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Automated Vial and Pre-Filled Syringe Counting in the Pharmaceutical Industry Using YOLO and SAHI Techniques

Ram Kumar Sridharan[1]
Research Associate
Aispry, Hyderabad, India

Anisa Xhafa[2]
Research Associate
Aispry, Hyderabad, India

Samruddhi Chaodhari[3]
Research Associate,
Aispry, Hyderabad, India

Sreekanth Putsala[4]
Team Leader,
Research and Development,
Aispry, Hyderabad, India.

Bharani Kumar Depuru[5]
[5]Director, Aispry, Hyderabad, India.

Abstract:- In the pharmaceutical industry, manual counting of vials and pre-filled syringes (PFS) is a time-consuming process prone to human error, which can lead to inventory discrepancies and operational inefficiencies. This research addresses these challenges by automating the counting process using state-of-the-art deep learning techniques. We employ the YOLO (You Only Look Once) architecture from the Ultralytics library, renowned for its real-time object detection capabilities. Our study compares three versions of the YOLO models (v8, v9, v10) to determine the most accurate and efficient model for this application and designed to handle both images and videos. In this study, we applied the Slicing Algorithms for Hyper Inference (SAHI) technique to enhance object detection by efficiently handling smaller objects within larger images, thereby aiming to improve the overall accuracy and robustness of the model. However, our experimental results did not show a significant improvement over existing methods which highlights the potential limitations of the SAHI technique in certain contexts, suggesting the need for further investigation into its effectiveness and adaptability across diverse applications. Using more than 6000 images, the model were trained with a result of high mean average precision of 0.969 showcasing their high detection precision. With a counting accuracy of more than 95%, the proposed model offers an effective solution by eliminating the need for manual counting, thus reducing the potential for human error inherent in traditional methods. Additionally, the developed system seamlessly integrates the counting values with existing inventory management platforms, ensuring up-to-date stock levels and enhancing inventory accuracy. This integration offers substantial time and cost savings for the pharmaceutical and healthcare industries.

Keywords:- *Artificial Intelligence, Counting Vials and Syringes, Image Preprocessing, Advanced Models, Pharmaceuticals and Health Care.*

I. INTRODUCTION

In the pharma production industry, vaccines are often manufactured and delivered using vials and pre-filled syringes containers. Accurate quantities of processed and available vials and pre-filled syringes are essential for efficient operations, maintaining the supply chain, keeping the right stock and ensuring the safety of patients by having timely availability of vaccines. The information about the number of vials and pre-filled syringes, are obtained by either manual counting or specialised tools and systems designed for this purpose. Owing to numerous challenges present in the physical environment of the production line, these traditional counting systems cannot be entirely accurate. Moreover, vial and PFS counting is a labour-intensive and error-prone process with significant consequences throughout the pharmaceutical industry. Time consumption not only leads to reduced operational efficiency, but also incurs significant costs. Furthermore, manual data entry in this process increases the risk of errors, which can spread to later stages of pharmaceutical operations, potentially jeopardizing the reliability and quality of pharmaceutical products. As a result, moving beyond manual counting and specific tools and methods becomes essential to increase efficiency, accuracy and long-term cost-effectiveness in pharma production units. The integration of Artificial Intelligence (AI) into pharma industrial systems has brought about significant advancements, transforming traditional practices. AI's ability to analyze large datasets and predict trends has revolutionized traditional inventory practices [1].

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Deep learning is a subfield of artificial intelligence rooted in artificial neural networks. Due to the development of advanced algorithms, the exponential growth of digitized data, and the development of high computing power hardware, in some cases, deep learning models are skilled at matching or even outperforming humans [6]. Deep Learning has made an impact in areas, such as cancer diagnosis, precision medicine, self-driving cars, predictive forecasting, and speech recognition. A deep neural network called Convolution Neural Network (CNN) can learn hierarchical levels of representations from a low-level input vector and successfully identify the higher-level object. CNNs can progressively extract higher representations of the image after each layer and finally recognize the image [7]. We have seen a shift from systems that are completely designed by humans to systems that are trained by computers using example data from which feature vectors are extracted. Computer algorithms define the optimal decision boundary in the high-dimensional feature space. A critical point in the design of such systems is the extraction of discriminant features from the images. The leading type of models for image analysis to date are convolutional neural networks (CNNs) [8]. The reason for CNNs becoming dominant architecture in this medial analysis field is that CNNs preserve spatial relationships when filtering input images [9].

In the field of poultry farm management and health monitoring of poultry farm chickens, delayed detection due to infrequent monitoring by humans can lead to increased mortality rates, decreased productivity, and financial losses. Addressing these challenges requires the integration of advanced technologies of image processing, such as CNN and sensor-based systems [10].

In addition to the object detection part of these computer algorithms, various applications depend on counting the number of objects in a given setting, for effective operation or preplanning. For example, the detection and counting of olive fruit flies. Early detection and quantification of these flies are especially pivotal due to their potential to cause substantial harm, with the ability to damage all harvested fruit and lead to an up to 80% reduction in the value of the ensuing olive oil [11].

Quantifying objects brings about numerous challenges. Models must learn the diversity of items in terms of their shape, size, orientation, and appearance. The objects themselves may be partially hidden and could be observed at diverse angles and resolutions. Additionally, differences in background, weather, and lighting conditions could vary significantly across scenarios. Achieving accurate object counting demands a robust model capable of differentiating objects amidst these fluctuations. A more efficient system for object tracking and counting was proposed by Dirir, A et al., which integrates YOLO (Yolo V5) for object detection and the Channel and Spatial Reliability Tracker (CSRT) for object tracking and counting [12].

Initially, object counting relied on edge extraction, necessitating clear differentiation of objects from the background. Conversely, modern deep learning-based counters offer the advantage of robust object detection across varied environments, a feat achievable with appropriate training data. Nevertheless, these object-detection models have constraints, particularly in scenarios with a high object density within the image [13].

CNN-powered object identification algorithms can be classified in two principal groups of two-step detection methods: two-step algorithms including Fast ReCNN, Faster ReCNN, and Mask ReCNN [15], [16] and one-step algorithms, such as the well-known You Only Look Once (YOLO) series algorithms [17] and single-pass multi-box detection models (SSD) algorithms [18], [19], among others. The YOLO algorithms have seen significant advancements and are universally acknowledged as some of the most potent algorithms in the field. Specifically, the YOLOv8 algorithm, unveiled in 2023, has achieved outstanding validity, surpassing its predecessors [20]. The YOLO algorithm is primarily designed to recognize baseline YOLOv8, outperforming contemporary models [21]. YOLO is a well-known deep object detection model based on learning algorithms and counting, and its model has been demonstrated to reach state-of-the and categorize objects that occupy the entire image. Empirical evaluations on the COCO dataset demonstrate a 2.1 % increase in mAP for objects under a certain size threshold compared to the -art performance on a wide range of benchmark datasets, all while maintaining high accuracy and smooth frame rates on high-end GPUs [22], [23].

One more technique that was experimented in this paper is Slicing Algorithms for Hyper Inference (SAHI). It is a technique that helps improve object detection in very large images. Instead of trying to process the whole big image at once, which can be tough on computer resources and might miss small details, SAHI slices the image into smaller, overlapping pieces. Each of these smaller pieces is then analyzed distinctly, allowing for more precise detection of objects, even those that are tiny or at the edges of the slices. Once all the pieces are processed, SAHI combines the results to provide a complete view of what's in the original large image. SAHI has already proven its application in fields like satellite imagery, medical scans, and surveillance, where you need to deal with high-resolution images efficiently. This research study follows the CRISP-ML(Q) methodology [Fig.1].

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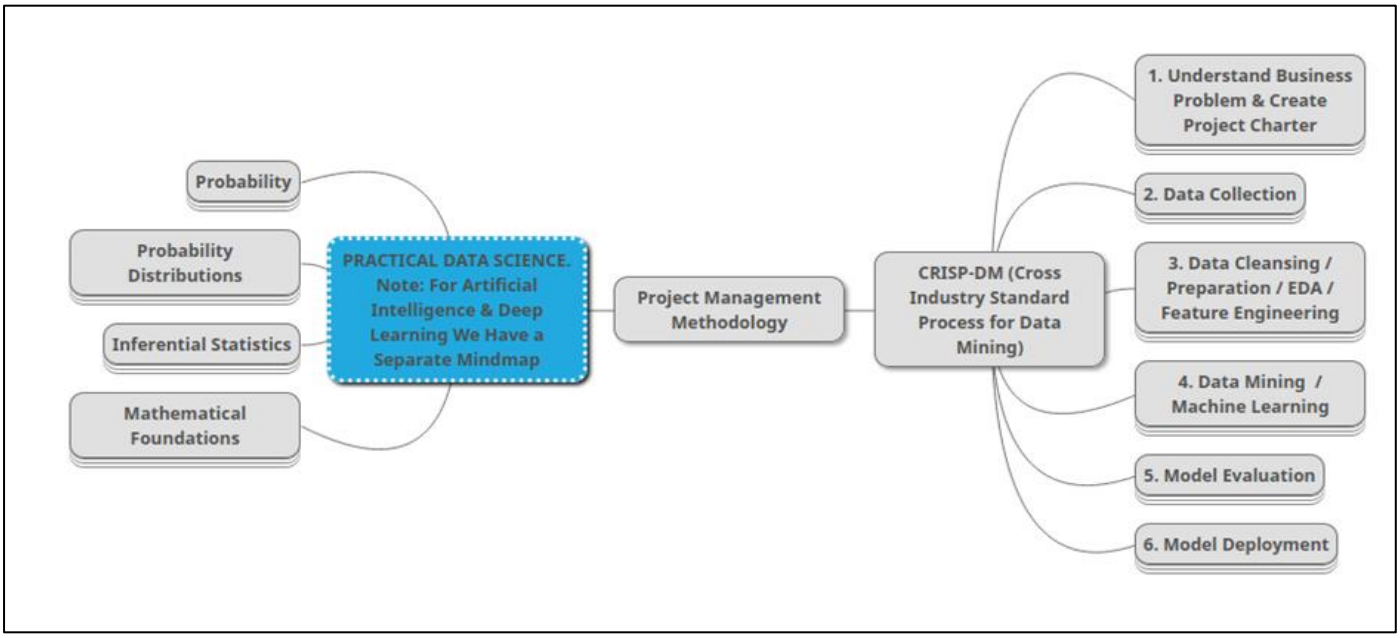

Fig 1 The Above Figure Displays the CRISP-ML(Q) Architecture that was Used for this Research Project.

II. METHODOLOGY

The proposed architecture for counting vials and syringes integrates advanced computer vision models like YOLOv8 with processed datasets to achieve accurate detection, counting and successful integration into real-world scenarios [Fig. 2].

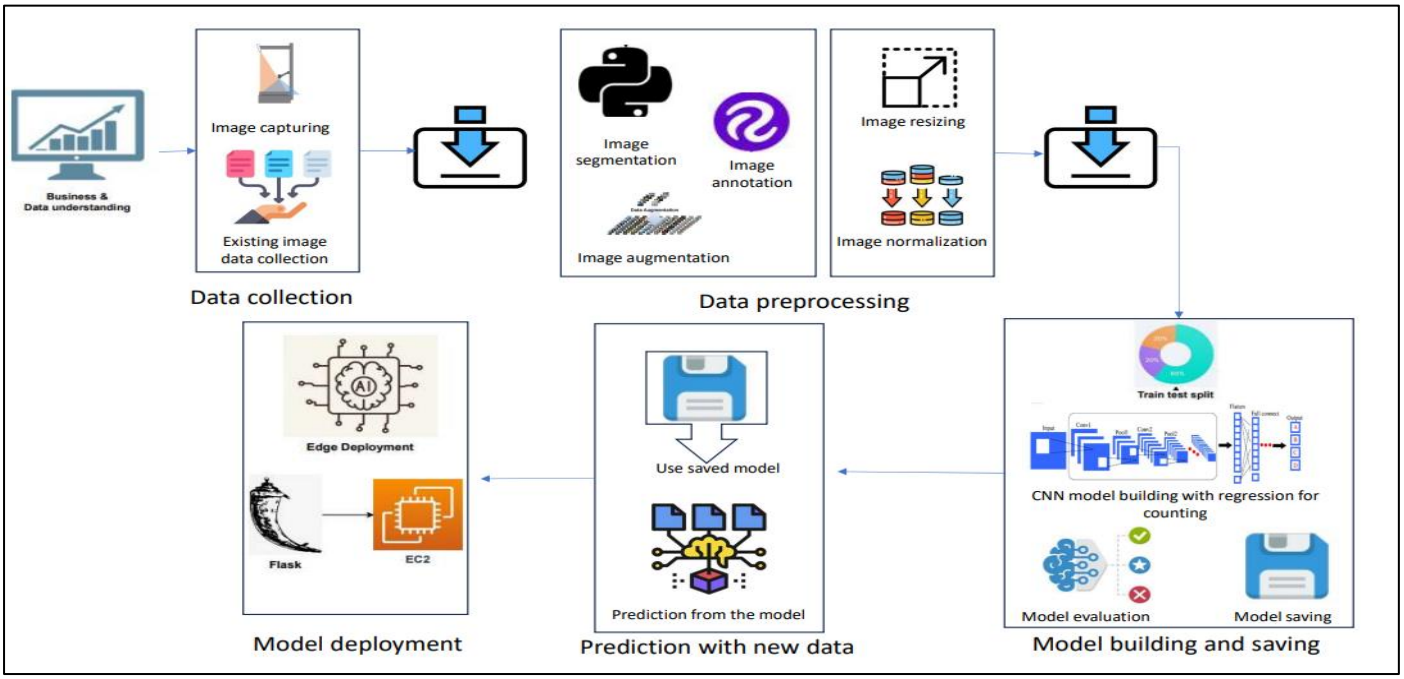

Fig 2 Project Architecture Diagram

The overall process starts with accurately understanding the business problem and the business domain to plan for the optimised solution. The data collection is directly from the primary sources which is the pharmaceutical company directly. The process then followed cleaning and organizing the data which involves data collection, annotation, data preprocessing, data augmentation and data splitting techniques. The organised data is then trained using different YOLO models. The model learns to recognize and count objects in images based on the training. After the training, the model is tested to evaluate its performance and accuracy in different situations. This step ensures that the model functions correctly. Once the model is tested and validated, it is deployed using the Streamlit framework, where it is used to detect and count objects in real-time. Once the model is in use, it will be continuously monitored and improved to ensure it provides accurate and reliable results for users.

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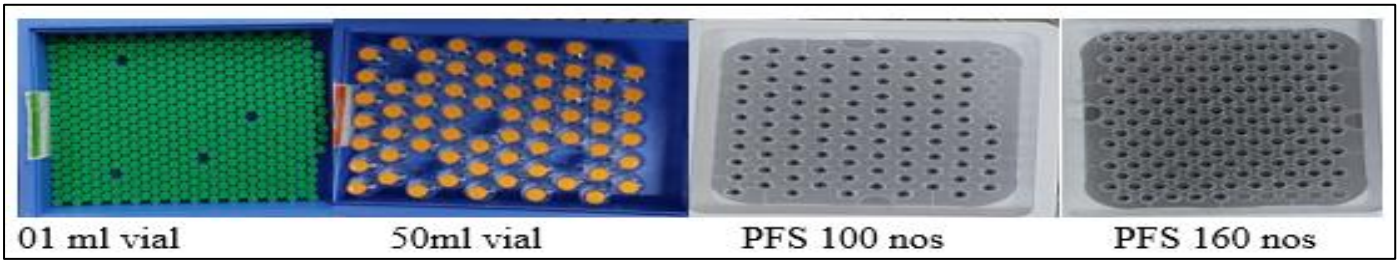
III. DATA PREPARATION

A. Data Collection

To ensure the model's effectiveness in real-world scenarios, a diverse dataset was compiled, consisting of various images of vials (with capacities of 01ml, 10ml, 15ml, 20ml, 50ml, and 60ml) and syringes. There are three types of datasets that have been used: dataset containing both vials and syringes, dataset containing only vials and dataset containing only syringes. This dataset captures a wide range of real-world conditions and scenarios that are representative of the complexities encountered in pharmaceutical inventory projects. The varied nature of the data is critical for training the model to accurately detect and count these objects across different contexts and conditions.

In the initial preparatory phase, 340 raw images were used, which serve as the basis for subsequent data augmentation. These 340 images were obtained from the following categories: All images (Vials and PFS)-160 and PFS images-180.



B. Data Preprocessing

Effective preprocessing of data is essential for successful machine learning outcomes, particularly when leveraging platforms like Roboflow.

RoboFlow is a widely used platform for creating, training, and deploying computer vision models, frequently applied in multiple fields, including, healthcare, for tasks such as counting vials and syringes. Roboflow's data preprocessing pipeline is both comprehensive and highly customizable, allowing researchers to tailor the process to meet specific needs.

Key aspects of this process include the standardisation of image dimensions, which ensures uniformity across the dataset, facilitating more reliable and effective training. Normalisation of pixel values is another crucial step, stabilising the training process by workflow by assuring that the input data is scaled appropriately.

C. Data Annotation

Data annotation is a pivotal phase in the research for automating the counting of vials and syringes. This step involves the meticulous labelling and categorization of each image or frame within the dataset. Each annotated image acts as a reference point, enabling the automated system to learn and accurately count vials and syringes. Quality assurance procedures are critical in the data annotation process, ensuring the accuracy of labels and minimising errors and inconsistencies within the dataset. This rigorous approach guarantees that the system is trained with high-quality, reliable data, thus enhancing its performance and accuracy

For vials, a polygon annotation method was employed, while for pre-filled syringes (PFS), both polygon and bounding box annotations were utilised. The data annotation process [Fig. 3] incorporates detailed information regarding other pertinent characteristics. This level of detail enhances the system's capability not only to detect vials and syringes but also to classify and count them, thereby contributing to a more thorough analysis.

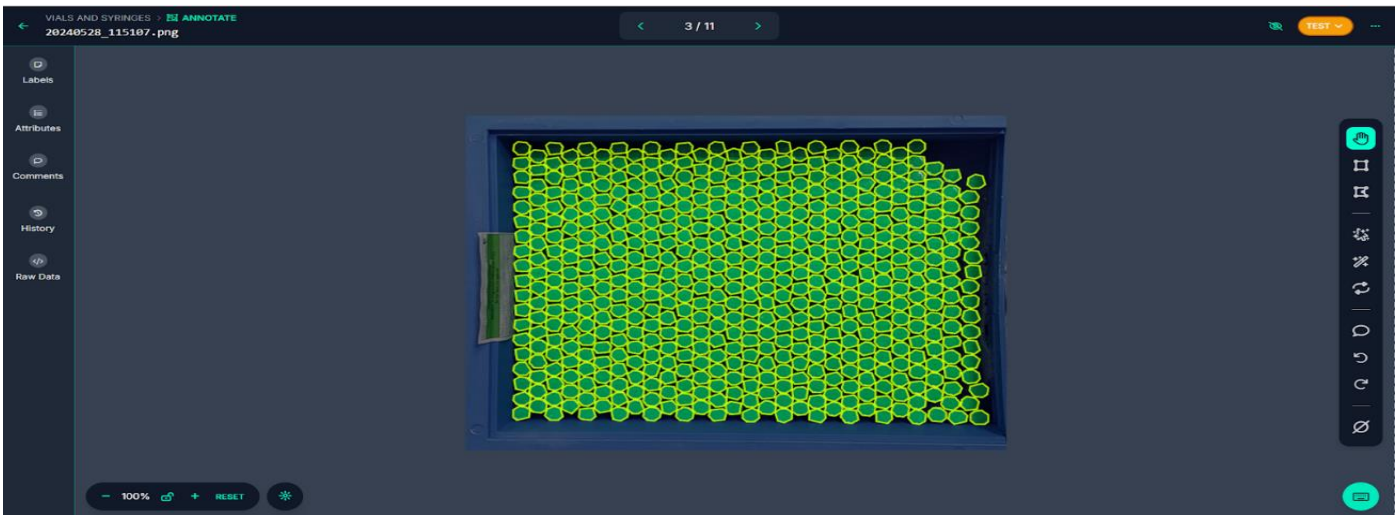


Fig 3 Sample Annotation of Data

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D. Data Augmentation

Data augmentation is a critical component in the automated vial and syringe counting process, allowing the dataset to be artificially expanded with variations that mimic real-world conditions. By employing techniques such as rotation, flipping, scaling, and colour adjustments, the dataset becomes more diverse, enabling the model to recognize vials and syringes from various perspectives and under different lighting conditions.

For vials, the augmentation process includes horizontal flipping, rotation within a range of -15° to +15°, and converting 15% of the images to grayscale. Saturation adjustments range from -25% to +25%, brightness modifications range from -15% to +15%, and additional effects such as blurring (up to 2.5 pixels) and adding noise (up to 0.1% of pixels) are applied. A similar augmentation process is followed for prefilled syringes (PFS), ensuring consistency across the dataset. As a result of these augmentation steps, the dataset size is significantly increased. This expanded dataset is crucial for mitigating overfitting, where the model might otherwise perform well on training data but fail in real-world scenarios. Ultimately, this dynamic approach to data augmentation is essential for maintaining the model's robustness over time, ensuring it can effectively adapt to a constantly changing environment and consistently achieve high accuracy in recognizing vials and syringes presented in different orientations, sizes, and lighting conditions.

All the image processing details in this study is shown in the table 1.

Table 1 Image Preprocessing of the Dataset

Category	Vials	PFS
Annotation type	Polygon	Polygon and Bounding box
Data Preprocessing	Standardisation of image dimensions. Normalisation of pixel values	Standardisation of image dimensions. Normalisation of pixel values
Augmentation Steps (pre-processing)	Flip: Horizontal, Rotation: Between -15° and +15°, Grayscale: Apply to 15% of images, Saturation: Between -25% and +25% Brightness: Between -15% and +15% Blur: Up to 2.5px, Noise: Up to 0.1% of pixels	Flip: Horizontal, Rotation: Between -15° and +15°, Grayscale: Apply to 15% of images Saturation: Between -25% and +25% Brightness: Between -15% and +15%, Blur: Up to 2.5px, Noise: Up to 0.1% of pixels

E. Dataset Splitting

The division of data groups is a pivotal step and involves categorizing the data into distinct subsets, each with a unique and clearly defined purpose. The training set forms the foundation for teaching whereas the validation set is utilized to monitor the model's capability during the training phase and to guide the tuning process, ensuring that the model generalises effectively and does not overfit to the training data alone. Dividing the data groups establishes a balance between the learning and fitting of the model, thereby increasing its performance and adaptability.

IV. MODEL BUILDING

Ultralytics offer a comprehensive platform that makes it easy to train and deploy object detection, segmentation, and other computer vision models. Ultralytics is particularly known for developing the YOLO (You Only Look Once) series of models.YOLOv8 introduces significant enhancements in speed and accuracy, making it ideal for real-time applications. The improved model architecture ensures better overall performance. Building on YOLOv8, YOLOv9 brings a new backbone architecture for enhanced feature extraction, especially in complex scenarios. It includes refinements in the neck and head components, optimizing feature aggregation and detection accuracy. The model also focuses on increasing inference speed without sacrificing accuracy, making it suitable for real-time tasks. YOLOv10 incorporates state-of-the-art features. It introduces a cutting-edge backbone network for superior detection performance and an innovative neck design for improved feature fusion and spatial resolution. The sophisticated head enhances bounding box predictions and class classifications. Additionally, YOLOv10 leverages next-generation training techniques, including advanced data augmentation and optimization strategies, ensuring exceptional model performance.

The table 2 presents the performance metrics of different model architectures and configurations evaluated on image datasets comprising vials and PFS (pre-filled syringes). The models are YoloV8, YoloV9, and YoloV10, each with various sub-versions (e.g., YoloV8n, YoloV8l). Different numbers of training epochs were used, and the models were tested on datasets containing only vials, only PFS, and a combined set of both.

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Table 2 The Performance Metrics of Different model Architectures and Configurations Evaluated on Image Datasets comprising vials and PFS (Pre-Filled Syringes)

	No of images	Annotation	After augmentation	Models Identified	epochs	mAP 50	mAP 50-90	Models Finalzed	Reasons behind the issues	No.of Images tested	No.of 100% accuracy Images	No.of Images with Issues
vials+PFS	372	polygon	1860	Yolov8n	10	0.969	0.707	Yolov8n	Detection was not happening with PFS images			
	372	polygon	1860	Yolov8n	15	0.994	0.695					
	372	polygon	1860	Yolov8l	10	0.996	0.692					
	372	polygon	1860	Yolov8l	30	0.996	0.692					
	372	polygon	1860	Yolov9c	100	0.883	0.469					
	372	polygon	1860	Yolov9t	15	0.93	0.669					
	372	polygon	1860	Yolov10n	15	0.893	0.569					
vials	253	polygon	760	Yolov8n	15	0.911	0.695	Yolov8l	Found some issues with some images and annotations for			
	253	polygon	760	Yolov8n	30	0.969	0.682					
	760	polygon	2340	Yolov8l	30	0.995	0.785					
	1000	polygon	3000	Yolov8l	60	0.995	0.744			100	98	2
vials (greyscale	103	polygon	310	Yolov8l	30	0.995	0.754		Training was required for greyscale images specifically			
PFS+Blank	270	polygon	810	Yolov8l	30	0.71	0.353	Yolov8l				
	270	polygon	810	Yolov8l	60	0.71	0.364					
PFS (Cropped)	205	Bounding Box	616	Yolov8l	60	0.995	0.754			114	111	3

In comparison to the different YOLO version models built as a part of this research study, YoloV8 variants demonstrated superior performance.

- YoloV8n trained for 10 epochs on the combined dataset (vials + PFS) achieved a high accuracy with a mAP 50 of 0.969. Similarly, YoloV8l trained for 30 epochs on the vials-only dataset achieved a very high mAP 50 of 0.996.
- YoloV9 variants showed varying results, with YoloV9c reaching an mAP 50 of 0.883 for the combined dataset when trained for 100 epochs, while YoloV9t, with only 15 epochs, garnered a lower mAP 50 of 0.933.
- On the other hand, YoloV10n matched YoloV9t's performance, obtaining a mAP 50 of 0.893 on the combined dataset after 15 epochs.

Overall, YoloV8 models consistently outperformed YoloV9 and YoloV10, particularly on the combined dataset, highlighting YoloV8n's exceptional accuracy at 10 epochs.

The analysis of critical hyperparameters demonstrated their fundamental role in shaping the model's behaviour. The default values provided a valuable starting point for further optimization, emphasising the importance of hyperparameter refinement in model evolution. However, the system is not without limitations. Challenges included are the quality and Data range and the necessity for persistent model updates.

V. MODEL DEPLOYMENT

The Deep learning model was subsequently deployed using the Streamlit framework. It accepts the image and the video files as the new input for detection and counting. Streamlit turns our ML script into a web app very quickly. The web app landing page is as shown in the figure 6 below.

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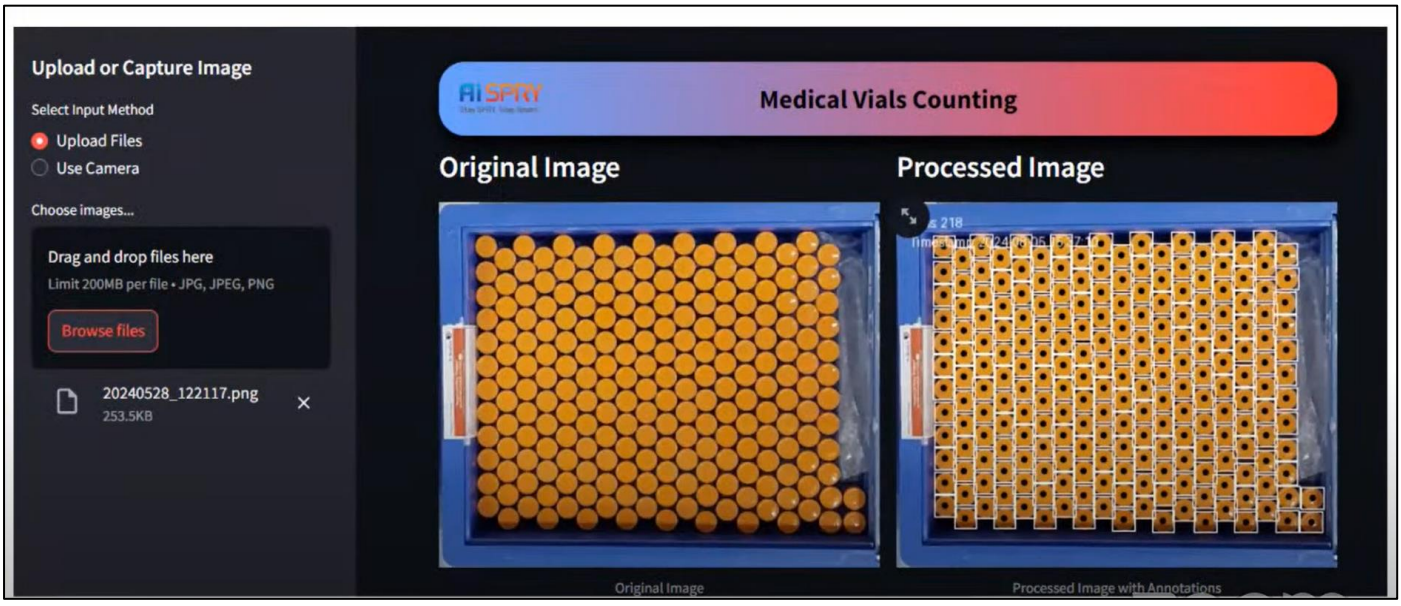

Fig 4 Web Deployment using Streamlit

The output of the deployed Vial and PFS counting YOLO model looks like the figure 7 below. The main result in the output sheet contains Image which is a batch process, classes whether it is vial or syringe, count of the vial or syringe and timestamp.

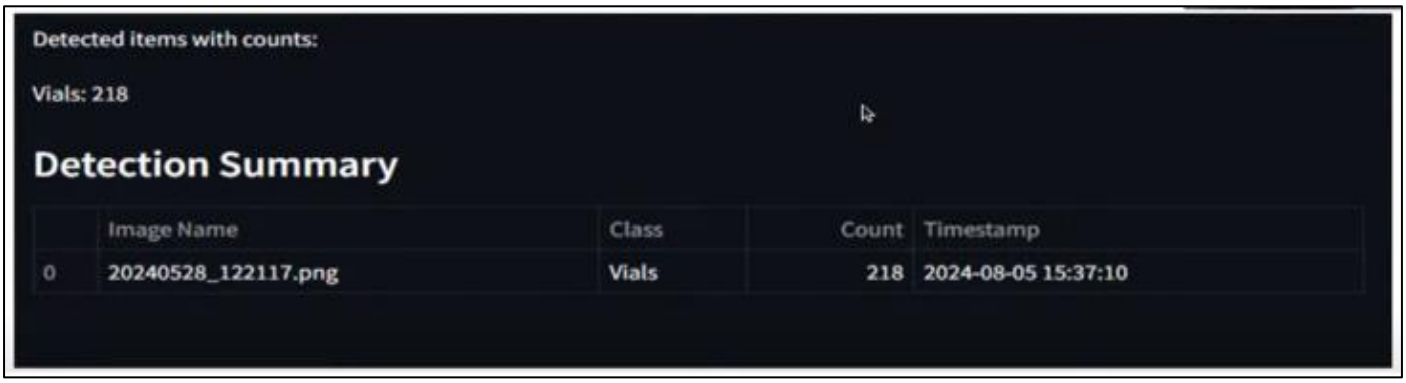

Fig 5 Result of the Vial and PFS Counting Model

VI. CONCLUSION

The comprehensive exploration of YOLO model versions has highlighted their exceptional performance, establishing YOLO as the ideal choice for counting vials and syringes. The model's accuracy in recognizing the characteristics of vials and syringes, including their diameters and positions, represents a significant breakthrough. This improvement in precision and error minimization is expected to enhance production processes, stock management, and sales operations.

Several YOLOv8 and YOLOv9 models have been successfully trained on various datasets, demonstrating high mean Average Precision (mAP) scores and effective detection capabilities. For example, YOLOv8n achieved remarkable precision on a combined Vials and PFS dataset, with a mAP 50 of 0.969 and a mAP 50-90 of 0.707. Similarly, YOLOv8l, trained on 310 greyscale vial images, attained even higher precision levels, with a mAP 50 of 0.995 and a mAP 50-90 of 0.785.

The investigation also underscored the importance of hyperparameter tuning in shaping the model's performance. While the default values provided a solid foundation, further optimization was necessary to enhance accuracy. However, the system is not without limitations, such as the quality and diversity of data and the need for continuous model updates. The future scope for leveraging YOLO models in vial and syringe counting could include several promising avenues for further development and application such as Integration with IoT and Real-time Monitoring, deployment on edge devices which minimizes latency and power consumption, enhancing their usability in settings with limited computational resources. The methodologies and advancements achieved through this project could be applied to other related requirements in the pharmaceutical domain that require object counting and classification.

In conclusion, the project demonstrates the transformative potential of YOLOv8 for the automated counting of vials and syringes, leading to significant improvements in safety, efficiency, and the integration of advanced technologies into future inventory management

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systems. The precise count of vials and pre-filled syringes can be seamlessly integrated into inventory management platforms for further processing and optimization, ensuring a more streamlined and effective operation.

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