Detection and Verification of the Status of Products Using YOLOv5

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Abstract: Supermarkets generally do not have an efficient supervisory mechanism for inventory and warehouse management that stockists can use in their day-to-day activities. Our goal is to develop an application based on computer vision models, for the detection, counting and verification of the status of bottled and canned products. Comparisons were made between the different models for the detection of objects through an image, under the verification of parameters, performance and metrics, in order to obtain the best models. Once the YOLOv5 object detection model was chosen, training began with a dataset of own images containing products in good and bad condition in order to identify if they are damaged. Finally, the trained model was coupled to the development of the application. This application allows the user to check which products are in a loaded or taken image, as well as their quantity and status. Additionally, to facilitate the registration tasks of the storekeepers, the application allows keeping a daily record of said products. The mAP@0.5 obtained by our model was 93.09%, while the mAP@0.5:0.95 was 89.04%. Therefore, given the results, this model can perform the task of detecting the status of proposed bottled and canned products.

1 INTRODUCTION

Currently, companies mostly do not have an efficient monitoring mechanism for inventory and warehouse management. This inefficiency is reflected in the delay in the dispatch of products and the poor distribution of products within the warehouse. This situation harms the company and generates additional expenses for inventory control and storage (Chen and He, 2022). Additionally, shrinkage also affects the availability of products in the warehouse. On many occasions these are offered without considering the condition in which they are found (deterioration or expiration), due to poor validation of existence, erroneous dispatches or staff failures.

Another problem is the disorder inside the warehouses, where the products that have just arrived and those that have not yet been dispatched are mixed (non-compliance with LIFO or FIFO principles). Due to this, there are products that do not generate profit and from which the investment made in them cannot be recovered (Hofstra and Spiliotopoulou, 2022). The cost of logistics is a very important issue related to storage management, since it must represent a minimum cost over sales.

In Peru, the estimated cost of logistics is 16% of the value of sales.

This percentage is high if we compare it with other countries such as the United States (8.7%), Colombia (12.6%), Paraguay (12.9%) or even the average for Latin America (14.7%). In addition, this logistics cost varies according to the size of the companies.

For larger companies, the percentage of cost is 15.7%, while for smaller ones it is 21.1%, a difference that is argued due to the few resources that micro-enterprises have in logistics[1]. As a solution to high costs, there are several cases in which companies in the retail sector try to have good logistics practices by implementing management systems.

An example is the proper implementation of inventory management in the company CENCOSUD[2]. The meat distribution center of this company has management based on the ABC Classification Method. This method implies: a total rearrangement of products in the warehouse, staff training to optimize handling and movement time in the warehouse, and optimal control of inventory and requirements.

This implementation achieved a productivity increase of 16.83% with respect to reception, storage

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[1] "The Logistics Costs of Enterprises in Peru are 16% on average, but 21.1% for Micro-Enterprises" (2022)- https://t.ly/P0st

[2] https://www.cencosud.com/

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and dispatch (Alan et al., 2014). However, these types of solutions are very general and solve partially the common problems, especially those presented by stockists when relocating products that are in incorrect locations or verifying the status of a large number of products that are available to the customer.

That is why many companies, including retailers, have begun to invest in the use of Artificial Intelligence (AI) to develop solutions to these problems. According to new research from Juniper Research, global spending by retailers on AI-enabled services will reach $12 billion by 2023. Retailers' use of AI will make back-office operations more efficient. Features such as demand forecasting and automated marketing, under the influence of AI, will allow retail businesses room for improvement and become more agile. In addition, it is predicted that there will be a dispute among retailers to include AI in their activities first. Those that include it will displace those that do not have it implemented. As a consequence of its implementation, the services offered will be superior and prices for customers will be optimized[3].

These types of investments are related to the development of AI-based applications, which have been increasing in recent years. It is increasingly common to see customers in supermarkets scanning products with their mobile phones to analyze them before buying them. These applications use computer vision models to offer different functionalities. The factor of automating processes thanks to computational vision is very important when developing these applications. There are, for example, applications for automatic image retouching. Clothing companies receive thousands of unique items that must be processed into a final product that is professional and appeals to buyers. This means that each image of each product must be classified and labeled. Such a process is quite expensive and prone to error if done by a person. Automating the process of retouching one of these images using computer vision can take up to 30 times less than if it were done by a professional.

Applications such as SolidGrids allow, through computer vision, to automatically retouch, sharpen and eliminate the background of the image of the desired product. Other types of applications are those that recommend products by visual similarity. This can be very useful, not only to be able to navigate between the different items in the catalogue, but also to solve the problems that the lack of stock of the first chosen product would generate. Each product can be represented under its attributes and a category to which it belongs, to perform, for example, filters that the customer requires when looking for a type of product, but without having a description or label (Santra and Mukherjee, 2019) .

Under the premise of this last class of application in the retail sector and in order to solve part of the problem that is stock management by storekeepers, we developed a user-friendly mobile app for stockists themselves. Through the training of the YOLOv5 object detection model, the model that will allow detecting, counting and detecting the status of products in an image was developed. Our work is limited to the detection of canned and bottled products through a photo taken or uploaded, within the context of current Peruvian supermarkets. Furthermore, detecting the current condition of the product simply indicates whether the product is in good or bad condition. The contributions of our work are the following:

- We implement the YOLOv5 object detection model for localization and state detection of bottled and canned products.
- We developed our own canned and bottled product image dataset for training the object detection model YOLOv5.
- We developed a mobile application for the management of products in supermarkets, which allows daily records of those products that are detected by uploading a photo.

In Section 2, similar works to ours are discussed. In Section 3, the main notions required to develop our work are detailed, and the main contributions of our work. In Section 4, all the experiments carried out are described to prove the feasibility of our proposal. Finally, Section 5 present the main conclusions.

2 RELATED WORKS

Next, a brief description will be made on different works and existing solutions for the product recognition with different technologies. Additionally, solutions were found that seek to detect the status of certain products, similar to the purpose of our proposal.

In (Selvam and Koilraj, 2022), the authors propose a framework for retail product detection consisting of three modules: Product Detection, Product Text Detection, and Product Recognition. For product detection it uses the YOLOv5 model. To improve the performance of the "TextSnake" algorithm in the second module by replacing the backbone and using the WHBBR (Width Height based Bounding Box Reconstruction) processing technique in order to detect reg-

[3]"AI Spending by Retailers to reach $12 billion by 2023, driven by the Promise of Improved Margins" - https://www.juniperresearch.com/press/ai-spending-by-retailers-reach-12-billion-2023

ular and irregular texts. Finally, in the final module they propose the use “SCATTER” a network to recognize the text information of the products. They used the Adam optimizer with the base parameters for data training. In our work we optimize the hyperparameters based on our own data set by using a evolutionary genetic algorithm to get the best hyperparameters.

In (Yao et al., 2021), the authors present a solution for Kiwi defect detection based on YOLOv5. To do this, they add a small object detection layer to improve the model’s ability to detect small defects; incorporates SELayer; introduced the CIoU loss function to make the regression more accurate and train the model based on transfer learning together with the CosineAnnealing algorithm to improve the effect. Their idea of the states is inherent to organic products such as fruits, vegetables, since they are perishable. This idea derives from the inspiration to propose the detection of states in canned and bottled products. However, there are quite clear differences and corresponding difficulties. Fruits are irregularly shaped and more difficult to detect and count when stacked in supermarkets. On the other hand, canned and bottled products are practically the same in size and model when looking at one specifically.

In (Tonioni et al., 2018), the authors reference recent advances in object detection and image retrieval to leverage state-of-the-art object detectors based on deep learning for product-independent initial item detection. They seek product recognition through a similarity search between computed global descriptors in clipped and reference query images. To maximize performance, use an ad-hoc global descriptor of a CNN trained on reference images based on an image embedding loss. They mention that it is a computationally expensive system at the time of training, but it can perform recognition quickly and accurately at the time of testing. Unlike our proposal, they seek to improve detection by adding a text detector of the products that can be found in the images, while we focus the training on product images from all angles so that recognition is optimal. On the other hand, the computational cost for training our model due to hyper-parameter optimization is very similar. Likewise, the search for fast detection is an idea that led us to the development of an application that detects through images and not in real time.

In (Algburi and Albayrak, 2017), the objective is to recognize the products in the image of a store’s shelves using Speed Up Robust Features (SURF) and color histogram. They argue that this combination helps provide greater accuracy in product categorization to help owners avoid issues such as out-of-stocks and misplaced products. Our proposal uses the YOLOv5s detection model, which has been proven to be one of the most powerful models for object recognition. Likewise, a fundamental difference lies in the use of Deep Learning. The dataset it uses is quite a bit smaller (675 products) compared to ours (1000 images per class). In this way we avoid overtraining in a few times and allow the model to have a greater diversity of images of each product.

3 PRODUCT DETECTION AND INVENTORY CONTROL USING YOLOv5

The stock management process carried out by storekeepers in supermarkets is practically manual and, therefore, quite laborious. The achievement of this task is linked to human capacity, which is why it is often not carried out satisfactorily. In addition, there are few technological tools that storekeepers present to facilitate the fulfillment of these tasks. This is due to the fact that it is difficult developing technological tools based on object detection models, which not only allow the object to be identified, but also to account for and verify the status of various products.

3.1 Preliminary Concepts

In the following sections we present the approaches involved in the development of the application and how it helps to address the problem at hand.

Stock Management: Stock is goods stored for future use or sale. Inventory management focuses on having stocks available at the time of sale or use, and is also governed by policies that allow monitoring when and how much should be replenished from time to time (Bragg, 2018). Stock management is going to be a possibility with our mobile application, since it is going to allow managing the goods by being able to count them and detect if there is a product that needs to be discarded, in such a way that only the products that are discarded can be counted. Likewise, each product count will be registered in a database that stores the stock of each type of product on a daily basis. There are variables that affect inventory management such as costs, demand, supply period, replenishment period, review period and restrictions (Bragg, 2018). One of the most common problems in stock replenishment is that the operator, when looking for a product on a shelf, finds it empty or with products that do not correspond to the section.

Computer Vision: Computer vision attempts to describe the world we see in one or more images and

Figure 1: Product detection results obtained by a modified Retina-Net model[4].

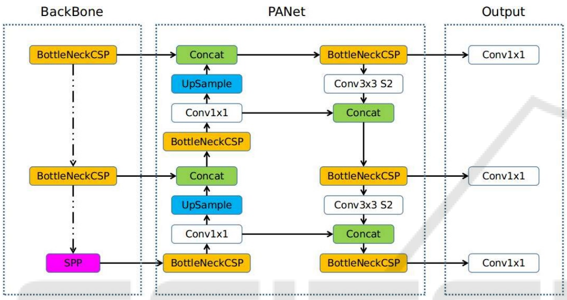


Figure 2: Architecture of Yolov5s[5].

reconstruct its properties, such as shape, lighting, and color distributions. Computer vision researchers have been developing, in parallel, mathematical techniques to recover the three-dimensional shape and appearance of objects in images. However, despite all these advances, the computer is far from being able to interpret images in the same way as a human being. Why is vision so difficult? In part, this is because the view is an inverse problem, in which some unknowns are attempted to be recovered given insufficient information to fully specify the solution. Therefore, probabilistic and physically based models must be used to eliminate the ambiguity between the possible solutions (Szeliski, 2022). Computer vision is in what our work is based on, since image processing is going to be carried out when taking screenshots with the mobile phone of bottled or canned products.

Product Recognition: The intention of product Recognition is to facilitate the management of retail products and improve consumers shopping experience (Wei et al., 2020). At present, barcode (Sriram et al., 1996) recognition is the most widely used technology not only in research but also in industries where automatic identification of commodities is used. By scanning barcode marks on each product package, the management of products can be easily facilitated. Normally, almost every item on the market has its corresponding barcode. However, due to the uncertainty of the printing position of the barcode, it often requires time to manually find the barcode and assist the machine in identifying the barcode at the checkout counter. As retail is evolving at an accelerated rate, enterprises are increasingly focusing on how to use artificial intelligence technology to reshape the retail industry's ecology and integrate online and offline experiences. Based on the study from Juniper Research, the global spending by retailers on AI services will increase over 300% from \$3.6 billion in 2019 to \$12 billion in 2023[3]. Also, with the improvement of living standards, supermarket staff and customers are greeted with more than countless retail products. In this scenario, a massive amount of human labour and a large percentage of the workload were required for recognising products so as to conduct goods management (Wei et al., 2022).

In Fig. 1, the recognition of products in the retail sector is a technological problem that has been studied over the last few years with greater importance. Furthermore, with the help of various electronic devices for photographing, image digital resources of products are growing rapidly every day. As such, for a tremendous amount of image data, how to effectively analyze and process them, as well as to be able to identify and classify the products in supermarkets, has become a key research issue in the product recognition field. Product Recognition refers to the use of technology which is mainly based on computer vision methods so that computers can replace the process of manually identifying and classifying products.

You Only Look Once (YOLO): YOLO is an object detection algorithm that divides images into a grid system. Each grid cell is responsible for detecting objects within itself. YOLO is one of the most famous object detection algorithms today due to its speed and accuracy, as well as belonging to the 1-stage models. YOLO is a large family of object detection models and architectures that have been trained with COCO, a special dataset, and is part of Ultralytics' research on forward-looking AI methods[6]. This model has been evolving and improving over time until reaching the YOLOV5 version, much more efficient and precise than previous versions.

In Fig. 2, Yolov5 architecture has 3 important

[4]"Deep Learning for Product Recognition on Retail Store Shelves" (2021) - https://indatalabs.com/blog/product-recognition

[5]"Overview of model structure about YOLOv5" (2020) - https://github.com/ultralytics/yolov5/issues/280

[6]"YOLOv5: The friendliest AI architecture you'll ever use" - https://ultralytics.com/yolov5

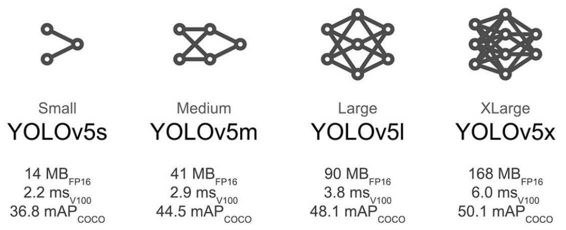


Figure 3: Variations from YOLOv5 are due to model size[7].

parts: the backbone (convolutional neural network that is responsible for forming the characteristics of the images), the neck (layers that combine the characteristics before passing to prediction) and the head (uses the characteristics to class prediction). Within a single version of YOLOv5, various architectures exist according to the size and purpose of the application.

In Fig. 3, although the larger the model size, the better the prediction metrics, each of them have particular use in object detection tasks.

3.2 Method

For the development of the application capable of allowing stock management in supermarkets, it was necessary to select an object detection model based on computational vision and deep learning that allows counting, classifying and verifying the status of the detected products. Additionally, the parameters and hyperparameters of the model were optimized to be trained specifically with datasets of images of canned and bottled products from the Peruvian retail sector.

3.2.1 Dataset Creation

In this section we will describe the datasets created and used for the benchmarking and training of the different object detection models based on computer vision using deep learning that were have studied.

Dataset 1 (CanBo-Pe): CANBO-Pe (Can + Bottle) is a dataset of self-made images, consisting of 10 products (bottles and cans) that are currently on sale in Peruvian supermarkets.

- Bottles:
  - Cielo (Water)
  - San Mateo (Water)
  - IncaKola (Soda)
  - IncaKola Sugar Free (Soda)
- Cans:
  - 360 Energy Drink
  - Monster Original Energy Drink
  - Monster Ultra Energy Drink
  - Monster Zero Sugar Energy Drink
  - Red Bull Energy Drink
  - Red Bull Sugar Free Energy Drink

[7] "Tips for Best Training Results" (2022) - https://github.com/ultralytics/yolov5/wiki/Tips-for-Best-Training-Results

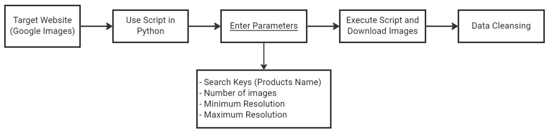


Figure 4: Workflow of web scrapping.

The dataset has more than 1600 images, both in situ (supermarket environment) and in vitro (ideal images of the product) for the training and validation of object detection models. Specifically, this dataset has been created for the experimentation of the YOLOv5s object detection model. The folders were structured to fit the model. This dataset also contains the labeling (boundingbox coordinates) of each of the images in .txt files, as required by the Yolo model. For the training of the models, the folder structure should have been created as shown in the following image. The images in the dataset must be divided into training and validation. Each image folder has its counterpart in the labels folder, where the corresponding image labels are located. This dataset has 1222 training images and 420 validation images.

Web Scrapping: The first method to obtain images of these products was through WebScrapping, a technique for extracting information from websites. In this case, by executing a small script, part of the images of the desired products were extracted from Google. In this program, you entered the name of the products you wanted to search for and the number of images you wanted to download through Google Images. For the operation of this code it was necessary to download the Google Chrome browser.

In Fig. 4, it's necessary to indicate the correct parameters to find the most accurate images possible. When the code is executed it will automatically open the Google Chrome browser, it will go to the images section and the entered search will be performed. Additionally it will go through each image on the page and download it to the specified directory. After downloading the images, a data cleanup was performed to remove images that are not related to the product. The second method was the capture of images through the camera of a mobile phone in the different supermarkets in Lima. The dimensions of the captured images are 1800×4000 px.

Dataset Labeling: Any dataset that is going to be used for training a Yolo model needs to be properly labeled. For this reason, the labeling program was used to generate the .txt files that indicate the coordinates

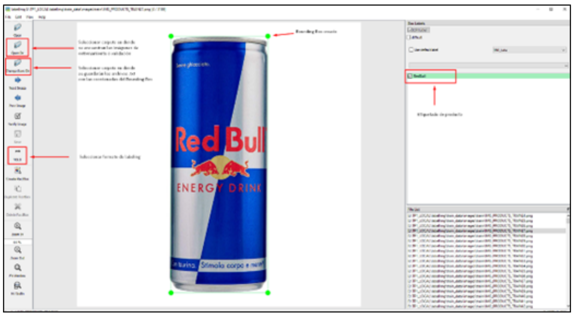


Figure 5: The interface presents various options for configuring image tagging.

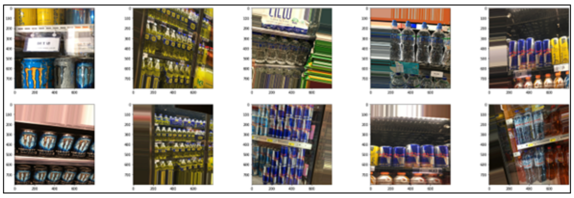


Figure 6: The images used for model validation.

of the Bounding Box of the corresponding product. In Fig. 5, the folder structure is the same as mentioned above.

A folder called train_data is created in the program directory. Once executed, the labeling option is changed to Yolo.

The folder where the training images are located is selected and then the labels folder is selected where the files containing the coordinates of the Bounding Box.

The labeling is saved in a .txt file with the same name as the image. The content is the coordinates of the bounding box. If there are more products of the mentioned classes they must also be labelled. Each row in the file is a tagged product.

Data Augmentation with Geometric Augmentation: Although Yolo's own model uses data augmentation at the time of training, the keras ImageDataGenerator library was used in order to generate new images for our dataset. This library allows to generate images through rotations, image scaling, zoom, brightness variation, etc. The generated images (see Fig. 6) were duly saved in the training and validation folders, then they will be labeled.

Dataset 2 (CanBo-Pe +Status): CANBO-Pe is a dataset of self-made images, consisting of 6 products (bottles and cans) that are currently on sale in Peruvian supermarkets. In this new dataset, the measurements of the products are identified, as it is necessary so that the trained Yolo model can optimally identify the status of each of the products.

Figure 7: The photos focus on different perspectives of the products to be detected.

- Bottles:
  - Cielo 2.5L (Water)
  - San Mateo 2L(Water)
  - IncaKola 1.5L (Soda)
- Cans:
  - Monster Original 473ml Energy Drink
  - Monster Zero Sugar 473ml Energy Drink
  - Red Bull 355ml Energy Drink

The dataset has augmented 2400 in vitro images (ideal product images) for Yolov5s model training and validation. Specifically, this data set has been created so that the model can recognize the products from different angles both in good and bad condition. For the training of the models, the folder structure had to be created. The dataset images should be divided into folders named after each product. Approximately the number of new images for each product is 400. For the creation of this dataset, it was necessary to purchase these products in order to have photos of each angle of these (see Fig. 7). For this very important considerations were taken:

- The products to be purchased must be in good condition (Any dent, bump or cut on the product was reason for discarding).
- The photos should be as close as possible so that the product stands out perfectly.
- Photos should be taken from all angles, since the model must be trained to be able to recognize as much as possible the product in question and the damage produced in any location.

The images were captured using a mobile phone camera (POCO X3 PRO and Iphone SE) in a clean environment with sunlight and white light. The dimensions of the captured images are 1800 x 4000 px.

3.2.2 Model Selection

An review of the different object detection models based on Deep Learning was carried out, of which 4 models were chosen: YOLOv5, EfficientDet, DETR (Detection Transformer) and Faster R-CNN. From

Table 1: Studied model training metrics.

Methods	Image Size	mAP 0.5	mAP 0.5:0.95
YOLOv5s	256×256	.960	.810
YOLOv5x	256×256	.951	.827
EfficientDet	256×256	.931	.703
DETR	256×256	.881	.685
Faster R-CNN	256×256	.921	.723

Table 2: Hyperparameters List.

Hyperparameter	Description
lr0	Initial learning rate
lrf	Final OneCycleLR learning rate
momentum	SGD momentum/Adam
weight_decay	Optimizer weight decay
warmup_epochs	Warmup epochs
warmup_momentum	Warmup initial momentum
warmup_bias_lr	Warmup initial bias lr
box	Box loss gain
cls	Cls loss gain
cls_pw	Cls BCELoss positive weight
obj	Object loss gain
obj_pw	Object BCELoss positive weight
iou_t	IoU training threshold
anchor_t	Anchor-multiple threshold
fl_gamma	Focal loss gamma
hsv_h	Image HSV-Hue augmentation
hsv_s	Image HSV-Saturation augmentation
hsv_v	Image HSV-Value augmentation
degrees	Image rotation
translate	Image translation
scale	Image scale
shear	Image shear
perspective	Image perspective
flipud	Image flip up-down
fliplr	Image flip left-right
mosaic	Image mosaic
mixup	Image mixup
copy_paste	Segment copy-paste
anchors	Anchors per output layer

here it was necessary to carry out a benchmarking in which we compare the metrics of the training and validation of each model, under the training in an image https://drive.google.com/file/d/1oPV9eJoUrAhdqbGpC2LYRidKHU6ZIFpe/view?usp=share_link created by us, which contains only 4 classes to be detected. To visualize the training in greater detail we have an https://docs.google.com/spreadsheets/d/1X0iF_hGa3GDKSqOxKoeDojUExHa9MtFU/edit?usp=share_link&ouid=117284723436874188109&rtpof=true&sd=true.

Table 1 summarizes the evaluation of the metrics obtained, where the YOLOv5 model was chosen since it has better results than the others. Despite the fact that the YOLOv5x model obtained better metrics, the YOLOv5s version was chosen since it is the one recommended for the development of mobile applications because it has less weight than its other versions and has a shorter execution time for detection.

3.2.3 Hyperparameter Optimization

Despite the benchmarking shown in the previous section, it is not enough to select the model directly, but it is necessary to perform a previous optimization, since there are parameters and hyperparameters that must be adjusted to obtain better metrics than those obtained as a base. Table 2 detail the optimization process of Yolov5s for the search of the appropriate parameters and hyperparameters that allow an optimal training, within the limit of existing resources. There are a total of 30 hyperparameters that are used for various training environments. The hyperparameters are located in a yaml file inside the /data directory of the yolov5 folder. Hyperparameters within Machine Learning control various aspects of training and it is challenging to find the optimal values. There are various methods, such as grid searches. However, it is possible for securities to quickly become untreatable for a number of reasons:

- High dimensional search space
- Unknown correlations between dimensions
- Expensive nature of assessing fitness at each point

That is why it uses the Hyperparameter Evolution technique, based on a genetic algorithm (GA), a much more suitable option for optimal hyperparameter searches. The hyperparameters will be tuned for each experiment, since parameters such as optimizers, batchsize or the image size of the image have an influence on the resulting metrics.

Metrics to Analyze: The metrics evaluated in this experimentation are based on the detection evaluation metrics used by COCO, which is the base dataset format used to test all object detection models. Therefore, there is no difference between the terms mAP and AP, as well as between AR and mAR[8].

Finetuning: Before performing the finnetuning, the initial parameters and the number of experiments to be performed were established. There are parameters when training and using the evolution algorithm, such as image size, batch size, epochs and the optimizer, that can affect the results. Given the available resources (GPU usage limits in Google Colab and Kaggle), it was determined to carry out experiments under the parameters in Table 3a

[8]'COCO - Common Objects in Context'" - https://cocodataset.org/

Table 3: Parameter for the experiments and their comparison for various metrics.

(a) Parameters set for each experiment.

Experiment	Optimizer	Image Size	Batch Size	Epochs
EXP01	SGD	640	32	10
EXP02	Adam	640	32	10
EXP03	SGD	800	32	10
EXP04	Adam	800	32	10

(b) Average precision metrics.

Experiment	max mAP@0.5	max mAP@0.5:0.95	Precision	Recall
EXP01	.735	**.550**	.918	.609
EXP02	.714	.544	.914	**.610**
EXP03	.712	.520	**.934**	.563
EXP04	**.742**	.544	.931	.593

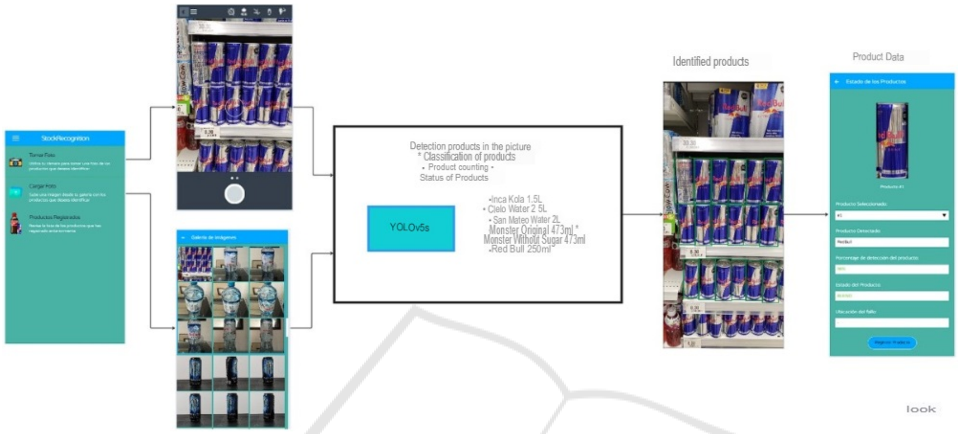


Figure 8: Product detection flow within the developed application.

The image size values are the minimum the model receives (640px) and the maximum available from RAM (800px). The BatchSize is the maximum possible given the environments RAM limit. Finally, the value of the epoch is due to the fact that it was used to perform the fine-tuning of the COCO128 dataset. Having a dataset with a similar structure, it was decided to use this value. For our case, the base scenario is the pre-trained Yolov5s model and the fine adjustment is made in relation to the created dataset (CANBO-Pe). Although it is recommended to carry out a minimum of 300 generations for each model, due to the time limitations of gpu use, 30-40 generations were carried out for each experiment. To find the best parameters, in this case 30 generations were performed. At the end of the execution, a .yaml will be generated with the parameters of the generation where there was the highest average precision (mAP).

Next, the training of the four versions with the previously obtained hyperparameters will be shown. The training parameters do not vary with respect to those used in fine tuning, except for the epochs. On this occasion, the epochs used for training are 300, because it is the minimum recommended for training this type of model[7]. The trainings were carried out both in the Google Colab and Kaggle environment. For the validations, the best training weights will be used.

In Table 3b, the two best values obtained in the validation are highlighted in the comparative table. As can be seen, based on the results, the best is the Yolov5s model with SGD optimizer and 640 image resolution (EXP01). The choice is based on the fact that the mean precision metrics mAP 0.5:0.95 are the best in both training and validation (Training 0.5564 / Validation 0.555). It also has the second best metrics in terms of mAP0.5 (Training: 0.7371 / Validation: 0.735) just below EXP04.

3.2.4 Products Detection Flow

This section details the detection flow that the application has to account for, classify and verify the status of the detected products. Fig. 8 depicts the detection flow that the application has to account for, classify and verify the status of the detected products.

First, an image, either uploaded or taken by a device, will be passed to the application. This image will go through the Yolov5s detection model, specifically trained with the CanBo-Pe +Status dataset.

The result voted by the model is an image similar to the original where the products that have been detected in the photo are highlighted, by means of colored rectangles.

In addition, the amount, average detection percentage and the names of the products detected can be seen.

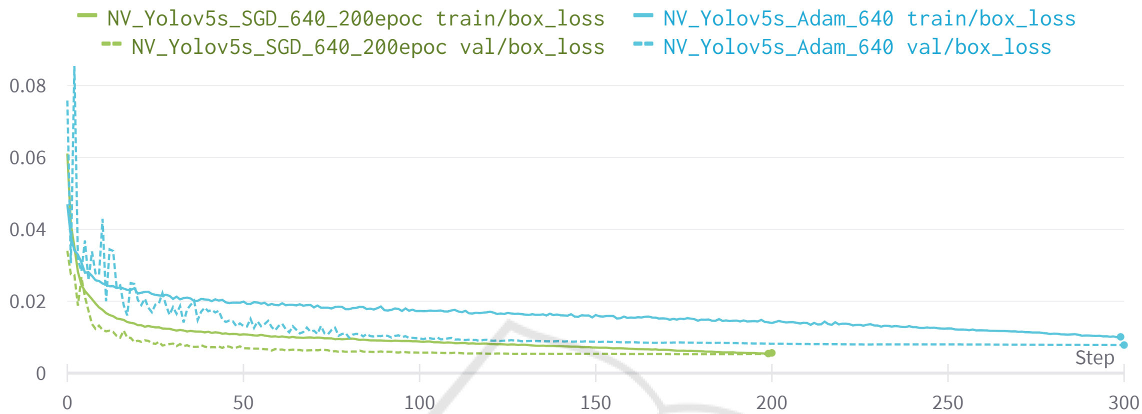
Likewise, these rectangles that frame the products

Optimizer	Batch Size	Img Size	mAP@0.5	mAP@0.5:0.95
SGD	32	640px	.931	.890
SGD	32	800px	.925	.877
SGD	64	640px	.935	.893
Adam	32	640px	.893	.818
Adam	32	800px	.861	.719

(a) SGD and Adam optimizer training comparison.

Optimizer	Batch Size	mAP@0.5	mAP@0.5:0.95
SGD Basic Hyper	32	.922	.886
SGD Finetuning Hyper	32	.931	.890
SGD 64BZ+Finetuning	64	.935	.893

(b) SGD Optimizer Training Comparison.



(c) Box Loss in YOLOV5s.

Figure 9: Summary of Results.

become new images that will go through the Yolov5s model to detect their status.

4 EXPERIMENTS

In this section we present the experiments that we have carried out, as well as what is necessary to replicate them and a discussion of the results obtained.

4.1 Experimental Protocol

The environment used as the main platforms in which the chosen models were trained in Google Collaboratory and Kaggle.

Google Collaboratory provides us with a total RAM of 12.68 GB and a Tesla T4 or Tesla P100 GPU. While Kaggle provides us with 13GB of RAM, 37 hours of GPU T4 x2 or GPU P100 and 33 hours of TPU v3-8.

For the storage of the training dataset, Google Drive was used, which provides 16GB of storage space. For the visualization and analysis of the metrics obtained, the WandB platform was used.

The dataset created for training is a set of images of canned and bottled products, which are divided into 12 classes, for products in good condition and poor condition.

The list of products is:

- InkaCola 1.5L,
- Cielo 2.5L,
- San Mateo 2.5L,
- Monster Original 473ml,
- Monster Zero Sugar 473ml and
- RedBull 250ml.

This dataset carries the corresponding labels to train the Yolov5s model based on the COCO dataset.

The dataset is divided into folders with images and labels, which in turn contain the training, validation and testing folders. The dataset has 5,300 training images, 1,990 validation images, and 2,580 test images.

To recreate the training it is necessary to download the dataset at https://drive.google.com/file/d/1C2Pf8cxKe6pb_cGwDzrIsXACHv15c9ku/view?usp=share_link.

All the trainings regarding the YOLOv5s model were carried out on the Google Colab and Kaggle platforms, using Pytorch on a Virtual GPU with a RAM memory limited to 13GB.

Likewise, the execution of the Evolve method for hyper-parameter fine-tuning was carried out on the same platforms. As for the training runs, these were a maximum of 6 hours, for 200 epochs, an image size of 640px-800px, and batches of 32 and 64 tuples with the SGD optimizer.

For training with the Adam optimizer, the runtime was a maximum of maximum 8 hours, for 200 epochs, an image size of 640px, and batches of 32 tuples.

In both trainings, it was always tried to verify that there is no overfiting in the validation and trying to minimize the value of loss by class, bounding boxes and objectivity.

From executing the training of the model in the indicated parameters, it is possible to analyze the progression of the training throughout the epochs. Total training time was approximately 16 hours.

The notebooks with the training code are publicly available at https://github.com/pieroHerreraT/STRG-TrainingNotebooks.git.

Additionally, all the models, parameters and libraries used are described.

The tables with the metrics and graphs resulting from the training, validation and testing can be viewed in greater detail at https://wandb.ai/stockrg/YOLOv5?workspace=user-pieroht.

4.2 Results

Given the experiments, it was found that the YOLOv5s model trained under the parameters of 640px image resolution, 32 tuples of batch size and SGD optimizer gave the best results for the detection of products in good and bad condition, as can be seen in Fig. 9a, both in metrics of mAP@0.5 and mAP@0.5:0.95.

As can be seen, the SGD optimizer achieves .935 mAP (for mAP@0.5) and .893 mAP (for mAP@0.5:0.95).

Likewise, in Fig. 9c, where we compare both optimizers in the parameters that achieved better mAP metrics, it can be seen that the loss values with respect to the bounding box are much lower with the SGD optimizer and avoids overfiting.

Additionally other experiments were done with the SGD optimizer.

On the one hand, the model would be trained with the same parameters as the model with better metrics, but without the optimized hyperparameters.

That is, the base hyperparameters offered by the YOLOv5 model were used.

The other experiment consisted of performing the training with a batch size equal to 64.

As can be seen from Fig. 9b, hyperparameter finetuning positively affects the metrics obtained.

Additionally, having a greater number of batches helps the model training to better generalize the delivered images and there is no overtraining.

4.3 Discusions

These results allow us to conclude that the proposed model of YOLOV5s with SGD optimizer is a great alternative for the detection of states of canned and bottled products, maintaining optimal performance when using evolutionary methods for the finetuning of the hyperparameters andes of its training.

It is important to emphasize that in order to obtain these metrics, it was necessary to create a dataset with in situ and in vitro images, where the in situ images contain images from different perspectives, which allows the model to better detect the products from any angle.

Thus, in this way the detection of the state is much simpler if the product presents a noticeable difference with respect to a product in optimal conditions.

Regarding the training with the Adam optimizer, this was only done at a maximum amount of 50 epochs, because the consumption of RAM memory exceeds the limits offered by services such as Google Colab and Kaggle base.

5 CONCLUSIONS

We conclude that the experiments of the YOLOv5s model with the SGD optimizer show better metric results compared to the Adam optimizer.

SGD tends to outperform Adam in deep learning models due to the generalization of SGD features that we could also observe in our resulting plots.

Likewise, by using an evolutionary genetic algorithm for hyperparameter finetuning, we conclude that model training and metrics has been improved by having the ability to find the best hyperparameters with respect to the dataset, parameters, and optimizer used.

In future works, our objective is to include Generative Antagonistic Networks (GAN) for the process of detecting the state of the products (Pautrat-Lertora et al., 2022), which would even allow detecting the specific location of the damage in products in poor condition (Aliaga-Vasquez et al., 2022).

Additionally, a parameter adjustment would be made to increase the average precision metrics (mAP) obtained (Torrico-Pacherre et al., 2022).

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