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An Embedded System With YOLOv5 for Automated Drug Delivery System

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ABSTRACT

The integration of technology into pharmaceutical operations has led to the development of automated drug delivery systems, bringing numerous benefits such as reducing medication errors and improving patient satisfaction. With advancements in technology, automated drug delivery systems have a huge growth potential. Their deployment can significantly improve healthcare services and drive the development of the pharmaceutical industry. In this study, an embedded system on Raspberry Pi integrated with the YOLOv5 deep learning model and a hardware system controlled by a Mitsubishi FX5U Programmable Logic Controller (PLC) is proposed for a drug dispensing system. Drug vials will be collected and their images analyzed by YOLOv5, and a proposed line cutting position determination algorithm will identify the necessary cutting positions. These positions will be communicated to the PLC and control the cutting system accordingly. The training results of the YOLOv5 model achieved an accuracy of over 99% for basic drug types. The optimal cutting path determination algorithm provides the correct cutting positions to the cutting system from the PLC. The research results contribute to the construction and development of automated drug dispensing devices and systems.

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1. Introduction

The development and advancement of automated drug dispensing machines are essential. Personalized drug delivery systems will be the future of treatment processes in healthcare [1]. Automated drug dispensing (ADD) systems are an emerging technology that positively impacts the efficiency of drug distribution by minimizing medication errors [2]. Ensuring an adequate drug supply requires precise automation in drug delivery systems, which will improve patient safety, reduce costs due to minimal drug consumption, and facilitate faster post-operative recovery [3]. Due to advancements in processing speed, closed-loop drug management has become prevalent for critically ill patients in intensive care units and in everyday life, such as providing personalized medication or implantable treatment devices. To develop a closed-loop drug delivery system, the control system operates with a set of technologies such as sensors, microfabrication, wireless technology, and pharmaceuticals. Recently, the integration of artificial intelligence techniques such as fuzzy logic, neural networks, and reinforcement learning with closed-loop drug delivery systems has brought their applications closer to fully intelligent automated healthcare systems [4].

Embedded systems are being researched and developed to build devices for medical applications. They have become an indispensable part of medical equipment, enabling functions such as patient monitoring, diagnosis, and treatment. Embedded systems also improve the efficiency and accuracy of healthcare professionals [5]. Technological advancements have enabled the design of smarter medical devices. Embedded sensor systems play a crucial role, both in monitoring and diagnostic devices for healthcare. The design and development of embedded sensor systems for medical devices must adhere to standards and regulations that depend on the intended use of the device as well as the technology employed [6]. Some studies have applied embedded systems in fetal monitoring devices, oximeters, and defibrillators [7].

The application of artificial intelligence, specifically the 'You Only Look Once' (YOLOv5) deep learning model, to medical image analysis has garnered significant attention in the research community. Cakir *et al.* [8] proposed a novel lightweight model, AVD-YOLOv5, designed for automated aortic valve detection in ultrasound images. This model incorporates several improvements to the YOLOv5 architecture. Notably, depthwise separable convolution contributes significantly to the model's lightweight design by reducing the number of parameters while maintaining accuracy. Wu *et al.* [9] proposed the ME-YOLO model, an improved one-stage detector. To enhance the feature extraction capability of the backbone, the authors proposed a feature fusion module (FFM) integrated with the C3 module, named C3_FFM. To preserve full semantic information and global features of the upsampled feature maps, an upsampling enhancement module (USEM) was also proposed for the task of face mask detection in COVID-19 prevention. An improved version YOLOv5 algorithm was proposed by Jiang et al. [10] for surgical instrument recognition. First, the squeeze-and-excitation (SE) attention module was added to the backbone to improve feature extraction. Second, the YOLOv5 loss function was improved with more global parameters to accelerate the convergence of the loss curve. Finally, an efficient convolution algorithm was added to the head's C3 module to reduce computational complexity and memory usage. YOLOv5 was also proposed by Aldughayfiq *et al.* [11] for detecting and classifying pressure ulcers into four stages and non-pressure ulcers. Bashir *et al.* [12] also proposed YOLOv5-M, a modified version of YOLOv5, for medical object detection tasks (PPE and masks). These studies demonstrate the effectiveness of deep learning models, especially the YOLO model, for medical applications.

The utility of programmable logic controllers (PLCs) in industrial applications has been well-established. Adaptive manufacturing systems integrate advanced technologies, automation, and data-driven methodologies to develop adaptable, efficient, and responsive manufacturing processes [13]. Pullaiah et al. [14] developed a PLC program for multi-parameter and multi-configuration logic control in industrial heat treatment applications. The development of a PLC program to control a sterilizer or oven must be capable of handling data acquisition, control, and monitoring of process parameters with the smooth operation of related subsystems. Researchers have successfully implemented an industrial-grade PLC to control the ventilation process of a bag-valve-mask emergency ventilator. Various mechanisms were observed and results were recorded [15].

In this study, the proposed system is a personalized drug dispensing system that combines the practicality of PLCs and the intelligence of artificial intelligence on an embedded system platform. The system will utilize the power of the YOLOv5 model to identify the positions of pills in blister packs, thereby constructing an algorithm to determine optimal cutting paths and sending requests to the PLC system to control the pill-cutting mechanism. The operation of the YOLOv5 model is performed on a Raspberry Pi 4 embedded board. The main contributions of this research include:

- Collecting images of drugs and utilizing YOLOv5 on a Raspberry Pi 4 embedded device to identify pill positions

- Proposing an algorithm to determine cutting paths for the hardware system.

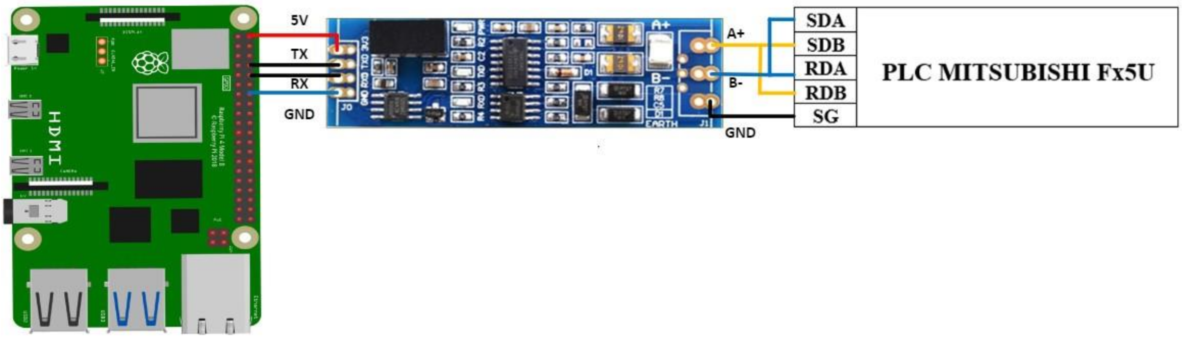
- Implementing communication between the Raspberry Pi 4 embedded system and the Mitsubishi FX5U PLC.

- Building a complete system to perform the task of taking blister packs and cutting them according to the required quantity.

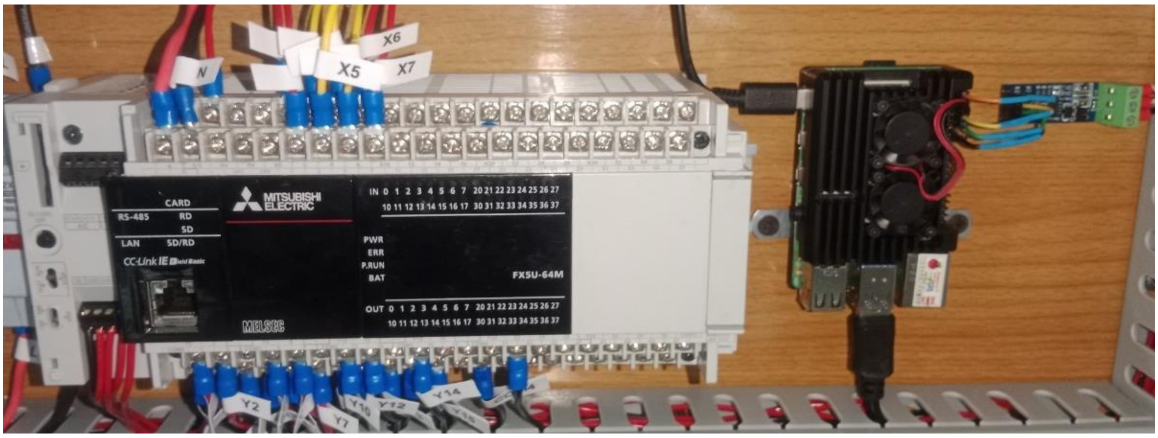
2. Methodology

2.1. System overview

The overall structure of the system consists of a Mitsubishi PLC connected to a Raspberry Pi 4 via RS485 communication. A system overview is illustrated in **Figure 1**. The proposed system operates as follows: The Raspberry Pi 4 embedded board collects data from a camera, and the YOLOv5 model analyzes the image to return the positions of the pills in the blister pack. Once the pill positions are obtained, a cutting path determination algorithm is used to find the optimal cutting path. The coordinates and cutting path are sent to the PLC via RS485 communication to control the cutting mechanism and perform the pill cutting task.



(a)



(b)

Figure 1. *System overview. (a) Connection diagram and (b) Actual hardware*

The structure of the medication cutting apparatus is illustrated in **Figure 2**. The cutting mechanism is automatically controlled by a Mitsubishi FX5U PLC and utilizes a camera to determine the position and quantity of pills to be cut. The system consists of the following main components:

- Positioning unit: A fixed camera is installed to observe the blister pack, allowing the computer to calculate the exact position of each pill.

- Clamping mechanism: A pneumatic cylinder is attached to a 10x40x8mm rectangular metal bar. A 10x15mm L-shaped pass is fixed opposite the metal bar. When the cylinder extends, it causes the metal bar and the L-shaped pass to clamp together, securely holding the blister pack.

- Cutting mechanism: Two specially designed cutting blades can move in two perpendicular directions to cut the pills vertically or horizontally.

- Movement system: Consists of two XY movement axes. Each axis has a 300mm T8 leadscrew controlled by a 42-step motor, combined with a slider and shaped aluminum to form a movement axis and an NPN SN-04 proximity sensor to determine the home position of the axis. The leadscrew system moves flexibly in the X and Y directions, bringing the blister pack holding mechanism to the correct position for the cutting mechanism to easily and accurately cut the pills.

The overall process is as follows: Once the blister pack is placed in the cutting apparatus, the cylinder in the pack-holding mechanism is activated to secure the pack. Simultaneously, the Raspberry Pi reads the required quantity of pills from the prescription and receives a signal from the PLC indicating that the clamping mechanism is complete. It then begins capturing images from the camera. The pre-trained YOLOv5 model is used to identify the number of pills and their positions. The Raspberry Pi 4 calculates the cutting positions to obtain the required quantity of pills and calculates the number of pulses to move the blister pack to the cutting mechanism. This data is then sent to the PLC to directly control the cutting mechanism. The cuts are made using a cutting mechanism with a parallel blade. By default, cutter 1 (parallel to the Y-axis) is used for a single cut. For two cuts, cutter 2 (parallel to the X-axis) is used for the remaining cut. For three cuts, cutter 1 is used for two cuts and cutter 2 for one cut. When the cutting position on the blister pack is aligned with the cutter, the Raspberry Pi sends a signal to the PLC to activate the cylinder of the cutting mechanism. Finally, the leadscrew system returns the blister pack-holding mechanism to the home position, completing the cutting process.

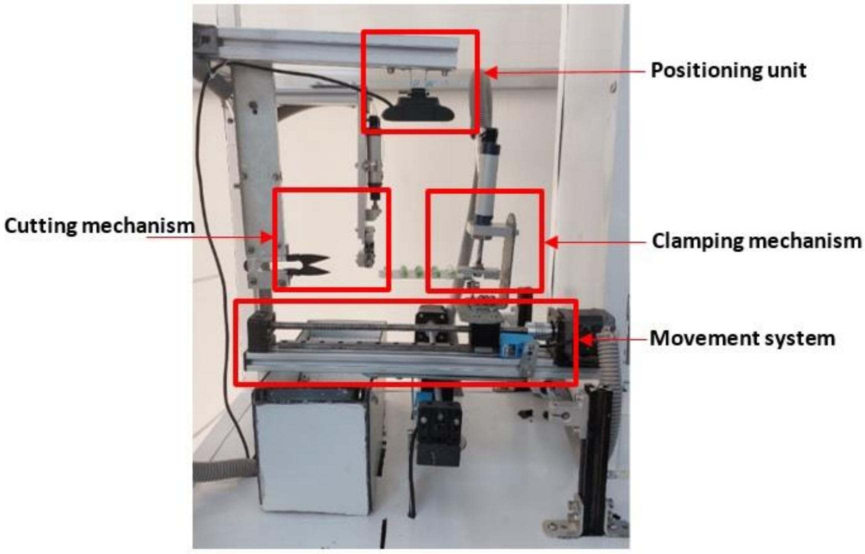


Figure 2. *The structure of the medication cutting apparatus*

2.2. Data collection and model YOLOv5 training

2.2.1. YOLOv5

YOLOv5 [16] is one of the most powerful and popular object detection models currently available. Developed by Ultralytics, YOLOv5 stands out for its fast processing speed, high accuracy, and easy customization. The architecture of the YOLOv5 model is shown in **Figure 3**. This model is widely used for various applications due to its excellent balance between speed and accuracy. Built on the PyTorch [17] framework and with an open-source library, it is easy to use, deploy, and customize. The YOLOv5 architecture consists of three main parts: Backbone is the first part of the model, responsible for extracting features from the input image. YOLOv5 uses CSPDarknet53 as its backbone, which is a modified version of the original Darknet53 neural network architecture. CSPDarknet53 utilizes CSPNet blocks to increase the model's speed and accuracy; Neck is the part that connects the backbone to the head. It is responsible for combining features from different stages of the backbone to create a single feature map. YOLOv5 uses Path Aggregation Network (PANet) as its neck. PANet combines feature maps from three different stages of the backbone in an efficient manner; Head is the final part of the model, responsible for predicting the position and class of objects in the image. YOLOv5 uses a simple head consisting of three convolutional layers and a fully connected layer.

YOLOv5 offers various versions tailored to devices with different performance capabilities. In this research, we selected the YOLOv5 nano version, which is suitable for the performance of the Raspberry Pi embedded system. For the system implemented in this study, real-time performance is not a requirement. This is because the process is performed individually for each drug image. The hardware-based sensor system will determine the timing for capturing and analyzing images.

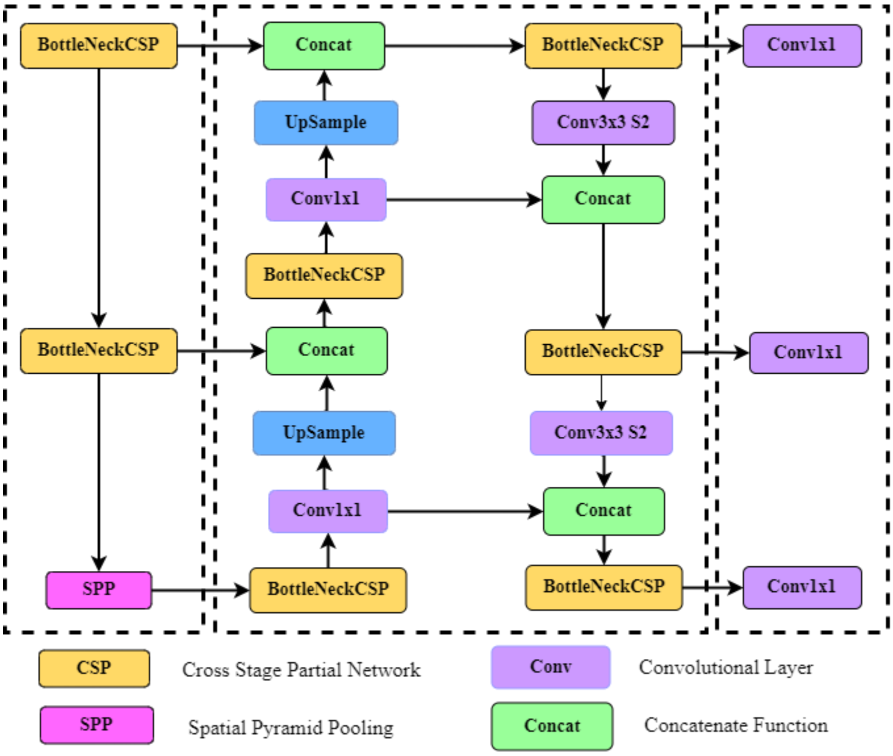


Figure 3. *The architecture of the YOLOv5 model*

2.2.2. Dataset and training process

In this study, the positions of pills on blister packs will be determined. The number of classes to be trained is 1, with the objective of locating pills in images captured by the camera. A total of 120 images of blister packs from 15 different types of drugs were collected and labeled. The blister packs contained an average of 8 to 12 pills. Approximately 1250 pills were labeled for training purposes. The blister packs used in this study contained oval and round pills. The pills on the blister packs were arranged symmetrically and positioned vertically, with no tilted pills. The labeled image data will be split into a training and validation set with a ratio of 8:2. **Figure 4** illustrates the labeling process for blister packs containing 12 pills.

Figure 4. *Demonstrating the process of labeling 12 pills on a blister pack*

2.3. Algorithm for determining pill cutting positions

The data on pill positions on the blister pack obtained from the YOLOv5 model processing will be combined with the input of the required number of pills entered through the Human-Machine Interface (HMI) connected to the PLC. This data needs to be transformed into cutting positions for the system to control the pill cutting mechanism. Details of the algorithm for determining cutting points and positions are shown on the **Algorithm 1**.

Algorithm 1. ***Determining pill cutting positions***

Input: *Pill positions; Number of pills to cut*

Output: *Coordinates and cutting paths on the pill image*

1. *Sort pill coordinates,*
2. *Create a matrix of left edges,*
3. *Sort rows by increasing x,*
4. *Assign the first two submatrices to y_max and y_min, representing max and min y-coordinates,*
5. *Draw the first cut from the y_max[0] to y_min[0],*
6. *gt[0] = lenght(from y_max[0] to y_min[0])*
7. *If (y_min[0] < 40):*
8.   *If (lenght (y_max[1] to y_min[1]) – 20) > gt[0]:*
9.   *Draw the second cut from the y_max[1] to y_min[1]*
10.   *gt[1] = lenght(from y_max[1] to y_min[1])*
11.   *Draw the third cut from the y_min[1] to y_min[0]*
12.   *gt[2] = lenght(from y_max[1] to y_min[0])*
13.   *Else:*
14.   *Draw the second cut with a length equal to the bounding box side,*
15.   *gt[1] = the length of the second cut*

End

2.4. Pill cutting mechanism control algorithm

In this study, we focus on blister packs with pills arranged in parallel rows. To obtain the required number of pills, the blister pack will be cut a maximum of three times. The pill cutting mechanism control algorithm is presented in **Algorithm 2**. The algorithm will run directly on the device controlling the pill cutting system. The algorithm's output will be a set of specific commands sent to the PLC to control the motors, sensors, and other components of the pill cutting system.

Algorithm 2. ***Pill cutting mechanism control***

Input: *Coordinates and cutting paths on the blister pack image*

Output: *Coordinates and PLC control commands.*

1. *Fix the blister pack,*
2. *Get the number of pills from HMI,*
3. *Capture image and analyze with YOLOv5,*
4. *Draw cutting positions,*
5. *Calculate pulse count,*
6. *If number of cuts = 1:*

```
        Move blister to puller 1 and cut
    If number of cuts = 2:
        Move blister to puller 1 and cut parallel to puller 1
        Move blister to puller 2 and cut remaining line
    If number of cuts = 3:
        Move blister to puller 1 and cut two parallel lines
        Move blister to puller 2 and cut remaining line
    Move to home position
End
```

3. Results and discussion

3.1. Results on YOLOv5

The YOLOv5 model was trained on Google Colab using a T4 GPU for 100 epochs. Model performance was evaluated using Precision, Recall, mAP@0.5, and mAP@0.5:0.95. These metrics are defined in equations (1) to (4). The evaluation results are presented in **Table 1**.

$$Precision = \frac{TP}{TP + FP} \tag{1}$$

$$Recall = \frac{TP}{TP + FN} \tag{2}$$

$$AP = \sum_{n} (Recall_n - Recall_{n-1}) \times Precision_n \tag{3}$$

$$mAP = \frac{1}{n} \sum_{i=1} AP_i \tag{4}$$

where TP is the set of correctly predicted positive class objects, FP is the set of false positive objects (predicted as positive but actually negative), and FN is the set of false negative objects (predicted as negative but actually positive). AP represents the average precision of the model for a specific class. A higher AP value, closer to 1, indicates better model performance. n denotes the number of object classes, and in this study, n = 1. mAP@0.5 is the mean average precision calculated at an Intersection over Union (IoU) threshold of 50%, while mAP@0.5:0.95 is the mean average precision calculated across various IoU thresholds ranging from 50% to 95%.

Table 1 presents the evaluation results on the validation set. The model achieved a Precision of 99.5%, indicating high confidence in pill detection. A Recall of 100% was obtained, ensuring that all pills were detected. The mAP@0.5 score of 99.2% demonstrates the model's ability to accurately classify objects as pills with a confidence threshold of 50%. **Figure 5** illustrates the training loss and validation accuracy curves of the YOLOv5 model. The training loss decreases steadily and reaches a plateau after 50 epochs, while the validation accuracy continues to improve until around the 100th epoch. This indicates that the model has achieved a good balance between training and generalization.

Table 1. *YOLOv5 model performance on the validation dataset*

Metrics	Precision (%)	Recall (%)	mAP@0.5(%)	mAP@0.5:0.95(%)

Result	99.5	100	99.2	80.2

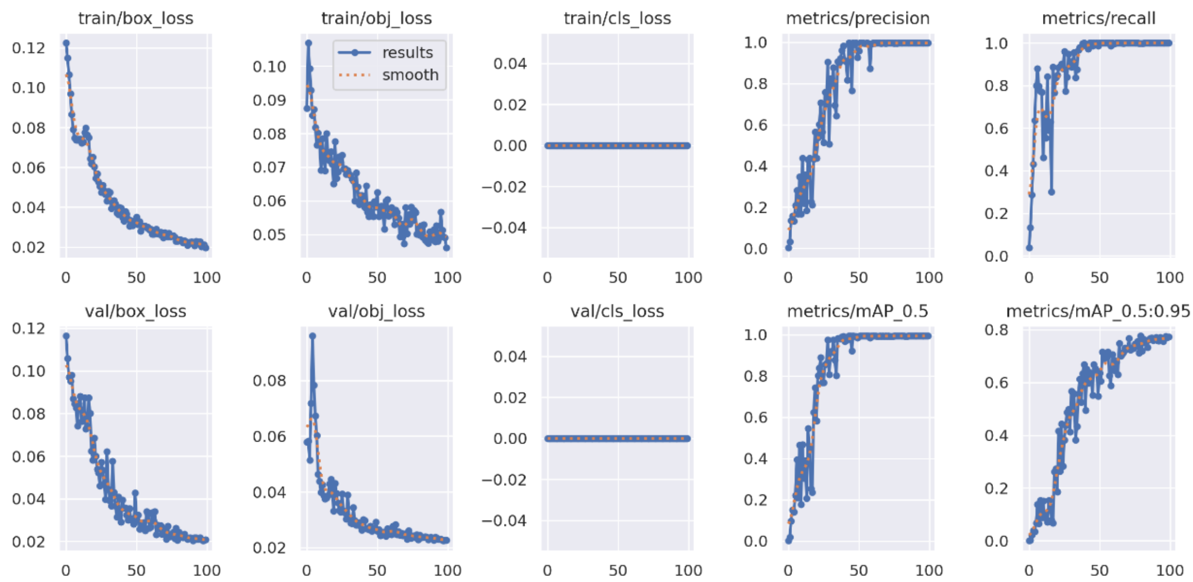


Figure 5. *The learning curve of the YOLOv5*

The training results demonstrate the model's accuracy in correctly identifying the positions of pills on blister packs. **Figure 6** illustrates an example of pill localization on a blister pack. The parameters shown in the figure indicate the model's confidence, with a localization accuracy of over 90%. This ensures the reliable determination of pill coordinates.

Figure 6. *Pill localization results on blister packs*

Table 2. *Study results using the YOLOv5 model for healthcare applications*

Applications	Models	Pre (%)	Re (%)	mAP@0.5(%)	mAP@0.5:0.95(%)
Medical Personal Protective Equipment detection [9]	ME-YOLO	-	-	97.2	-
Aortic valve detection [8]	AVD-YOLOv5	94.3	86.8	-	89.6
Surgical Instrument detection [10]	Im-YOLOv5	-	-	-	88.7
Medical pill detecion (Ours)	YOLOv5	99.5	100	99.2	80.2

Table 2 provides an overview of research findings related to the application of the YOLOv5 model in healthcare. The results presented in **Table 2** support the efficacy of the YOLO model for healthcare tasks. The obtained precision, recall, and mAP scores are in line with our expectations. In this work, we have further investigated the utilization of object detection models to optimize drug dilivery processes.

3.2. Determine the cutting path

The cutting paths for blister packs, as determined by the algorithm, are illustrated in **Figure 7**. Depending on the number of pills and their positions on the blister pack, the algorithm will determine the cutting paths. The pill-cutting mechanism was equipped with two cutters: one horizontal and one vertical. The algorithm specifically determines which cutter will be used for each cut. Specifically, if the number of pills is even, there will be one cut, and the cutting position depends on the exact quantity. If the number of pills is odd, there will be two or three cuts**. Figure 7(a)** illustrates a case where three pills need to be cut, resulting in three cutting paths. In **Figure 7(b),** where only two pills are required, the algorithm determines a single cut. **Figure 7(c)** shows a case where 1 pill needs to be cut from the blister pack, requiring two cuts. In the case of **Figure 7(a)**, two cuts could be made, but to ensure that the blister pack can be reused for future cuts, the algorithm prioritizes cutting from one side.

(a) *(b)* *(c)*

Figure 7. *Illustrates the cutting paths determined by the algorithm. (a) A case with 3 cuts, (b) a case with 2 cuts, and (c) a case with 1 cut. The red line represents the cut made by cutter 1, and the blue line represents the cut made by cutter 2*

3.3. Limitations

The blister packs used in this study are of the horizontal and vertical arrangement type. The cutting path determination method had not yet been applied to blister packs with angled pills. The system's performance depends on the accuracy of the mechanical components, especially the process of moving the blister packs to the cutting position. If the blister pack is not placed straight, it may lead to inaccuracies in determining the cutting path. Cutting an odd number of pills has not yielded an optimal solution. For example, in **Figure 7(a)**, a more optimal solution could be achieved with two cuts.

In future studies, we will focus on improving the stability of the hardware system. We will also add a pill blister rotation function. Currently, the blister pack is fixed at a right angle to the two cutting mechanisms. This function will allow for cutting blister packs with pills that are not aligned. Additionally, the cutting path algorithm will be modified to identify the starting and ending points of the pills, enabling diagonal cuts. To enhance the generalization ability of the YOLOv5 model, the training dataset will be improved to include a wider variety of blister packs. Image augmentation techniques will be applied to increase the model's robustness.

4. Conclusion

This study proposes a solution that integrates artificial intelligence on an embedded operating system and communicates with industrial PLC devices for an automated drug dispensing system. Data collection and training of the YOLOv5 deep learning model achieved an accuracy of over 99%. The cutting position determination algorithm on the Raspberry Pi 4 embedded board demonstrated reliable performance. The research results demonstrate the feasibility of applying deep learning models to embedded devices, enabling communication with industrial equipment and ensuring the intelligence and reliability of automated systems. Specifically in the healthcare sector, this research contributes to addressing the challenges in drug dispensing.

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Conflict of Interest

The authors declare that they have no conflict of interest.

Data Availability Statement

The data for this study were collected by the authors.

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