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Automated On-shelf Stock Availability By Using CNN Algorithm

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Abstract: In this paper, Monitoring and surveying are increasingly used in retail shops, since they improve the overall performance of the warehouses and reduce the manpower by using this project. The aim is to develop an algorithm for early detection of out-of-stock situations with regard to perishable goods stored in countertop shelves, refrigerated counters, baskets or crates. By using Surveillance camera to automatically detect Shelf Out of Stock (SOOS) based on Convolutional Neural Networks (CNNs). To ensure high on-shelf availability, which is a key factor for improving profits in retail stores. Our method first detects empty spaces in the shelves. It then classifies the detected change regions into several classes representing the actual changes on the shelves, such as “Non empty (full of stock)” and “empty (out of stock)”, by supervised learning using convolutional neural networks. It finally updates the shelf condition representing the presence/absence of products using classification results and computes. The output of the system can be used to generate alerts for store managers where shelf out of stock occur, as well as to continuously update empty and non-empty shelves for automated stock ordering and replenishment.

Index Terms: **convolutional neural network, on-shelf availability, surveillance camera, retail, SOOS (shelf out of stock)**

I. Introduction

In the retail industry, an important issue is the incidence of shelf out of stock (SOOS) occurrences. Planogram design, which depicts how stock keeping units (SKUs) are organized on shelves, is frequently closely tied to SOOS events. Retailers experience roughly 4% sales losses due to the 8% global average out-of-stock rate. Out-of-stock circumstances can occur for a number of causes, but the main one is poor shelf replenishment techniques (surveying and restocking), which cause 70% to 90% of occurrences to result in SOOS. Store-OOS is a result of another 10% to 30% of supply chain issues [1]. With the introduction of RFID technology, the retail sector is going through a significant transformation.

Since they precisely identify the products in real-time, radio frequency identification (RFID) tags assist us in understanding the quantity of merchandise on the shelves. Since we can restock products before they run out of stock, we can maintain a high level of on-shelf availability. The RFID-based approach, however, has issues with the exponential cost of installing sensors and the labor-intensive process of attaching tags to each product and removing them again at a billing counter. (i.e., it is a high-cost solution).

We use an image processing technique on a picture of the shelves to create a low-cost fix. Fig 1 depicts an overview of our target application, which uses video from a surveillance camera mounted on the ceiling to monitor the shelves in retail stores in order to ensure high on-shelf availability. It makes an estimate of the number of products on the shelves that are visible in the photograph and notifies the store staff when it's time to restock stock or rearrange the shelves when there aren't enough things there.

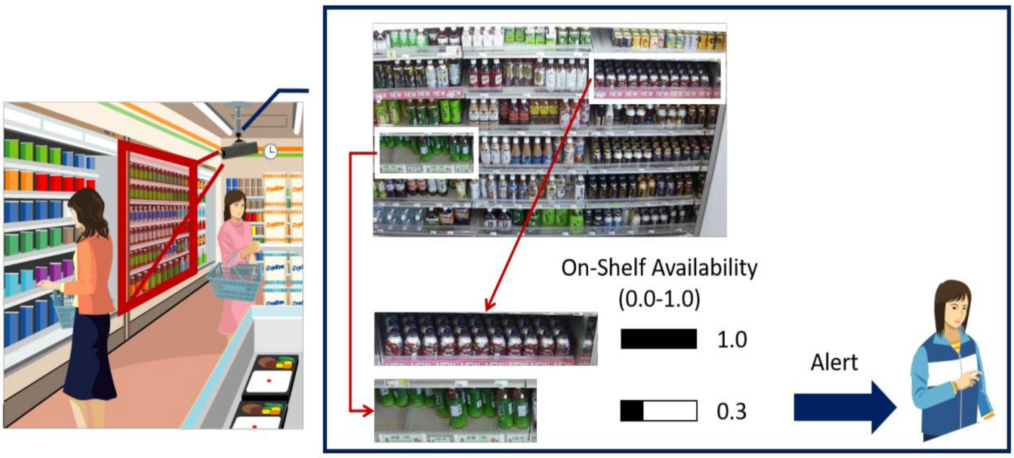


Fig. 1 Monitor the shelves in retail stores using a surveillance camera for maintaining high on-shelf availability.

II. DEEP LEARNING

A neural network with three or more layers is essentially what a neural network with deep learning refers to as. These neural networks aim to mimic how the human brain behaves by mimicking its capacity for "learning" from vast volumes of data. Additional hidden layers can help to optimize and refine for accuracy even if a neural network with only one layer can still make approximation predictions.

It makes use of artificial neural networks, where several processing layers are applied to extract progressively more complex aspects from the data.

A neural network with deep learning is essentially a neural network with three or more layers. These neural networks emulate the brain's ability to "learn" from enormous amounts of data in an effort to act like the human brain. Even though a neural network with only one layer can still produce approximation predictions, more hidden layers can aid in optimization and refinement for accuracy.

Utilizing artificial neural networks, it applies many processing layers to the data in order to extract progressively more sophisticated features.

- **CNN (Convolutional neural networks)**

Convolutional neural networks are distinguished from other neural networks by their superior performance with image, speech, or audio signal inputs. They have three main types of layers, which are:

a) Convolution layer
b) RELU Layer (Rectified Linear Unit)
c) Pooling Layer
d) Fully Connected Layer

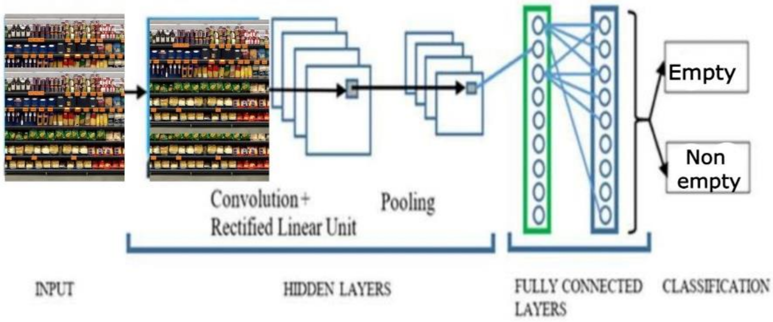


Fig. 2: - How Convolution Neural Network works

CNNs (Convolutional Neural Networks) can be used to address the problem of shelf out-of-stock by identifying the products that are missing from the shelf. The process can be broken down into the following steps:

1. Data Collection: A dataset of images of fully stocked shelves can be collected for the model to learn from. These images can be taken from various angles and perspectives to ensure the model can identify products from any view. The Dataset used in it SKU dataset(https://drive.google.com/file/d/1iq93lCdhaPUN0fWbLieMtzfB1850pKwd/edit)
2. Preprocessing: The collected data will need to be preprocessed to prepare it for training. This includes resizing images to a standard size, converting to grayscale, and normalization to make it easier for the model to learn.
3. Training: A CNN can be trained using the collected and preprocessed data. The model can be trained to identify specific products and their location on the shelf.
4. Testing and Validation: The trained model can then be tested and validated using images of partially stocked shelves or shelves with missing products. The model should be able to accurately identify which products are missing and their location on the shelf.
5. Deployment: Once the model has been successfully trained and validated, it can be deployed in stores to monitor the shelves in real-time. The model can be integrated with cameras placed in the store, which will constantly capture images of the shelves. The model can then be applied to identify items that are out of stock and notify shop staff to restock. Required code is access by using this link(https://drive.google.com/file/d/1Z7Jt2-pk8ocm_8X9IJx0mdWTqbTEGuo3/view?usp=share_link)

Overall, CNNs can be a useful tool in addressing the problem of shelf out-of-stock. By using computer vision, stores can monitor their shelves more efficiently and ensure that customers always find the products they are looking for.

III. PROPOSED METHOD

The proposed method robustly monitors the shelves by detecting and classifying changes in products regarding increases/decreases in product amount, such as “product taken (decrease)” and “product replenished/returned (increase)”, using images from a surveillance camera and by updating the shelf condition representing presence/absence of products on the front of the shelves from the initial shelf condition given in advance. Background subtraction (or foreground detection), which is a widely used approach for detecting changes in images as foregrounds, cannot distinguish between “product taken” and “product replenished/returned” since it detects regions that do not match a reference image, often called “background image” or “background model”. Hence, background subtraction alone is not sufficient for robustly monitoring the shelves for maintaining high on-shelf availability. To solve this problem, we need to classify the changes in the image into the actual changes in products on the shelves, such as “product taken” and “product replenished/returned”. It first detects change regions of the shelves in the image by background subtraction on the basis of statistical information of pixels. To reduce false positives of change regions such as shoppers, it tracks detected foregrounds between consecutive images and removes them on the basis of their moving distance.

It finally updates the shelf condition representing presence/absence of products on the front of the shelves using classification results and computes the product amount visible in the image as on-shelf availability.

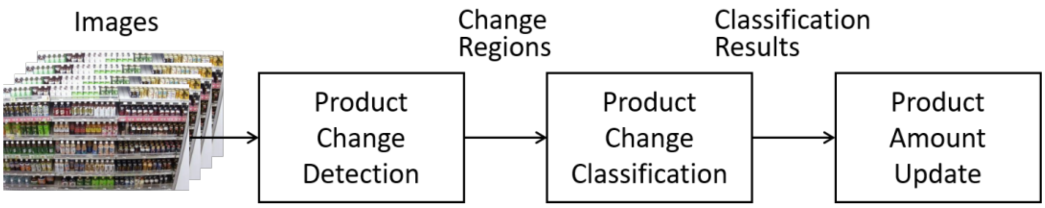


Fig. 3 . Process flow of proposed method

Detection of Product

By subtracting the backdrop from the image and then removing moving objects, we can precisely identify only the product change zones on the shelves. Using background subtraction, our technique recognizes change regions in images as foregrounds [6]. However, background subtraction not only recognizes the product's changing regions but also false positives like moving objects. (i.e., shoppers and store clerks).

As a result, we track the foregrounds between photographs and eliminate them based on how far they are travelling. The foregrounds that move more than Td pixels are eliminated as moving objects, whereas the foregrounds that remain static for longer than Ts seconds are chosen as the product change regions.

The Hungarian method [7], which is a combinatorial optimization algorithm that solves the assignment problem, is used for tracking the foregrounds in the consecutive images. In particular, the foregrounds are tracked by minimizing the summation of assignment cost among N foregrounds detected in a current image and M foregrounds detected in a previous image. The cost matrix of the Hungarian method used in our method is as follows:

$$C_{i,j} = \begin{bmatrix} c_{1,1} & \cdots & c_{1,N} \\ \vdots & \ddots & \vdots \\ c_{M,1} & \cdots & c_{M,N} \\ c_{def} & & c_{max} \\ & \ddots & \\ c_{max} & & c_{def} \end{bmatrix}. \tag{1}$$

Here, the parameters cde f and cmax are a default value and a value sufficiently larger than the default value, respectively.

The assignment cost ci,j consists of the similarity of the color histograms in the foregrounds, area ratio of the foregrounds and aspect ratio of bounding rectangles of the foregrounds. The similarity cost $c^{color}_{i,j}$ is computed as,

$$c^{color}_{i,j} = 1.0 - \frac{\Sigma_k (H^j_t(k) - \bar{H}^j_t)(H^i_{t-1}(k) - \bar{H}^i_{t-1})}{\sqrt{\Sigma_k (H^j_t(k) - \bar{H}^j_t)^2 \Sigma_k (H^i_{t-1}(k) - \bar{H}^i_{t-1})^2}}, \tag{2}$$

$$\bar{H}^n_m = \frac{1}{K}\Sigma_k H^n_m(k), \tag{3}$$

where H j t and Hi t−1 are color histograms of the jth and ith foregrounds in the current and previous images, respectively. K is the number of bins. Note that the total area of a histogram has been normalized to 1.0. The area ratio cost c area i,j is computed as,

$$c^{area}_{i,j} = 1.0 - \begin{cases} S^j_t / S^i_{t-1} & \text{if } S^j_t < S^i_{t-1} \\ S^i_{t-1} / S^j_t & \text{else} \end{cases}, \tag{4}$$

where S j t and S i t−1 are areas of the jth and ith foregrounds in the current and previous images, respectively. The aspect ratio cost c

$$c^{aspect}_{i,j} = 1.0 - \begin{cases} A^j_t / A^i_{t-1} & \text{if } A^j_t < A^i_{t-1} \\ A^i_{t-1} / A^j_t & \text{else} \end{cases}, \tag{5}$$

aspect i,j is computed as,

where A^j_t and A^i_{t-1} are aspect ratio of the bounding rectangle for the jth and ith foregrounds in the current and previous images, respectively. Finally, the assignment cost ci,j is computed as,

$$c_{i,j} = w_1 \times c^{color}_{i,j} + w_2 \times c^{area}_{i,j} + w_3 \times c^{aspect}_{i,j}, \tag{6}$$

where w means weight.

Update of Product Amount

Our method updates the shelf condition representing presence/absence of products on the front of the shelves using the classification results and computes the product amount visible in the image as on-shelf availability using the updated shelf condition and predefined monitoring areas

After updating the shelf condition, our method computes on-shelf availability (product amount) visible in the image between the range of 0.0 and 1.0 using the predefined monitoring areas

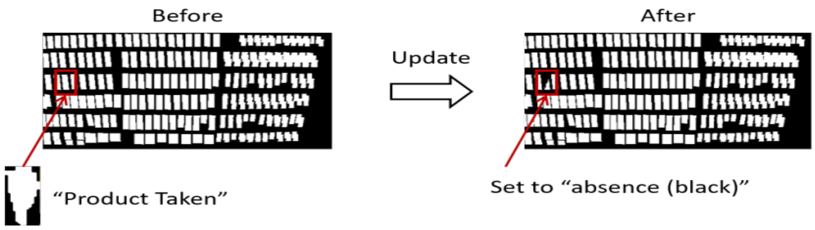
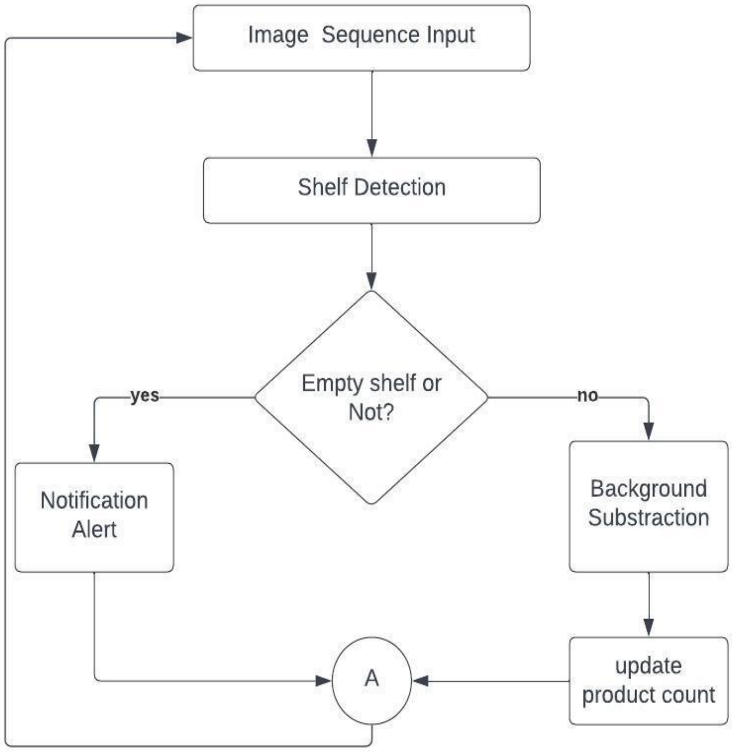


Fig. 4 when product taken then results updated

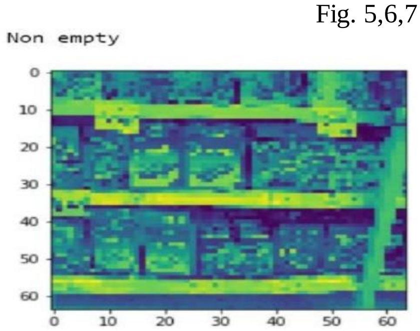
IV. EXPERIMENT RESULTS

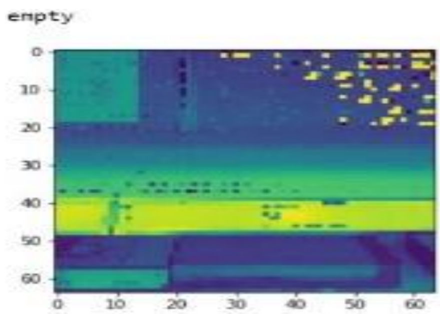
1. Flow chart of the work flow



1. Treat shelves with no items as empty and those with items as non-empty.
2. Monitor the shelves in real-time.
3. If a shelf is detected as empty, send an alert to the shop manager that the item is out of stock.
4. Use background subtraction to track changes in the amount of products on the shelves.
5. Update the inventory levels based on the changes detected by the algorithm

Fig. 5,6,7 Some sample results



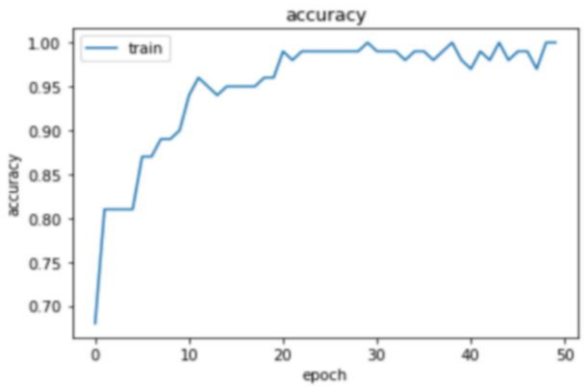


2. Accuracy and Loss

Two measures that are frequently used to assess the effectiveness of a machine learning model, including deep learning models like neural networks, are accuracy and loss.

The percentage of correctly categorized examples in the test set, or how effectively the model can forecast the right result given a new input, is known as accuracy. For instance, a classification accuracy of 0.85 indicates that the model correctly identified 85% of the test set samples.

Conversely, loss quantifies how well the model can fit the training set of data. It indicates the discrepancy between the expected and actual results for a particular input. In other words, it calculates the average amount of "wrongness" in the model. the objective of neural network training is to minimize the loss on the training data, while still achieving a high accuracy on the test set.



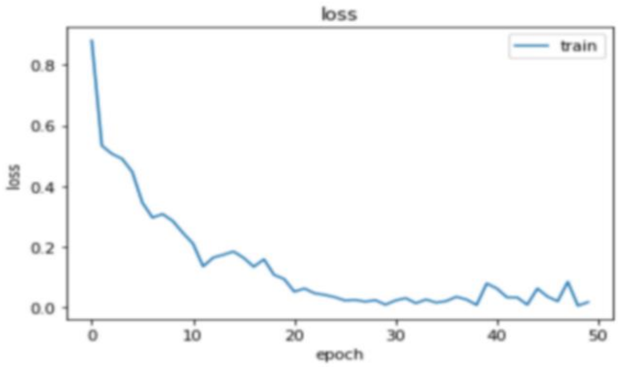


Fig. 8&9 Accuracy and loss of the model

CONCLUSION

This work proposes an innovative monitor shelf in retail stores using supervised learning for improving on-shelf availability. To ensure high on-shelf availability, which is a key factor for improving profits in retail stores, we focused on understanding finding the shelfs where out of stock is occur. Our method first accurately detects only empty and non-empty shelfs in an image by using background subtraction followed by moving object removal for removing detected change regions unrelated to the changes of products (i.e., shoppers and store clerks). To reduce the moving objects, we track detected foregrounds between consecutive images and remove them on the basis of their moving distance. The detected change regions are representing the actual changes on the shelves, such as “product taken (decrease)” by supervised learning using convolutional neural networks for accurately understanding increases/decreases in the product amount. Finally, the shelf condition representing presence/absence of products on the front of the shelves is accurately updated using classification results and the product amount visible in the image is computed as on-shelf availability using the updated shelf condition and predefined monitoring areas.

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