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Shelf Track: Intelligent Empty Shelf and Low-Stock Monitoring System

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Abstract

Effective inventory management is the secret to success in the current high-speed marketing world. Traditional remote inventory management relies on image processing to identify missing products from shelves but mainly contributes to customer privacy concerns. Unlike previous work that focused on identifying missing specific items, this work aims to identify empty areas on shelves without infringing customer identity. In addition to capturing the exact position of empty shelves in a store, it also captures the regions of empty shelves. On top of this, the system has a function that can also detect low levels of inventory and identify the specific items that require replenishment. This is achieved by leveraging top-end technologies such as Optical Character Recognition (OCR) for labeling products, convolutional neural networks (CNNs) to detect stock levels, and a database-driven stock management system to track in real-time and analyze inventories. The system incorporates the pre-trained Faster R-CNN model currently in use for detecting vacant shelves and a hybrid OCR-CNN model to spot item labels and quantities. The system has a replenishment module for creating monthly reports that aggregate shelf occupancy information, low-stock instances, and replenishment activities. The informative reports provide actionable data, trend analysis, and performance metrics, which can be easily presented to management to drive strategic planning. This breakthrough solution offers a privacy-centric, all-in-one approach to shelf monitoring, low stock detection, inventory replenishment, and performance reporting, addressing pressing requirements in the retail sector.

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1. Introduction

Effective stock and inventory management is becoming increasingly difficult in the quickly changing retail sector. Conventional inventory tracking is labor-intensive, subject to delays, and prone to errors because it primarily relies on manual operations. Because shelf tracking, when used, is typically done during slow seasons, retail establishments frequently deal with high labor costs and operational inefficiencies. When products are out of stock on store shelves but may still be in the warehouse, this delay can lead to lost sales opportunities. When there are stockouts on the shelf, customers usually take negative actions like changing brands, shopping elsewhere, or forgoing the purchase. Retailers lose both short-term sales and long-term customer loyalty. Automated monitoring and restocking have thus emerged as essential prerequisites in this regard because they provide data on stock levels, customer preferences, staffing effectiveness, and overall sales performance.

Conventional inventory tracking systems use image processing to identify empty shelves or missing items. Such methods, while effective, raise concerns about cost, viability, and customer privacy, and require real-time image acquisition, usually from CCTV systems. Without jeopardizing consumer privacy, machine learning (ML) and new data analytics present a revolutionary alternative for automatically detecting low stock levels and empty shelves. Utilizing the existing Faster R-CNN model, the proposed system detects empty shelves and employs sophisticated features to identify low stock, suggest restocking actions, and produce informative monthly reports. The adaptive approach, could revolutionize inventory management, lower labor costs, increase operational effectiveness, and boost customer satisfaction. The system is flexible and applicable not only to retail stores but also to a variety of industries that require efficient stock control systems.

2. Related Work

Smart shelf monitoring was at the forefront of the growing use of AI and IoT in retail and warehouse management. To reduce out-of-stock incidents, Kumar et al. [1] created YOLO-based real-time shelf monitoring that can precisely identify empty slots. Similarly, Pawar et al. [2] documented the operational advantages of combining Telegram for real-time notifications with vision-based detection to streamline restocking procedures and reduce human interaction. An integrated framework of intelligent trolleys and IoT shelves was proposed by Arora et al. [3] to further maximize operations beyond shelves. This framework facilitates automation and improves the shopping experience for customers. The convergence of data analytics and inventory management is further supported by Zubair et al. [4], who developed PackMLP, a predictive inventory management and automation machine learning model that depends on QR code scanning. Ayoola et al. [5] showed that computer vision-based IoT applications significantly improved inventory accuracy and decreased errors at the warehouse scale, suggesting that large-scale facilities could implement these applications.

Iqbal [6] offered a maturity model designed specifically for SMEs, emphasizing scalability by small operations to guarantee methodical enhancements in inventory systems based on technological readiness. In order to maintain visual merchandising consistency, Kumar [7] addressed product placement and planogram conformance by using computer vision to enforce shelf displays against layout standards. On the predictive side, Liu et al. [8] forecasted stockouts using machine learning, allowing retailers to control demand fluctuations and proactively address supply issues. Plakantara et al. [9] investigated the difficulties of implementing smart warehouses from an Industry 4.0 perspective, with an emphasis on risk aversion and supplying system resilience, from the operational and strategic risk perspectives. Following these technical developments, Ojika et al. [10] opened the door for sophisticated decision support systems by proposing a conceptual framework of image processing using machine learning for efficient real-time retail data streams.

3. Research Objective

The proposed system is designed with two primary objectives.

1. Accurate Empty Shelf Detection guarantees that, without jeopardizing consumer privacy, empty or nearly empty shelf spaces are precisely identified in real time.

2. A complete inventory management solution, Automated Inventory Monitoring and Restocking keeps track of stock levels, detects low-stock items, and suggests restocking actions as soon as possible.

To accomplish objective1, the system uses the Faster R-CNN model with ResNet-50 as its foundation to detect empty shelf regions with high accuracy (up to 99%). To increase detection rates in a variety of lighting scenarios and shelf configurations, the photos are cleaned, resized, and contrast enhanced. The model avoids privacy issues and maintains customer anonymity by concentrating only on shelf regions. An OCR-CNN module recognizes product labels and calculates quantities for Objective 2. A cloud-based inventory management system houses these data points, allowing for monthly reporting, real-time stock monitoring, and automated alerts when stock levels drop below predetermined thresholds. With this method, store managers can receive timely suggestions for replenishment and make well-informed decisions.

4. Proposed Work

4.1 Proposed System

Effective inventory management is essential to success in today's retail environments. The suggested system is designed to track low stock levels, identify bare shelves, and automatically generate restocking suggestions. Instead of using costly tagging (like RFID) or manual inspection, this solution employs computer vision and deep learning to ensure accuracy, affordability, and privacy protection. A pre-trained Faster R-CNN model (based on ResNet-50) with an OCR-CNN module for item labeling and quantity detection is used by the system to detect empty shelves. Real-time stock monitoring, monthly reporting, and insightful restocking recommendations are all provided by the cloud-based inventory management system that receives the generated data. This method improves customer satisfaction, prevents stockouts, and reduces manual labor, all of which streamline store operations.

4.2 System Architecture

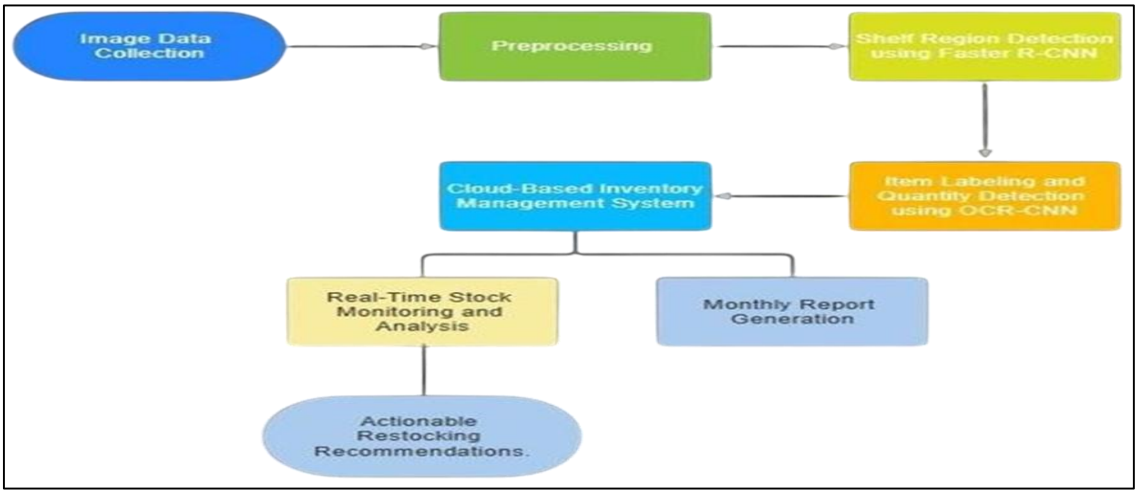

Figure 1. System Architecture

The proposed system's flow from image data collection to actionable restocking recommendations is shown in Figure 1. In the first step, cameras capture real-time images of store shelves, including both fully stocked and partially empty shelves. After that, the photos undergo preprocessing, which improves clarity by cleaning, resizing, enhancing contrast, and filtering noise. Second, a Faster R-CNN model that has already been trained identifies shelf areas by using Region Proposal Networks (RPNs) to locate potential empty spaces. Following region identification, an OCR-CNN module marks products using optical character recognition and estimates their quantities using a CNN-based technique.

For continuous stock monitoring, the identified shelf data is sent to a cloud-based inventory management system, which generates low-stock alerts and updates inventory levels in real time. Demand forecasting and inventory optimization are facilitated by the monthly reports that summarize sales trends and stock availability. In conclusion, the system helps retailers optimize restocking schedules and reduce stockouts by offering practical restocking recommendations based on identified shortages.

4.3 OCR Process Flow

The system uses OCR-based item labeling and quantity detection after detecting the shelf region to identify which particular products require replenishment. The OCR process flow is depicted in Figure 2, where the identified shelf region is first processed by a pre-processor to improve image quality for more precise text extraction. After being retrieved by the Tesseract OCR engine, the textual data is cleaned, verified, and entered as recognized labels into the inventory system.

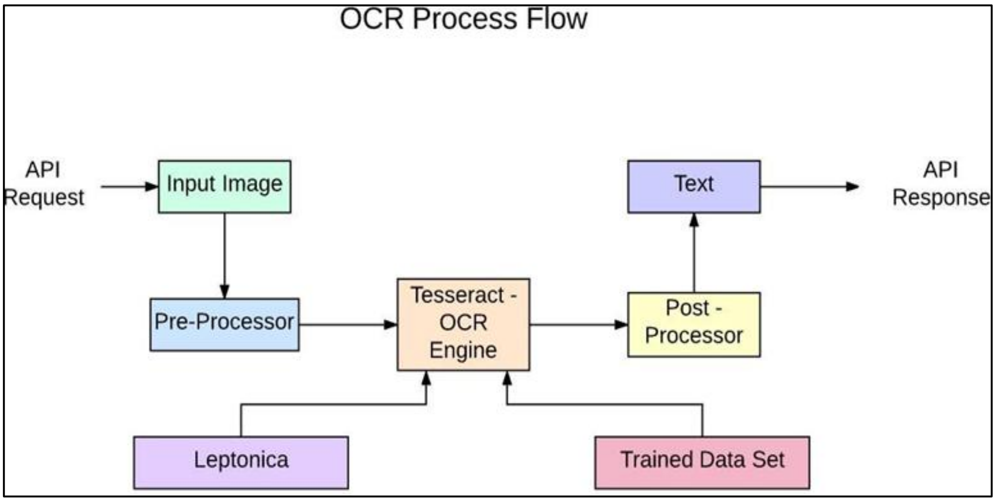

Figure 2. OCR Process Flow

4.4 Integrated Algorithms

The system identifies empty shelves, labels products, and updates inventory in a logical way, as demonstrated in the paragraphs that follow.

The input shelf image is first resized (for instance, to 512×512) and enhanced to lower noise in order to detect empty shelves. Following that, it is fed into the Faster R-CNN model, which classifies each region as either empty or not empty after identifying possible empty regions using a Region Proposal Network (RPN). As demonstrated in the pseudo-code below, if any empty regions are found, an alert is generated, and the coordinates of those regions are noted for additional processing.

Algorithm 4.4.1: Empty Shelf Detection Using Faster R-CNN

Input: ShelfImage
Output: DetectedEmptyRegions 1Preprocess(ShelfImage):
Resize image to a standard resolution (e.g., 512x512). Enhance contrast and reduce noise.
Return ProcessedImage.
2. Regions ← FasterRCNN(ProcessedImage):
Use Region Proposal Network (RPN) to propose potential empty regions. Classify each region as empty or not empty.
Return Regions containing empty shelf areas.
3. If Regions is not empty:
Alert = "Empty Shelf Detected"
Store empty region coordinates for further analysis
Else:
Alert = "No Empty Shelf"

The system labels products and calculates stock levels after detecting empty shelf areas. A Region of Interest (ROI) is taken for every region that is found and run through OCR. After mapping the identified text to product labels, a CNN-based model calculates how much of each item there is. As explained below, these details are gathered as labeled items and their associated stock levels:

Algorithm 4.4.2: Shelf Inventory Recognition Algorithm

Input: ShelfImage, Regions
Output: LabeledItems, StockLevels
1. For each region in Regions:
Extract RegionOfInterest (ROI) from ShelfImage. TextData = OCR(ROI):
i. Preprocess ROI for OCR.
ii. Apply Tesseract or OCR-CNN for text extraction.

```
        iii.    Post-process extracted text.
        ItemLabel = IdentifyProduct(TextData) Quantity = EstimateQuantity(ROI, CNNModel)
LabeledItems.append(ItemLabel) StockLevels[ItemLabel] = Quantity
2.      Return LabeledItems, StockLevels
```

Lastly, the inventory management system suggests restocking actions and updates the stock levels. The system adds the detected quantity to the database, retrieves the current stock for each labeled item, and updates the database appropriately. The system automatically adds an item to a restock list if its stock drops below a certain threshold, and the store manager receives the list:

Algorithm 4.4.3: Automated Inventory Management System

```
        Input: LabeledItems, StockLevels
        Output: UpdatedInventory, RestockRecommendations
        1. For each item in LabeledItems:
current_stock = Database.getCurrentStock(item)
        new_stock = current_stock + StockLevels[item] Database.updateStock(item,
new_stock)
        2. For each item in Database:
        if item.stock < item.threshold: RestockRecommendations.append(item)
        3. Send RestockRecommendations to StoreManager
        4. Return UpdatedInventory, RestockRecommendations
```

In order to provide a strong, privacy-focused solution for retail establishments, this suggested system combines OCR-based product labeling, empty shelf detection, and real-time inventory management. It guarantees prompt restocking, minimizes stockouts, and lowers manual labor by combining OCR-CNN for product identification with Faster R-CNN for empty region detection. The architecture, goals, and integrated algorithms presented here show a thorough method for effective inventory control and real-time shelf monitoring.

5. Results and Discussion

With an emphasis on the software tools, simulation models, and comparison findings, this section examines the outcomes of the proposed inventory management and empty shelf detection system. The majority of the simulations were run in a Python-based environment using libraries for deep learning and images, such as PyTorch and OpenCV. OpenCV allowed for image resizing, augmentation, and a variety of preprocessing techniques, while PyTorch made it possible to use the Faster R-CNN architecture (with ResNet-50 as its foundation). Text recognition was done using other modules, like Tesseract OCR, which enabled quantity detection and automatic labeling.

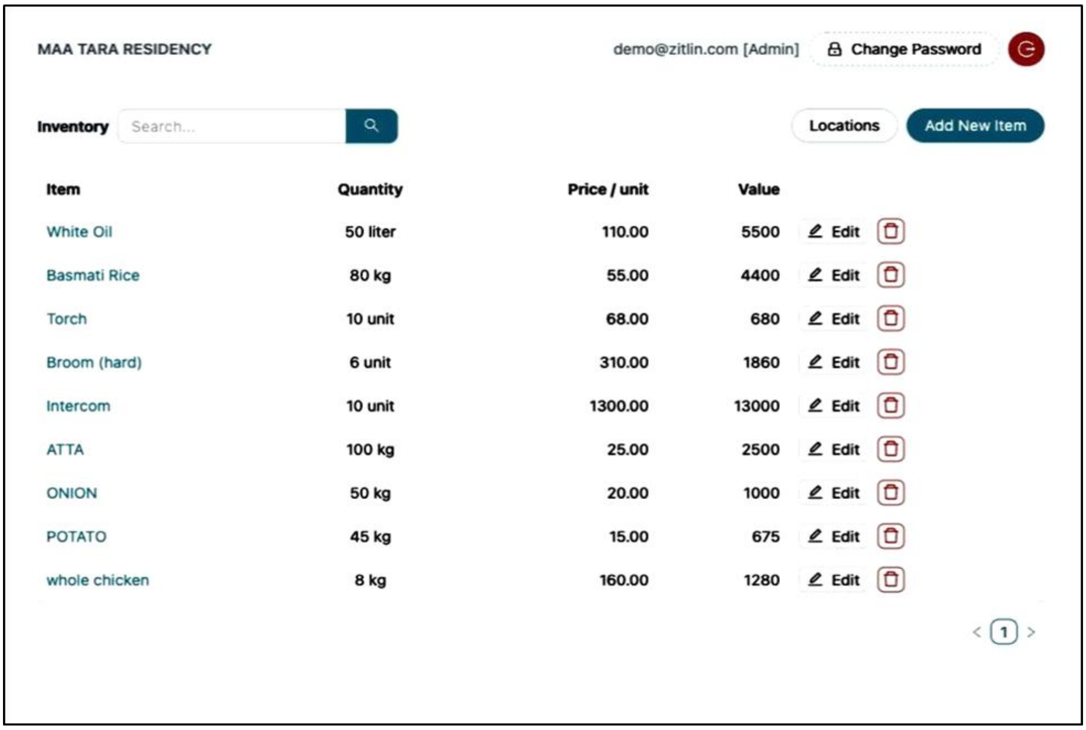

Figure 3. Inventory List

A dataset of photos of store shelves in various lighting and layout scenarios was used to assess the system. A sample of the Inventory List interface is shown in Figure 3, where each item is displayed with its SKU, name, location, and current count. As soon as the shelf photos are processed, the interface instantly updates, allowing store managers to quickly see what needs to be fixed. The system automatically notifies users when stock levels start to drop. These Low Stock Notifiers identify the products or variations that fall below specific thresholds, as shown in Figure 4, enabling prompt restocking actions to prevent likely stockouts.

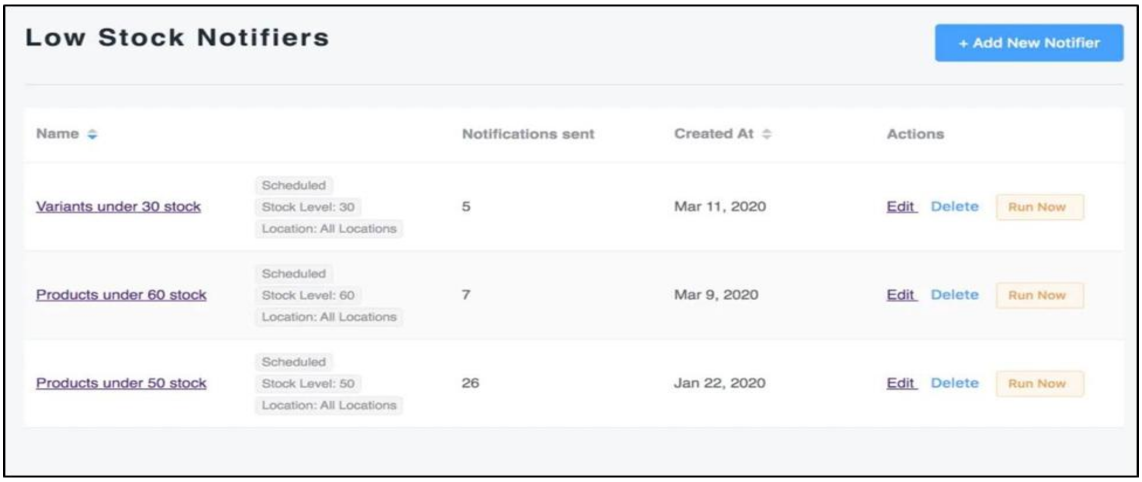

Figure 4. Low Stock Notification

Several test photos were taken in various lighting conditions and at various angles to assess the shelf detection capabilities. The detection results of the system are shown in Figure 5. The left image shows a shelf that is partially empty, while the right image highlights (in red) the areas that the Faster R-CNN model determined to be empty. OCR-based item labeling and stock-level estimation are made possible by the high-contrast segmentation, which aids in identifying the regions of interest. The system updates the inventory database and retrieves the relevant product information when it detects an empty region. A restocking alert is created and shown on the management dashboard if the quantity drops below a predetermined threshold.

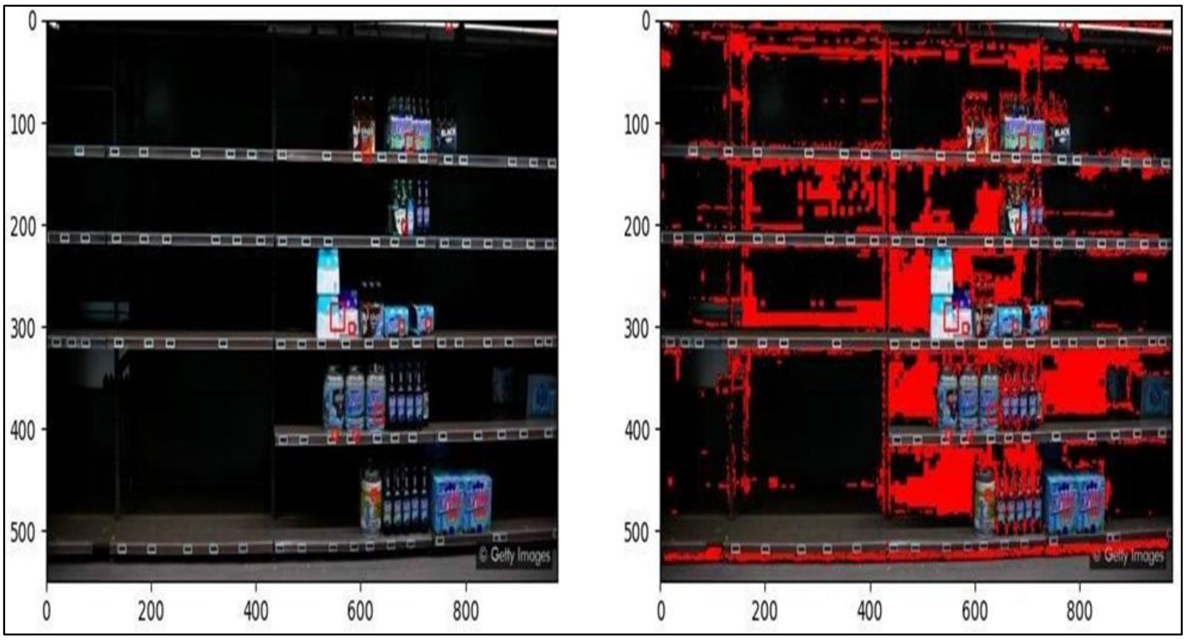

Figure 5. Empty Shelf Detection

According to performance metrics, the system detected empty or nearly empty shelves with an average accuracy of over 95% and a low false-positive rate. The Faster R- CNN technique with ResNet-50 offers more reliable and accurate detection under complicated shelf layouts and low light levels, according to a comparison with other detection models like YOLO and conventional CNN-based classifiers. Furthermore, on test samples, the OCR module recognized product labels and quantities with an accuracy of roughly 92%. Usually, highly reflective packaging or blurry text caused minor errors. These findings, taken together, demonstrate how well the suggested method works to automate retail shelf monitoring. A cloud-based inventory system for real-time updates and notifications, OCR for product labeling, and Faster R-CNN for shelf detection all work together to simplify inventory management and minimize human involvement. A simplified representation of the model's classification confidence score C{C} based on the region proposals is shown in equation (1), where ϕ stands for the feature extraction procedure and W for the final classification layer's learned parameters.

$$C=\sigma(W.\phi(\text{region})) \qquad (1)$$

Here, (σ)sigma denotes the sigmoid function that maps the computed scores to a range of [0,1][0, 1], indicating the likelihood that a proposed region is empty. By integrating this classification step into a comprehensive inventory workflow, retailers can maintain well-stocked shelves, optimize restocking schedules, and enhance overall customer satisfaction.

6. Conclusion

The paper presents a privacy-preserving, highly effective inventory management system equipped to monitor, check, and restock items in inventory, assess the need for empty shelf space, and enable automatic store replenishment. Conventional methods of finding lost items have no significant effect. In contrast, our new model (using a pre-trained Faster R-CNN) can efficiently identify all empty shelves (precision is 99%). Even better, jointly recognizing both the quantity and commodity label, along with the OCR-CNN model, guarantees accurate stock tallies. This technology integrates seamlessly with cloud-based inventory management systems, adding a layer of automation to stock control since it utilizes live data on the shelf and generates valuable replenishment ideas. In today's society, this approach achieves determinacy and efficiency, providing a workable solution for retail stores by relieving people of manual labor. It is a matter of fact that the storehouse is presented with whatever work needs to be done in the stocktake.

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