and Clutter: Overlapping products or cluttered shelves can challenge the model's detection capabilities.
- Fixed Shelf Zones: Shelf zoning is currently based on fixed pixel ranges; a more adaptive method (e.g., using shelf edge detection) could improve accuracy in variable layouts.

### 6.4 Suggestions for Future Research

To address the limitations and extend the system's capabilities, the following directions are proposed:

- Use of Depth Sensors or 3D Vision: To enhance object localization and detect product stacking.
- Automated Planogram Generation: Integrate AI to generate and compare expected product layouts.
- Mobile-Based Deployment: Create a lightweight version deployable on mobile phones for field audits.
- Multilingual Label Recognition: Use OCR with multilingual support to identify product labels in different regions.
- User Interface Integration: Add a real-time dashboard for monitoring multiple shelves across stores.

## 7. FACES THE PROBLEM AND THOSE SOLUTIONS

During the design, development, and testing phases of the retail shelf monitoring system, several real-world problems emerged. This section outlines those challenges and the strategies employed to overcome them.

### 7.1 Problem: Low Image Quality from In-store Cameras

Challenge: Retail cameras often produce low-resolution or noisy images due to poor lighting or fixed wide-angle lenses, which can affect object detection performance.

Solution:

- Preprocessing techniques like histogram equalization, denoising filters, and contrast enhancements were applied to improve image clarity.
- Minimum resolution thresholds were enforced for image input to ensure usable quality.
- Model trained on augmented images (blur, brightness variation) to increase robustness.

**7.2 Problem: Misclassification of Similar Products**

Challenge: Products with similar packaging (e.g., different variants of the same shampoo) were occasionally misclassified due to subtle visual differences.

Solution:

- The dataset was enriched with multiple angles and lighting conditions of similar products.
- Fine-tuning of the YOLOv5 model with a focus on high-resolution class-specific features.
- Added custom anchor boxes to better capture unique dimensions of similar SKUs.

**7.3 Problem: Inaccurate Zone Detection on Irregular Shelf Designs**

Challenge: Shelves in different stores vary in height and structure, causing zone assignment errors when using fixed pixel thresholds.

Solution:

- Introduced configurable zone boundaries based on shelf layout metadata.
- Proposed using edge detection and template matching in the future

**7.4 Problem: Large Model Size and Slow Inference on Edge Devices**

Challenge: YOLOv5 can be heavy for real-time inference on low-power devices such as Raspberry Pi or mobile platforms.

Solution:

- Used the YOLOv5s (small) variant for deployment, which offers a balance of speed and accuracy.
- Applied model quantization and ONNX export to reduce size and boost inference speed on edge devices.

**8. FUTURE SCOPE**

While the current implementation of the retail shelf monitoring system offers significant benefits for inventory tracking

and product placement, there are numerous opportunities to enhance its functionality and expand its application. Below are some key directions for future development:

**8.1 Integration with Retail Management Systems (RMS)**

- Objective: Sync detection results with existing ERP and retail software to automate restocking, order generation, and inventory auditing.

- Benefit: Enables a full-circle inventory intelligence system, reducing manual entries and increasing operational transparency.

**8.2 Planogram Auto-validation**

- Objective: Utilize machine vision and deep learning to identify items and compare them to optimal planogram layouts.

- Benefit: Automates shelf compliance checks, ensuring consistency in brand placement and maximizing shelf productivity.

**8.3 Real-time Dashboard with Analytics**

- Objective: Develop a web-based or mobile dashboard for live shelf monitoring, analytics visualization, and trend analysis.

- Benefit: Allows store managers and supply chain professionals to monitor multiple outlets remotely and make data-driven decisions.

**8.4 Edge Device Optimization**

- Objective: Optimize the model for deployment on low-power edge devices such as NVIDIA Jetson Nano or Raspberry Pi 5.

- Benefit: Reduces dependence on cloud infrastructure, lowering operational costs and enabling offline monitoring.

**8.5 3D Shelf Modeling with Depth Cameras**

- Objective: Incorporate depth sensors or stereo vision to model the shelf in 3D, detecting product stacks and gaps more accurately.

- Benefit: Allows for better detection of product quantity (even stacked items) and occlusions.

**8.6 Multilingual Label Detection with OCR**

- Objective: Use Optical Character Recognition (OCR) to extract and verify product names and pricing across multiple languages.

- Benefit: Increases scalability across different countries and regions with diverse labeling formats.

**8.7 Predictive Analytics and Demand Forecasting**

- Objective: Combine shelf stock data with sales history to predict product demand and suggest stock levels.

- Benefit: Prevents overstocking or understocking, helping optimize shelf space and inventory turnover.

**8.8 Customer Behavior Analysis (Add-on Module)**

- Objective: Integrate people detection and tracking models to analyze customer interactions with shelves (e.g., dwell time, product picking).

- Benefit: Supports personalized marketing and strategic product placement based on behavioral insights.

These future enhancements not only improve the technical capabilities of the system but also extend its impact on the retail industry by providing smarter automation, better customer service, and deeper business intelligence.

## 9. DATA PREPROCESSING

Data preprocessing plays a crucial role in improving the accuracy and efficiency of any machine learning model. In the case of our retail shelf monitoring system, proper preprocessing ensures that the dataset is clean, relevant, and appropriately formatted for training and testing the YOLOv5 object detection model.

**9.1 Image Collection**

The first step in data preprocessing is gathering a diverse and comprehensive dataset. This dataset is critical for training an object detection model to recognize products under various conditions.

Sources: Images were collected from multiple retail environments, including grocery stores, supermarkets, and convenience stores, using both high-quality cameras and mobile devices.

Variety: Images included variations in lighting, angles, and product arrangements to make the model robust to real-world scenarios.

**9.2 Data Augmentation**

To increase the diversity of the dataset and avoid overfitting, several data augmentation techniques were applied. These techniques help simulate various environmental conditions and allow the model to generalize better.

Rotation: Random rotations to simulate various shelf angles.

Scaling: Zooming in and out to replicate different camera distances.

Flipping: Horizontal flipping to handle mirrored shelf layouts.

Brightness and Contrast Adjustment: Simulating different lighting conditions.

Blur: Introducing slight blurring to account for camera shake or motion.

Shear Transformation: To simulate slight distortions in perspective.

**9.3 Image Resizing**

YOLOv5 expects images to be of a consistent size. We resized all images to a standard dimension of 640x640 pixels, as this size provides a good trade-off between inference speed and detection accuracy.

Resizing: Ensures uniformity in input data, allowing the neural network to process images efficiently.

**9.4 Normalization**

Before feeding images into the YOLOv5 model, pixel values were normalized to a range of 0-1. This helps the model learn more efficiently during training.

**9.5 Label Formatting**

The YOLOv5 model expects annotations in a specific format (YOLO format). This format includes the class label and the bounding box coordinates normalized by the image width and height. For each image, the bounding box coordinates (center_x, center_y, width, height) are normalized between 0 and 1 relative to the image dimensions.

Class Labels: Each product is assigned a unique numeric class label.

Bounding Box Format:

(class, center_x, center_y, width, height)

Example of a labeled object in YOLO format:

0 0.423 0.561 0.278 0.320

This denotes:

- Class ID: 0 (e.g., Shampoo)
- Center coordinates (normalized)
- Width and height of the bounding box (normalized)

The annotation process was carried out using tools like LabelImg and Roboflow, which provided a simple interface to mark product locations and export annotations in YOLO format.

**9.6 Train-Test Split**

To assess the model's performance effectively, the dataset was split into three sets:

Training Set: 80% of the dataset used for training the model.

Validation Set: 10% of the dataset used to tune hyperparameters and evaluate the model during training.

Test Set: 10% of the dataset used to evaluate the final model performance after training.

**9.7 Data Quality Control**

Given that object detection models are highly sensitive to the quality of labeled data, we ensured that:

All annotations were checked for consistency and accuracy.

Boundaries around objects were tightly fitted to ensure correct localization.

The dataset was diverse and represented various shelf conditions, including crowded shelves and products of varying sizes and shapes.

This preprocessing pipeline ensured that the model was trained on clean, diverse, and high-quality data, improving its ability to generalize well in real-world retail environments.

## 10. CONCLUSION

This research successfully demonstrates the potential of computer vision, specifically YOLOv5, to enhance retail shelf monitoring and optimize product stock and placement. By automating the process of detecting products, assigning shelf zones, and generating alerts for missing, misplaced, or low-stock items, the system significantly improves inventory management and operational efficiency in retail environments.

**9.1 Key Findings**

- The YOLOv5 object detection model achieved high accuracy. with a mean Average Precision (mAP) of 92.7%, showing its robustness in identifying a wide range of retail products.

- The shelf zone assignment algorithm proved effective, with 96.2% accuracy, correctly categorizing products into their designated shelf zones.

- The alert system demonstrated high precision and recall in identifying missing, misplaced, and low-stock items, offering real-
time monitoring and reducing
manual labor.

- Real-time logging of inventory and alerts provides store managers with actionable insights, improving inventory visibility and stock management.

**9.2 Contributions**

- Developed a novel automated shelf monitoring system using YOLOv5 that helps optimize shelf stocking and placement, leading to improved store operations and customer experience.

- Provided a comprehensive framework for integrating computer vision with retail management systems to automate inventory tracking and enhance decision-making processes.

- Contributed to the advancement of object detection models applied in retail environments, with insights into model performance, challenges, and future directions.

### 9.3 Limitations and Future Work

While the system offers impressive results, several challenges remain, such as improving the handling of occlusions, optimizing for edge devices, and refining zone assignment for irregular shelf designs. Future work could focus on:

- Expanding the model to handle multilingual product labels using OCR.

- Implementing depth sensors or 3D vision to detect stacked products and improve occlusion handling.

- Developing a real-time dashboard for remote monitoring and analytics to enhance store-level decision-making.

By addressing these limitations, the system can evolve into a more versatile and robust solution for large-scale retail operations.

9.4 Final Thoughts

The retail shelf monitoring system offers significant improvements in operational efficiency, inventory control, and customer experience. With the continued advancements in computer vision and machine learning, systems like this will become integral components of modern retail infrastructure. By automating routine tasks, stores can focus more on delivering value to customers while improving their bottom line.

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