International Journal of Engineering Trends and Technology
ISSN: 2231-5381/ https://doi.org/10.14445/22315381/IJETT-V74I7P117

Volume 74 Issue 7, 243-262, July 2026


*Original Article*

# Deep Learning-Based Application for Automatic Product Detection in a Commercial Sector Company in Trujillo

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Received: 29 January 2026 Revised: 06 June 2026 Accepted: 18 June 2026 Published: 28 July 2026

***Abstract -*** *This research focuses on developing a system using deep learning techniques for the automatic detection of products at the company Negociaciones 7 E.I.R.L., with the aim of reducing errors and providing a clear, efficient alternative to traditional record-keeping. To this end, three architectural models were evaluated: YOLO11n, YOLOv8s, and YOLOv8n, taking into account metrics such as accuracy, recall, mAP, and detection time. The results show that YOLOv8s performs best, achieving an accuracy of 92%, a recall of 90%, and an mAP50 of 91%, standing out for its balance between accuracy and speed. In contrast, YOLOv8n demonstrated a rapid response, albeit with intermediate performance (85% accuracy and an mAP50 of 87%), whilst YOLO11n showed low accuracy and stability at 80%. The implementation of the system enabled a 80% reduction in registration errors and optimised operational efficiency. The process was guided by the CRISP-DM methodology, covering everything from image processing and data collection to integration with SQL Server. Furthermore, statistical validation, using non-parametric tests such as the Mann-Whitney U, Kolmogorov-Smirnov, and Welch's t-tests, confirmed the significance of the improvements. The results demonstrate that the YOLO architecture optimizes productivity, aids inventory management, and contributes to digital transformation in the retail sector. Furthermore, in the context of Peru, particularly in Trujillo, there are few similar studies, which highlights its innovative nature.*

***Keywords -*** *Automatic Detection, Deep Learning, Inventory Management, Retail Sector, YOLOv8s.*

## 1. Introduction

In recent years, Artificial Intelligence (AI) has played a significant role in the global digital transformation across all organisations. In this regard, Deep Learning is a key tool as it has enabled major advances in the processing of large amounts of unstructured data, notably through its use in computer vision for the pre-identification, selection, and automatic recognition of objects and, in turn, real products [1-3]. According to Oracle [4], AI-based tools such as Deep Learning help to reduce errors, anticipate demand, and minimise resource usage, thereby enhancing competitiveness in the market. However, despite these technological advances, there remains a gap between theoretical developments and their application in real-world businesses, particularly in organisations where manual and traditional processes are still in place [5, 6].

In Europe, the implementation of intelligent systems such as deep learning within Industry 4.0 has been restricted in order to streamline logistics and commercial processes, as their contribution does not ensure consistent transparency. At the same time, whilst large companies are adopting systems based on real-time visual detection to streamline their processes, many Micro, Small, and Medium-Sized Enterprises (MSMEs) still struggle to adapt to this digitalisation in order to gain greater control over their organisations [7, 8]. This demonstrates that technological availability alone does not guarantee an increase in efficiency; rather, it must be aligned with the actual needs of the company's processes [9].

In Latin America, this problem is reflected in a range of organisational constraints. Scientific research shows that SMEs recognise the potential of deep learning, but at the same time report low levels of digitalisation adoption, primarily due to financial constraints, a lack of digital processes, and a shortage of specialised staff [10, 11]. As a result, there are still companies that rely on manual processes such as stock control, product identification, and inventory verification, which leads to frequent errors, loss of information, and reduced reliability, directly impacting the competitiveness of these businesses [12].

At the national level, in Peru, similar situations are evident. The National Institute of Statistics and Informatics (INEI) [13] notes that a large proportion of companies still lack technological tools, which means there is no competition in the market. Furthermore, various studies indicate that the adoption of deep learning tools remains negligible, as manual and traditional processes still predominate, resulting in limited accuracy, traceability, and responsiveness [14, 15]. This situation highlights the lack of logic in the stock-taking process, a lack of coordination between the client and the difficulty in identifying missing products, which demonstrates a technological gap between the operational capacity of Peruvian companies and market demand [16].

At a local level, the company Negociaciones 7 E.I.R.L., based in the city of Trujillo, faces the same problem. Currently, product identification is carried out manually and relies on technological tools that are heavily dependent on human intervention. This issue results in frequent errors in product identification, difficulties in providing good customer service, inventory problems, and poor traceability of information, which has a negative impact on the efficiency of commercial and logistics processes. Furthermore, the company lacks an Artificial Intelligence solution based on computer vision that enables better control by identifying products in real time using Deep Learning techniques, which limits its ability to optimise processes and operate competitively in an increasingly digitalised environment. There is a limited body of research demonstrating the implementation of automated product detection systems; previous studies provide scant information regarding operational conditions, new technology, and product variety across different scenarios [3, 7]. Furthermore, there is minimal integration of deep learning with sales management systems in Micro, Small, and Medium-Sized Enterprises (MSMEs), which hinders the automation of processes in real time [17].

In recent years, the use of deep learning has evolved into more efficient applications in real-world scenarios, reflecting the use of *edge computing* to run models directly on local devices and reduce latency [2]. Similarly, the YOLO model architecture has demonstrated high levels of accuracy and effectiveness in the retail sector. However, technological progress in this sector remains limited, particularly in the city of Trujillo, where processes are still carried out using traditional methods. This highlights a gap between technological advancement and its implementation in businesses, which limits the optimisation of processes for the automatic detection of products.

In a global context, companies have advanced technologies and automated systems in place for inventory processes, which have brought about a major revolution. Meanwhile, in the city of Trujillo, Micro and Small Enterprises (MSEs) still use manual processes. [10, 12]. This situation brings with it specific challenges, which are evident in financial resources, a lack of integration with new technology, and difficulties in implementing a computer vision system [3, 7]. Given this situation, implementing the Deep Learning tool presents a significant challenge, which in turn offers a great opportunity to optimise resources, resulting in a more accurate and effective system [18].

In light of this issue, it is necessary to implement a deep learning system for automatic product identification, with the aim of bridging the gap between technological advancements and their implementation within companies. The proposed solution utilises the YOLOv8s model architecture, which is integrated into the system within the real-time sales process. In contrast to other studies, this preliminary research not only demonstrates the architecture's performance but also constitutes a real-time system. This system demonstrates a reduction in errors in processes traditionally carried out, more accurate and efficient product identification, as well as inventory optimisation, thereby enabling better market decisions. Thus, the proposal presented not only aims to improve the operational performance of Negociaciones 7 E.I.R.L., but also seeks to promote the adoption of new smart technologies, in combination with digital transformation and the principles of Industry 4.0 within the Peruvian business context.

Consequently, the company's overarching problem was formulated as follows: How does the development of a deep learning-based application improve automatic product detection at Negociaciones 7 E.I.R.L, Trujillo – 2025? Similarly, the following specific problems were established: How does the development of a Deep Learning-based application reduce costs in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025? How does the development of a Deep Learning-based application reduce processing times in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025? How does the development of a Deep Learning-based application improve operational efficiency in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025? And how does the development of a Deep Learning-based application improve the quality of records in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025?.

Consequently, the overall objective was set to develop a deep learning-based application for automatic product detection at the company Negociaciones 7 E.I.R.L, Trujillo - 2025, and the specific objectives were: To determine how the development of a Deep Learning-based application reduces costs in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo - 2025; To determine how the development of a Deep Learning-based application reduces processing times in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo - 2025, To determine how the development of a Deep Learning-based application improves operational efficiency in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025 and Determine how the development of a Deep Learning-based application improves the quality of records in Automatic Product Detection at the company Negociaciones 7 E.I.R.L, Trujillo – 2025.

This article is structured as follows: Section 1 presents the introduction to the study, Section 2 provides a review of the literature, Section 3 details the materials and methods used, Section 4 outlines the methodology for implementing the solution, Section 5 presents the results obtained, Section 6 analyses the findings, and Section 7 presents the final conclusions of the study; finally, ethical considerations and acknowledgements are included.

## 2. Literature Review

In recent years, the development of deep learning has seen a surge in the creation of systems for the automatic detection of products, making a significant contribution to companies-whether in industry or the retail sector-in terms of automated inventory management. These advances are largely due to the development of architectures such as Convolutional Neural Networks (CNNs) and real-time detection models such as YOLO.

According to [19], an analysis was carried out on the previous evaluation of deep learning-based algorithms for automatic object detection; this implementation was evaluated in various scenarios. To this end, a quantitative approach with an experimental design was employed, using public datasets. The results demonstrated speed in recognition, with high accuracy from the optimised models. However, a limitation was identified regarding the ability of these models to adapt to different contexts. The findings highlight the progress of the model used, with efficiency achieved in real time; however, the model does not demonstrate adequate adaptation to specific scenarios such as the retail sector.

According to [20], the study focused on analysing the relationship between product detection and deep learning. To this end, a quantitative methodology with an experimental design was employed, based on the use of neural networks. The results showed that the use of deep learning outperforms traditional methods. However, the high computational cost involved was highlighted. At the same time, the study emphasises the significant role of deep learning as an effective tool; however, its implementation does not have a real-time impact, with a delay in response.

Similarly, [21] conducted an analysis of recent advances in the use of deep learning for automatic object detection. To this end, a quantitative approach with an experimental design was employed to support the analysis of public datasets. The results show that models such as Faster R-CNN and YOLO achieve high levels of speed and accuracy. However, there is significant difficulty in performing well in complex scenarios. Their contribution reflects the great progress made in practical applications; however, there is no adaptation to specific scenarios, such as commercial inventory, nor to factors such as variations in lighting in real-world environments. According to [22], their research involved developing an object detection-based implementation using deep learning applied to the construction environment. To this end, they employed a methodology with a quantitative approach and experimental design, utilising real-time images. Consequently, limitations were observed in relation to lighting conditions. Their work demonstrates the feasibility of real-time implementation; however, the study is limited to the construction sector and has not been evaluated in other sectors, such as retail, whilst also presenting challenges when faced with changes in lighting conditions.

In [23], the authors prioritise improving the YOLOv5 model with the aim of optimising object detection in remote sensing images. To this end, they employed a quantitative experimental methodology, using satellite datasets. The results demonstrate high performance in terms of accuracy, particularly when detecting small objects. However, there is a limitation in terms of computational capacity requirements. Their contribution reflects performance in complex scenarios; nevertheless, the model used demands high processing resources and has not been validated in a commercial environment with an automated system.

In contrast, [24] proposed the EfficientDet model in their research as a solution for automatic object detection. To this end, an experimental approach was used with public datasets such as COCO. The results demonstrated a balance between computational efficiency and accuracy. However, it is limited to the use of the model in the application environment. Its contribution reflects the model's stability; however, details of hyperparameters are required, and there is no performance evaluation in specific contexts, such as shops, when identifying products in real time.

Similarly, [25] implemented the ESF-YOLO model using neural networks that incorporate attention mechanisms. To this end, an experimental methodology with a quantitative approach was applied. The results demonstrate the model's accuracy. However, an increase in computational complexity was observed. Its contribution highlights the evolution of YOLO models; nevertheless, it involves excessive use of resources, and its real-time implementation in the commercial sector has not yet been verified. According to [26], the research involved the implementation of an object detection system based on deep learning. To this end, the researchers employed a quantitative methodology supported by video data. The results demonstrate an efficient implementation developed in real time. However, there is a limitation in the need for specialised hardware. Their contribution highlights the integration process in relation to monitoring and detection. Nevertheless, the implementation requires specific equipment, is not evaluated using low-cost devices, and focuses on automated identification in the retail sector.

In [27], the performance of the YOLO model was demonstrated using the COCO dataset in real-time scenarios, through a quantitative experimental approach. The results show that YOLO offers greater accuracy and high speed. However, it has limitations when recognising small objects. Its contribution lies in comparing the performance of the implementation across various scenarios; nevertheless, it struggles to detect small objects without using specific datasets tailored to objects in the commercial sector.

In [28], the authors present the TIA-YOLOv5 model for real-time detection in the agricultural sector. They employed an experimental approach using a specific dataset. The results reflect the accuracy of the standard version of YOLOv5. However, there is a limitation in one specific situation. Its contribution demonstrates the model's efficiency; however, as it is based on the agricultural sector, its application is limited in the retail sector.

Finally, [29] developed a system in their study that combines the YOLO model with OpenCV for automatic identification. To this end, they employed a methodology based on a quantitative approach. The results demonstrate an increase in real-time accuracy levels. However, there is a limitation regarding the size and clarity of the data used. Their contribution lies in its real-time implementation; however, there is no comparison with models currently in use, nor is there any performance data in the retail sector involving multiple products.

The research presented reflects progress in deep learning techniques, demonstrating that the YOLOv8s model offers high accuracy and efficiency across a range of scenarios. However, several of the studies analysed use public datasets, which limits their applicability in real-world scenarios-where factors such as lighting conditions, product availability, and environmental conditions come into play. Given this, there is a scarcity of datasets for testing in real-world settings, as well as a limitation in testing the model's performance. In this context, the research makes a significant contribution to the automatic identification of products using the deep learning model employed in the system, through the collection of data for the real business environment in Trujillo and the evaluation of various models, which enables us to obtain more accurate results and greater efficiency in the local context.

**Table 1. Comparison of studies on product detection using deep learning with previous work on product detection using deep learning**

| Study | Purpose | Dataset | Variable 1: Deep Learning | Variable 2: Object Detection | Results | Limitations |
|---|---|---|---|---|---|---|
| [19] | Analyze progress and model optimization | Data: various benchmarks (not a single dataset) | Optimized YOLO | Real-time detection | Improved speed and accuracy | Limited generalization |
| [20] | Analyze the use of DL in detection | Public: general computer vision datasets | CNN | General detection | Higher accuracy compared to traditional methods | High computational cost |
| [21] | Analyze recent advances | Public: COCO and Pascal VOC (standard datasets) | YOLO, Faster R-CNN | General detection | High performance in accuracy and speed | Problems in complex scenarios |
| [22] | Detecting objects at construction sites | Private: real-world construction images | YOLO, CNN | Real-world detection | High real-time accuracy | Lighting-sensitive |
| [23] | Detecting objects in satellite images | Public: remote sensing dataset (high-resolution images) | Improved YOLOv5 | Small object detection | Improved accuracy | High computational cost |
| [24] | Optimizing efficient detection | Public: COCO (≈330,000 images) | EfficientDet | Scalable detection | Accuracy–efficiency balance | Requires fine-tuning |
| [25] | Improving the YOLO model | Public: COCO + additional validation | ESF-YOLO | Robust detection | Higher accuracy | Greater complexity |
| [26] | Implementing detection and tracking | Private: real-time videos | YOLO, CNN | Detection + tracking | Real-time operation | Hardware required |
| [27] | Evaluating YOLO in | Mixed: COCO + | YOLO | General | High speed | Low accuracy |

| | | | | | | |
|---|---|---|---|---|---|---|
| | different scenarios | real-world images | | detection | and accuracy | for small objects |
| [28] | Improving detection in agriculture | Public: agricultural dataset (crops/weeds) | Enhanced YOLOv5 | Field detection | High accuracy in real time | Specific application |
| [29] | Implementing a practical application | Private: proprietary dataset (captured images) | YOLO | Real-time detection | Good performance | Dependence on the dataset |
| Research proposal | Training and deployment of an automatic object detection system using an environment configured with `train`, `val`, and `dataset.yaml`, and executed via `train_yolo.py`. Various pre-trained weights were analysed (yolo11n.pt, yolov8n.pt, yolov8s.pt), with YOLOv8s selected for its balance between accuracy and efficiency | A total of 1,200 images were used, with around 70 images per product, captured in a real-world environment and divided into training (train) and validation (val) sets. | YOLOv8s, YOLOv8n y YOLO11n | Automatic product detection | High accuracy and reduced processing time | Dependence on the dataset |

## 3. Materials and Methods

Deep learning is currently the most advanced technique in computer vision, enabling the recognition and detection of objects with a high degree of accuracy, even in the most challenging environments [30]. This approach relies on deep neural networks that are capable of learning hierarchical representations from large volumes of data, which significantly enhances performance in detection and classification tasks [31]. In turn, recent research highlights its implementation in the retail sector, where architecture-based models such as YOLO have been of great help in optimising inventory processes and real-time automated recognition [32].

### *3.1. Type of Research*

This is an applied research study employing a quantitative approach, which involves the analysis of measurable data such as processing time, precision, and accuracy, with the aim of assessing the system's effectiveness and evaluating the hypothesis objectively. It features a pre-experimental design, as it works with a single dataset for measurement before and after implementation, which helps to determine the impact of the system's implementation without the need for a control group. Furthermore, it has an explanatory scope, as it seeks to identify a cause-and-effect relationship between the efficiency of product identification and the implementation of the model.

### *3.2. Population, Sample, and Sampling*

The population consists of approximately 1,200 products, as well as the staff responsible for managing them, as detailed in Table 2. The population is understood to be the set of products included in the study, which enables the scope of the research to be defined and delimited [33].

**Table 2. Study population**

| Population | Number |
|---|---|
| Inventory items | 1,200 |

In this study, the sample was drawn from the population available for the research. A non-probabilistic convenience sample was selected, comprising a total of 1,200 products, which were used for the initial training and evaluation of the deep learning model in a real-world setting.

The dataset was thus compiled; the data were selected in order to verify that the instruments met the proposed objectives; following this verification, they were deemed suitable for use.

In turn, the data obtained were analysed using descriptive and inferential statistics with SPSS and Microsoft Excel software, applying the Kolmogorov-Smirnov normality test ($\alpha = 0.05$).

### 3.3. Dataset

The dataset was compiled using images of products from the inventory of the company Negociaciones 7 E.I.R.L., which were initially gathered from internal sources and supplemented with some external images to enhance its effectiveness.

The images vary in terms of lighting conditions, shooting angles, and background types, enabling us to represent them in a range of real-world scenarios. Prior to training, they were resized to a standard resolution of 640×640 pixels, and data augmentation techniques-such as rotations, brightness variations, and horizontal flips-were applied to them in order to improve the model's generalisation ability.

### 3.4. Pre-trained Models

To validate product recognition, models from the YOLO family were used, which are widely recognised for their excellent performance in real-time automatic detection. This study evaluated architectures such as YOLOv8n, YOLOv8s, and YOLO11, taking into account their performance levels and complexity.

The proposed models were developed in Python using the Ultralytics library, employing pre-trained weights to speed up the training process. YOLOv8 was chosen for its balance between response speed and accuracy, making it suitable for deployment in commercial settings that require rapid, real-time responses.

### 3.5. Experimental Process

The experimental process focused on the stages of data loading, training, validation, and model evaluation. The dataset was divided into training and evaluation sets, which enabled performance to be monitored during the learning process.

During the training process, hardware resources with the highest accelerated processing capacity were utilised, which helped to optimise execution times.

In addition, metrics such as precision, recall, and mAP were monitored, which proved invaluable in evaluating the performance of each model and selecting the most suitable one.

The evaluation focused on assessing the system's ability to automatically recognise products in real time, taking into account its accuracy and effectiveness under the model in various scenarios.

### 3.6. Hyperparameters Used in Training

During model training, various hyperparameters were identified that have a direct influence on performance, including the number of epochs, batch size, learning rate, and image input resolution.

These parameters help to control the model's learning processes, improving its accuracy and reducing the risk of overfitting. The values used during training are shown in Table 3.

**Table 3. Hyperparameters used**

| Hyperparameter | Value | Description |
|---|---|---|
| Epochs | 1,200 | Number of complete iterations |
| Batch size | 16 | Number of images processed per batch |
| Learning rate | 0.01 | Learning rate |
| Image size | 640x640 | Input resolution |

### 3.7. Model Generalization

Furthermore, in terms of generalisation ability, the model has demonstrated excellent performance across various scenarios, such as changes in lighting, angles, and product availability. Furthermore, the system has been developed using a single dataset from the company, which has resulted in highly effective and accurate product recommendations during training using this model, which can be adapted for similar retail outlets.

However, it is recognised that this implementation may be affected in different environments, so it is recommended that it be validated in different establishments and with a wide variety of products.

### 3.8. Ethical Considerations

The study was conducted in accordance with fundamental ethical principles, thereby ensuring confidentiality and the appropriate use of the information provided by the retail company. The images collected were used solely for academic purposes, avoiding the inclusion of sensitive data and in compliance with current data protection regulations. Furthermore, the necessary authorisation for the use of the information was obtained from the company manager, ensuring the transparency of the process. Finally, the results of the implementation will be presented truthfully and objectively, without manipulating the data, thereby contributing responsibly to technological and scientific development.

## 4. Implementation methodology

The development of the deep learning-based application for automatic product detection is based on the CRISP-DM methodology, which provides a structured approach to data management and the construction of predictive models throughout the entire project lifecycle. Furthermore, the application was designed using a client-server architecture, which facilitates centralised management of information and access to it from different departments within the company. Figure 1 shows the sequence of phases corresponding to the CRISP-DM methodology.

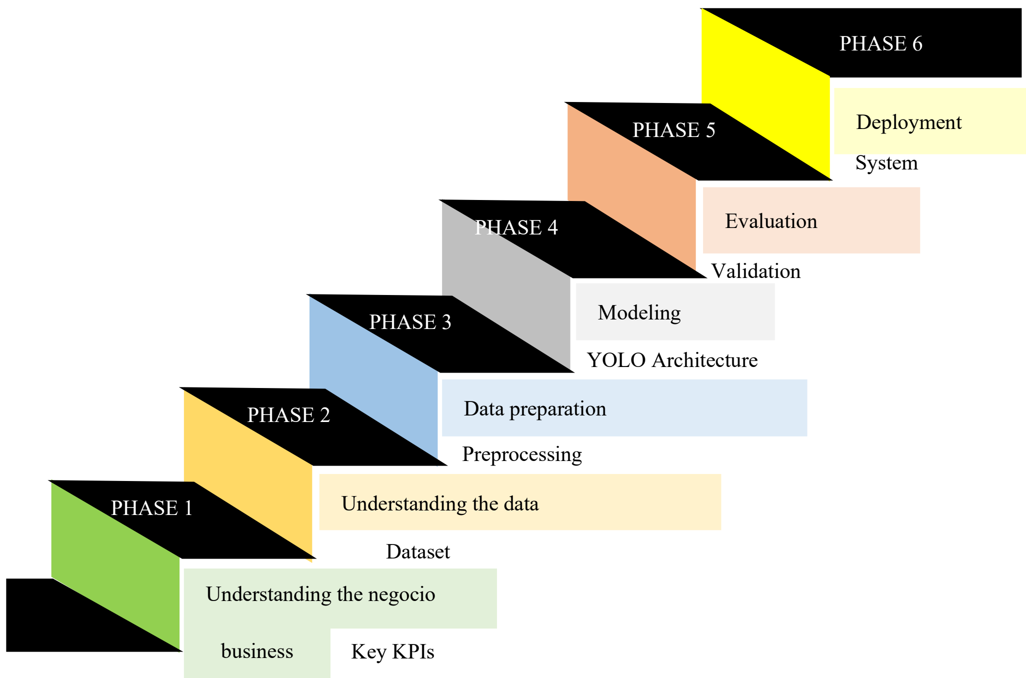


**Fig. 1 Stages of the CRISP-DM methodology**

### *4.1. Business Understanding*

During this phase, a clear report was drawn up detailing the needs, constraints, and objectives of the company Negociaciones 7 E.I.R.L., identifying key issues such as the manual detection and classification of products-processes that are time-consuming-as well as errors in record-keeping and difficulties in achieving efficient inventory control.

In response to this challenge, a deep learning-based system has been developed for the automatic detection of products through image analysis.

Key objectives:

- Reduce response times for product identification.
- Improve recognition accuracy.
- Implement the system in accordance with the established requirements.

Constraints:

- Availability of technological devices.
- A wide range of products is available.

Expected impact:

- Make sound decisions.
- Reduce inventory errors.
- Drive digital transformation.

### *4.2. Understanding the Data*

In this phase, the quality, characteristics, and dataset used for the pre-training of the automatic product detection model were evaluated. The dataset consists of digital images of products from the company Negociaciones 7 E.I.R.L., which were collected from internal sources and, in some cases, from external sources.

The images collected are in PNG and JPG formats, featuring a variety of angles and lighting conditions. There are a total of 1,200 products, with an average of 70 images per product, thus forming a labelled dataset for training. Each image is classified by category, and the quality and reliability of the information are recorded for model testing. The evaluation data was collected manually using tools compatible with the YOLO format, employing bounding boxes to locate the product in each image. This process was closely supervised during the labelling stage, ensuring greater reliability for the training.

### *4.3. Data Preparation*

At this stage, pre-processing techniques were used to improve the quality of the dataset. This enabled the appropriate selection of images, removing those of poor quality and low resolution. In addition, the dataset was cleaned to ensure there were no duplicate images and to avoid errors in the selection process.

The images were then standardised to ensure they were of an appropriate size. To this end, techniques were employed to enhance brightness, quality, and angles, with the aim of increasing the diversity of the dataset.

During this phase, the quality of the records was validated, correcting any errors in the products and the labelling assignments. Furthermore, data was selected based on varying conditions regarding angles, background, lighting, and partial orientations, which helps to achieve better model alignment.

The aim is therefore to strike a balance between the different product classes, thereby avoiding issues in various categories and ensuring more effective and rigorous training of the deep learning model.

Finally, the dataset was organized according to the YOLO format as shown in Figure 2 and divided into training (train) and validation (val) sets, which allowed for adequate Preparation for the modeling stage. Figure 3 shows the organization of the images for the preliminary training of the model.

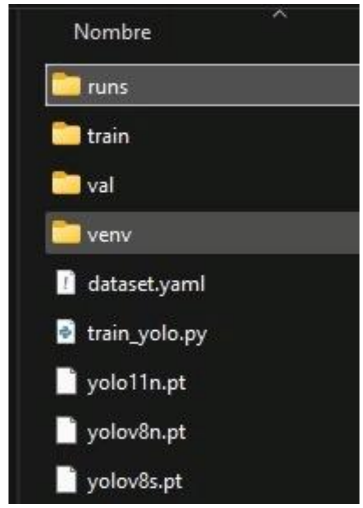


**Fig. 2 Organization of the dataset for training the YOLO model**

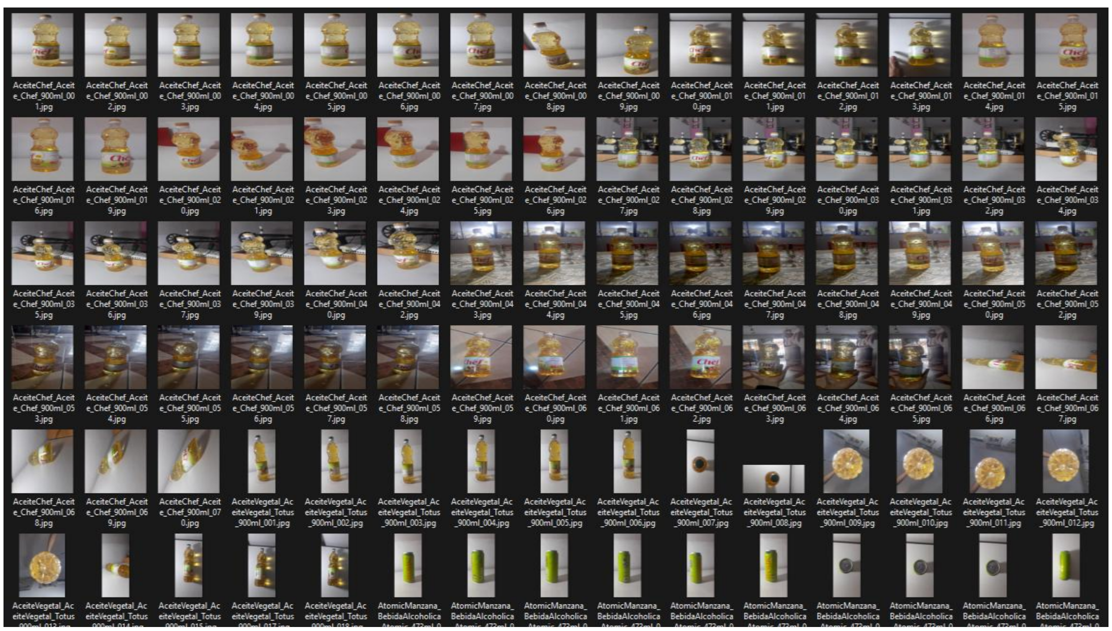

**Fig. 3 Training and validation data sets**

### *4.4. Modeling*

At this stage, deep learning models from the YOLO family-renowned for their high efficiency in the automatic detection of products in real time-were trained and developed. The aim of this study was to compare various alternatives and arrive at a clear choice for the context of the company Negociaciones 7 E.I.R.L.

- The following configurations were analysed for this research
- YOLOv8n (yolov8n.pt): a model designed to run on limited computational resources and provide rapid object detection.
- YOLOv8s (yolov8s.pt): a model of medium complexity that strikes a balance between performance and accuracy in real-time implementation.
- YOLOv11n (yolo11n.pt): an experimental version used as a benchmark to evaluate its fast response and generalization ability.

The models were trained using neural networks, employing transfer learning with pre-trained weights, which helped to optimise the learning process based on selected data. This made it possible to compare the performance of the models under equivalent conditions. Consequently, a set of trained models was developed with the aim of determining which offered the highest accuracy and the greatest ability to classify products based on real-time images; YOLOv8s emerged as the most suitable architecture for the system's implementation, as shown in Figure 4.

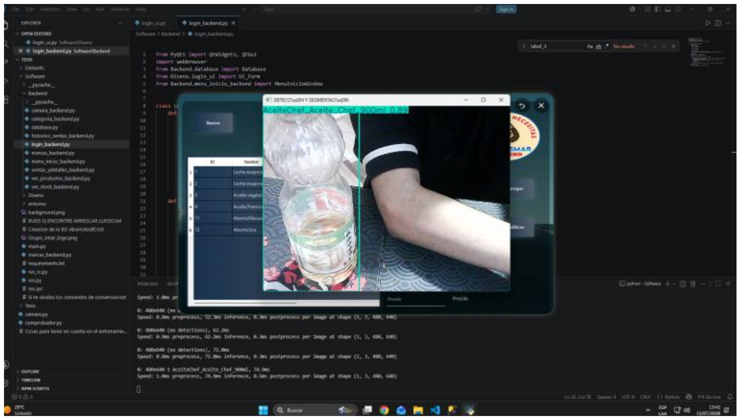

**Fig. 4 Training model**

### *4.5. Evaluation*

In this phase, the performance of the trained YOLO models were evaluated to confirm their compliance with system requirements. A set of standard computer vision metrics

The performance metrics evaluated were:

- Precision: indicates correct detection

$$Precisión = \frac{TP}{\mathrm{TP+FP}} \quad (1)$$

- Recall: the ability to correctly identify the product.

$$Recall = \frac{TP}{\mathrm{TP+FN}} \quad (2)$$

- Model stability: the model's behaviour in real time
- Detection time: rapid identification of the product.

$$Tiempo\ de\ detección = \frac{\sum_{i=1}^{n} t_i}{n} \quad (3)$$

Where:

- True Positives (TP): correctly identified products.
- False Positives (FP): incorrectly detected products, where non-existent products are identified.
- False Negatives (FN): products not detected by the model.
- $t_i$: detection time.
- n: total number of observations evaluated.

The results show that lightweight models offer fast processing speeds; however, they lack accuracy when identifying products with similar features. Meanwhile, YOLOv8s performs exceptionally well, standing out for its greater accuracy and consistency in identification. Similarly, the evaluation carried out using the confusion matrix helped to provide greater clarity in product identification, particularly for products with similar features.

### *4.6. Deployment or Implementation*

Taking the results into account, it was decided to use the YOLOv8s model for the implementation phase, which will be deployed in the system based on a client-server architecture. This system enables the automatic identification of products in real time using the camera, thereby enabling automatic updates to inventory management and sales data in the SQL Server database. The implementation reflects a thorough evaluation and the clear choice of deep learning model, which is of fundamental importance for the reliability, accuracy and efficiency of the system in real-world scenarios.

### *4.7. System Scalability and Integration*

This model was developed taking into account the requirements and processes of the company Negociaciones 7 E.I.R.L. The system interfaces directly with the SQL Server database, enabling automatic recording; the products identified by the camera and real-time updates help ensure clear control over inventory. This implementation helps to optimise workflow, reducing staff intervention and improving operational efficiency. In terms of scalability, the system's integration demonstrates its ability to adapt to the market, which enables us to integrate new products into the system and retrain the deep learning model. As such, this solution can be replicated in companies with similar requirements, whilst maintaining consistent performance in real-world scenarios. Finally, the integration of technologies in both on-premises and cloud environments helps to ensure that the system can be expanded over time, making it easier to roll out across different points of sale and supporting its scalability for use in the retail sector.

### *4.8. Desktop Application Using the Best-Performing Model*

This section presents the evaluation results obtained following the implementation of a deep learning-based automatic product detection system. To select the most suitable model, a comparison was carried out between three versions: YOLOv8n, YOLOv8s and YOLOv11n, taking into account metrics such as accuracy, recall and detection time. The results showed that the lighter models were quicker at identifying the product, with immediate processing speed, but with lower accuracy when identifying products with similar characteristics. Meanwhile, YOLOv8s demonstrates high accuracy in overall performance, showcasing precise balance and rapid product identification. Consequently, the YOLOv8s model was implemented in the desktop application, enabling rapid product identification via the camera. The system allows for direct integration with the SQL Server database and updates inventory in real time.

**Table 4. Comparison of YOLO models**

| Model | Accuracy | Recall | mAP50 | F1-score |
|---|---|---|---|---|
| YOLOv8n | 85% | 83% | 87% | 84% |
| YOLOv8s | 92% | 90% | 91% | 91% |
| YOLO11n | 80% | 78% | 85% | 79% |

Table 4 shows a comparison of the performance of the models evaluated. It shows that YOLOv8s achieves the best results in terms of accuracy (92%) and recall (90%), mAP50 (91%) and F1-score (91%), demonstrating an optimal balance between accuracy and detection capability.

### *4.9. Confusion Matrices*

To complement the results presented in Table 2, Confusion matrices were used to provide an accurate assessment of the model's training. These matrices highlight similarities between incorrect and correct predictions, clearly illustrating the models' performance by category. In particular, the confusion matrix for the YOLOv8s model shows a higher concentration of values along the main diagonal, indicating a high number of correct classifications. Errors occur in cases involving products with similar characteristics and in low-light conditions, which is common in this type of application. The confusion matrices for the evaluated models are shown in Figure 5, 6 and 7, which illustrate their performance during the training and validation stages. Overall, the results obtained demonstrate satisfactory training, with the YOLOv8s model standing out as the most accurate and precise architecture for automatic product detection.

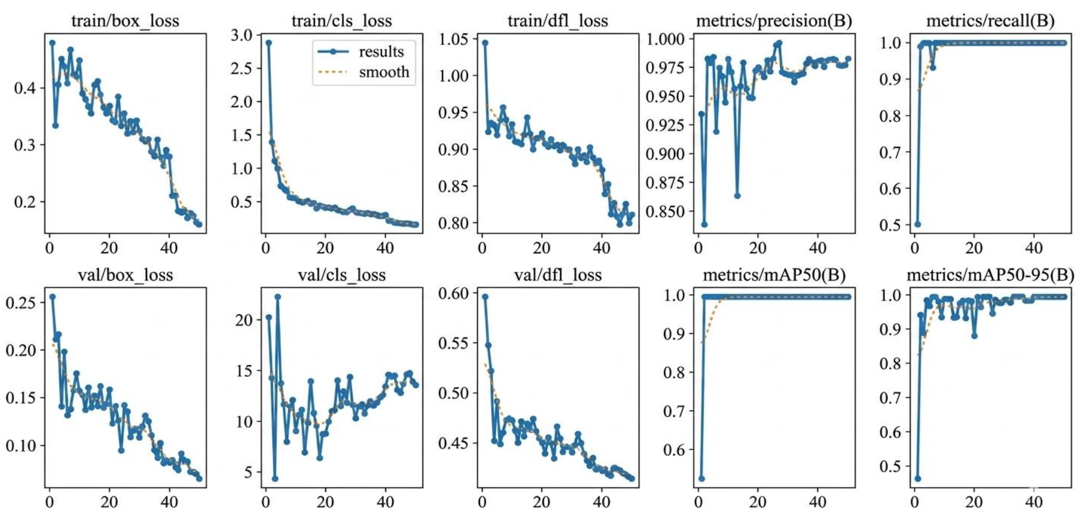


**Fig. 5 YOLOv8n model result**

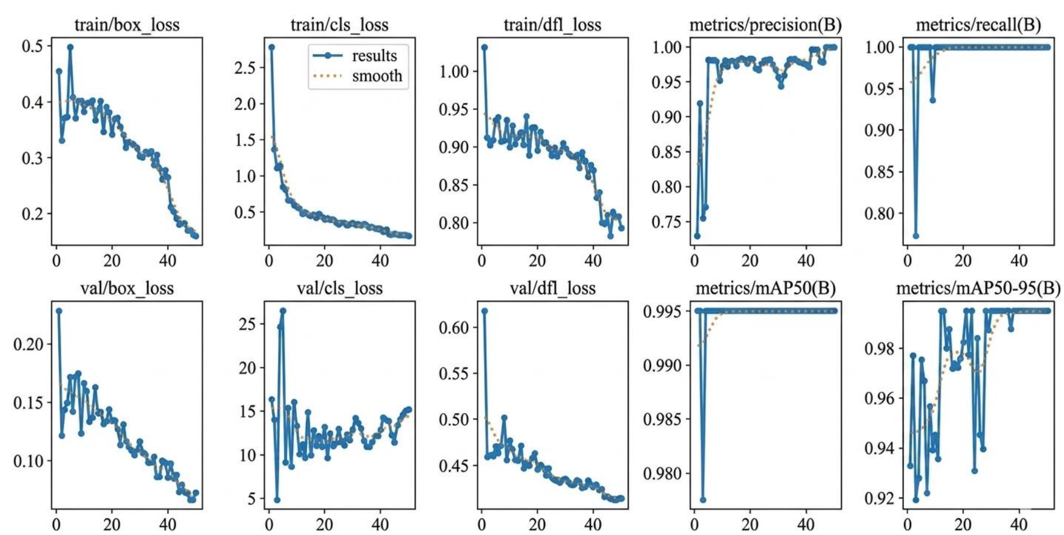


**Fig. 6 YOLOv8s model result**

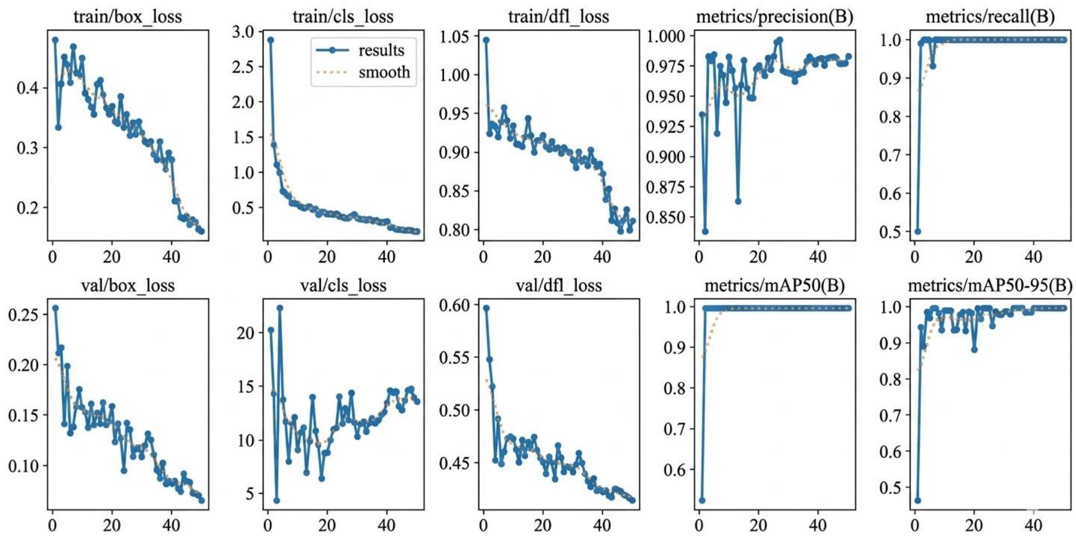

Fig. 7 YOLOv11n model result

# 5. Results
## *5.1. About the Prototype*

The operational prototype created combines the front-end (graphical interface) and the back-end (system logic). This section presents screenshots demonstrating the graphical user interface, such as the example of the application's internal functionality. At the same time, it highlights the application of Deep Learning architecture together with automation in product management. To start with the login screen, enter your username and password as shown in Figure 8, and you will be taken to the next page. If you make a mistake in either of these two fields, a box will appear saying "Incorrect username or password," as shown in Figure 9.

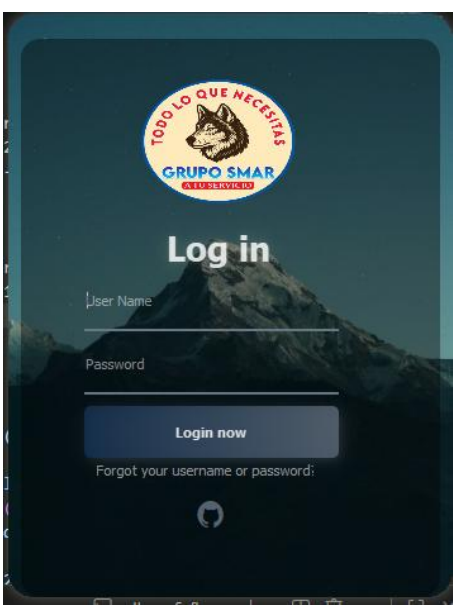

Fig. 8 System login screen

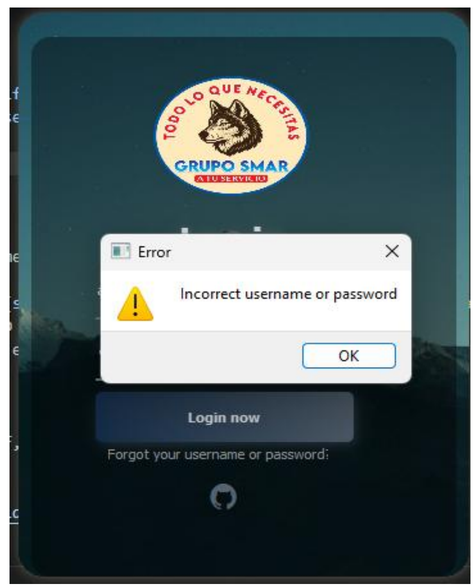

Fig. 9 Company login screen with incorrect data

The PyQt5 library was implemented, which is a library for creating Graphical User Interfaces (GUIs) in Python. Libraries such as sys and res were also used, where sys was used to interact with the operating system and res for the images or icons used in PyQt5.

It is a start menu screen with various buttons, as can be seen in Figure 10, which shows the following forms: View Products, View Categories, View Brands, Make Sales, and most importantly, Add Product (CAM), where products are added directly to the database through the training carried out.

This uses three modules from the library: QtCore, which contains essential classes for signals, events, configuration, and attributes; QtGui, which is used for everything related to color, images, fonts, and graphics; and QtWidgets, which includes the visual elements displayed in the interface.


**Fig. 10 Start menu screen**

In order to view the details of the sale, the operation is only shown as a message, as shown in Figures 11, 12, and 13, which illustrate the process for making a sale automatically so that the process is carried out more quickly when making a sale.

This demonstrates that the Deep Learning-based application for Automatic Product Detection is feasible for the company and, above all, reliable. It also shows that it works well.

This code uses the following libraries:

- Cv2: allows you to work with images and video, open them, process them, and detect objects, faces, colors, and contours.
- Torch: used for deep learning, where it allows you to create and train neural networks, manipulate tensors, and make inferences.
- Ultralytics import yolo: this library allows you to use the famous Yolo model for object and image detection and to load the trained model for real-time object detection.

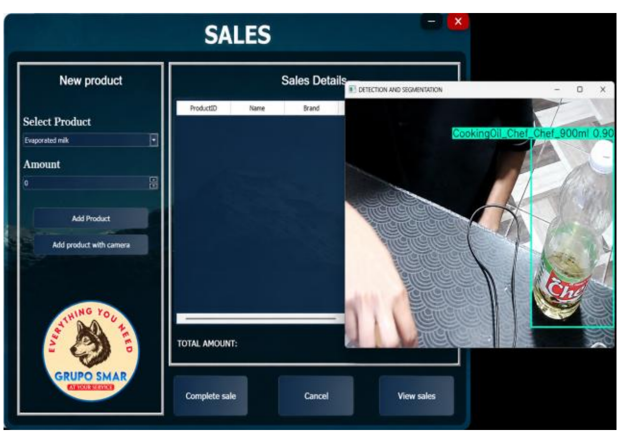


**Fig. 11 Automatic product detection using a camera**

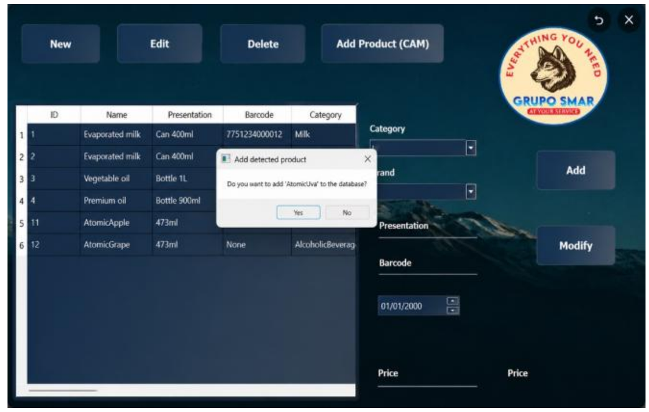


**Fig. 12 Automatic detection for sale**

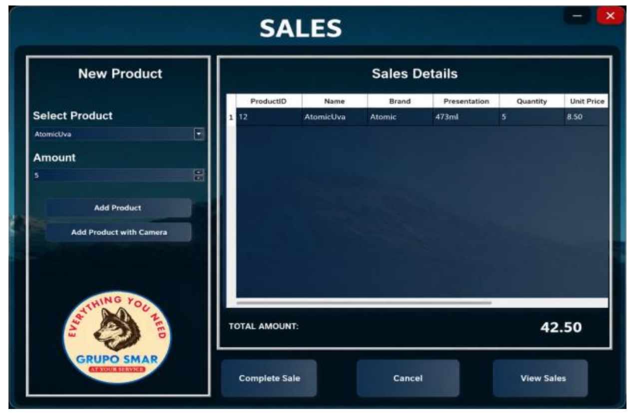


**Fig. 13 REGISTERED product**

### *5.2. About the Population*

The population for this research consists of all the products managed by the company Negociaciones 7 E.I.R.L in its inventory, with a total of approximately 1,200 registered units. Twenty-one products will be tested in order to test the software. According to Sierra [26], the population is defined as a group of individuals or elements that helps the researcher to precisely delimit what is to be studied, thus ensuring the validity and relevance of the results for the research in question.

### *5.3. About the Indicators*

The descriptive analysis was performed using basic statistical indicators and system performance metrics, which were evaluated in 21 observations before and after the implementation of the Artificial Intelligence system.

#### *5.3.1. KPI – Average Product Detection Time:*

Figure 14 shows the analysis of the average detection time per product required for product registration. In the pre-implementation phase, the average time was 12.5976 seconds, while in the post-implementation phase it decreased to 4.9905 seconds, with an absolute decrease of 7.61 seconds per product. Likewise, the minimum time went from 12 seconds to 4.75 seconds and the maximum from 13.1 seconds to 5.25 seconds, reflecting a notable decrease in external values.

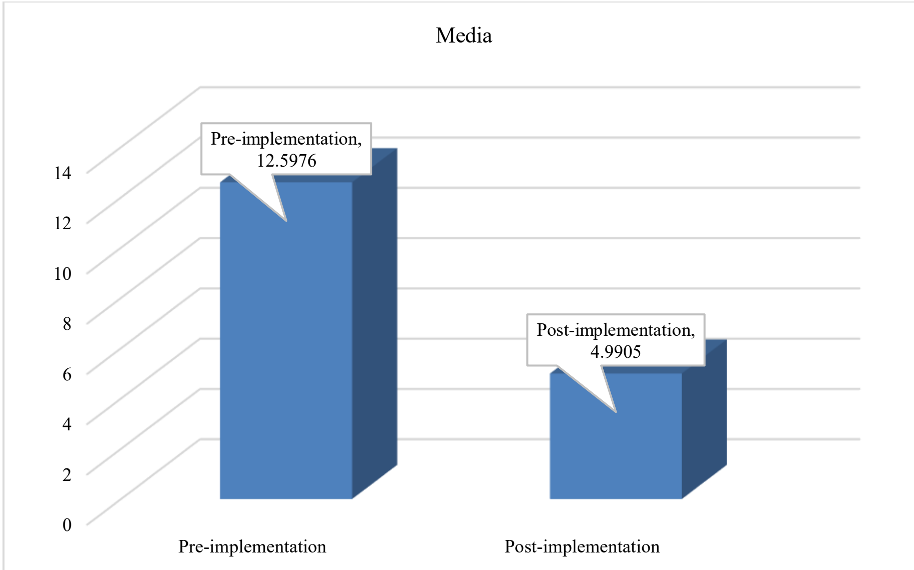


**Fig. 14 Comparative graph of average detection time by product**

The standard dispersion was 0.31 seconds in the pre-implementation phase compared to 0.14 seconds in the post-implementation phase, showing greater consistency and uniformity in product detection.

The results clearly reflect not only a substantial decrease in product detection time, but also greater consistency and stability in the process following the incorporation of Artificial Intelligence.

*5.3.2. KPI - Accuracy of Detection of the Number of Products Registered Per Day*

Figure 15 shows the analysis of the number of products registered per day. This indicator shows the pre-implementation stage, where manual processes are performed, with an average accuracy of 5.24%, with values ranging from 80% to 90%, reflecting a moderate dispersion of a standard deviation of 3.69%. Meanwhile, in the post-implementation stage, where the procedure is performed automatically using Artificial Intelligence, the average accuracy increased by 95%, reaching values between 95% and 100%, showing a lower standard deviation dispersion of 2.24%. This shows a significant improvement of 9.76 percentage points in registration accuracy, indicating that 2 additional products were correctly identified for every 20 reviewed. In turn, the reduction in variability indicates a more uniform and stable process. Consequently, the results show that the implementation of the intelligent system not only optimized the accuracy of product detection, but also contributed to greater reliability and consistency in the inventory process.

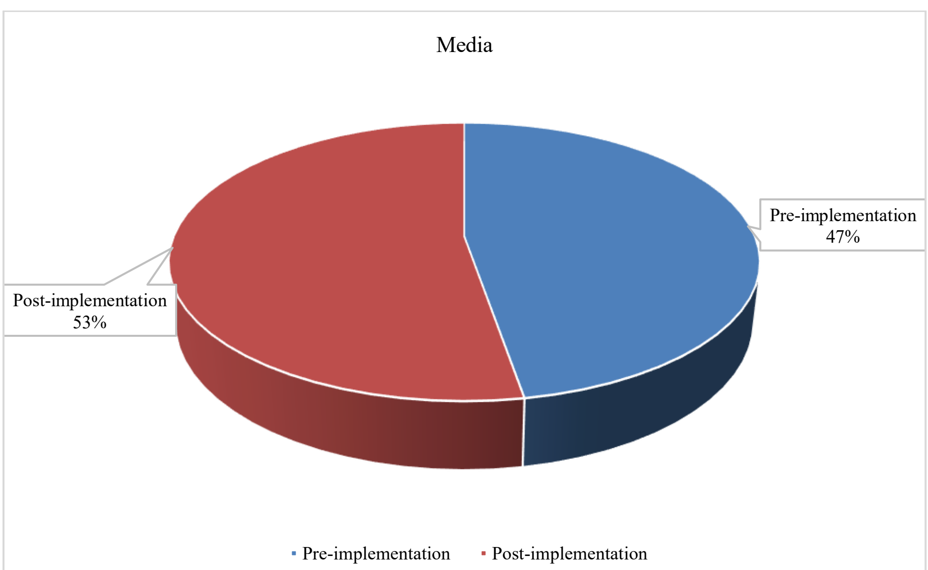


**Fig. 15 Comparative graph of product detection accuracy**

*5.3.3. KPI – Number of Error-Free Entries Per Day:*

Figure 16 shows that, in the pre-implementation stage with manual processes, the average accuracy was 80.48%, with a higher probability of errors and a standard deviation of 3.42%. Following the implementation of the AI-powered automatic recognition system, accuracy reached 96.90%, with a reduction in variability of 2.28%, representing an increase of 16.42 percentage points. These results show a reduction in manual errors, with greater efficiency, reliability and coordination in inventory management.

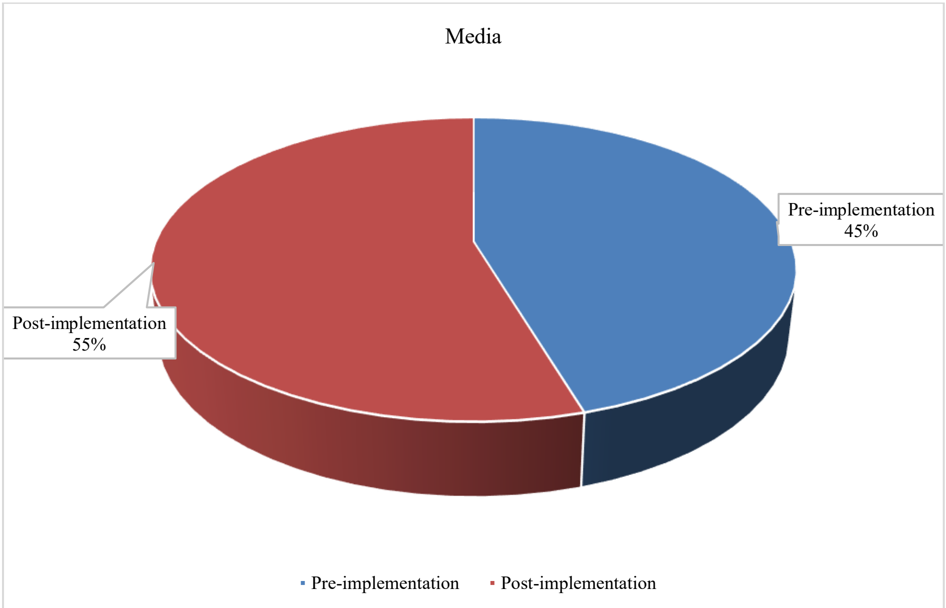


**Fig. 16 Comparative graph of error-free recording accuracy**

*5.3.4. KPI - Correct Stock Updates*

Figure 17 the evidence shows that, during the pre-implementation phase using traditional processes, the average accuracy of stock updates was 85%, with a standard deviation of 3.62%, indicating a high probability of errors.

Following the implementation of the AI-powered automated system, accuracy rose to 98.09% with low variability (2.18%), reflecting an improvement of 13.09 percentage points. The results confirm that this AI-based system enhances the accuracy, reliability and consistency of the inventory updating process.

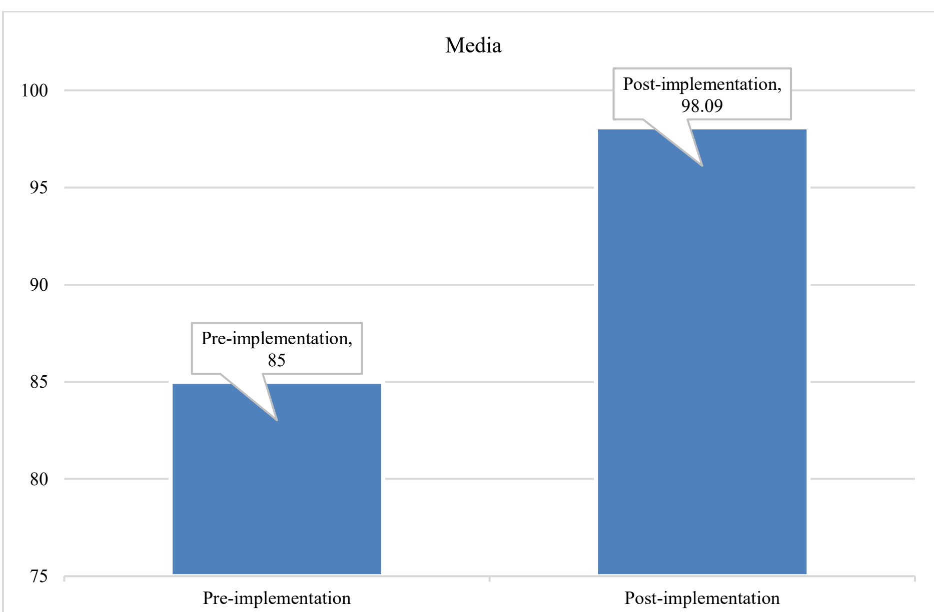


**Fig. 17 Comparative graph of accurate stock update accuracy**

### *5.4. About the Methodology*

The research was carried out using the CRISP-DM methodology, which enabled the implementation of automatic product detection to be structured, from the Preparation of the dataset through to the preliminary implementation of the model architecture in a business environment.

**Table 5. Validity indicators of the instrument**

| Indicator | Criterion | Expert 1 | Expert 2 | Expert 3 |
|---|---|---|---|---|
| Clarity | The content is formulated using appropriate and understandable technical language. | 85% | 90% | 88% |
| Objectivity | The information is presented in a logical and coherent manner. | 90% | 85% | 88% |
| Timeliness | The system is consistent with current advances in deep learning and computer vision. | 92% | 90% | 95% |
| Organization | There is a logical structure between the methodological and technical phases. | 88% | 85% | 90% |
| Sufficiency | The activities described cover the objectives of the system. | 90% | 88% | 85% |
| Intentionality | The system responds to the real needs of the business environment. | 95% | 90% | 92% |
| Consistency | There is consistency between the models used and the results obtained. | 92% | 88% | 90% |
| Coherence | The structure of the system is appropriate for the type of end user. | 90% | 85% | 88% |
| Methodology | The strategy applied responds to the research objectives | 88% | 90% | 92% |
| Relevance | The system effectively addresses the research problem | 90% | 88% | 92% |

Table 6 provides an overview of the phases of the CRISP-DM methodology in comparison with the activities carried out by each team, offering a detailed insight into the research processes and productivity.

**Table 6. Methodology used based on CRISP-DM**

| Stage | Activity performed |
|---|---|
| Business understanding | Identification of the problem of manual product registration; analysis of functional and non-functional requirements; definition of system objectives. |
| Data understanding | Collection of images of the company's products; analysis of data quality, format, and visual variability. |
| Data preparation | Image cleaning, normalization, data augmentation, organization into train and val folders, and configuration of the dataset.yaml file. |
| Modeling | Training of YOLO models (YOLOv8n, YOLOv8s, and YOLOv11n) using transfer learning and convolutional neural networks. |
| Evaluation | Comparison of model performance using precision and recall metrics and confusion matrix analysis. |
| Desktop application with the best model | Implementation of the YOLOv8s model in a desktop application for automatic product detection and real-time inventory updating. |

This approach clearly demonstrated the alignment of theory with practice, thereby ensuring that the research and technical validation objectives were met through the development process. The methodology employed demonstrates scientific rigour at every stage and supports the efficiency of the proposed system for product identification.

### *5.5. About the Survey and Expert Evaluation*

The validity of the deep learning-based system was assessed through expert judgement, with experts evaluating its methodological and technical suitability; these enabled adjustments to be made to ensure the system met its objectives. The preliminary assessment was carried out using a percentage scale, classified as follows:

- Poor: 0–20%
- Fair: 21–40%
- Good: 41–60%
- Very good: 61–80%
- Excellent: 81–100%

Table 5 presents the indicators used in the instrument validation process, along with the scores given by each expert.

### *5.6. About User Validation of the Design*

The system was evaluated in a real-world setting through user surveys, taking into account criteria such as effectiveness, usability and functionality. As shown in Table 7, an overall average score of 4.23 was obtained on a 5-point Likert scale, indicating a ‘very high’ level of acceptance.

The results show that the system is faster at identifying products, reducing traditional errors and facilitating user interaction with the system. Furthermore, users highlighted its accuracy, effectiveness and simplicity compared to traditional methods, confirming its viability within the company. Figure 18 shows the distribution of user responses according to the Likert scale levels. There is a marked concentration in the "Good" and "Excellent" categories, especially regarding the functionality criterion, which indicates high acceptance of the system in a real-world context.

**Table 7. User evaluations of the system in a real-world context**

| Criterion | Evaluation aspect | Average | D.E | Level |
|---|---|---|---|---|
| **Effectiveness** | The system facilitates product registration more efficiently than the manual procedure | 4.30 | 0.85 | Very high |
| | The system's response is appropriate for detection | 4.25 | 0.90 | Very high |
| | The system operates without interruptions while in use | 4.10 | 0.95 | High |
| Usability | The system has a very user-friendly interface | 4.20 | 0.88 | Very high |
| | It is easy to understand how to use the system | 4.15 | 0.92 | Very high |
| | Navigation within the system is intuitive | 4.05 | 0.8 | High |
| Functionality | The system accurately identifies products | 4.35 | 0.82 | Very high |
| | The system reduces errors in product registration | 4.40 | 0.75 | Very high |
| | The system meets the requirements of the sales process | 4.25 | 0.89 | Very high |
| Average | | 4.23 | 0.86 | Very high |

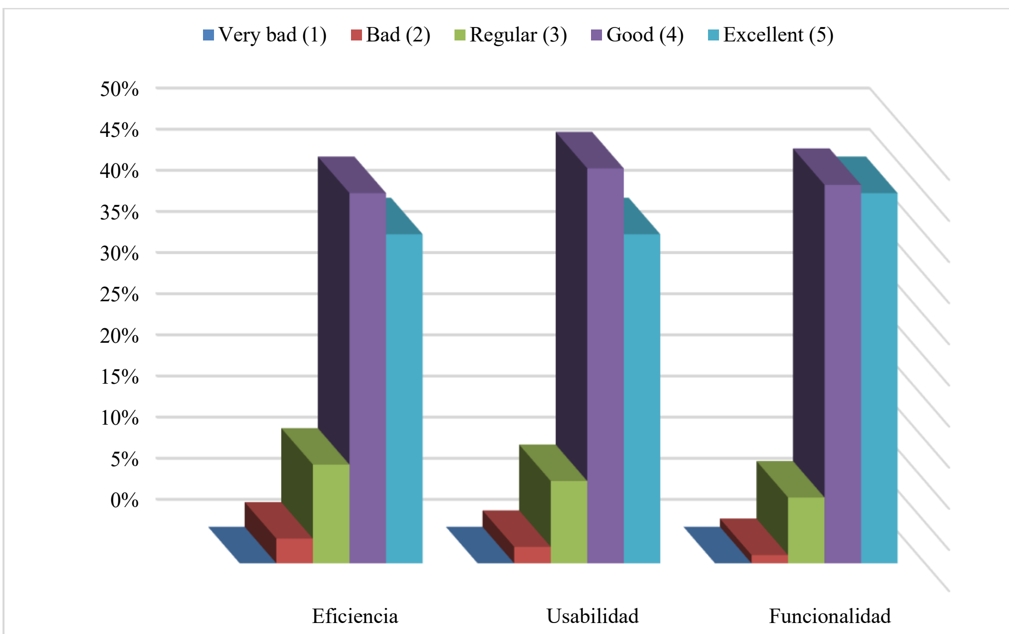


**Fig. 18 User evaluation**

## 6. Discussion

### *6.1. About KPIs*

The results demonstrate improved operational efficiency within the company following the implementation of an AI-powered automatic product detection system. The average detection time was reduced from 12.6 seconds to 4.99 seconds, whilst the accuracy of the daily log increased from 85.24% to 95.00%. Consequently, error-free records rose from 80.48% to 96.90%, and correct inventory updates exceeded 98.09%, which helped to optimise stock management processes and improve the company's productivity.

In light of this situation, the research analysed the implementation of a deep learning system for the automatic detection of products at the company Negociaciones 7 E.I.R.L., examining the impact on Key Performance

Indicators (KPIs) such as accuracy, response time, reduction in manual errors and operational efficiency. The results show significant improvements in the indicators assessed, demonstrating the enhanced efficiency of deep learning models-particularly the YOLOv8s architecture-in real-time automated recognition tasks.

Furthermore, as reflected in study [32], which proposed a computer vision and deep learning-based monitoring system implemented in shops in real time-comprising a model for detecting shelves and products-this system achieved high levels of accuracy in classifying and identifying products, optimised visual audits, and reduced the amount of work previously carried out manually. Furthermore, study [41] confirms that the use of a computer vision model for the early detection of stock-outs on shelves improves the control process and reduces operational errors. In line with this research, there is a significant reduction in response time for product identification through the implementation of the YOLOv8s model. Consequently, the first hypothesis is verified, demonstrating acceptable results compared to previous work, due to the similarity of the problem and the proposed solution. Therefore, it is concluded that the implementation based on Deep Learning reduces detection time and optimises processes within the company.

In contrast, other studies demonstrate the use of public data, such as the works cited in [15, 18, 21], which rely on pre-existing datasets for model training and evaluation; the present research, however, evaluates the system in a real-world business environment. In this context, the data was captured on-site, yielding multiple images with varying angles, lighting conditions and backgrounds. Subsequently, the captured images were selected and used for pre-training, which enabled us to work with our own data that is representative of the operational context. This adds further value in terms of the practical implementation of the system.

Furthermore, recent studies have proposed the use of deep learning and computer vision in the retail sector, enabling better control over inventory and product availability. A clear example is study [17], which demonstrates a platform based on Artificial Intelligence and computer vision for the preliminary recognition and classification of products using images captured in real time, resulting in reduced counting time and greater efficiency in product registration, which helps to make sound decisions and respond quickly to stock shortages. Similarly, [42] establishes that the implementation of deep learning models in the retail sector demonstrates clear inventory management, as it facilitates sound decision-making and enables competition in the market through proactive control. Consequently, the second hypothesis is validated, and the results obtained in this study are accepted on the basis of their performance. It is therefore concluded that inventory control using deep learning significantly increases its effectiveness and optimises the company's internal processes.

Furthermore, according to the authors [43], the implementation of the deep learning model in MYPES helps to reduce processes and financial losses associated with traditional methods. Similarly, [44] highlights the incorporation of the intelligent system into inventory management, which increases the accuracy of product registration. In line with these findings, the results show a significant increase in the number of products recorded daily without errors using traditional methods, which validates the third hypothesis. This demonstrates that Deep Learning-based implementation yields efficient results in inventory control and enhances the reliability of previously recorded information.

Furthermore, several studies show that intelligent computer vision systems not only increase accuracy but also improve the reliability of data when making decisions. A clear example is the work in [18], which shows that by integrating computer vision, products on the shelf can be detected immediately, enabling effective monitoring, the generation of more accurate databases, and operational management in the retail sector. In line with these studies, this research demonstrates the reliability of inventory records, achieving an accuracy level of 95%. Consequently, the fourth hypothesis is verified, and the results obtained are considered in relation to other studies analysed. It is therefore concluded that the implementation of the intelligent system based on Deep Learning helps to achieve better control and rapid product identification, whilst ensuring inventory reliability.

### *6.2. About the Models*

This research utilised three deep learning-based object detection models from the YOLO (You Only Look Once) family: YOLOv8n, YOLOv8s and YOLOv11n. These architectures were selected for their high capacity to perform automatic detection effectively and quickly in real time, aiding inventory control management, as evidenced in recent studies employing computer vision for the preliminary analysis of products and shelves [21, 27].

The YOLOv8n model is a variant designed to run with low computational resource consumption, allowing it to be deployed on systems with hardware limitations. This type of model has demonstrated clear efficiency in product detection, providing rapid, real-time identification, which is essential [29]. However, its structural complexity can affect its performance in scenarios with high visual variability.

For its part, YOLOv8s features a mid-level architecture that balances efficiency and accuracy, with a strong ability to extract relevant features. Research into the model's application in stock-out detection and compliance with standards has shown that deeper models tend to yield more reliable results in real-world retail businesses [21, 28]. In this work, YOLOv8s demonstrates consistently high performance in both the training and evaluation phases, maintaining higher values for recall and precision; consequently, it was selected as the main model for the proposed system.

Finally, YOLOv11n is an architecture designed to increase recognition speed and processing efficiency, whilst maintaining a lightweight architecture. In computer vision applications aimed at the retail sector, it has been shown that these optimisations help to reduce response times without affecting the system's accuracy [27]. However, the evaluation took into account the model's stability and its alignment with metrics when compared to other previously analysed models.

The three models were compared under equivalent experimental conditions, which helped to identify the most reliable architecture for the automatic detection of products in sales and inventory management processes, taking into account key criteria such as accuracy, system stability and detection time.

### *6.3. About the Limitations*

However, this study has some limitations that must be taken into account when evaluating the results. Firstly, the Deep Learning-based implementation was designed for a single company in the retail sector, which limits its use in other companies with different technological characteristics. Furthermore, the evaluation was conducted over a limited period of time, which helped to analyse the model's long-term performance, bearing in mind that its performance could improve as the volume of training data increases. Furthermore, performance may be affected by factors such as lighting, product availability, and the quality of the captured images, which creates a challenge for automatic recognition. However, these limitations present opportunities for future research focused on optimising the model and adapting it to different environments. Finally, with regard to future work, it is recommended that real-time automatic alerts be implemented to detect low stock levels or products nearing their expiry date, with the aim of reducing financial losses and optimising inventory management. In turn, it is proposed to expand the Deep Learning model using a broader dataset that incorporates new products, alongside automatic training to ensure the system is constantly updated. Similarly, it would be beneficial to integrate the solution into a web platform or app, which would facilitate remote access to the information, thereby enhancing security measures and providing database backup, which in turn underpins the company's reliability and the system's operational continuity.

## 7. Conclusion

With regard to the first specific objective, which focuses on reducing the average product detection time, it is confirmed that during the pre-implementation phase the average time was 12.60 seconds per product; in contrast, during the subsequent implementation phase this was reduced by 4.99 seconds, representing a decrease of 7.61 seconds. Similarly, the daily report showed an average saving of 152.14 seconds (equivalent to 2 minutes and 32 seconds), demonstrating that the implementation of Artificial Intelligence clearly increases operational efficiency in the automatic detection of products. With regard to the second specific objective, which focuses on the accuracy of product detection in daily records, the data obtained show that during the system's implementation phase, the average accuracy was 85.24%; following automation via deep learning, this rose to 95.00%, representing an improvement of 9.76 percentage points. This increase demonstrates the high accuracy and efficiency of the rapid product identification response, as well as a reduction in errors generated by traditional methods. With regard to the third specific objective, which focuses on the number of error-free records, it is evident that during this pre-implementation phase the average accuracy was 80.48%, whereas in the post-implementation phase it increased significantly to 96.90%. This increase of 16.42 percentage points demonstrates a reduction in the number of records containing errors, thereby contributing to high reliability, consistency and stability in information management. Finally, with regard to the fourth specific objective, which focuses on accurate stock updates, the average accuracy rate rose from 85.00% in the pre-implementation phase to 98.09% in the post-implementation phase, representing an improvement of 13.09 percentage points. This finding shows that automation using Artificial Intelligence significantly contributes to the accuracy of inventory updates, which reduces recording errors and strengthens stock control.

## Acknowledgments

The authors would like to thank Mr Wilmer Aguirre Alvarado, Managing Director of NEGOCIACIONES 7 E.I.R.L., for allowing us to conduct this study in a real-world operational setting, as well as for providing us with the information necessary to develop the system. His collaboration was essential in understanding the challenges of inventory management and proposing a technological solution aimed at improving operational efficiency and contributing to the company's digital transformation process.

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