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Theme

Machine Learning Tools For Hospital Pharmacy Supply Chain: Inventory Management Tasks

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ABSTRACT

The pharmaceutical supply chain (PSC) plays a critical role in ensuring the availability, quality, and timely delivery of pharmaceutical products to patients. However, the PSC faces numerous challenges, including maintaining product integrity, combating counterfeit drugs, and addressing supply shortages, which can impact healthcare system efficiency and patient access to medications. This study focuses on improving the PSC, specifically within the Central Pharmacy of Hospitals (PCH) in Algeria. The PCH faced challenges related to medication calculations, efficiency, paperwork, and inventory management. To address these challenges, an intelligent supply chain system is developed with the objectives of improving efficiency, reducing errors, simplifying documentation, and optimizing inventory management.The developed system comprises modules for inventory management, analytics and reporting, and workflow automation. This system utilizes object detection techniques, specifically YOLO and Faster R-CNN algorithms, for medication detection and classification. A custom dataset is generated, encompassing diverse images of medications from various angles and lighting conditions. The dataset is annotated and augmented to enhance performance. Limitations and challenges such as data quality, technical expertise, implementation costs, privacy, security, and system integration are considered. Despite these challenges, the proposed intelligent supply chain system has the potential to simplify operations and enhance the effectiveness of pharmaceutical supply chains, eventually benefiting healthcare establishments and improving patient access to essential pharmaceutical products.

Keyswords: Pharmaceutical Supply Chain, Pharmacie Centrale des Hopitaux, Object Detection, YOLO, Faster RCNN

ملخص

تلعب سلسلة التوريد الصيدلانية (PSC) دورًا حاسمًا في ضمان توفر وجودة وتسليم المنتجات الصيدلانية في الوقت المناسب للمرضى. ومع ذلك، تواجه سلسلة التوريد الصيدلانية العديد من التحديات، بما في ذلك الحفاظ على سلامة المنتج، ومكافحة الأدوية المزيفة، ومعالجة نقص الإمدادات، وهو ما يمكن أن يؤثر على كفاءة النظام الصحي ووصول المرضى إلى الأدوية. تركز هذا الدراسة على تحسين سلسلة التوريد الصيدلانية في صيدلية المستشفيات المركزية في الجزائر. تواجه صيدلية المستشفيات المركزية تحديات تتعلق بحساب الأدوية، ونقص الكفاءة، والأعمال الورقية، وإدارة المخزون. لمعالجة هذه التحديات، تم تطوير نظام ذكي لسلسلة التوريد بهداف تحسين الكفاءة، وتقليل الأخطاء، وتبسيط الوثائق، وتحسين إدارة المخزون. يتألف النظام المطور من وحدات لإدارة المخزون، وتحليل البيانات والتقارير، وتطوير سير العمل. يستخدم هذا النظام تقنيات كشف الكائنات، باستعمال خوارزميات YOLO و Faster R-CNN ، لاكتشاف الأدوية وتصنيفها. تم إنشاء مجموعة بيانات مخصصة، تضم صورًا متنوعة للأدوية من زوايا وظروف إضاءة مختلفة البيانات لتحسين الأداء. تؤخذ في الاعتبار القيود والتحديات مثل جودة البيانات، والخبرة التقنية، وتكاليف التنفيذ، والخصوصية، والأمان، وتكامل النظام. على الرغم من هذه التحديات، يتمتع النظام الذكي المقترح لسلسلة التوريد الصيدلانية بإمكانية تبسيط العمليات وتعزيز فعالية سلاسل التوريد الصيدلانية، مما يعود في النهاية بالفائدة على المؤسسات الصحية ويحسن وصول المرضى إلى المنتجات الصيدلانية الأساسية. **الكلمات المفتاحية:** سلسلة التوريد الصيدلانية، صيدلية المستشفيات المركزية، كشف الكائنات، YOLO, Faster R-CNN

RÉSUMÉ

La chaîne d'approvisionnement pharmaceutique (PSC) joue un rôle crucial dans la garantie de la disponibilité, de la qualité et de la livraison en temps voulu des produits pharmaceutiques aux patients. Cependant, la PSC est confrontée à de nombreux défis, notamment le maintien de l'intégrité des produits, la lutte contre les médicaments contrefaits et la résolution des pénuries d'approvisionnement, ce qui peut avoir un impact sur l'efficacité du système de santé et l'accès des patients aux médicaments. Cette étude se concentre sur l'amélioration de la PSC, plus précisément au sein de la Pharmacie Centrale des Hôpitaux (PCH) en Algérie. La PCH était confrontée à des défis liés aux calculs médicamenteux, à l'efficacité, à la paperasserie et à la gestion des stocks. Pour relever ces défis, un système intelligent de chaîne d'approvisionnement a été développé avec pour objectifs d'améliorer l'efficacité, de réduire les erreurs, de simplifier la documentation et d'optimiser la gestion des stocks. Le système développé comprend des modules de gestion des stocks, d'analyse et de reporting, ainsi que d'automatisation des flux de travail. Ce système utilise des techniques de détection d'objets, plus précisément les algorithmes YOLO et Faster R-CNN, pour la détection et la classification des médicaments. Un ensemble de données personnalisé est généré, comprenant des images variées de médicaments prises sous différents angles et conditions d'éclairage. L'ensemble de données est annoté et augmenté pour améliorer les performances. Les limites et les défis tels que la qualité des données, l'expertise technique, les coûts de mise en œuvre, la confidentialité, la sécurité et l'intégration du système sont pris en compte. Malgré ces défis, le système intelligent de chaîne d'approvisionnement proposé a le potentiel de simplifier les opérations et d'améliorer l'efficacité des chaînes d'approvisionnement pharmaceutiques, ce qui bénéficiera finalement aux établissements de santé et améliorera l'accès des patients aux produits pharmaceutiques essentiels.
Mots-clés: Chaîne d'approvisionnement pharmaceutique, Pharmacie Centrale des Hôpitaux, Détection d'objets, YOLO, Faster RCNN

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General Introduction

The pharmaceutical supply chain (PSC) is a complex network responsible for ensuring the availability, quality, and timely delivery of pharmaceutical products to patients [4, 5]. However, the PSC faces numerous challenges such as maintaining product integrity, combating counterfeit drugs, and addressing supply shortages [6]. Disruptions in the PSC can lead to medicine shortages and impact the efficiency of healthcare systems. Therefore, it is crucial to optimize the PSC and hold innovative technologies and approaches to ensure safe and efficient medication delivery [4].

In Algeria, the Central Pharmacy of Hospitals (PCH) plays an important role in ensuring the timely availability of medicines to hospitals and healthcare facilities in the country [7]. However, the PCH faces challenges related to time-consuming conformity control, lack of efficiency, complicated paperwork, and limited automation. The high inventory costs in the healthcare sector further emphasize the need for measures to optimize inventory management [7].

To address these challenges, our thesis aims to develop an intelligent supply chain system specifically for PCH. The objectives of this system include improving efficiency, reducing errors, simplifying documentation, enhancing communication, and optimizing inventory management. By achieving these objectives, our system aims to simplify the PCH products reception process, and improve inventory management, to ensure timely access.

Our contributions focus on three key tasks within the intelligent supply chain system: inventory management, Analytics and reporting, and workflow automation. We propose an intelligent Inventory Management module that utilizes object detection techniques to control the number of medications, optimize stock levels, and thus minimize time waste, to ensure an adequate supply of

medications.

One Challenging problem we encountered is the lack of a pertinent data set specific to our study requirements. As a result, we had to generate our own dataset, which required substantial effort and resources. We made use of annotation techniques such as bounding boxes to label the dataset and utilized data augmentation techniques to enhance diversity. Finally, our custom dataset serves as an important factor for training and evaluating the performance of our intelligent detection system.

Since we aim to address the problem of medication detection through the application of object detection techniques, we make use of two effective object detection algorithms, YOLO (You Only Look Once) and Faster R-CNN (Region Convolutional Neural Network). These algorithms have been proven successful in accurately localizing and classifying objects within images [8, 9]. By utilizing these models, we seek to leverage their capabilities to identify and classify medications within our custom dataset. The use of YOLO and Faster R-CNN allowed us to achieve accurate medication recognition, enabling us to make significant advancements in this ambitious project.

Our thesis is structured as follows:

- In Chapter 1, we provide an introduction to the pharmaceutical supply chain problem, emphasizing its importance and challenges. We then conduct a literature review on the utilization of machine learning and artificial intelligence within this domain. We subsequently shift our attention towards the Central Hospital Pharmacy, a governmental institution responsible for the provision of medicine and medical products to public hospitals, offering an in-depth examination of their procedures and protocol.

- Chapter 2 is dedicated to our view of an intelligent supply chain system, where we explore various tasks that can benefit from the integration of artificial intelligence. We then emphasize the objectives of this work, outlining the specific goals we aim to achieve.

- Chapter 3 centers around image recognition and more specifically, object detection task. We delve into the various methods that we have employed in this work, with a particular emphasis on their architecture and their learning process.

- Chapter 4 is devoted to data generation. As mentioned previously, this is a fundamental aspect of our research. Hence, we provide a comprehensive explanation of the processes involved in creating, annotating, and augmenting the dataset used in our study.

- In addition to the details of experiments and results regarding the object detection task, we provide in Chapter 5 a description of the process of counting medicine and automatic reports generation, completing the tasks set in this work.

CHAPTER 1

PHARMACEUTICAL SUPPLY CHAIN

1 INTRODUCTION

In this chapter, we review the challenges within the pharmaceutical supply chain (PSC), with a particular focus on the context of Algeria's Central Pharmacy of Hospitals (PCH). Additionally, we explore the potential solutions and innovative technologies that can optimize the PSC and address the challenges faced by the PCH, such as time-consuming medication calculations, inefficiency, paperwork complexities, and limited automation. Furthermore, we discuss the importance of effective inventory management in the healthcare sector and propose measures to optimize inventory control. By delving into these topics, we aim to enhance the understanding of the PSC's intricacies and identify strategies to ensure safe and efficient medication delivery in Algeria.

2 PHARMACEUTICAL SUPPLY CHAIN OVERVIEW

The pharmaceutical supply chain (PSC) is a complex network that ensures the availability, quality, and timely delivery of pharmaceutical products to patients [4, 5]. It includes the production and distribution of pharmaceuticals by manufacturers, the distribution and sale of drugs by wholesalers and retailers, and the dispensing of drugs by pharmacies [4, 5]. It involves various interconnected processes and stakeholders, including manufacturers, distributors, wholesalers, pharmacies, healthcare providers, and patients. Key activities in the PSC include sourcing raw materials, manufacturing, packaging, storage, transportation, and distribution of pharmaceutical products. The PSC faces

numerous challenges, such as maintaining product integrity, combating counterfeit drugs, ensuring temperature control, addressing supply shortages, and complying with regulations. To optimize the PSC and ensure safe and efficient medication delivery, innovative technologies and approaches have been explored and adopted. Disruptions in the PSC can disrupt the supply of medicines and impact the efficiency of healthcare systems [6].

Figure 1.1 shows the key elements of the pharmaceutical supply chain which refers to the series of steps and processes involved in the distribution and delivery of prescription and over-the-counter medications from manufacturers to patients [10].

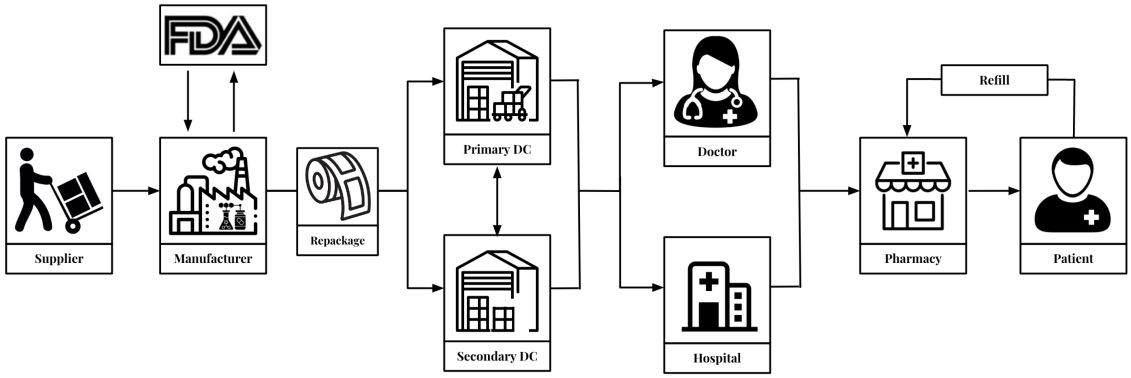

Figure 1.1: Pharmaceutical supply chain. [1]

2.1 IMPORTANCE OF THE PHARMACEUTICAL SUPPLY CHAIN

The pharmaceutical industry plays a crucial role in providing life-saving medicines. According to the IQVIA "Institute for Human Data Science", drug spending worldwide in 2021 was estimated at USD 1.5 trillion. Eleven (11) markets [6, 11] The operation of the PSC is a critical element in this process. Any disruption to the PSC supply chains can lead to medicine shortages and undermine the effectiveness of health systems [4, 6]. Pharmaceutical companies manage highly complex supply networks that involve coordinating diverse products, markets, processes, and intermediaries. They must ensure timely delivery of products to the right place and customers. These companies face various risks along the supply chain, including raw material shortages, product quality issues, short product life cycles, and supplier failures, as described by Milind and Sriram (2020) that "... disruptions that occur along the pharmaceutical supply chain, hindering the regular supply of products... mainly caused by a shortage of raw materials, product quality issues, short product life cycles, or sustainable supplier failure... irregularities that may generate lead time loss, late deliveries, backorders, production losses and supply shortages leading to uncertainty in the volume of

sales and income" [6]. Such disruptions can result in delays, backorders, production losses, and supply shortages, leading to uncertainty in sales and income.

2.2 IMPLICATIONS OF THE COVID-19 PANDEMIC

The COVID-19 pandemic exposed vulnerabilities in modern supply chain logistics, particularly in the healthcare sector. Developing countries relying on external suppliers experienced drug supply shortages and disruptions. The global shortage of pharmaceutical ingredients, driven by high demand for antiviral agents, resulted in increased prices. This crisis highlighted the limitations of free trade in the face of a global health and humanitarian emergency [6, 12].

2.3 BUILDING RESILIENT SUPPLY CHAINS

In the post-pandemic era, pharmaceutical companies recognize the need to build resilient supply chains capable of withstanding future disruptions [12].Due to shortages in the global pharma supply chain over the past few years and the complex nature of free trade and its limitations when confronted by a major global health and humanitarian crisis, many countries have taken steps to mitigate the risks of disruption, including, Experts have proposed recommendations to protect supply chain operations, including diversification approaches to avoid dependence on a single supplier, increasing emergency stock, and even nationalizing medical supply chains. [6, 12] These measures aim to mitigate the fallout from the crisis and enhance the long-term resiliency of pharmaceutical companies.

Figure 1 is a graphic representation of the PSC showing the different inputs resulting in the manufacture of pharmaceutical specialties distributed in consumer markets.

3 ARTIFICIAL INTELLIGENCE FOR PSC

Artificial intelligence, digitization, and data analytics are popular areas of study and research because they can make use of the large amount of data generated by modern systems, known as big data. Data analytics involves using mathematical and computer science techniques to extract useful information from this data [13]. It can be applied in various fields, including medicine. For example, machine learning algorithms can assist in medical diagnosis and drug development. Data analytics also holds promise in improving healthcare systems, such as pharmaceutical supply chains. The pharmaceutical industry faces challenges in terms of operational performance, but analytics and artificial intelligence can help optimize costs, manage inventories, reduce shortages, and

ensure transparency. By analyzing traceability data and using predictive models, valuable insights can be gained to address future needs and disruptions. The field of data analytics in pharmaceutical supply chains is expected to grow significantly in the coming years [12].

3.1 LITERATURE REVIEW AND CONTRIBUTIONS:

Previous research has explored data analytics for supply chain management (DA-SCM) from various angles. Some authors have conducted literature reviews to gain insights into research directions and challenges in supply chain operations [14]. They have examined different industry types, such as finance, healthcare, and manufacturing, to understand the main challenges. The COVID-19 pandemic has also brought attention to data analytics for supply chain resilience and crisis managemen [12, 15].

Here are examples of data analytics techniques applied in the pharmaceutical supply chain (PSC):

1-Demand Forecasting with Artificial Neural Networks (ANNs)

Koulouriotis and Mantas (2012) [16] utilized ANNs, inspired by the neuron cell structure, to develop computational models that can learn and optimize task performance. They applied this technique to predict future medicine demand.

2-Product Segmentation with K-means Clustering

Amalnick et al. (2020) [17] employed the K-means algorithm to segment pharmaceutical products based on their characteristics. This approach allowed them to enhance demand forecasting accuracy by training specific models for each product cluster.

3-Adulteration Detection with Principal Component Analysis (PCA)

Cantor, Gupta, and Khan (2014) [18] utilized PCA, a dimensionality reduction method, to analyze physicochemical properties of drugs, such as Near Infrared Spectra (NIRS). They used this technique to detect intentional or unintentional adulteration in chemicals.

4-Quality Control using K-nearest Neighbors (KNN) Classification

Bahaghighat, Akbari, and Xin (2019) [19] developed a quality control system for pharmaceuticals using the KNN classification method. They employed pre-processed images and employed KNN to classify the images and count blisters in drug packages.

5-Drug Authentication with Support Vector Machine (SVM) Classification

Bahaghighat, Akbari, and Xin (2019) [20] utilized SVM, a machine learning model, for drug authentication. SVM constructs hyperplanes to consistently separate data in the feature space, making it suitable for classifying and authenticating drugs.

These examples demonstrate how different data analytics techniques, such as predictive modeling, clustering, descriptive analysis, and classification, was applied to various aspects of the pharmaceutical supply chain to address specific challenges, to enhance decision-making and improve operational efficiency.

4 PHARMACEUTICAL SUPPLY CHAIN IN ALGERIA

4.1 OVERVIEW

The pharmaceutical supply chain in Algeria refers to the process of producing, distributing, and delivering pharmaceutical products within the country. Here's an overview of the pharmaceutical supply chain in Algeria[1].

Pharmaceutical Manufacturing

Algeria has a domestic pharmaceutical manufacturing industry, with several companies producing a wide range of medicines. These companies manufacture both generic and branded pharmaceutical products. The manufacturing facilities adhere to Good Manufacturing Practices (GMP) standards to ensure quality and safety.

Regulatory Authorities

The regulatory body responsible for overseeing the pharmaceutical sector in Algeria is the National Agency for the Drug Evaluation and Research (ANEP). ANEP is responsible for the registration, regulation, and control of pharmaceutical products in the country. They ensure that pharmaceutical manufacturers comply with the required standards and regulations [21].

Importation of Pharmaceutical Products

Algeria relies on the importation of pharmaceutical products to meet the demand for medicines that are not manufactured domestically. Importation is subject to regulations and requires approval from ANEP. Importers need to provide necessary documentation, including product registration, import licenses, and quality certificates.

[1]The National Agency for the Drug Evaluation and Research (ANEP) in Algeria website: http://www.anep.com.dz/siege/

Distribution and Wholesale

After the pharmaceutical products are manufactured or imported, they are distributed to various wholesalers and distributors across the country. These wholesalers play a crucial role in the supply chain by supplying products to pharmacies, hospitals, and other healthcare facilities. They maintain proper storage conditions and ensure the products' integrity throughout the distribution process.

Pharmacies and Retailers

Pharmacies serve as the primary point of access for patients to obtain pharmaceutical products. They receive supplies from wholesalers and provide medicines directly to consumers. Pharmacies must comply with regulations related to storage, dispensing, and record-keeping. There are also specialized retail pharmacies in hospitals and clinics.

Hospitals and Healthcare Facilities

Hospitals and healthcare facilities have their own pharmacies that manage the procurement, storage, and dispensing of medicines internally. They often have larger inventory and specialized pharmaceutical needs, and they may procure directly from manufacturers or wholesalers [21].

4.2 CENTRAL PHARMACY OF HOSPITALS (PCH)

The Central Pharmacy of Hospitals is a Public Industrial and Commercial Establishment (EPIC) placed under the supervision of the Ministry of Health. It is an essential supplier for Public Health Establishments. whose purpose is to supply pharmaceutical products to hospital establishments. Its clientele and suppliers are both public and private[2].

Within the framework of the national health policy, the Central Pharmacy has the mission of procuring and distributing pharmaceutical products to healthcare establishments throughout the national territory. The Central Pharmacy is also entrusted with public service missions related to the establishment of a strategic stock and an emergency stockpile.

Due to its status, the Central Pharmacy of Hospitals operates within a commercial, industrial, and public service framework, aiming to ensure the availability of pharmaceutical products under the best conditions of delivery, storage, and cost for over 1000 client references.

The Central Pharmacy of Hospitals has a distribution network in five (05) regions, including three (03) in the north, namely Algiers, Oran, Annaba, and two (02) in the south, Biskra and Bechar,

[2]Official Central Pharmacy of Hospitals in Algeria website: http://www.pch.dz/

to be in closer proximity to healthcare establishments. As a preferred tool in the healthcare sector in the pharmaceutical field, the Central Pharmacy procures from nearly 250 suppliers, including 89 local and 158 foreign suppliers, for public healthcare establishments and various clients. The Central Pharmacy also aims to invest in the pharmaceutical industry in order to contribute to our country's reduced dependence on the global drug market.

In order to fully fulfill its mission within the framework of the national health policy, the Central Pharmacy of Hospitals ensures the satisfaction of the needs of Public Health Establishments in pharmaceutical and para-pharmaceutical products through the procurement procedure on behalf of these establishments. The Central Pharmacy is authorized to market pharmaceutical products for other clients, such as private healthcare establishments.

This industrial structure participates in planning, particularly in the development and implementation of supply programs based on domestic production, as well as import programs for pharmaceutical products based on the national needs expressed by the Minister of Health. To avoid any shortage of medication, the Central Pharmacy establishes strategic and emergency (ORSEC) stocks in accordance with the standards set by health authorities. Nevertheless, the Central Pharmacy is committed to carrying out regulatory actions in the procurement of pharmaceutical products in accordance with the applicable laws.

Table 1.1: The Central Pharmacy of Hospitals in Numbers

Employees	More than 1000
Annex	05
Clients	621 public health establishments 1,396 various clients
Suppliers	89 local suppliers 158 foreign suppliers
Marketed products	1760 Products

4.3 THE MISSIONS OF THE CENTRAL PHARMACY OF HOSPITALS

As part of the national health policy, the central pharmacy has the following missions[3]:

1. To supply public healthcare establishments with pharmaceutical products and medical devices, within the framework of procurement procedures on behalf of these establishments. The list of products is determined by decision of the Minister of Health.

[3]Official Central Pharmacy of Hospitals in Algeria website: http://www.pch.dz/

2. To develop and implement supply programs based on domestic production.
3. To develop an import program for pharmaceutical products based on national needs expressed by the Ministry of Health.
4. To market pharmaceutical products for the benefit of public and private healthcare establishments.
5. To market pharmaceutical products to authorized establishments responsible for the distribution of pharmaceutical products and to pharmacies.
6. To carry out actions to regulate the supply of pharmaceutical products in accordance with applicable legislation and regulations.
7. To manufacture medicines, including generic drugs.
8. To carry out the packaging of pharmaceutical products.
9. To establish retail outlets for pharmaceutical products to ensure product availability throughout the national territory.
10. To provide technical assistance, as part of a partnership, to any operator involved in the pharmaceutical industry.
11. To carry out public service obligations defined in Article 4 bis in accordance with the specifications attached to the decree.

4.4 THE CENTRAL PHARMACY OF HOSPITALS RESPONSIBILITY

And as part of public service obligations, the central pharmacy is responsible for [7]:
1. Holding a strategic stock of pharmaceutical products.
2. Holding an emergency stockpile (ORSEC) of pharmaceutical products determined by the Ministry of Health.
3. Supplying public healthcare establishments with pharmaceutical products intended for the treatment of rare diseases and life-threatening conditions. The lists of diseases and the corresponding pharmaceutical products are determined by order of the Minister of Health.
4. Supplying public healthcare establishments with pharmaceutical products as part of national prevention programs and national health plans, as well as the related pharmaceutical products, as determined by order of the Minister of Health.

5. The central pharmacy has exclusive rights in the importation and commercialization of blood products and narcotics.

4.5 PROCEDURE FOR PHARMACEUTICAL AND MEDICAL DEVICE RECEPTION IN PCH

The information presented in this section is sourced from the Procedure for Pharmaceutical and Medical Device Reception in PCH documents [22]. Figure 1.2 presents a concise overview of the information discussed in the subsequent sections. The procedure involves several key steps to ensure the smooth reception and verification of pharmaceutical and medical device deliveries in The Central Pharmacy of Hospitals.

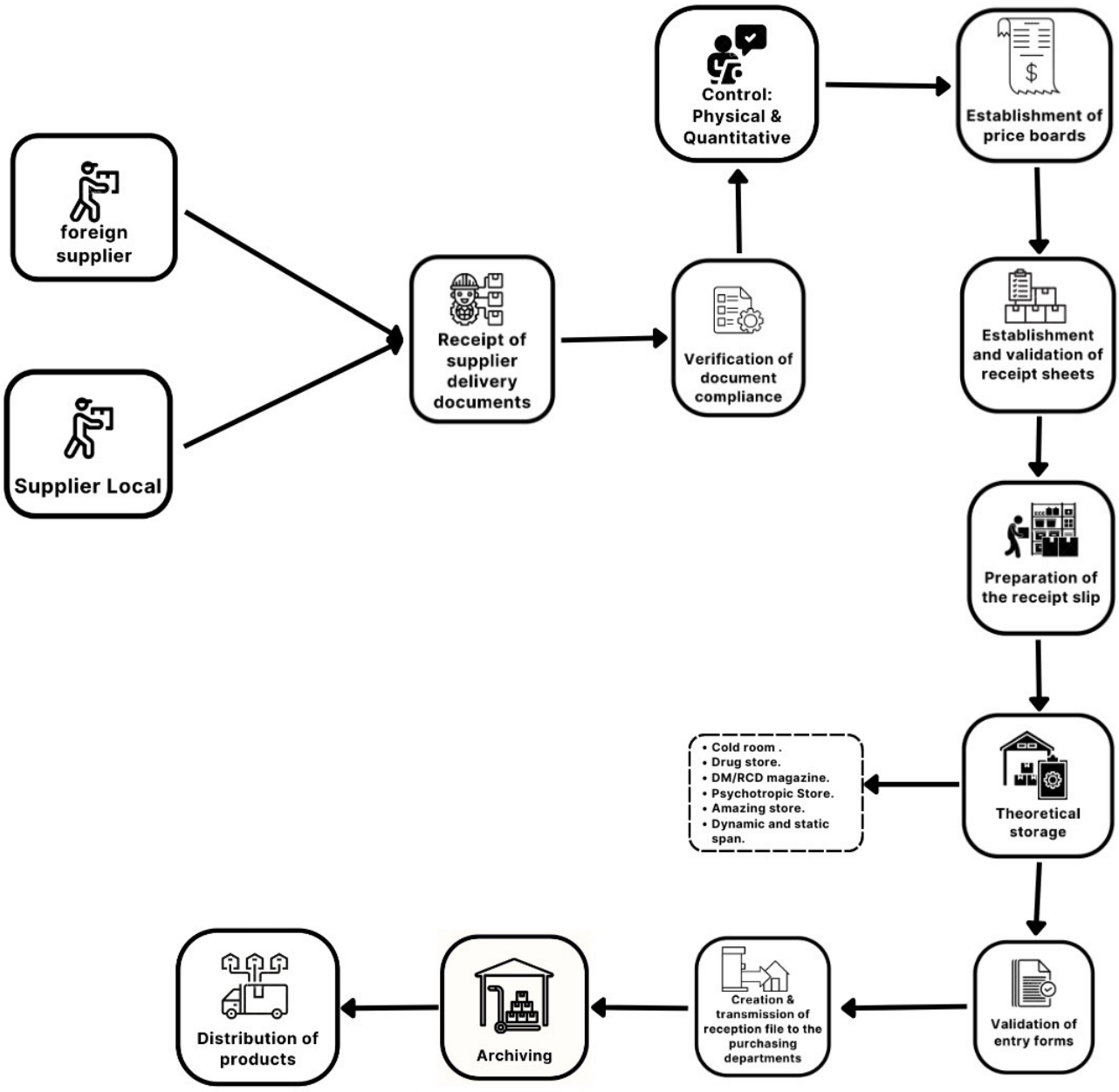

Figure 1.2: Procedure for Pharmaceutical and Medical Device Reception in PCH

- **Receipt of Supplier Delivery Documents**

  The reception of delivery documents from both local and foreign suppliers is handled by the respective department head responsible for receiving medicines and medical devices. Local suppliers are required to provide documents such as invoices, supplier delivery notes, and additional technical documents based on their status. For foreign suppliers, the necessary

documents include invoices, transit delivery notes, customs documents, packing lists, import programs, and transportation notes. In cases of transfers between annexes, invoices and delivery notes are required. These processes ensure smooth operations and compliance in the supply chain [22].

- **Document Verification**

  The heads of the receiving department and the pharmacist carefully check the presence and accuracy of all the documents mentioned in section 6.1. For local suppliers, if any issues with the documents are found, the goods are not received. In the case of foreign suppliers, if there are any documentary anomalies, the goods are received, and a request for rectification or additional documents is made to the relevant department. Priority is given to products with specific storage requirements or security measures [22].

- **Physical Inspection**

  the department head or pharmacist conducts a qualitative check based on the delivery documents, product information, and purchase order. They verify essential details such as product designation, dosage, unit of measurement, lot number, and expiry date. The reception personnel subsequently unload the goods as per standard procedures [22].

- **Quantity Control**

  The department head and their team count the received goods. They follow steps such as sorting the products and lots, counting the units for each lot, and palletizing if necessary. Once all verifications are completed, the delivery note with acknowledgment of receipt is given to the local supplier or transit agent. In case of any qualitative or quantitative discrepancies, an anomaly report is prepared, and if there is a quantity discrepancy, it is noted on the delivery note [22].

- **Creation and Validation of Receipt Records**

  The procurement department enters the purchase order data into the system. The data entry agent then fills in and prints the receipt record using the SNAKE application, including information such as supplier details, date of receipt, invoice and delivery note numbers, product details, quantities, and observations. The record is reviewed, signed, and validated by the pharmacist and the head of the receiving department. The validated receipt records and relevant documents are transmitted to the appropriate departments [22].

- **Price List Creation**

  The pricing department, headed by the pricing manager or tariff specialist, establishes the

price list based on the validated receipt records for each type of supplier. The information from the validated receipt records is used to create the price list for each product. For foreign suppliers, additional information from the customs document D10 is taken into account to determine the prices. The completed price list is signed by the tariff specialist and validated by the pricing department head [22].

- **Receipt Preparation**
  The pricing department prepares the receipt note based on the validated price lists. Each note is assigned a sequential number and may include observations if necessary. A discrepancy note is created for any discrepancies in the delivered quantity compared to the invoiced quantity. The provisional receipt note and discrepancy note, if applicable, are reviewed and signed by relevant personnel during the receipt process [22].

- **Theoretical Storage**
  The receiving department proceeds with the theoretical storage of the received goods using the PROSTOCK application. Addresses are assigned based on the storage conditions, nature, and specificities of the product, such as cold storage room, medication warehouse, medical devices/reagents warehouse, psychotropic storage, controlled substance storage, dynamic and static aisles. Entry forms, storage receipts, and address sheets are printed. The pallets are labeled with the corresponding address sheets for dynamic and static storage. The products, accompanied by the storage receipts (dynamic/static storage and warehouses), are handed over to the storage and distribution department for physical storage [22].

- **Validation of Entry Forms**
  The entry form contains the recorded information of the received product, including:
  - Supplier name and country
  - Invoice number and date
  - Contract number and date
  - Receipt note number and date
  - Product code and description
  - Invoiced quantity and delivered quantity
  - Lot number and unit of measurement
  - DDP (Delivery Duty Paid)

- Any relevant observations

The entry form is reviewed and validated by the head of the receiving department and the pharmacist of the department [22].

- **Reception File Compilation and Transmission**
The reception file is compiled and sent to the purchasing departments in the following steps [22]:
  - Ensure all necessary documents are included in the reception file.
  - Prepare a dispatch register for the reception files.
  - Obtain signatures on the reception form from the head of the reception department, the deputy director of operations, and the director of DSD.
  - Perform a final check of the reception file and the dispatch register.
  - Send the dispatch register to the purchasing departments.
  - Record the date of receipt acknowledgment.
  - Send the reception files to the archives for storage.

- **Archiving**
the archivist compiles and organizes the reception files. This includes verifying the presence of all necessary documents, such as signed reception forms, invoices, delivery notes, pricing sheets, and storage records. The documents are digitized through scanning and stored appropriately. The files are then classified and archived based on the year, supplier name, and reception form number. The archived files are kept in the reception department's archive room and may also be transferred to the central archive of the organization [22].

4.6 CRITICISMS OF THE PROCEDURE

- **Time-consuming in calculation process:** A major criticism of these methods is that the drug calculation process is time-consuming. The stages of quantifying and verifying the quantity of each product can take some time and cause delays in the overall collection process. Given the importance of quick access to medicines, this can be seen as a major disadvantage.

- **Lack of Efficiency:** Numerous manual checks, documentation and calculations related to the receiving process contribute to inefficiency and increase the risk of error. Relying on manual tasks can lead to delays, redundant tasks, and an increased chance of errors. This inefficiency

not only wastes valuable time, but also jeopardizes inventory management and patient care. Implementing streamlined procedures and using technologies such as automated data entry and digital documentation can help improve efficiencies, reduce errors, and increase the overall efficiency of PCH.

- **Complicated paperwork:** The high amount of paperwork in the approval process increases the administrative effort and costs valuable time. The need for proper document organization and storage adds complexity. Streamlining and digitizing documentation can alleviate these challenges, streamlining the process and reducing the time and effort required for document management. In addition, sending acceptance documents for validation and approval can cause communication delays. Timely collaboration and communication between relevant departments and employees is essential for efficient operations.Implementing effective communication channels and establishing clear protocols for document exchange can help reduce these delays and improve overall workflow efficiency.

- **Limited Automation:** The procedures appear to rely heavily on manual data entry and paper-based documentation, which can be prone to errors and time-consuming. The lack of automation or digital systems may hinder the ability to streamline processes, track data efficiently, and generate accurate reports.

4.7 OBJECTIVES AND MOTIVATION

Pharmaceutical components constitute a significant part of the operating expenses of hospitals. It was pointed out by many researchers that inventory costs in the health sector are estimated to be more than 10% of total expenses [23]

Therefore, any measure to control inventory costs can have a significant impact on the overall efficiency of the whole system. This is the main purpose of the hospital supply chain, which is an internal supply chain that aims, in terms of pharmaceutical products, to ensure that patients are to obtain timely, reliable access to their therapies at minimum cost.
The motivation behind the creation of an intelligent system is to address the existing challenges and limitations of the reception procedures for pharmaceutical products and medical devices and facilate the PCH missions .

These procedures often involve time-consuming calculations, extensive paperwork, potential errors, and delayed communication. To overcome these issues, the objectives of the intelligent system are to improve efficiency, reduce errors, simplify documentation, and enhance communication

within the supply chain. By achieving these objectives, the system aims to streamline the reception process, optimize inventory management, and ensure timely access to vital information.

Limitations of Barcode Usage in Medication Calculation

In considering potential solutions to improve the calculation of medications, one approach that may come to mind is the use of barcodes. However, implementing barcode scanning for medication calculation poses its own challenges. Firstly, many medication packages do not come pre-equipped with barcodes, necessitating the manual affixing of barcodes to each package. This process is not only time-consuming but also impractical due to the large number of medications involved. Additionally, the adhesive nature of barcode labels may not adhere well to certain medication packaging materials, leading to potential scanning errors and inaccuracies. Another limitation of using barcodes for medication calculation is the potential for scanning errors. While barcode scanning is commonly used in supermarkets and retail environments, the process is not always foolproof. There can be instances where the barcode does not scan automatically on the first attempt, requiring manual intervention to ensure accurate scanning. In a critical setting like medication calculation, where precision is paramount, relying solely on barcode scanning could introduce delays and increase the likelihood of errors if manual confirmation becomes necessary. Given these constraints, alternative methods need to be explored to ensure efficient and accurate medication calculation without relying solely on barcodes.

Given these constraints, alternative methods need to be explored to ensure efficient and accurate medication calculation without relying solely on barcodes. In light of this, our intelligent recognition system presents a promising solution. In the upcoming chapter, we will delve into the details of our system, which leverages advanced object recognition techniques to streamline the medication calculation process. By eliminating the need for barcodes and offering a more efficient and reliable approach, our system aims to address the challenges associated with manual barcode scanning and enhance the overall efficiency and accuracy of medication calculation.

5 CONCLUSION

In summary, the application of machine learning techniques in the pharmaceutical supply chain (PSC) is very important to improve its efficiency and effectiveness. PCH plays a key role in ensuring drug availability for patients in Algeria, and its effact directly on healthcare outcomes.

Given the challenges PCH faces, including the need to facilitate inventory management, and

logistics , it becomes clear that an intelligent supply chain system is required. This system, which will be discussed in the next chapter, aims to use algorithms and machine learning techniques to overcome these challenges and help PCH achieve its goals.

CHAPTER 2

INTELLIGENT SUPPLY CHAIN SYSTEM FOR PCH

1 INTRODUCTION:

In this chapter, we present our intelligent supply chain system tailored to address the unique requirements of the Central Pharmacy of Hospitals (PCH). This system represents a comprehensive approach that encompasses various aspects of the pharmaceutical supply chain, leveraging advanced algorithms and machine learning techniques. While this thesis focuses on a specific component of the overall system, it is essential to understand the broader context in which the PCH operates. It is important to recognize that this intelligent supply chain system represents a holistic and interconnected approach to transforming the PCH's operations and aims to revolutionize the operations of the PCH by streamlining processes, optimizing inventory management practices, and enhancing drug discovery capabilities. By harnessing the power of machine learning (ML) algorithms and techniques, the PCH can achieve higher levels of accuracy, efficiency, and resilience in managing the pharmaceutical supply chain in Algeria, and overcome challenges such as inventory management, logistics optimization, and medication recognition, thereby significantly improving the efficiency and effectiveness of the entire pharmaceutical supply chain in Algeria.

2 INTELLIGENT SUPPLY CHAIN SYSTEM:

Figure 2.1: Intelligent Supply Chain System

3 OUR OBJECTIVES :

Our contribution to this project primarily focuses on three key tasks within the intelligent supply chain system as described above.

- In Task 2, we propose to develop an advanced Inventory Management module that employs object recognition techniques to control the number of medications that is available in the center and therefore optimize stock levels, minimize waste, and ensure an adequate supply of medications to meet demand.
- We suggest adding an Analytics and Reporting module (Task 7). This component generates comprehensive reports on the number of medications in the center, providing valuable insights into inventory trends, consumption patterns, and potential areas for improvement.
- To enhance operational efficiency and streamline communication, propose to integrate Task 6, an automated report distribution system: Once the reports are generated in Task 7, this module automatically sends them to the responsible personnel, eliminating the need for manual distribution and ensuring timely access to vital information. By automating this process, we not only save valuable time and effort but also enable prompt action and enable proactive measures to maintain optimal medication stock levels.

Our contributions in these areas empower the Pharmacy Centrale des Hôpitaux (PCH) to effectively manage its medication inventory, make data-driven decisions, and streamline its reporting processes. Ultimately, this enhances the overall efficiency and productivity of the supply chain, enabling PCH to better fulfill its mission of providing essential pharmaceutical products to public and private healthcare establishments.

3.1 DETAILED DESCRIPTION OF OUR SYSTEM

This segment outlines the steps involved in our intelligent supply chain system. Figure 2.2 provides an overview depiction of the process. We focus on a specific part of our system, which involves the use of AI for efficient inventory management.

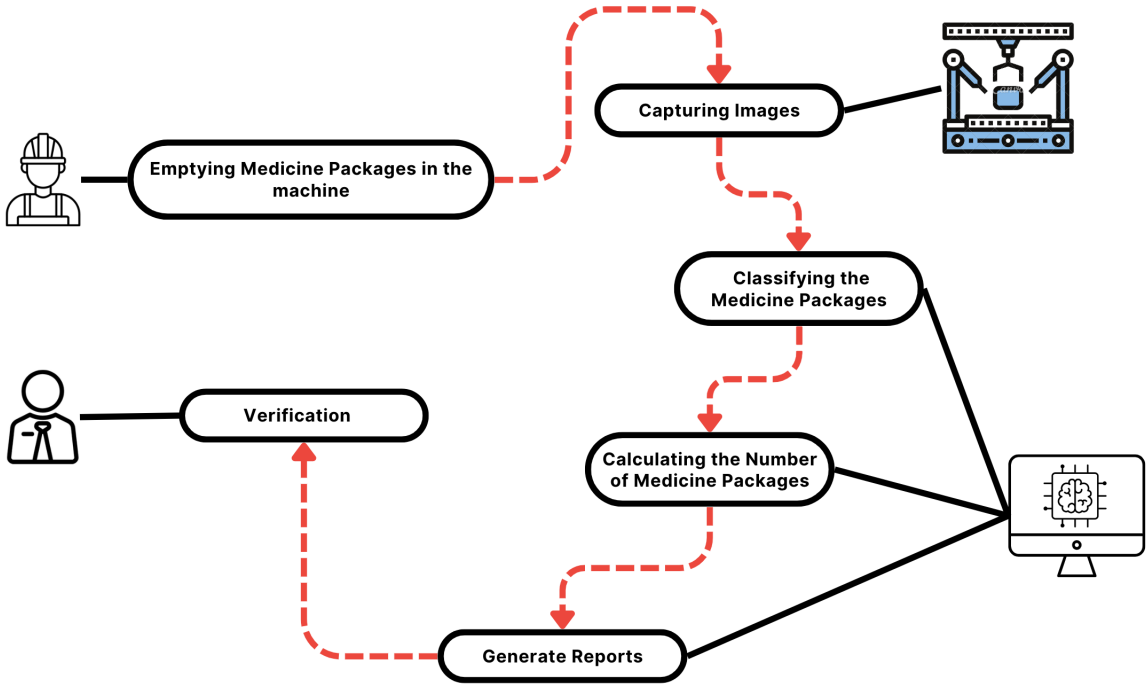

Figure 2.2: Our project process

Step 1: Emptying medicine packages and capturing images

The first step involves the workers emptying the medicine packages onto a wide surface, such as a table. Then, images are taken of the packages from the top using a camera.

Step 2: Detecting and classifying the medicine packages

The second step involves using AI to recognize each medicine package through the captured image. The AI algorithm uses machine learning techniques to identify the unique features of each medicine package, such as its color, shape, and size, to classify it into a specific category.

Step 3: Calculating the number of medicine packages

The third step involves using an algorithm to count the number of medicine packages in each class. The algorithm can analyze the images to determine the number of packages based on their unique features and characteristics.

Step 4: Generating Reports

The final step involves generating reports on the number of medicines of each class, their type, and all the details. The reports can be sent automatically to the workers in real-time, allowing the latter to make informed decisions about inventory management.

3.2 BENEFITS OF THE PROPOSED SOLUTION

The proposed solution offers several benefits over the traditional manual counting method. The use of AI eliminates the need for manual counting, reducing the time and effort required for the task. Additionally, AI algorithms are highly accurate and can reduce the risk of human error in counting medicines. The use of AI can also provide real-time data on medicine availability, allowing for more efficient inventory management and reducing the risk of overstocking or stockouts.

4 CHALLENGES

While using AI to improve pharmaceutical supply chain management through automated medicine counting can offer many benefits, there are also some challenges that need to be addressed. Some of these challenges include:

• **Data Quality:** The effectiveness of AI in counting medicine packages relies on the quality of the images used. If the images are blurry, distorted or have poor lighting, it can lead to inaccurate classification and counting of medicine packages.

• **Technical Expertise:** The implementation of an AI-powered solution requires technical expertise to set up and maintain the system. It may be challenging for some organizations to find and hire qualified personnel with the necessary skills and expertise to set up and operate the system.

• **Cost:** Implementing an AI-powered solution requires an investment in technology, equipment, and personnel. The cost of implementing such a system may be a barrier for some organizations, particularly those with limited resources.

• **Privacy and Security:** The use of AI in managing sensitive data related to patient health and medicine inventory requires appropriate privacy and security measures to be in place to prevent unauthorized access and data breaches.

• **Integration with Existing Systems:** Integrating an AI-powered solution with existing systems such as inventory management and electronic health records can be challenging. This requires careful planning and collaboration between different departments within the organization.

• **Scalability:** The solution may need to be scalable to meet the needs of different hospital sizes

and locations, which may require additional resources and technical expertise.
Addressing these challenges requires careful planning, implementation, and ongoing maintenance of the AI-powered solution. Overall, overcoming these challenges can lead to improved efficiency, accuracy, and cost-effectiveness in pharmaceutical supply chain management.

5 CONCLUSION

In this chapter we presented an overview of our perspective about an intelligent supply chain system for the Central Hospital Pharmacy and the involved tasks.
In this thesis we mainly focus on three tasks: Inventory management, reporting, and partial automation of the workflow.
Our proposed solution represents a substantial stride forward in the management of the supply chain in PCH. By harnessing the capabilities of artificial intelligence (AI) technology, specifically in the field of medicine recognition and counting, we aim to develop a system that facilitates inventory management processes as well as the automation of the workflow by sending automatically generated reports, which will lead to reducing time and effort.
An integral part of our solution's success the type of data. Since the data that address our problem domain in not available, we create a suitable dataset for PCH, we ensured that by creating our custom dataset, This personalized approach strengthens the reliability and accuracy of our system, further enhancing its practical utility within the pharmaceutical supply chain management domain.
Looking ahead to the next chapter, we focus into the critical process of data generation. This chapter will provide a detailed overview of the methodology and techniques employed to create a custom dataset for training and testing our AI models.

CHAPTER 3

DATA GENERATION

1 INTRODUCTION

In this chapter, we provide the process of generating a custom dataset for our research project. We faced many challenges where existing datasets did not adequately address our problem domain. Therefore, we decided to create our dataset. We give an overview of the data generation process, including dataset collection, data preprocessing, annotation steps, data augmentation techniques, and dataset splitting strategies.

2 GENERATING THE DATASET:

2.1 DATASET COLLECTION:

Since the data that address our problem domain is not available we collected data from the pharmacy, we took multiple pictures of each medication class from different angles and lighting conditions to ensure that the dataset is diverse and representative. Since the quantities of these rare medications are limited in the pharmacy, it is challenging to capture enough images to train the AI model. However, by taking multiple pictures of each medication, we were able to increase the size and diversity of the dataset, which is very important for training an accurate model, Figure 3.1 shows more details about each medication.

Medication	class	Dosage	Conditioning	Indications
Adipine LP	Nifédipine	20mg	30 Microgranule release capsule	• For adults from 18 years old. • Indicated in the treatment of arterial hypertension.
Biorava	Immunosuppresseur	20 mg	20 comprimés pelliculé	• For adults from 18 years old. • This drug is an immunosuppressant. It decreases the immune defenses and the chronic inflammation of the joints. It has a slow-acting antirheumatic effect.
NOLVADEX	ANTIESTROGENE	20 mg	30 comprimés pelliculé	• For adults from 18 years old. • In adjuvant treatment of breast carcinoma
Pulsagen	Nicardipine	50 mg	60 Microgranule release capsule	• For adults from 18 years old. • This medication is indicated for the treatment of high blood pressure.
TRIMETAZIDINE B	Anti Angineux	20 mg	30 comprimés pelliculé	• For adults from 18 years old. • Prophylaxis of Angina Chest Attacks, Adjunctive in Dizziness and Tinnitus
SETREME	Ondansétron	8 mg	28 comprimés pelliculé	• For adults and children from 6 years old. • Indicated for the prevention and treatment of nausea and vomiting induced by chemotherapy and radiotherapy.
Clovirax	Aciclovir	200 mg	30 comprimés pelliculé	• For adults and children from 6 years old. • Indicated in Infections of the skin or mucous membranes and Infections of the eyes Arterial hypertension
Moxonidine	BIOGARAN	o.4 mg	30 comprimés pelliculé	• For adults from 18 years old. • Is used in the treatment of high blood pressure (hypertension).
Nostrogene	PROGYNOVA	1 mg	30 comprimés pelliculé	• For women over 65 years old. • Hormone replacement therapy (HRT) for symptoms of estrogen deficiency in postmenopausal women (at least 6 months since the last menstrual period).
OXYPTANE BR	Chlorhydrate	5mg	60 comprimés pelliculé	• For adults and children from 6 years old. • Urinary incontinence (involuntary emission of urine day or night)

Figure 3.1: Medication Information

2.2 DATA PREPROCESSING:

In the data preprocessing phase, the collected images from the pharmacy were prepared for further analysis. The process involved two main steps: removing irrelevant images and manually creating composite images that contain multiple medications in a single image. **Filtering and Cleaning:** The first step was to clean the collected images and identify any images that were irrelevant, a filtering step was performed to eliminate any images with poor quality, or low resolution. This ensured that the dataset only included clear and usable images for further analysis. Therefore, any images that did not meet the predefined criteria were also removed.

Creating composite images

After removing the irrelevant images, the next step involved manually creating composite images that contain multiple medications in a single image. This process was done by carefully arranging and positioning individual medication images together to form a composite image, some images contained repetitions of the same medication, while others consisted of a mixture of different medications within a single image as depicted in Figures 3.2 and 3.3 . The aim was to ensure clear visibility and readability of each medication within the composite image.

Figure 3.2: Different medications within a single image

Figure 3.3: Same medication within a single image

Creating these composite images manually offers several advantages. It provides more control over the arrangement and positioning of medications, allowing for better visualization and analysis.

2.3 ANNOTATED IMAGES AND GROUND TRUTH:

Image annotation is the task of annotating an image with labels. It ensures that the model recognizes an annotated area as a distinct object or class in a given image [24]. This involves creating bounding boxes "for object detection" to distinguish between objects of different classes. [24]
Image annotation is often used to generate training data sets for learning algorithms. In our project we used Roboflow for annotation using two different tools :

a) Bounding box

The bounding box involves drawing a rectangle around a certain object in a given image. The edges of bounding boxes ought to touch the outermost pixels of the labeled object.

b) Polygon tool

We picked the Polygon tool and simply we started drawing a line made of individual points around the object in the image. The line doesn't need not be perfect, as once the starting and ending points are connected around the object, roboflow will automatically create anchor points that can be adjusted for the desired accuracy.

Figure 3.4: Example of images Annotation

2.4 DATA AUGMENTATION

For data augmentation in medicament recognition, traditional methods can often yield satisfactory. In this study, the used traditional data augmentation techniques were employed: Grayscale, Blur, and Noise.

1. Grayscale: Grayscale conversion involves transforming the original color image into a grayscale representation. This technique reduces the dimensionality of the data and removes color information, while retaining essential text features. Grayscale augmentation can be beneficial as it simplifies the image, making it easier for subsequent recognition algorithms to focus on the textual content without being distracted by color variations [25].

Figure 3.5: Example of image with Grayscale.

2. Blur: Blur augmentation applies a blur filter to the image, simulating the effect of out-of-focus or motion blur. This technique introduces slight blurriness to the image, which can help in the real-world scenarios where the quality of the captured images may vary due to factors such as camera movement or imperfect focus. By augmenting with blur, the model is exposed to a wider range of image variations, enhancing its ability to recognize text even in less sharp or blurry images [26].

Figure 3.6: Example of image with Blur.

3. Noise: Noise augmentation involves introducing random variations to the pixel values of the image. This technique helps simulate image imperfections. By adding noise to the image, the model becomes more robust to such distortions and can generalize better to unseen images with similar imperfections [27].

Figure 3.7: Example of image with Noise.

By applying grayscale, blur, and noise augmentation, the dataset is augmented with a diverse range of variations, allowing the model to learn and adapt to different image qualities, lighting conditions, and noise levels.

2.5 DATA GENERATION USING DIFFUSION BASED MODELS

Dall-E and Stable Diffusion Image Variations, despite their impressive capabilities in generating images, may face challenges when tasked with generating images with text and capture spelling information from the image [28].
We tried to using Diffusion Models like Dall-E and Stable Diffusion to generate more Image however Image Variations may not yield satisfactory results, As its showing in the Figures 3.8 and 3.9 .

Figure 3.8: Images generated by DALL-E

Figure 3.9: Image generated by Stable Diffusion

2.6 DATASET SPLIT

In order to prepare the data for the model, we divided the data into three subsets: a training set comprising 87% (432 samples), a test set comprising 5% (23 samples), and a validation set

comprising 8% (40 samples). As part of the preprocessing, data augmentation techniques were applied exclusively to the training set. This augmentation process resulted in the generation of three additional images for each original image.

Table 3.1 shows more details about the data.

Parameter	Value
Medication Classes	10
Number of images for each class	7-12
All images before augmentation	207
Number of images after augmentation	495

Table 3.1: Summary of Medication Classes and Image Data

3 CONCLUSION

In conclusion, the process of generating a custom dataset has played a crucial role in the success of our solution, specifically in addressing the problem domain of pharmaceutical supply chain management (PCH).

By collecting data directly from the pharmacy, we ensured that our dataset captured the unique characteristics and variations present in real-world scenarios. The annotation process, added valuable ground truth information to the dataset. This enabled the model to distinguish between different medication classes, enhancing its accuracy in medication recognition tasks.

The creation of composite images, data augmentation techniques allowed for better visualization and analysis. This manual approach provided greater accuracy and reliability of our system.

The dataset we generated has proven to be an invaluable asset in the development our system. By addressing the lack of available data and tailoring the dataset to our specific needs, In the next chapter we have ensured the effectiveness and relevance of our solution in real-world PCH applications, by delve into the image recognition task and its use in the inventory management task, with a specific focus on the methods we will make use of in our system.

CHAPTER 4

IMAGE RECOGNITION

1 INTRODUCTION

Image recognition is a subfield of artificial intelligence (AI) and computer vision that focuses on the development of algorithms and techniques to enable machines to understand and interpret visual data, specifically digital images [29].
By analyzing the pixel values and patterns present in an image, image recognition algorithms can identify and classify objects, detect specific attributes or characteristics, and make predictions based on the visual information provided [29].

In our contribution, we address the image recognition problem in the context of medication information extraction. we used Optical Character Recognition (OCR) techniques to extract the textual information from medication images. However, the results obtained from OCR did not align with the requirements of our problem. Consequently, we moved to object detection techniques to achieve our objectives.

Image recognition systems leverage machine learning and deep learning techniques, particularly convolutional neural networks (CNNs), to extract meaningful features from images and make accurate predictions [29]. In this chapter, we review the relevant literature on object detection methods, such as YOLO (You Only Look Once) algorithm and the Faster RCNN (Region-based Convolutional Neural Networks) algorithm.

2 OPTICAL CHARACTER RECOGNITION

2.1 OVERVIEW:

OCR is a technology that convert different types of documents such as scanned paper documents or images captured by a digital camera into editable and searchable data. It involves transforming the visual representation of characters into machine-readable text [30]. Image recognition for OCR typically utilizes a combination of image preprocessing techniques, feature extraction, and machine learning algorithms. These algorithms are trained on large datasets of annotated images containing text to learn the patterns and structures of characters, allowing the AI system to recognize and extract text accurately from various sources [30].

2.2 OCR FOR OUR SYSTEM

The recognition of text within the boxes of medicaments is crucial for our System, including inventory management. Optical Character Recognition (OCR) has traditionally been a popular method for text extraction, we applied OCR with Tesseract for recognizing the text within the boxes of medicaments, To perform this, our algorithm goes through these important steps:
1. loading the image
2.Initialize the text recognition module " easyocr" for the input image.
3.Iterate over the detected results.
4.Extract the bounding box coordinates and recognized text.
5.If the extracting text matches the word "Adapin",we drow a bonding box in it's coordinates.
6.Display the modified image
The Figure 4.1 shows the output after applying OCR for one of our images as we can see that it doesn't detect the text from all the boxes of medicaments.

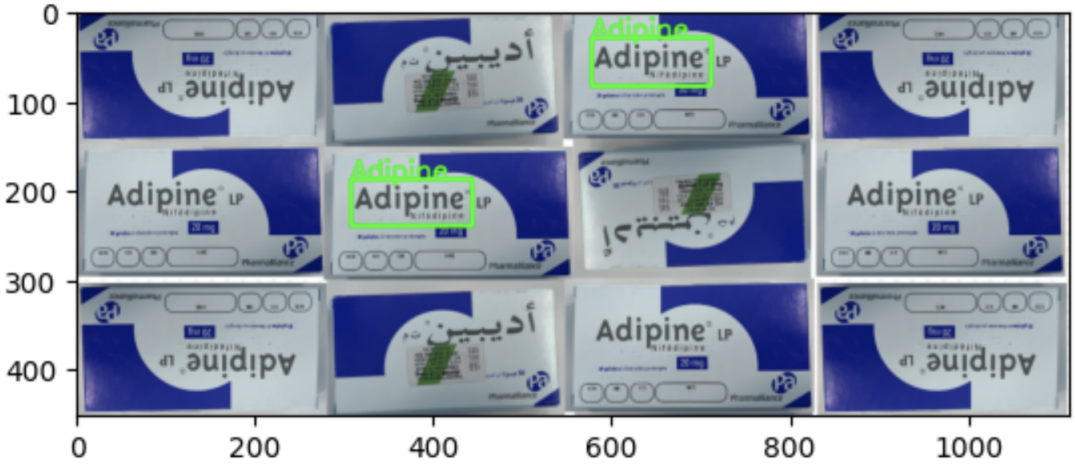

Figure 4.1: Example of Optical Character Recognition results

2.3 LIMITATIONS OF OCR IN MEDICAMENT RECOGNITION

While OCR has made significant advancements in recent years, it still falls short in terms of accuracy when compared to a second-grade child how can comprehend and reproduce text with relative accuracy [31].
This is some limitations that we faced in OCR on our project:

- **Lack of Contextual Relationship Extraction** OCR algorithms typically extract text in a character-by-character manner without considering the context or relationship between different textual elements. This limitation hampers the accurate association of dosage information with the respective medicament name.

- **Inadequate Handling of Rotated Boxes** When the boxes of medicaments are rotated in the image, OCR algorithms often fail to extract the text accurately. This limitation results in a significant drop in the overall recognition performance.
  This research aims to focuses on the recognition of text within the boxes of medicaments from images, with the aim of extracting accurate information such as the names of all the medicaments and their corresponding dosages. The conventional Optical Character Recognition (OCR) method was initially considered for this task, but its performance was found to be inadequate due to the inability to establish a reliable relationship between the extracted dosage and the corresponding medicament name. Additionally, OCR struggled with extracting information accurately from rotated boxes. As a result, alternative approaches are explored in

this study to overcome these limitations and enhance the overall performance of medicament recognition.

3 OBJECT DETECTION

3.1 OVERVIEW

Object detection refers to the task of identifying and localizing multiple objects within an image or video [32]. It combines both classifying the objects and specifying their precise locations using bounding boxes [33]. Object detection algorithms are capable of detecting and labeling multiple objects simultaneously 4.2. Image classification involves predicting the class of one object in an image. Object localization refers to identifying the location of one or more objects in an image and drawing abounding box around their extent.

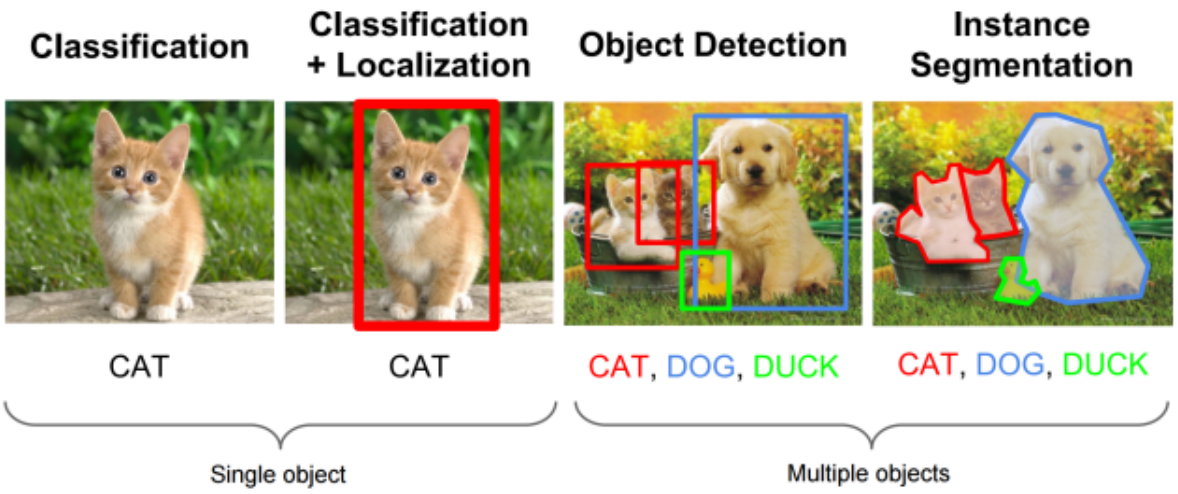

Figure 4.2: Overview of Object Recognition Tasks

As such, we can distinguish between these three computer vision tasks:

1. **Classification:** Predict the type or class of an object in an image.
   - Input: An image with a single object, such as a photograph.
   - Output: A class label (e.g. one or more integers that are mapped to class labels).
2. **Localization:** Locate the objects in an image and indicate their location with a bounding box.
   - Input: An image with one or more objects, such as a photograph.

- Output: One or more bounding boxes (e.g. defined by a point, width, and height).

3. Object Detection: Locate the presence of objects with a bounding box and types or classes of the located objects in an image [32].

- Input: An image with one or more objects, such as a photograph.
- Output: One or more bounding boxes (e.g. defined by a point, width, and height), and a class label for each bounding box.

One further extension to computer vision tasks is object segmentation, also called "object instance segmentation" or "semantic segmentation," where instances of recognized objects are indicated by highlighting the specific pixels of the object instead of a coarse bounding box.

3.2 DEEP LEARNING METHODS FOR OBJECT DETECTION

In the field of deep learning (DL) there are various methods used in object detection domain, and each one of them gives a different results. In this section we will see those methods and the architecture of each one. Those methods are presented under two categories as it shown in Figure 4.3

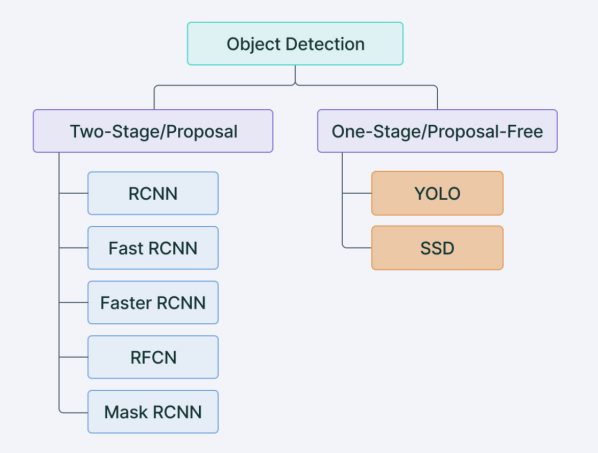

Figure 4.3: One and two stage detectors [2]

TWO STAGE PROPOSAL

In Two Stage Proposal method they divide the detection process in two steps. The first step uses a Region Proposal Network to generate regions of interests that have a high probability of being

an object [2]. The second step then performs the final classification and bounding-box regression of objects by taking these regions as input. These two steps are named the Region Proposal Step and the Object Detection Step respectively. Such models reach the highest accuracy rates, but are typically slow [34]. Figure 4.4 shows the Two stage proposal Architecture.

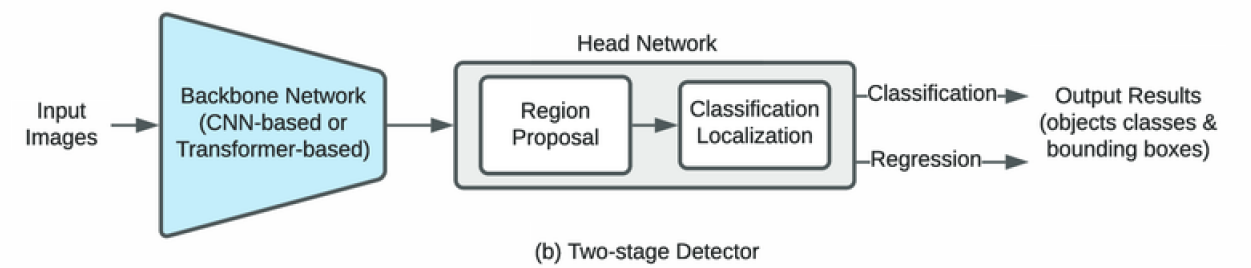

Figure 4.4: Two stage proposal Architecture

4 FASTER RCNN (REGION-BASED CONVOLUTIONAL NEURAL NETWORKS):

4.1 OVERVIEW:

The Faster R-CNN model, developed by a group of researchers at Microsoft, is a deep convolutional network used for object detection. It appears to the user as a single, end-to-end, unified network and can accurately and quickly predict the locations of different objects. To fully understand Faster R-CNN, it is important to be familiar with its predecessors, R-CNN and Fast R-CNN. Faster R-CNN is an extension of Fast R-CNN and is faster thanks to the region proposal network (RPN) [9].

Faster R-CNN is a single unified model, the architecture is comprised of two modules:

RPN (Region Proposal Network) : Convolutional neural network for proposing regions and the type of object to consider in the region [9].

Fast R-CNN : Convolutional neural network for extracting features from the proposed regions and outputting the bounding box and class labels.

Both modules operate on the same output of a deep CNN. The region proposal network RPN acts as an attention mechanism for the Fast R-CNN network, informing the second network of where to look or pay attention [9].

Faster R-CNN is a popular version of the R-CNN family and utilizes specific search algorithms for proposing regions . These algorithms take a few seconds per image and run on CPU computation. The introduction of RPN reduces the region proposal generation time from seconds to milliseconds per image [35].

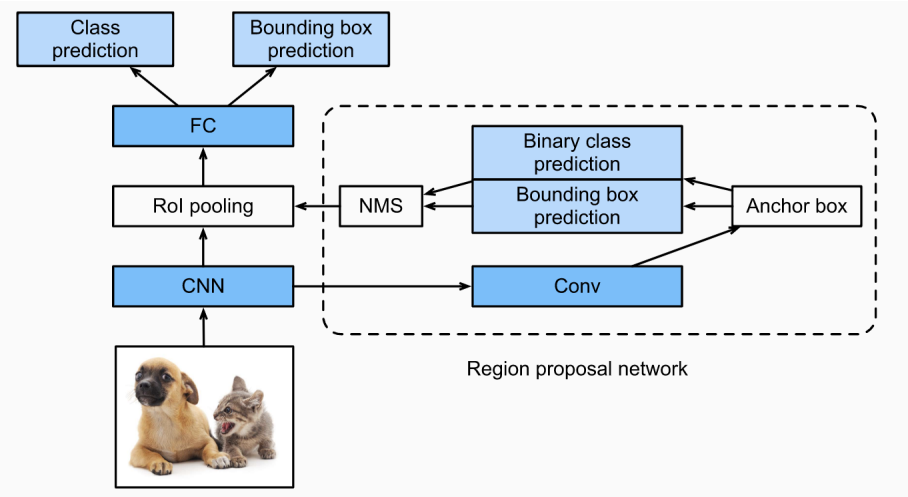

Figure 4.5: The Faster RCNN.

4.2 FASTER R-CNN ARCHITECTURE:

In the Faster R-CNN architecture:

- The RPN is used to generate bounding boxes that specify the position, class, and confidence of an object [36].
- CNN is typically used to generate features of these objects. Region proposal is performed on the final feature image, which is then input into the ROI pooling layer. [36]
- The output from the ROI pooling layer has a size of (N, 7, 7, 512), where N is the number of proposals.
- After passing through two fully connected layers, the features are fed into the classification and regression branches [36].
- The classification layer determines the object's class. [36]
- The regression layer refines the coordinates of the bounding boxes for greater precision and fewer errors [36].
- Anchors are introduced in the RPN to handle different scales and aspect ratios of objects. Each anchor is associated with a scale and aspect ratio and is located at the center of each spatial window [37].

4.3 FASTER RCNN TRAINING PROCESS

In the training process of Faster R-CNN, there are two main types of loss functions used: classification loss and regression loss.

1. RPN Loss: The region proposal network (RPN) is trained to generate accurate region proposals [38]. It involves two loss components:

a. RPN Classification Loss: This loss measures the discrepancy between the predicted probabilities and the ground truth labels for the anchors. The binary cross-entropy loss function is commonly used for this [38]:

$$L_{\text{cls}}^{\text{RPN}} = -\frac{1}{N_{\text{cls}}} \sum_{i=1}^{N_{\text{cls}}} y_i^{\text{RPN}} \log(p_i^{\text{RPN}}) + (1 - y_i^{\text{RPN}}) \log(1 - p_i^{\text{RPN}}) \tag{4.1}$$

b. RPN Regression Loss: This loss measures the difference between the predicted bounding box coordinates and the ground truth bounding box coordinates for positive anchors. The smooth L1 loss function is commonly used for this:

$$L_{\text{reg}}^{\text{RPN}} = \frac{1}{N_{\text{reg}}} \sum_{i=1}^{N_{\text{reg}}} \text{Smooth}_{L1}(t_i^{\text{RPN}} - t_i^{\text{RPN,gt}}) \tag{4.2}$$

2. Object Detection Loss: The object detection network is trained to classify and refine the proposed regions [38]. It also involves two loss components:

a. Object Detection Classification Loss: This loss measures the discrepancy between the predicted class probabilities and the ground truth class labels for the proposed regions [38]. The softmax cross-entropy loss function is commonly used for this:

$$L_{\text{cls}} = -\frac{1}{N_{\text{cls}}} \sum_{i=1}^{N_{\text{cls}}} y_i \log(p_i) \tag{4.3}$$

b. Object Detection Regression Loss: This loss measures the difference between the predicted bounding box coordinates and the ground truth bounding box coordinates for positive proposed regions [38]. The smooth L1 loss function is commonly used for this:

$$L_{\text{reg}} = \frac{1}{N_{\text{reg}}} \sum_{i=1}^{N_{\text{reg}}} \text{Smooth}_{L1}(t_i - t_i^{\text{gt}}) \tag{4.4}$$

These loss functions capture the differences between the predicted and ground truth values for both the region proposals and the proposed regions, guiding the network's training process in Faster R-CNN [38].

There are existing libraries and frameworks, such as Detectron2, mmdetection, and TensorFlow Object Detection API, that provide pre-implemented Faster R-CNN architectures and training pipelines [38]. These libraries can simplify the training process by providing convenient APIs and utilities for dataset handling, model configuration, and training loops.

ONE STAGE PROPOSAL

In one stage they treat object detection as a simple regression problem by taking an input image and learning the class probabilities and bounding box coordinates [34]. The approach is simple and elegant because it completely eliminates region proposal generation, encapsulating all computation in a single network [2]. Such models are much faster than two-stage object detectors and shown higher memory efficiency. Figure 4.6 shows the Two stage proposal Architecture.

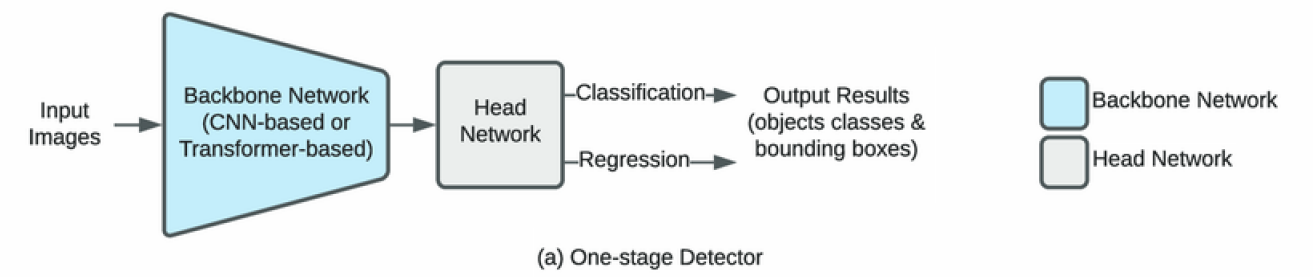

Figure 4.6: One stage proposal Architecture

5 YOLO (YOU ONLY LOOK ONCE)

5.1 OVERVIEW

The YOLO algorithm, introduced by Redmon et al. (2016), revolutionized object detection by introducing a single-shot approach. Unlike traditional methods that use region proposal techniques, YOLO divides the input image into a grid and predicts bounding boxes and class probabilities directly. This enables real-time object detection with impressive accuracy [8]. YOLO achieves this by utilizing a deep convolutional neural network architecture, which extracts high-level features from

the input image and performs object classification and localization simultaneously. One key advantage of YOLO is its speed, making it suitable for applications that require real-time performance. However, YOLO's grid-based approach may lead to localization inaccuracies for small objects or objects with complex spatial structures [8].

This thesis focuses on the latest version of YOLO, YOLO v8, which builds upon the foundation laid by its predecessors. YOLO v8 showcases several significant improvements that contribute to its state-of-the-art performance in object detection tasks. These advancements include novel architectural designs, refined training strategies, and the integration of cutting-edge deep learning techniques. By exploring these developments, we aim to provide a comprehensive understanding of the capabilities and advancements of YOLO v8, shedding light on its relevance and potential in the field of computer vision.

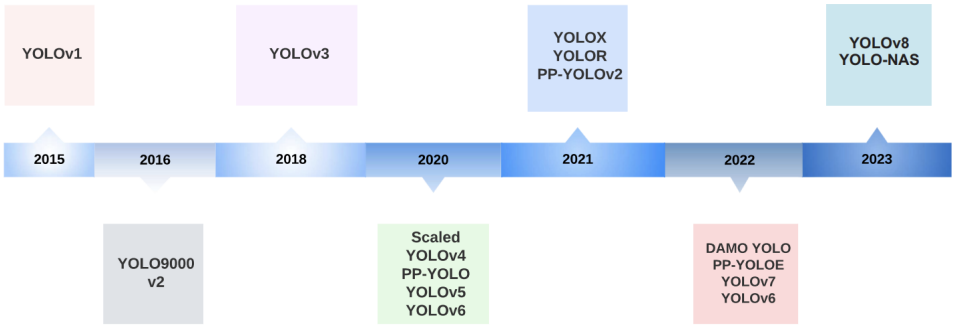

Figure 4.7: Yolo timeline [3]

5.2 YOLO ARCHITECTURE

YOLO is divided into four parts: Input, Backbone, Neck, and Output [39] as showing in the Figure 4.11.

Model Backbone

The backbone is a pre-trained network used to extract rich feature representation for images. This helps reducing the spatial resolution of the image and increasing its feature (channel) resolution. YOLO v8 typically utilizes Darknet, a deep convolutional neural network, as the backbone [39]. The backbone network processes the image through multiple convolutional layers to capture hierarchical features.

Model Neck

The model neck is used to extract feature pyramids. This helps the model to generalize well to objects on different sizes and scales [39].

Model Head

The model head is used to perform the final stage operations. It applies anchor boxes on feature maps and render the final output: classes , objectness scores and bounding boxes [39].

5.3 HOW DOES YOLO FUNCTION

Residual blocks

This first step starts by dividing the original image into NxN grid cells of equal shape, where N in our case is 7 as it is shown on the image on the right. Each cell in the grid is responsible for localizing and predicting the class of the object that it covers, along with the probability/confidence value.

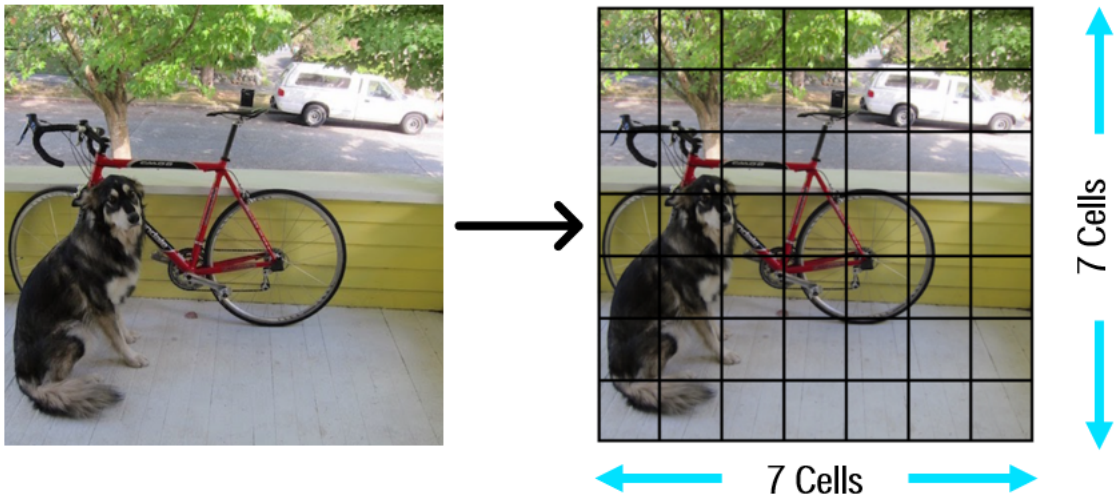

Figure 4.8: 7x7 grid cells

Anchor Boxes

Anchor boxes are pre-defined bounding boxes of different sizes and aspect ratios that are used to predict object locations and sizes in YOLO-based object detection algorithms [3]. The next step is to determine the bounding boxes which correspond to rectangles highlighting all the objects in the image. We can have as many bounding boxes as there are objects within a given image. YOLO determines the attributes of these bounding boxes using a single regression module in the following format, where Y is the final vector representation for each bounding box.

Y = [pc, bx, by, bh, bw, c1, c2]

This is especially important during the training phase of the model.

pc : Corresponds to the probability score of the grid containing an object.

bx, by : Are the x and y coordinates of the center of the bounding box with respect to the enveloping grid cell.
bh, bw : Correspond to the height and the width of the bounding box with respect to the enveloping grid cell.
c1, c2 : Correspond to the classes. We can have as many classes as use case requires.

Prediction

Each grid cell predicts bounding boxes and class probabilitiesas it showing in Figure 4.9 .
For each anchor box, the model predicts four coordinates (x, y, w, h) representing the bounding box's center, width, and height.
The class probabilities are computed for each grid cell and indicate the likelihood of an object belonging to a specific class [3].

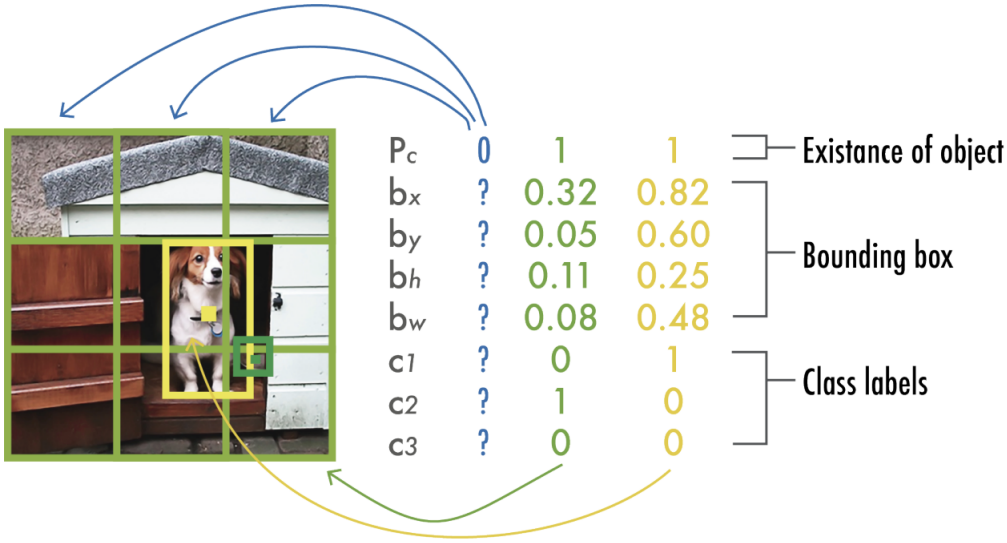

Figure 4.9: YOLO output prediction [3]

Confidence of the existence of the object

Each candidate bounding box predicted by YOLO is assigned a confidence score. This score indicates the likelihood that the box contains an object and reflects the accuracy of the predicted object. Higher confidence scores imply a higher probability of object presence [40].

$$P_o = P_r(\text{Class}_i \mid \text{Object}) \times P_r(\text{Object}) \times \text{IOU}_{\text{pred}}^{\text{truth}} \tag{4.5}$$

Po: represents the confidence score of the object detection candidate.
Pr(class object): is the predicted probability of the class i given the presence of an object. It indicates the likelihood of the candidate belonging to the specific class i [40].
Pr(object): is the predicted probability of the presence of an object. It represents the confidence score assigned to the existence of an object in the candidate bounding box [40].
IOU: the Intersection over Union (IOU) between the predicted bounding box and the ground truth bounding box. It measures the extent of overlap between the two boxes, providing an indication of the accuracy of the detection [3].

Non-Max Suppression (NMS)

Setting a threshold for the IOU is not always enough because an object can have multiple boxes with IOU beyond the threshold, and leaving all those boxes might include noise. Here is where we can use NMS to keep only the boxes with the highest probability score of detection.
NMS eliminates redundant bounding box detections and keeps only the most confident ones based on a threshold [3].
It helps to remove overlapping detections and improve the final results.

$$\text{NMS}(B, \text{IOU}_{\text{threshold}}) = \{b_i \in B : \text{IOU}(b_i, b_j) < \text{IOU}_{\text{threshold}}$$

for all $b_j \in B$ and b_i has the highest confidence score in its class

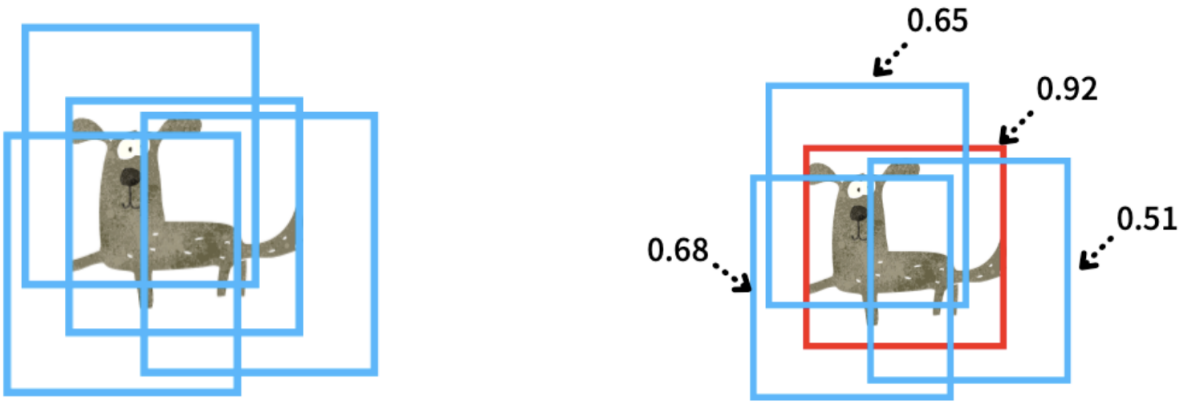

Figure 4.10: Before and After Non-Max Suppression (NMS)

5.4 YOLO TRAINING PROCESS

YOLO uses a custom loss function that combines the localization loss, classification loss, and confidence loss. The localization loss measures the accuracy of the bounding box predictions, while the classification loss measures the accuracy of the predicted class labels. The confidence loss measures the reliability of the confidence scores assigned to each bounding box prediction. These three components are combined to form the total loss function used for training the YOLO model [3].

$$L_{\text{total}} = L_{\text{loc}} + L_{\text{cls}} + L_{\text{conf}} \tag{4.6}$$

Localization Loss (Bounding Box Regression Loss): During training, YOLO v8 utilizes a localization loss function to evaluate the accuracy of bounding box predictions. The localization loss measures the discrepancy between the predicted bounding box coordinates and the ground truth bounding box coordinates. By minimizing the localization loss, YOLO v8 learns to accurately localize objects within the image [3].

$$\text{Localization Loss} = \lambda_{\text{coord}} \left[(x - x')^2 + (y - y')^2 + \left(\sqrt{w} - \sqrt{w'}\right)^2 + \left(\sqrt{h} - \sqrt{h'}\right)^2 \right] \tag{4.7}$$

Confidence Loss: YOLO v8 also employs a confidence loss function to assess the confidence scores associated with each bounding box prediction. The confidence loss penalizes incorrect predictions and encourages higher confidence scores for accurate detections. This loss function helps YOLO v8 distinguish between true positive and false positive detections, improving the overall precision of object detection [3].

$$\text{Confidence Loss} = \lambda_{\text{noobj}} \left[\text{noobj\_mask} \cdot \log(1 - \text{confidence}) + \text{obj\_mask} \cdot \log(\text{confidence}) \right] \tag{4.8}$$

Classification Loss: In addition to localization and confidence losses, YOLO v8 incorporates a classification loss function to assess the accuracy of class predictions. The classification loss measures the discrepancy between the predicted class probabilities and the ground truth class labels. By minimizing the classification loss, YOLO v8 learns to assign the correct object classes to the predicted bounding boxes [3].

$$\text{Classification Loss} = \lambda_{\text{cls}} \cdot \text{class\_mask} \cdot (\text{class\_prediction} - \text{class\_label})^2 \tag{4.9}$$

5.5 YOLO v8

Figure 4.11 shows the detailed architecture of YOLOv8. YOLOv8 uses a similar backbone as YOLOv5 with some changes on the CSPLayer, now called the C2f module. The C2f module (cross-stage partial bottleneck with two convolutions) combines high-level features with contextual information to improve detection accuracy. YOLOv8 uses an anchor-free model with a decoupled head to independently process objectness, classification, and regression tasks. This design allows each branch to focus on its task and improves the model's overall accuracy [3]. In the output layer of YOLOv8, they used the sigmoid function as the activation function for the objectness score, representing the probability that the bounding box contains an object. The sigmoid function can be written as:

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{4.10}$$

It uses the softmax function for the class probabilities, representing the objects probabilities belonging to each possible class. The softmax function can be written as:

$$\text{softmax}(x_i) = \frac{e^{x_i}}{\sum_{j=1}^{n} e^{x_j}} \tag{4.11}$$

YOLOv8 uses CIoU [41] and DFL [3] loss functions for bounding box loss and binary cross-entropy for classification loss. These losses have improved object detection performance, particularly when dealing with smaller objects.

The CIoU loss function, referenced as [41], can be written as:

$$\text{CIoU}(B, \hat{B}) = 1 - \text{IoU}(B, \hat{B}) + \frac{d^2_{\text{center}}}{c^2} + \alpha \cdot v \tag{4.12}$$

where B and $\hat{B}$ are the predicted and ground truth bounding boxes, respectively. d_{center} represents the distance between the centers of the bounding boxes, c is the diagonal of the smallest enclosing box, and α is a parameter that balances the impact of the distance and aspect ratio terms. v is a term that encourages better localization and is defined as:

$$v = \frac{4}{\pi^2} \cdot \left(\arctan\left(\frac{w_{\hat{B}}}{h_{\hat{B}}}\right) - \arctan\left(\frac{w_B}{h_B}\right) \right)^2. \tag{4.13}$$

The DFL loss function, referenced as [3], can be written as:

$$\text{DFL}(B, \hat{B}) = \text{IoU}(B, \hat{B}) - \log\left(\frac{d^2_{\text{center}}}{c^2}\right) \tag{4.14}$$

where B and $\hat{B}$ are the predicted and ground truth bounding boxes, respectively. d_{center} represents the distance between the centers of the bounding boxes, and c is the diagonal of the smallest enclosing box.

YOLOv8 also provides a semantic segmentation model called YOLOv8-Seg model. The backbone is a CSPDarknet53 feature extractor, followed by a C2f module instead of the traditional YOLO neck architecture. The C2f module is followed by two segmentation heads, which learn to predict the semantic segmentation masks for the input image [3]. The model has similar detection heads to YOLOv8, consisting of five detection modules and a prediction layer. The YOLOv8-Seg model has achieved state-of-the-art results on various object detection and semantic segmentation benchmarks while maintaining high speed and efficiency [3].

Data augmentation techniques such as random flipping, scaling, translation, and mosaic augmentation are employed during training to enhance the model's generalization capabilities. The training process includes the use of albumentations library for data augmentation. The training data is processed with blur, median blur, grayscale conversion, and contrast-limited adaptive histogram equalization (CLAHE) transformations [3].
Evaluated on MS COCO dataset test-dev 2017, YOLOv8x achieved an AP of 53.9% with an image size of 640 pixels (compared to 50.7% of YOLOv5 on the same input size) with a speed of 280 FPS on an NVIDIA A100 and TensorRT. YOLOv8 can be run from the command line interface (CLI), or it can also be installed as a PIP package.

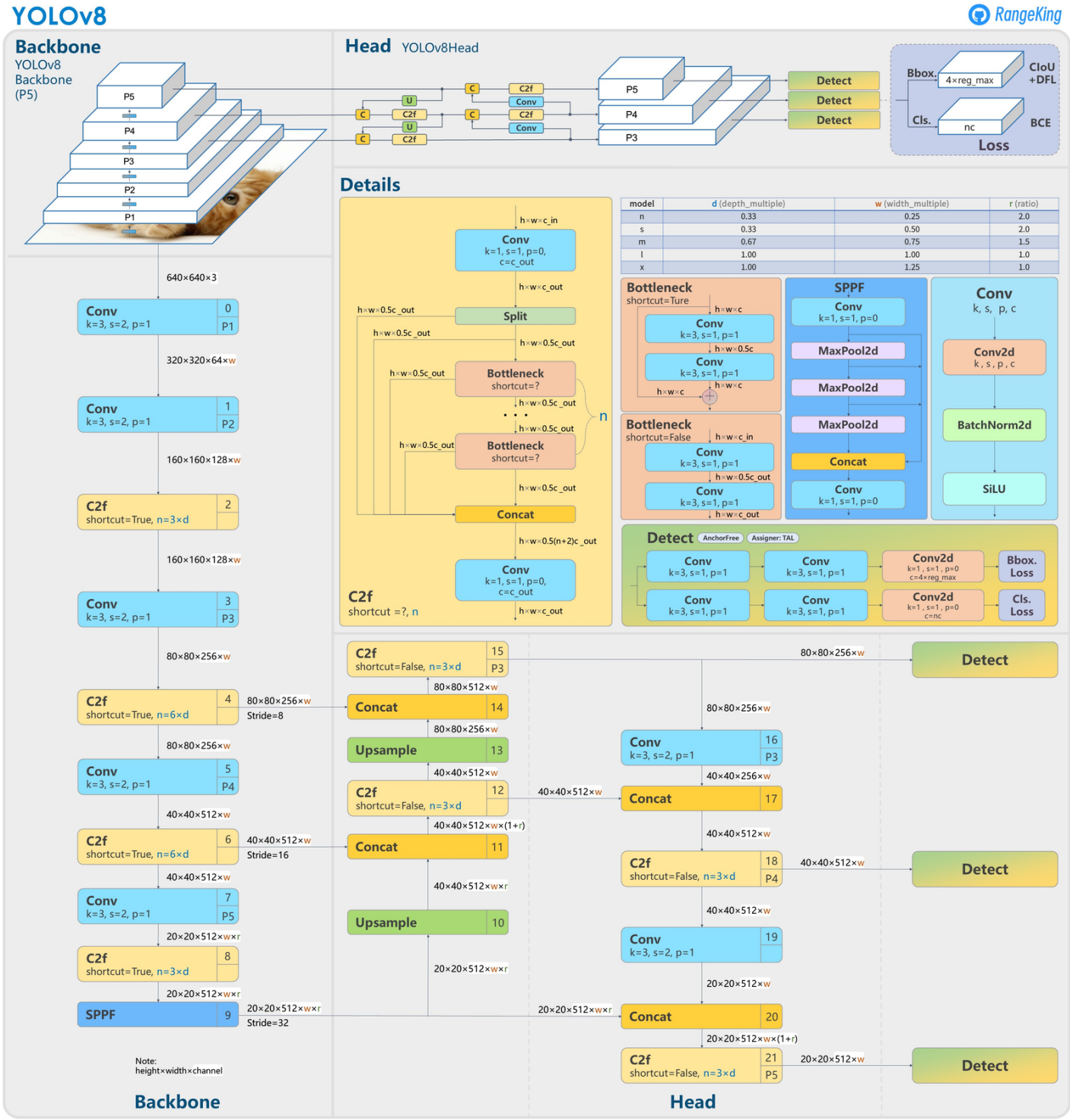

Figure 4.11: YOLO v8 Architecture

6 CONCLUSION

In this chapter, we have delved into various image recognition tasks and techniques. We have discussed two deep Learning techniques for object detection, such as YOLO ana Faster RCNN . By examining these tasks and techniques, we have gained valuable insights into the diverse aspects of image recognition.

In the next chapter, we further explore the performance of the YOLO and Faster RCNN models by conducting fine-tuning experiments. Fine-tuning involves training the pre-trained models on a specific dataset to improve their performance on a our task. By fine-tuning both the YOLO and Faster RCNN models, we aim to enhance their accuracy and speed in object detection, and comparing there the results obtained that allow us to determine their strengths and weaknesses in different scenarios.

CHAPTER 5

EXPERIMENT AND RESULTS

1 INTRODUCTION

In this chapter, we delve into the experimental phase of our research, where we aim to assess the performance and effectiveness of different object detection models on a custom dataset. The objective is to gain insights into the capabilities and limitations of popular models, such as YOLOv8 and Faster R-CNN, through transfer learning and fine-tuning processes. By conducting rigorous evaluations and analyzing the results, we aim to resolve on the applicability of these models in real-world scenarios.

2 CUSTOM DATASET DESCRIPTION

The custom dataset used for training and evaluation in this project consists of a total of 207 images, with each image containing multiple medications. Some Images contain over than 30 medications, belonging to 10 different types of medicament.
To facilitate the training process, annotations have been created for each image, resulting in a total of 2780 annotations. These annotations provide important information about the medications coordinates and the classes in the images, enabling the development of accurate models for medication recognition and classification, Figure 5.1 shows the classes balance and the number of annotations for each medication.

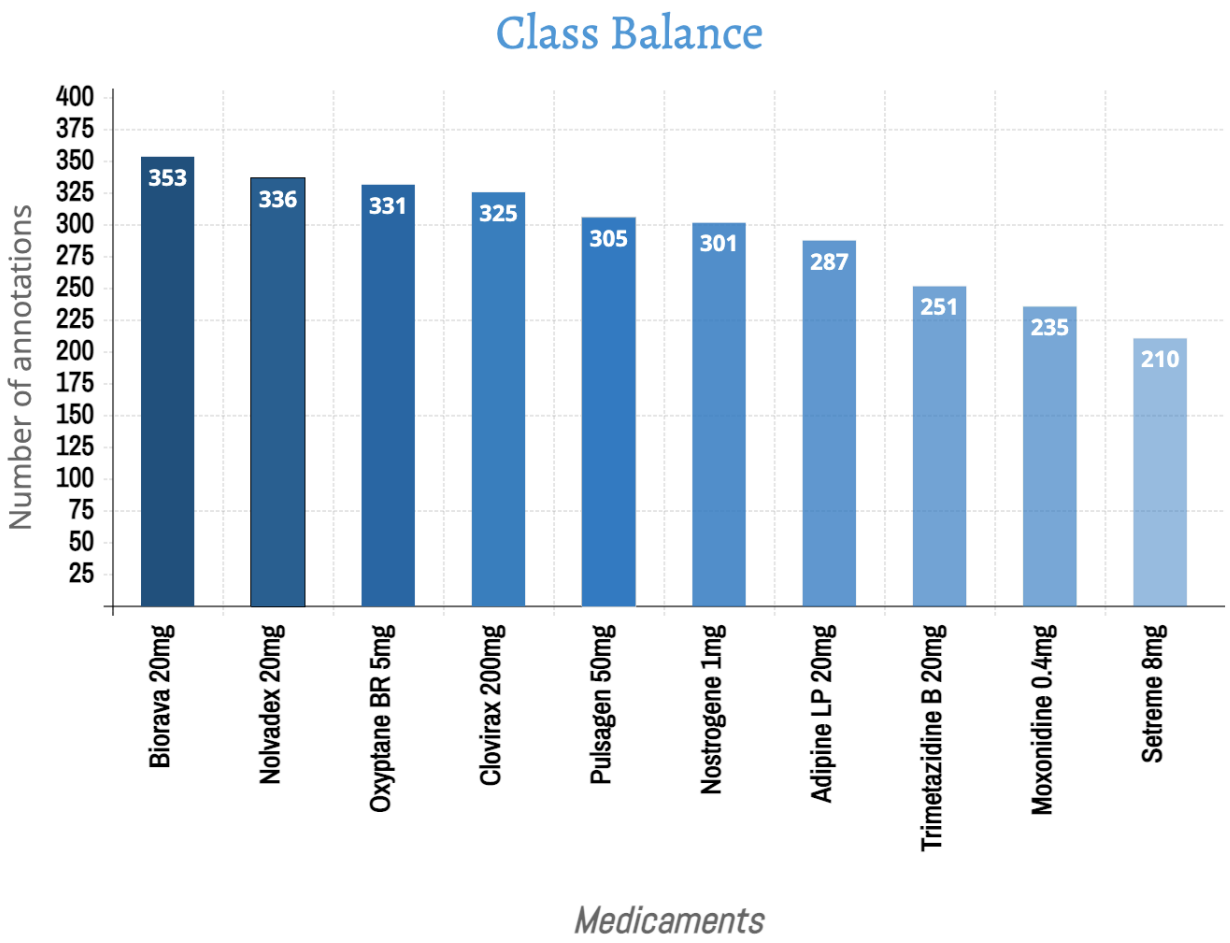

Figure 5.1: Number of annotations for each medication

Our custom dataset, with its comprehensive collection of images and detailed annotations, provides a valuable resource for training and evaluating medication detection models, the Table 5.1 shows more statistics details about our custom dataset.

Table 5.1: Custom Dataset Statistics

Category	Value
Images	207
Annotations	2,934
Annotations per Image (Average)	14.2
Classes	10
Average Image Size	2.95 MP
Minimum Image Size	0.17 MP
Maximum Image Size	12.19 MP
Median Image Ratio	2236x1462 (wide)

3 FINE-TUNING

In the Fine-tuning approach for both YOLOv8 and Faster R-CNN, pre-trained models are utilized and updating the wights. This allows the models to benefit from the knowledge learned on large-scale datasets such as ImageNet and adapt it to our specific object detection task.

3.1 FASTER R-CNN FINE-TUNING

For Faster R-CNN, the pre-trained model provided by **the Detectron2 library** . The model **faster-rcnn-X-101-32x8d-FPN-3x**, pre-trained on the COCO (Common Objects in Context) dataset. This model demonstrates strong performance in object detection tasks and can effectively handle complex scenes and diverse object categories. Similar to YOLOv8, the transfer learning process for Faster R-CNN involves fine-tuning the pre-trained model on the target dataset.

During the transfer learning process, adjustments are made to the network's hyperparameters. These modifications may include tuning the learning rate, batch size, and the number of training iterations to achieve optimal performance on the target dataset.

In the case of Faster R-CNN using Detectron2, the hyperparameters and settings used for transfer learning are as follows:

Batch size: The batch size used for training is set to 4. This means that the model processes four images in each training iteration before updating the weights.

Learning rate: The base learning rate is set to 0.001. This value determines the step size for updating the model's weights during training.

Maximum iterations: The maximum number of iterations is set to 500. This value can be adjusted

based on the validation mean Average Precision (mAP) to prevent overfitting or underfitting.
Learning rate schedule: The learning rate is adjusted at specific steps during training. In this case, the schedule is set to (200, 500), indicating that the learning rate is decreased at those iterations.
Gamma value: The gamma value used for adjusting the learning rate is set to 0.05.

3.2 YOLOv8 FINE-TUNING

For YOLOv8, the transfer learning process begins with the utilization of the pre-trained model yolov8s.pt. This model is trained on a large dataset containing various object categories. The choice of this model as the starting point is based on its effective architecture for object detection tasks, as well as its ability to handle small-sized objects. We used the 'detact' as a task in YOLOv8. The model architecture is specified in the **yolov8s.yaml** configuration file. The training data is provided through the data.yaml file. The model is trained for **250 epochs**, using a **batch size of 16** and images resized to a dimension of **224x224 pixels**. The transfer learning process involves optimizing the model using the Stochastic Gradient Descent (SGD) optimizer with a **learning rate of 0.01**, a **momentum of 0.937**, and a **weight decay of 0.001**. The learning rate is adjusted dynamically during training, with a warm-up period of 3 epochs.

The transfer learning on our dataset consisting of 10 classes, and the predictions are evaluated using an intersection over union (IoU) threshold of 0.7 and a confidence threshold of 0.001. The maximum number of detections per image is set to 300.

Table 5.2: Comparison of YOLOv8 and Faster R-CNN

Configuration	YOLOv8	Faster R-CNN
Task	Detect	Detect
Mode	Train	Train
Model	yolov8s.yaml	faster_rcnn_X_101_32x8d_FPN_3x.yaml
Epochs	250	500
Batch Size	16	4
Image Size	224x224	800x800
Learning Rate	0.01	0.001

4 RESULTS AND ANALYSIS

4.1 PERFORMANCE EVALUATION METRICS

We evaluated our methods using average precision (AP) and its mean (mAP) for both YOLO v8 an Faster RCNN.

Precision-Recall Curve

Precision-Recall Curve (P-R Curve) is a curve with recall as the x-axis and precision as the y-axis. Each point represents a different threshold value, and all points are connected as a curve. The recall (R) and precision (P) are calculated according to the following equations:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}, \quad \text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

where True Positive (TP) denotes the prediction result as a positive class and is judged to be true; False Positive (FP) denotes the prediction result as a positive class but is judged to be false, and False Negative (FN) denotes the prediction result as a negative class but is judged to be false.

Mean Average Precision

MAP is numerically equal to the average value of the AP sum across all categories, and this value is used to evaluate the overall performance of the model. The definition is shown in Formula

$$\text{MAP} = \frac{1}{n} \sum_{i=1}^{n} \text{AP}_i$$

The mAP is a good measure of the sensitivity of thenetwork while not raising many false alarms.

4.2 RESULTS OF YOLO V8

Performance of YOLO on the test dataset

After the implementation of YOLO v8 on our Custom Dataset the results that we get are representing in the following Figure 5.2 and 5.3 :

Figure 5.2: Yolo v8 results in Train

Figure 5.3: Yolo v8 results in Validation

The results obtained from the object detection using YOLOv8 are presented in the table 5.3. The model summary indicates that the network architecture consists of 168 layers with a total of 11,129,454 parameters.

Table 5.3: Performance Evaluation of YOLO v8

Class	Images	Instances	Box(P)	R	mAP50	mAP50-95
Adipine LP 20mg	40	31	0.956	0.935	0.964	0.937
Biorava 20mg	40	92	0.993	1	0.995	0.979
Clovirax 200mg	40	15	0.988	1	0.995	0.951
Moxonidine 0.4mg	40	28	0.951	0.929	0.903	0.885
Nolvadex 20mg	40	93	0.997	0.989	0.99	0.988
Nostrogene 1mg	40	88	0.999	1	0.995	0.966
Oxyptane BR 5mg	40	97	0.7	0.99	0.707	0.696
Pulsagen 50mg	40	75	0.963	0.427	0.547	0.518
Setreme 8mg	40	34	0.997	1	0.995	0.956
Trimetazidine B 20mg	40	71	0.972	0.985	0.991	0.947
All	**40**	**624**	**0.952**	**0.925**	**0.908**	**0.882**
Time	**250 epochs completed in 2.899 hours**					

Analyzing the detection performance, we observe the overall results includes a total of 40 images and 624 instances. The Box Precision (Box(P)) achieved is 0.952, indicating a high proportion of correct bounding box predictions, while the recall (R) is 0.925, representing a high rate of successful detection. The mean average precision at 50% IoU threshold (mAP50) is 0.908, indicating a good trade-off between precision and recall. The mAP50-95, which measures the mean average precision across various IoU thresholds, is 0.882.

Inspecting the individual classes, we observe varying detection performance. For "Adipine LP 20mg" achieves a precision of 0.956 and a recall of 0.935, resulting in a high mAP50 score of 0.964. Similarly, "Biorava 20mg" achieves a precision of 0.993, recall of 1.0, and an impressive mAP50 score of 0.995. On the other hand, "Pulsagen 50mg" exhibits lower precision (0.963) and recall (0.427), resulting in a lower mAP50 score of 0.547.

Regarding computational speed, the model demonstrates efficient performance. The inference time per image is 1.8ms, indicating fast processing of each input. The post-processing time per image is 1.2ms, suggesting efficient handling of the detected objects.

Performance Metrics of YOLO v8

The YOLO v8 model achieved satisfactory results in the object detection task as it showing in the Figure 5.4 , with generally high accuracies for most classes.

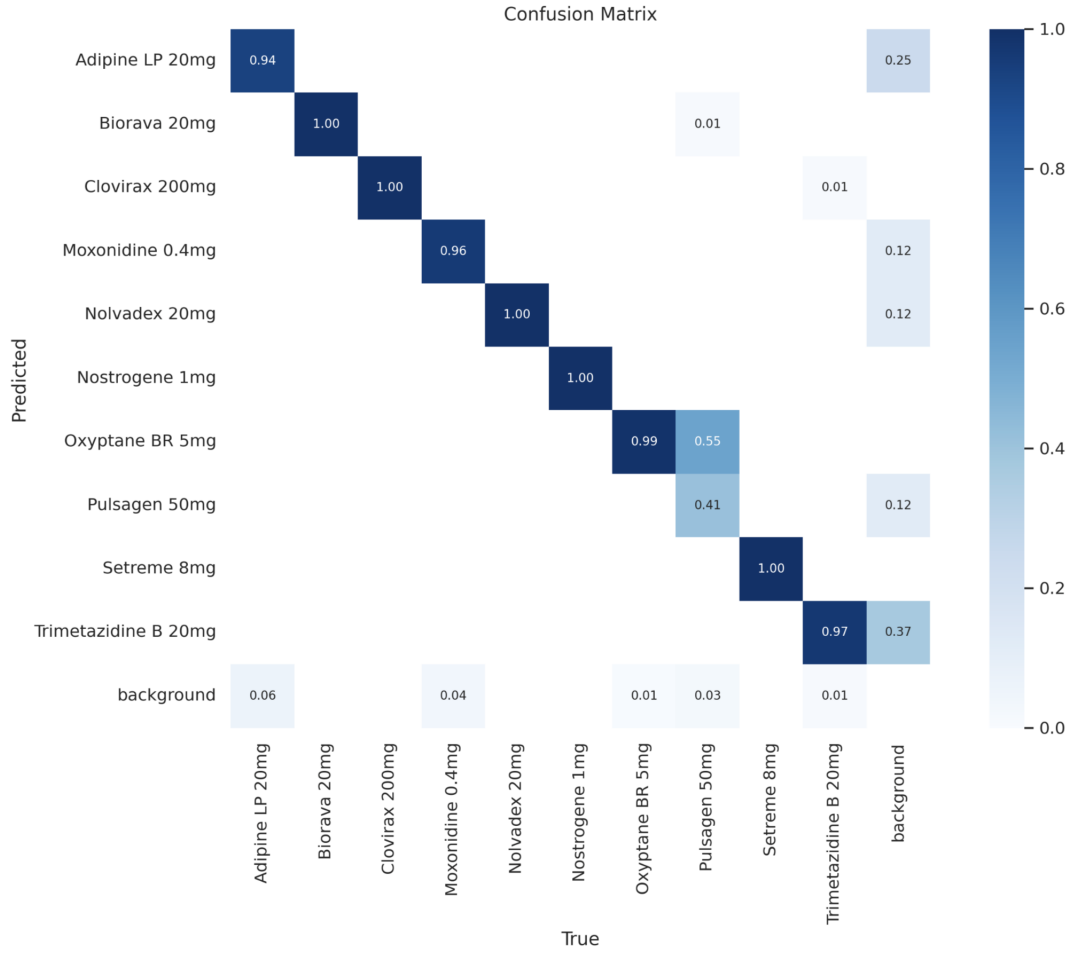

Figure 5.4: Confusion Matrix of YOLO v8

This is some Key observations from the confusion matrix:

- Adipine LP 20mg: The model achieved a notable accuracy of 94% in detecting Adipine LP 20mg, with only a 6% misclassification rate as a background.
- Biorava 20mg, Clovirax 200mg, Setreme 8mg, Nolvadex 20mg and Nostrogene 1mg : The model exhibited perfect accuracies of 100% for both classes, indicating accurate classification without any misclassifications.
- Moxonidine 0.4mg: The model showed a high accuracy of 96% in correctly identifying Moxonidine 0.4mg, with only a 4% misclassification as a background.
- Oxyptane BR 5mg: The model exhibited a high accuracy of 99% in correctly detecting Oxyptane BR 5mg, with only a 1% misclassification as a background.

- Pulsagen 50mg: The model showed a moderate accuracy of 41% in correctly identifying Pulsagen 50mg. Additionally, it had a higher accuracy of 55% in classifying them as Oxyptane BR 5mg, but no misclassifications were observed into other classes.

- Trimetazidine B 20mg: The model exhibited a high accuracy of 97% in correctly identifying Trimetazidine B 20mg. It had a minor misclassification as a background (1%), but no misclassifications occurred into other classes.

The YOLO v8 model demonstrated promising performance in detecting various pharmaceutical classes, with high accuracies observed for most classes.

Over multiple epochs, The loss values for box, class, and detection focal loss decrease, indicating improved localization, classification, and detection refinement as it showing in the Figure 5.5 of Training Curves and Figure 5.6 Validation Curves. Metrics such as precision, recall, mAP@50, and mAP@50-95 gradually improve, indicating increasing accuracy it showing in the Figure 5.7. Overfitting is not observed as the validation performance is consistent with the training set. The learning rate remains constant, and the model's performance stabilizes after a certain number of epochs. Overall, the results show promising advancements in the model's ability to detect and localize objects accurately.

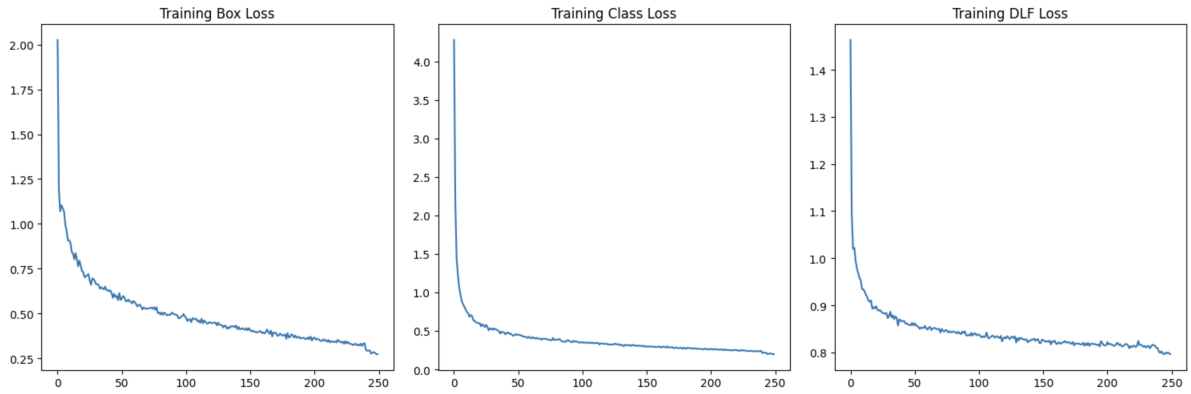

Figure 5.5: Training Curves

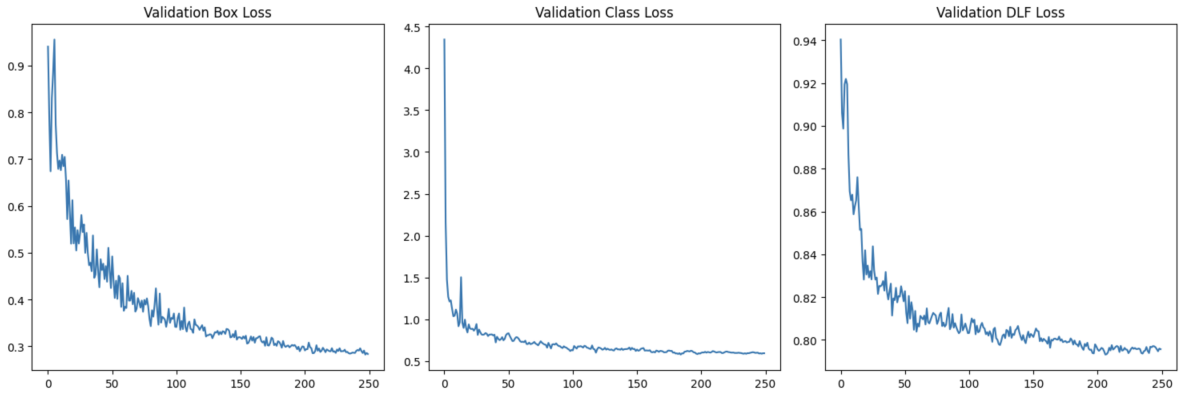

Figure 5.6: Validation Curves

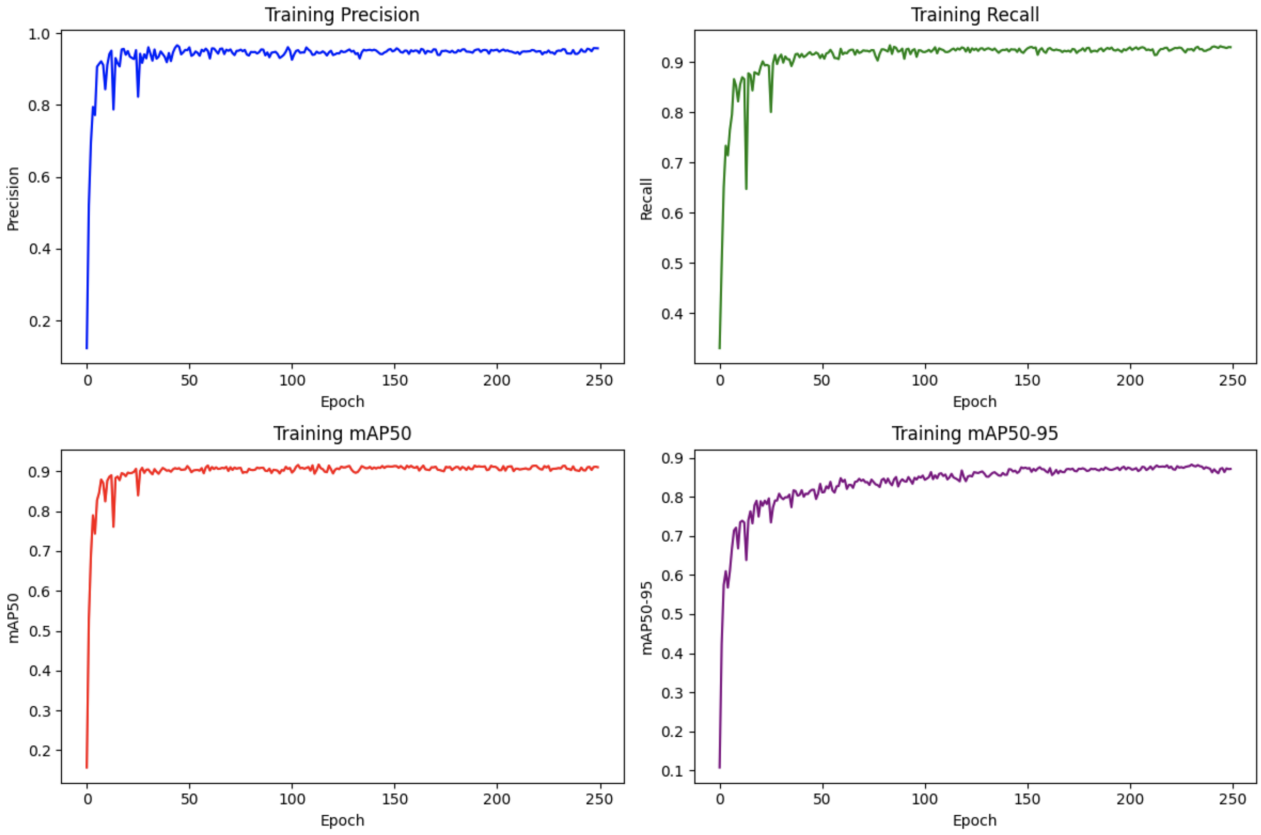

Figure 5.7: Training Metrics Progression

4.3 RESULTS OF FASTER RCNN

After the implementation of Faster RCNN on our Custom Dataset the results that we get are representing in the following Figure 5.8 :

Figure 5.8: Result of Faster RCNN

Performance of Faster RCNN on the test dataset

For Faster R-CNN model The following discussion focuses on the different loss components, including total loss, loss-cls, loss-box-reg, loss-rpn-cls, loss-rpn-loc, and loss-mask, as it showing in Figure 5.9 :

Total Loss: The total loss is an overall measure of the model's performance. It gradually decreases as the training progresses, indicating that the model is learning and improving its detection capabilities. The total loss values decrease from 3.473 to 0.6994 over the iterations.

Loss-cls: This loss component represents the classification loss, measuring the accuracy of predicting object classes. It exhibits a similar decreasing trend as the total loss, indicating that the model improves its ability to classify objects correctly. The loss-cls values decrease from 2.442 to 0.2781 over the iterations.

Loss-box-reg: This loss component corresponds to the regression loss for refining the bounding box coordinates of detected objects. The decrease in loss-box-reg indicates that the model becomes

more accurate in localizing objects with improved bounding box regression. The loss-box-reg values decrease from 0.825 to 0.2781 over the iterations.

Loss-rpn-cls: The loss-rpn-cls represents the classification loss for the region proposal network (RPN), which generates candidate object proposals. The decreasing trend in loss-rpn-cls suggests that the RPN becomes more effective in proposing regions likely to contain objects. The loss-rpn-cls values decrease from 0.1815 to 0.00172 over the iterations.

Loss-rpn-loc: This loss component measures the regression loss for refining the region proposals' bounding box coordinates. The decreasing values of loss-rpn-loc indicate that the model improves in accurately localizing the proposed regions. The loss-rpn-loc values decrease from 0.04677 to 0.005684 over the iterations.

Loss-mask: The loss-mask represents the segmentation loss, measuring the accuracy of object instance segmentation. The decreasing trend in loss-mask indicates that the model improves in accurately segmenting the objects. The loss-mask values decrease from 0.9785 to 0.2807 over the iterations.

Overall, the decreasing trends in the different loss components demonstrate the model's improvement over the training iterations.

It is important to note that the loss values alone do not provide a complete assessment of the model's performance. in the next step we discus average precision performance, to measure the model's accuracy and detection capabilities on a separate validation or test dataset.

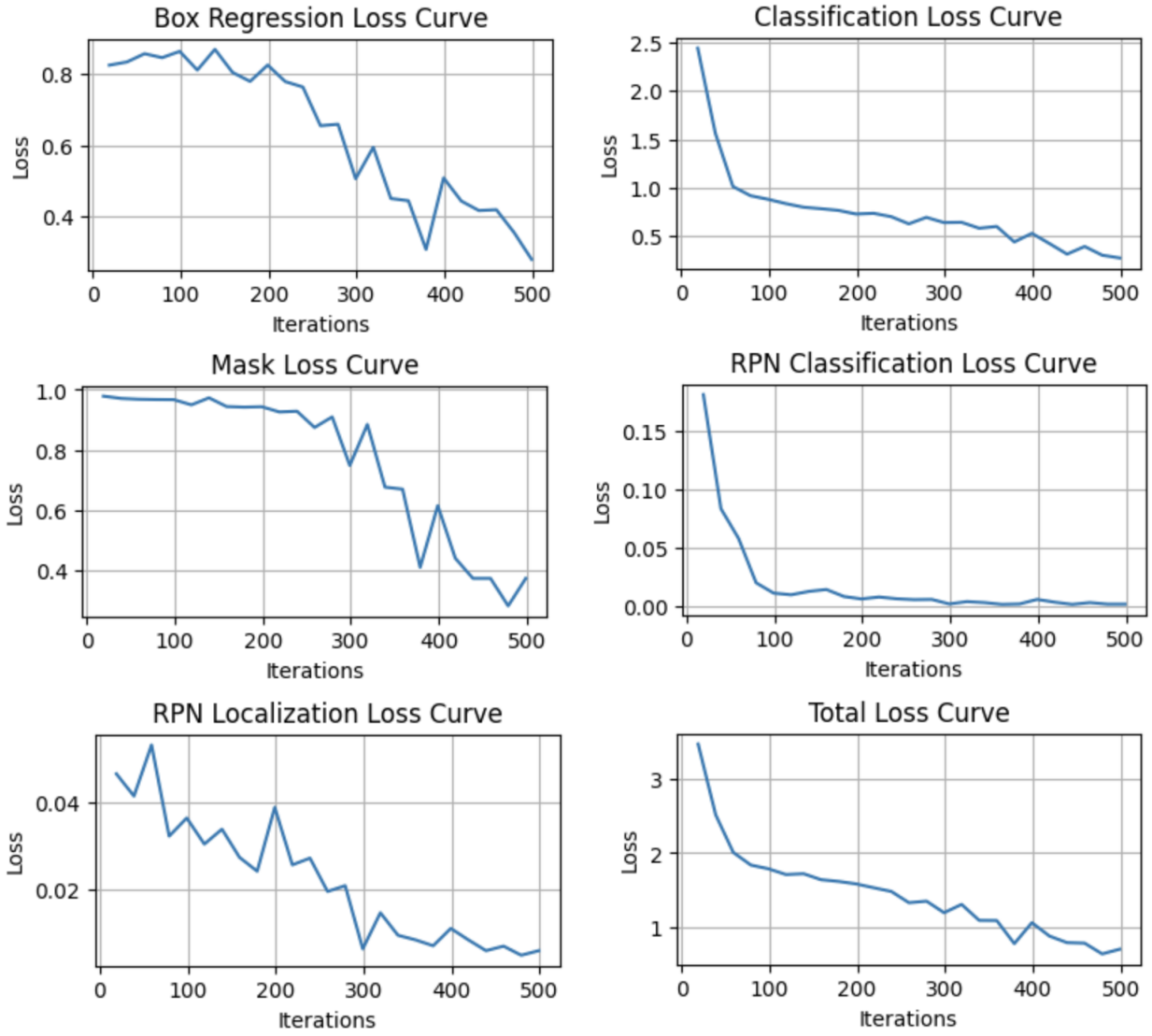

Figure 5.9: Curves Result of Faster RCNN

Average precision performance for Faster RCNN

The evaluation results for Faster R-CNN indicate the performance of the model in terms of average precision (AP) and its variations at different intersection-over-union (IoU) thresholds presented in the table 5.4 and 5.5. The total results reveal an AP of 4.26, AP50 of 7.91, and AP75 of 4.02. The APs value is listed as NaN, indicating that the model might not perform well on small objects. The APm value is 3.41, indicating moderate performance on medium-sized objects, while the APl value is 5.80, suggesting better performance on large objects.

Analyzing the individual classes, we can observe the AP results for each category. Notably, the "Oxyptane BR 5mg" class achieves the highest AP of 17.07, some classes such as "Moxonidine 0.4mg," "Nostrogene 1mg," and "Trimetazidine B 20mg" have very low AP values, suggesting poor detection performance for these classes.

It is important to note that the performance of Faster R-CNN can vary across different object categories. For instance, the "Adipine LP 20mg" class achieves an AP of 7.45, indicating relatively good detection performance. However, the "Biorava 20mg" class has a very low AP of 0.11, suggesting that the model struggles to accurately detect instances of this category.

The results highlight the varying effectiveness of the Faster R-CNN model for different object classes. Some classes demonstrate relatively good performance, while others show room for improvement. The model performs best on the "Oxyptane BR 5mg" class, while the "Moxonidine 0.4mg," "Nostrogene 1mg," and "Trimetazidine B 20mg" classes exhibit poor performance.

Table 5.4: Performance Evaluation of Faster R-CNN for each class

Class	AP
Adipine LP 20mg	7.446
Biorava 20mg	0.114
Clovirax 200mg	5.709
Moxonidine 0.4mg	0.000
Nostrogene 1mg	0.132
Oxyptane BR 5mg	17.067
Setreme 8mg	1.071
Trimetazidine B 20mg	0.320
Nolvadex 20mg	3.404
Pulsagen 50mg	7.360

Table 5.5: Total Performance Evaluation of Faster R-CNN

Total Evaluation results for bbox	
AP	4.26
AP50	7.91
AP75	4.02
APs	NaN
APm	3.41
APl	5.80

4.4 PERFORMANCE COMPARISON OF YOLO AND FASTER RCNN

When comparing the performance of YOLOv8 and Faster RCNN for object detection, several notable differences can be observed.

Starting with YOLOv8, the model demonstrated satisfactory results with high accuracies for most classes. It achieves 0.908 in mean average precision (mAP), indicating its ability to accurately detect objects in the given dataset. The individual AP scores for each class ranged from 0.707 to 0.997, with some classes achieving perfect precision and recall. Additionally, the YOLOv8 model had a relatively fast inference time of 1.8ms and a post-processing time of 1.2ms per image, suggesting its efficiency in real-time applications.

On the other hand, the Faster RCNN showed a different results. The overall mAP for Faster RCNN was 4.262, significantly lower compared to YOLOv8. This suggests that Faster RCNN might struggle with accurately detecting objects in the given dataset. The individual AP scores for each class varied, ranging from 0.0 to 17.067. This indicates a significant variation in the model's performance across different classes, with some classes achieving very low precision.

Analyzing the loss curves for both models revealed additional insights. YOLOv8 achieved a decreasing total loss throughout the training iterations, indicating the model's ability to effectively optimize its parameters. but Faster RCNN showed a fluctuating total loss, suggesting potential challenges in convergence or model stability.

In terms of computational efficiency, YOLOv8 demonstrated faster inference and post-processing times compared to Faster RCNN. This can be attributed to YOLOv8's single-stage architecture, which allows for parallel processing and real-time object detection.

In conclusion, YOLOv8 outperformed Faster RCNN in terms of overall accuracy and computational efficiency. YOLOv8 achieved higher mAP scores and demonstrated faster inference times.

4.5 LIMITATIONS OF YOLO V8

The performance of YOLO v8 in object detection using medication images reveals both strengths and weaknesses. After loading the model weights we tested with a new medication image that does not belong to the trained medication class, it fails to detect any objects. However, when a new

medication image that bears some resemblance to one of the known classes is chosen, the model detects it with a confidence of 55% as it showing in Figure 5.10. And this is incorrect since the recognized medication is not even the same as the one in the image. These observations highlight the model's limitations and the need for further improvements. Specifically, in our case, it is crucial for the model to accurately recognize the same medication with different dosages. Enhancing the model's capability to handle such variations is essential to ensure reliable and precise medication identification.

Figure 5.10: Amoxicillin 1000 mg detected as Biorava 20 mg

4.6 CONTINUING METHOD AND GENERATING REPORTS

The chosen method for calculating the number of medications detected in the test image involves utilizing the Roboflow library. This method provides an efficient way to perform inference on the test image and extract information about the detected medication objects.

We use our API key, workspace, and our project details. This allows us to interact with the desired project and model within Roboflow.

Once the model is downloaded, we proceed to perform inference on the test image using the prediction method. We add the test image path and can optionally set the confidence threshold and overlap parameters to control the detection sensitivity of the results as it is shown in Figure 5.11 with threshold = 50% and overlap = 50% . The result of the prediction is a JSON response containing information about the detected objects, such as their class labels, bounding box coordinates, and confidence scores.

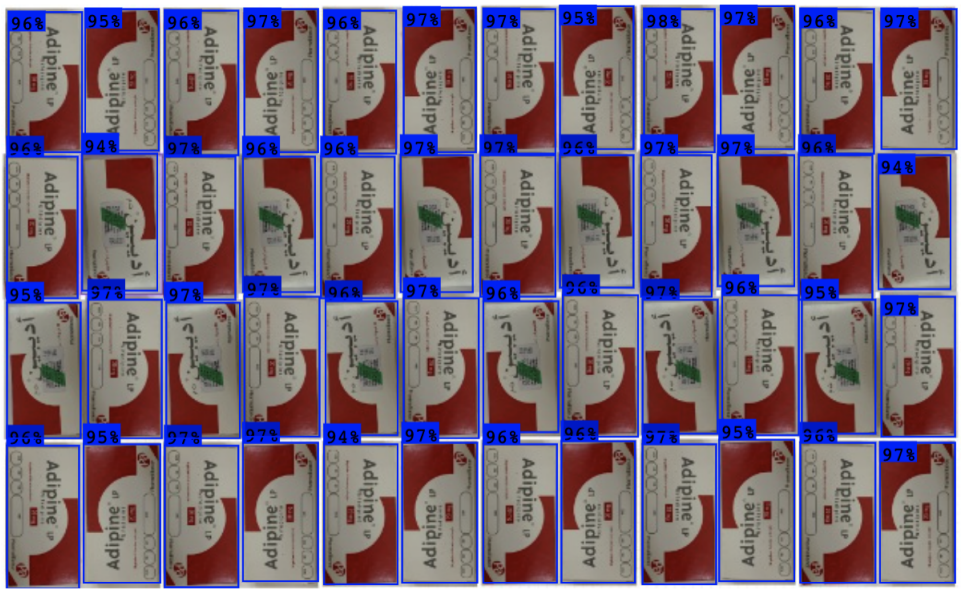

Figure 5.11: calculating the number of medication in testing image

To compute the number of detected medications, we extract the medication objects from the JSON response. By accessing the 'predictions' key in the response, we obtain a list of detected objects. The length of this list corresponds to the number of medications detected in the test image for each class as its showing in the Figure 5.12 .

This chosen method provides an automated way to determine the count of medications in the test image without the need for manual inspection.

```
print(f"Number of medications detected: {num_medications}")

# Iterate over the medication detections and print details
for index, medication in enumerate(medications, start=1):
    print(f"Medication :")
    print(f"    Class: {medication['class']}")
    print()
```

```
Number of medications detected: 48
Medication :
    Class: Adipine LP 20mg
```

Figure 5.12: calculating the number Results

After calculating the number of medicines detected, we generates a simple report that includes all the details about results statistics. This report automatically sent to the responsible via email

using the server **send-message method**.

By automating this process, the responsible person can receive the medication detection report directly in their email inbox. This eliminates the need for manual intervention, and saving time.

5 CONCLUSION

In this chapter, and for the medication recognition task in the hospital pharmacy supply chain, the object detection models YOLOv8 and Faster RCNN were evaluated and compared. YOLOv8 demonstrated better results in accurately detecting and localizing medication objects in our custom dataset, achieving a mean average precision (mAP) of 0.908. Its efficient performance makes it highly suitable for real-time applications in the hospital pharmacy supply chain.

On the other hand, Faster RCNN showed lower mAP scores (4.262) and performance across different medication classes. While it still provided some level of detection accuracy, it may not be the most optimal choice for medication recognition tasks in terms of accuracy and efficiency.

Considering the specific requirements of the hospital pharmacy supply chain, where accurate and efficient medication recognition is crucial, YOLOv8 emerged as the preferred choice. Its superior performance and reliability make it well-suited for ensuring the best accuracy of medication recognition tasks in the pharmacy supply chain.

General Conclusion

In this thesis, we aimed to highlight the importance of applying machine learning techniques in the pharmaceutical supply chain (PSC) to upgrade its efficiency and effectiveness. Our focus was on the particular case of the Central Hospital Pharmacy (PCH), the unique supplier of medicine and medical products for Algerian public hospitals.

For this purpose, we first provided an overview of our perspective on a pharmaceutical supply chain system, explicating different tasks, then we focused on tasks that constitute the main part of this work, which is medicine inventory management.

The proposed solution presented in this thesis represents a substantial advancement in managing. By using the power of artificial intelligence (AI) technology, specifically in medicine recognition and counting, the system facilitates inventory management processes, saving time and effort.

Object detection techniques, such as YOLO and Faster RCNN, have been explored to upgrade the system's capabilities. Custom datasets adapt to the specific needs of the PSC have been generated, ensuring the reliability and accuracy of the system. This personalized approach strengthens the practical utility of the system in real-world PSC applications.

The evaluation of object detection models, YOLOv8 and Faster RCNN, for medication recognition tasks in the hospital pharmacy supply chain, has provided valuable vision. YOLOv8 demonstrated excellent performance, accurately detecting and localizing medication objects with high precision. This makes it the preferred choice for real-time applications in medicine inventory management, ensuring accurate and efficient medication recognition.

However, it is important to mention that regarding the sensitive task we aim to perform, the accuracy of the system must be enhanced in order to attain better accuracy.

In conclusion, the application of machine learning techniques, using image recognition on our custom datasets, offers a valuable solution to optimize the pharmaceutical supply chain. The pro-

posed approach can make a starting point in the design of an intelligent pharmaceutical supply chain.

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