國立高雄大學資訊工程學系

碩士論文

應用 M3-YOLOv5 物件偵測演算法於晶片輪廓檢測

Applying M3-YOLOv5 Object Detection Algorithm to Chip Contour Inspection

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摘要

本研究將 M3-YOLOv5 物件偵測演算法部署在嵌入式平台 Jetson Xavier NX 上，實現晶片槽內晶片輪廓的即時物件偵測和影像辨識的優異性能。只要檢測到有缺陷的晶片，它就會立即發出警告，並記錄晶片插槽的位置和發生的時間戳記。當警報響起時，操作將暫停一段時間，操作人員可以立即取出有缺陷的晶片，以避免擠入該晶片槽中的下一個晶片。本研究的目的是分析和比較 M3-YOLOv5 物件偵測演算法、GSEH-YOLOv5 物件偵測演算法和傳統 YOLOv5 物件偵測演算法在物件偵測和影像辨識方面的性能。實驗結果顯示，我們提出的方法使用在嵌入式平台 Jetson Xavier NX 的準確度為 98.9%，速度為 25 fps。分析實驗結果得證，與傳統的 YOLOv5 相比，所提出的方法可以提高 0.4% 的準確度和 12.6% 的執行速度。與 GSEH-YOLOv5 相比執行速度略差是因為 GSEH-YOLOv5 旨在提高速度但是犧牲較多的準確度。

關鍵字：Jetson Xavier NX、即時物件偵測、即時影像感知與辨識、M3-YOLOv5、注意力機制。

Applying M3-YOLOv5 Object Detection Algorithm to Chip Contour Inspection

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ABSTRACT

In this paper, M3-YOLOv5 algorithm is deployed on the embedded platform, Jetson Xavier NX, to implement the excellent performance for real-time object detection and image recognition of the chip contour in the chip slot. As long as a defective chip is detected, it will immediately issue a warning and record the position in which chip slots and the timestamp of occurrence. When the alarm goes off, the operation will be paused for a while and the operators can immediately remove the defective chip to avoid squeezing the next chip in that chip slot. The objective of this paper is to analyze and compare the performance of object detection and image recognition among the M3-YOLOv5 algorithm, the GSEH-YOLOv5 algorithm, and the traditional YOLOv5 algorithm. Experimental results show that our proposed method has an accuracy of 98.9% and a speed of 25 fps on the embedded platform Jetson Xavier NX. The analysis of the experimental results proves that the proposed method can improve the accuracy by 0.4% and the execution speed by 12.6% compared with the traditional YOLOv5, and the execution speed is slightly worse compared with GSEH-YOLOv5 because GSEH-YOLOv5 aims to improve the execution speed but sacrifices more accuracy.

Keywords: Jetson Xavier NX, Real-time Object detection, Real-time Image Sensing and Recognition, M3-YOLOv5, and Attention Mechanism.

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在研究所的求學生涯中，因為有張老師的悉心指導，不僅學會進行學術研究應具備的能力與正向積極的人生態度，也學到為人處事的圓融與學術研究以外的解決方針，更讓我利用實驗室完善的資源獲得許多研究領域上的實質幫助。這些研究上的建議，讓繁瑣的挑戰能夠化繁為簡，再大的困難都能迎刃而解。此外，張老師的研究主軸都是現今學術界與企業界蓬勃發展的最新技術，可以讓我在未來投入職場能夠游刃有餘，一切將歸功於老師的遠見。如今我即將畢業了，心中的感激之情難以言表。接下來要感謝的是研究所的學長姊們郁傑、炯霖、函霖，我們一同分享不同領域的知識，也會一同討論課業上的問題。在研究中你們熱心的給我建議，讓我的研究得以順利的進行。再來要特別感謝即將一同畢業的同儕冠儒，從大學時期就認識的我們選擇相同的道路，學業期間相互扶持與勉勵對方，成為我最強而有力的後盾，也成為我堅持下去的力量。也感謝學弟翔宇，給予我許多研究之外的幫助，研究所期間非常感謝能遇見你們。

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Chapter 1. Introduction

With the development of Industry 4.0, modern information and communication technologies help factories improve economic efficiency, including big data analysis, cloud computing, and autonomous or automation systems into factories, which significantly improve the production capacity of factories. When the production line is automatically transporting chips, if the production machine accidentally crushes and leave the current chip sticking in the slot, the next round of placing a chip onto the same specitial location will cause the damage for both of chips, that is, making a production loss. Therefore, how to minimize the loss is the primary goal of this study. This paper intoduces innovative deep learning model to implement the real-time image detection for solving the problem. Generally speaking, the technique of object detection have two modes – single-stage and two-stage. Single-stage combines the localization and the classification. Two-stage separates the localization and the classification. According to the classic object detection algorithms, two-stage object detection algorithms are better than single-stage object detection algorithms in accuracy. Typical two-stage object detection models are Fast R-CNN [1], Faster R-CNN [2], and Masked R-CNN [3]. However, the enormous amount of computation is the disadvantage of two-stage object detection. As long as there are a large number of framed targets in the picture, the next step of object classification will require a large number of crafted targets to be classified, which is really time-consuming. Many applications in daily life need real-time object detection. Specific applications include mask-wearing detection, operator clothing detection, and product detection in factories. Nevertheless, through continuous technical improvement of single-stage object detection, it can implement at a fast speed and maintain a high accuracy ratio. This study intends to use single-stage object

detection for the application of image recognition, and chooses YOLOv5 model recently published in 2020 [4]− [11] due to the high speed of object detection and the high accuracy of image recognition.

Chapter 2. Related Work

2.1 Literature review

The core concept of YOLOv1 model proposed by Redmon and Farhadi et al. is to split the input as a grid with the same height and width, then predict the targets in each grid. In the beginning, YOLOv1 uses two bounding boxes to predict objects in each grid, and only one object with the highest category probability could be expected in the same grid [7]. Redmon et al. proposed an improved method for YOLOv1, called YOLOv2. The primary purpose is to enhance the execution speed and accuracy of the model, mainly by adding the anchor box and batch normalization mechanisms [8].

Redmon et al. added a residual network [9] to YOLOv2 to improve the accuracy of YOLOv2 later. After deepening the network structure, people referred it to as YOLOv3. YOLOv3 dramatically improves its accuracy while maintaining the same speed as YOLOv2 [10]. Bochkovskiy and the others proposed the YOLOv4 architecture, with the primary goal of designing a fast operating system with new functions. The object detection applied in the mass production system can optimize parallel computation to improve the operational speed dramatically, not just reducing the theoretical computation indicator, billion float operations per second (BFLOPS). After that, Bochkovskiy and the others have further integrated the new methods to YOLOv4 to achieve the best performance of the object detection. This is called CSPNet that can significantly improves both the speed and the accuracy [11] concurrently.

Marco et al. found that adopting the model compression algorithms to shorten the model are most likely to reduce the inference time; however, it would pay the cost of lower accuracy. Alternatively, they gave another method, running the program in the embedded platform, which can dynamically determine which DNN model used to

obtain the required the accuracy and inference time according to the input data [12]. Sun et al. proposed an object detection network built in an embedded platform. Based on that the Mobile-YOLO (M-YOLO) model [13] combines the residual module and the depthwise separable convolution [14] into the network to reduce the computational burden.

Howard et al. intoduced MobileNet [15] which uses depthwise separable convolution to build a lightweight [16] deep neural network. The depthwise separable convolution can obtain a feature map similar to the traditional convolution with less computation for object detection. This is because it implements the depthwise separable convolution operation in the feature selection layer.

MobileNetV2 [17] is based on the inverted residual structure in which the shortcut connections are between the thin bottleneck layers. The intermediate expansion layer uses lightweight depthwise convolution to filter the features that are sources of non-linearity. In terms of the mobile phone CPU, MobileNetV3 [18] adjusts to it through a novel architecture of using hardware-aware network architecture search (NAS) and NetAdapt algorithm to improves its advancements. This study explores how automatic search algorithms and network design work together with complementary methods to come up with the contemporary technique level.

Vaswani et al. deviced the superior sequence conversion model based on a complex recursive or convolutional neural network, including an encoder and a decoder. The best-performing model connects the encoder and decoder through the attention mechanism [19]. The innovation of the SENet network proposed by Hu et al. is to pay attention to the important features and reduce the weights of the useless features [20].

2.2 Traditional YOLOv5 model

YOLOv5 uses some special techniques, such as mosaic data enhancement, adaptive image scaling, and the addition of a unique focus structure. Using these techniques can get an outstanding improvement in the field of object detection. Mosaic can significantly improve the detection ability of the YOLO series in small objects through the method of splicing and randomly zooming the image ratio. Object detection mainly used Image scaling to scale the length and width of the input image during detection, which can effectively reduce the short side length, reduce the amount of computation, and increase the speed of inference. The focus structure particularly increases the computation to splice and combine so that the feature map does not cause the loss of feature information due to compression. The architecture of the traditional YOLOv5 model is shown in Figure 1 to Figure 4.

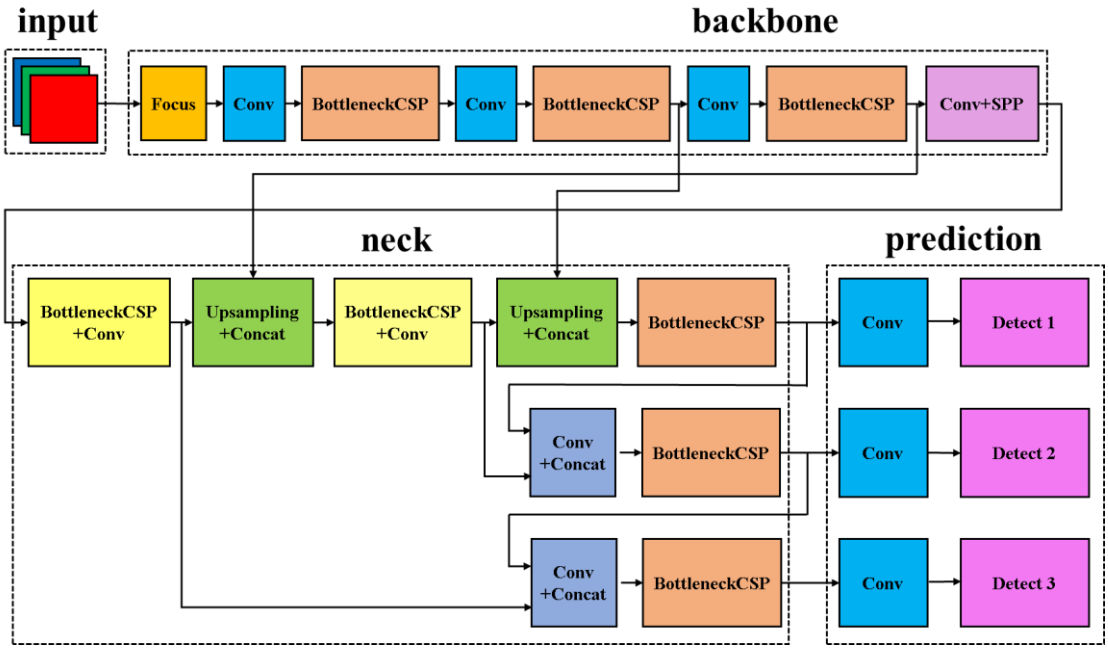


Figure 1. The architecture of the traditional YOLOv5 model

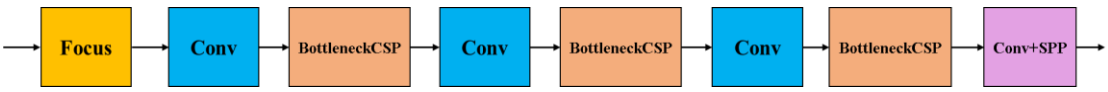


Figure 2. The backbone structure of the traditional YOLOv5 model

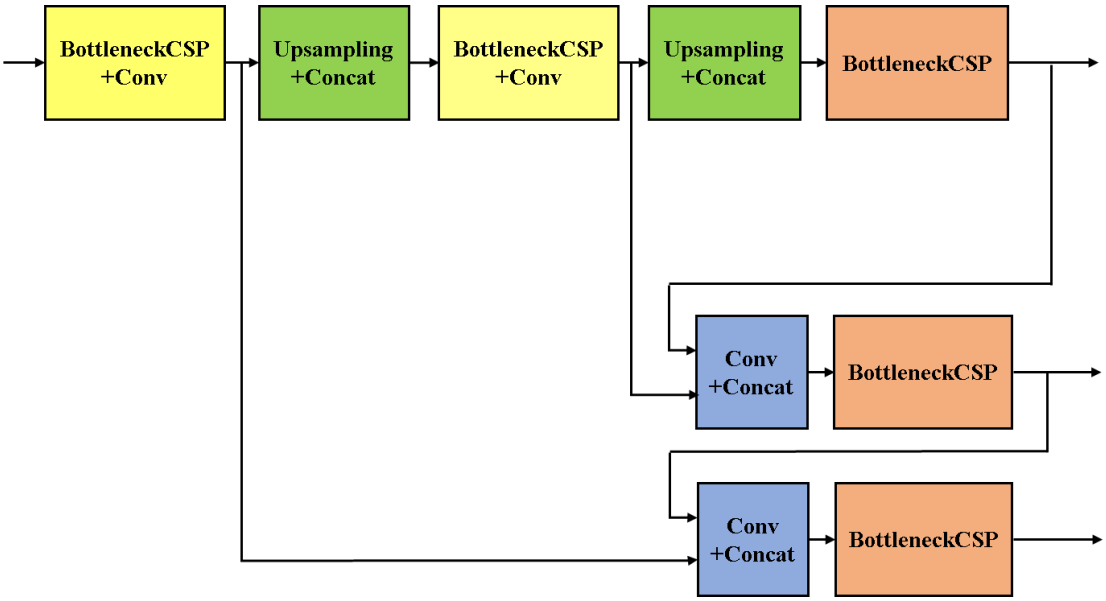


Figure 3. The neck structure of the traditional YOLOv5 model

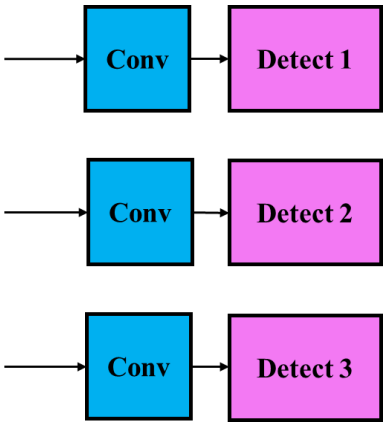


Figure 4. The prediction structure of the traditional YOLOv5 model

2.3 Alternative model GSEH-YOLOv5

Here introduced an alternative model, GSEH-YOLOv5, and its architecture is shown in Figure 5 to Figure 7. The prediction structure of the GSEH-YOLOv5 is the same as Figure 4. The difference between GSEH-YOLOv5 [21] and traditional YOLOv5 is that the GhostNet module with the attention mechanism replaces the CSP module. Moreover, the attention module replaces the remaining CSP module. The purpose of using the GhostNet module is to reduce unnecessary convolutional

computations. The introduction of GhostNet allows the traditional YOLOv5 model to effectively reduce the number of computations and parameters during the inference. Since the method proposed in this study requires real-time inference in an embedded platform, its primary purpose is to maximize the speed of performance while maintaining the accuracy of the result as much as possible.

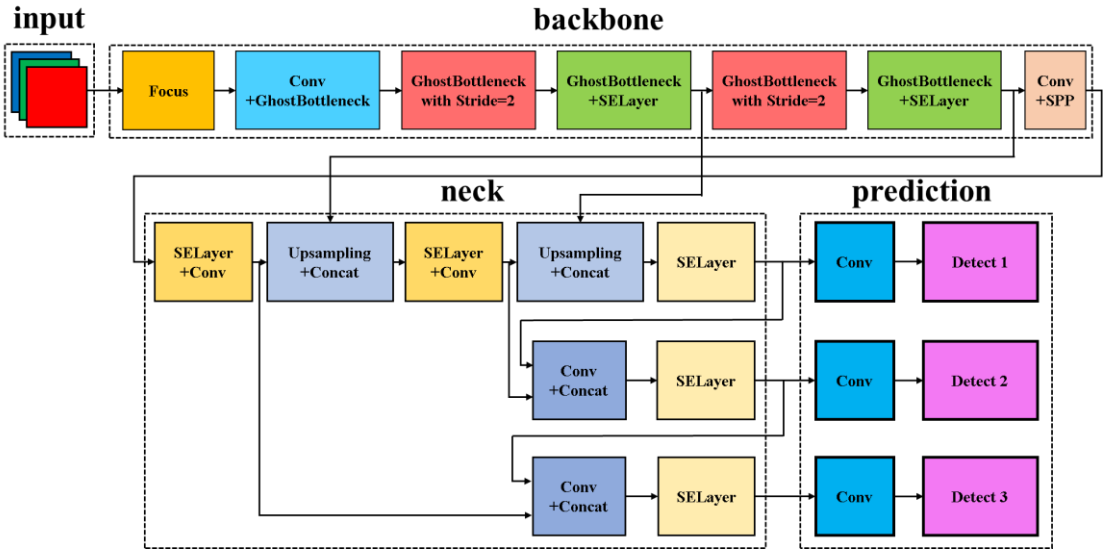


Figure 5. The architecture of the GSEH-YOLOv5 model

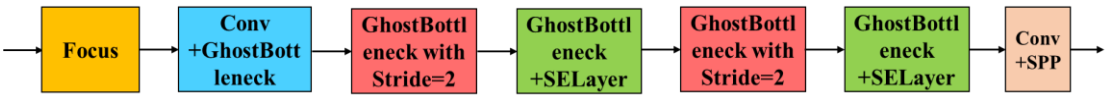


Figure 6. The backbone structure of the GSEH-YOLOv5 model

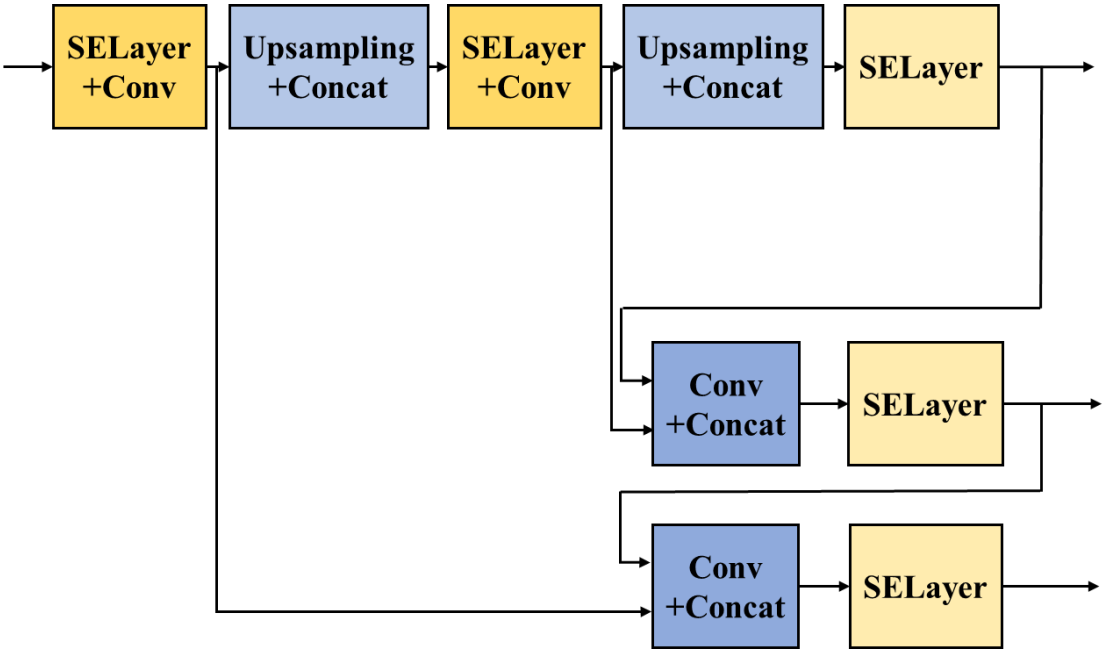


Figure 7. The neck structure of the GSEH-YOLOv5 model

Chapter 3. Research Method

3.1 Data preparation and labeling

It is beginning to do manually labeling with data set provided by A semiconductor company in Taiwan. The Image labeling with LabelImg goes through a total of 553 training data and 89 validation data [22] where a single datum represents a frame. Next, we manually label the position with the target in each frame. After position labeling, there are three conditions — empty slot, slot occupied with an intact chip or a defective chip, as shown in Figure 8. In other words, we refer these to as empty condition, occupied condition, or defective condition in the following sections.

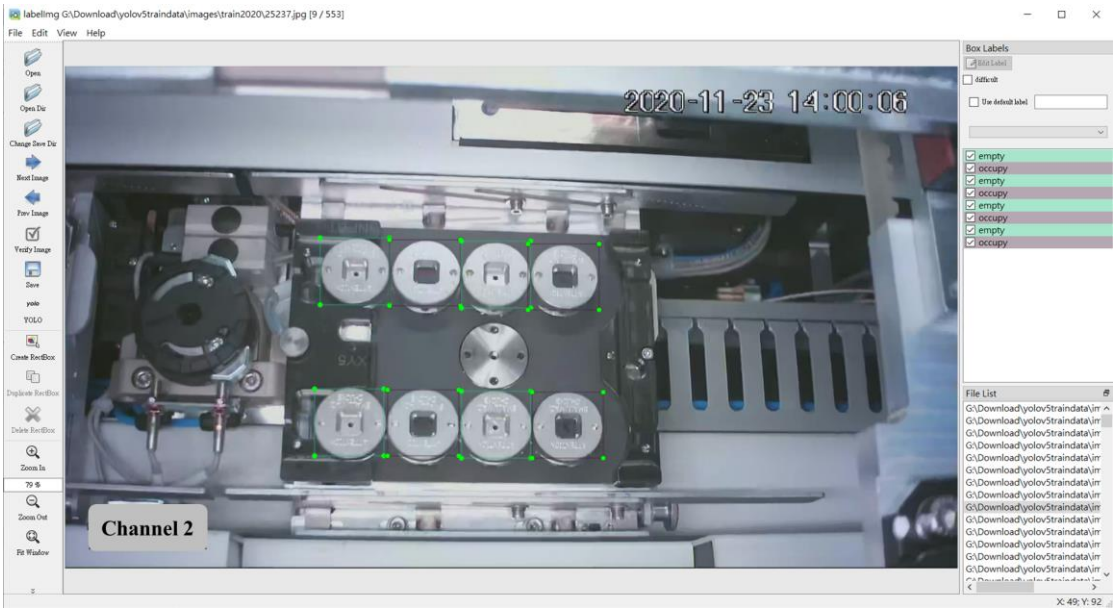


Figure 8. Image labeling with LabelImg

3.2 Model training and mAP

This study uses the training framework called PyTorch [23] and uses the training dataset collected and labeled to train a suitable model for the situation. The training process of the screenshot is shown in Figure 9. If the accuracy is not as expected, we

need to check the adjustment parameters and inspect whether the mark quality of the dataset is good. The mAP uses to evaluate the quality of the model. The closer the value of mAP is to one, the better the model's performance, as shown in Figure 10.

Epoch	gpu_mem	box	obj	cls	total	targets	img_size	
1/1999	6.24G	0.1059	0.2519	0.03734	0.3951	972	416:	11%
1/1999	6.24G	0.1066	0.2513	0.03752	0.3954	1009	416:	11%
1/1999	6.24G	0.1066	0.2513	0.03752	0.3954	1009	416:	22%
1/1999	6.24G	0.1057	0.2469	0.03742	0.39	894	416:	22%
1/1999	6.24G	0.1057	0.2469	0.03742	0.39	894	416:	33%
1/1999	6.24G	0.1057	0.2474	0.03729	0.3904	1011	416:	33%
1/1999	6.24G	0.1057	0.2474	0.03729	0.3904	1011	416:	44%
1/1999	6.24G	0.1055	0.2492	0.0373	0.392	1004	416:	44%
1/1999	6.24G	0.1055	0.2492	0.0373	0.392	1004	416:	56%
1/1999	6.24G	0.1051	0.2506	0.03728	0.393	974	416:	56%
1/1999	6.24G	0.1051	0.2506	0.03728	0.393	974	416:	67%
1/1999	6.24G	0.1049	0.251	0.03717	0.393	993	416:	67%
1/1999	6.24G	0.1049	0.251	0.03717	0.393	993	416:	78%
1/1999	6.24G	0.1048	0.2524	0.03709	0.3943	1050	416:	78%
1/1999	6.24G	0.1048	0.2524	0.03709	0.3943	1050	416:	89%
1/1999	6.24G	0.1045	0.2527	0.03699	0.3942	620	416:	89%
1/1999	6.24G	0.1045	0.2527	0.03699	0.3942	620	416:	100%
1/1999	6.24G	0.1045	0.2527	0.03699	0.3942	620	416:	100%

Figure 9. Screenshot of the actual training process record

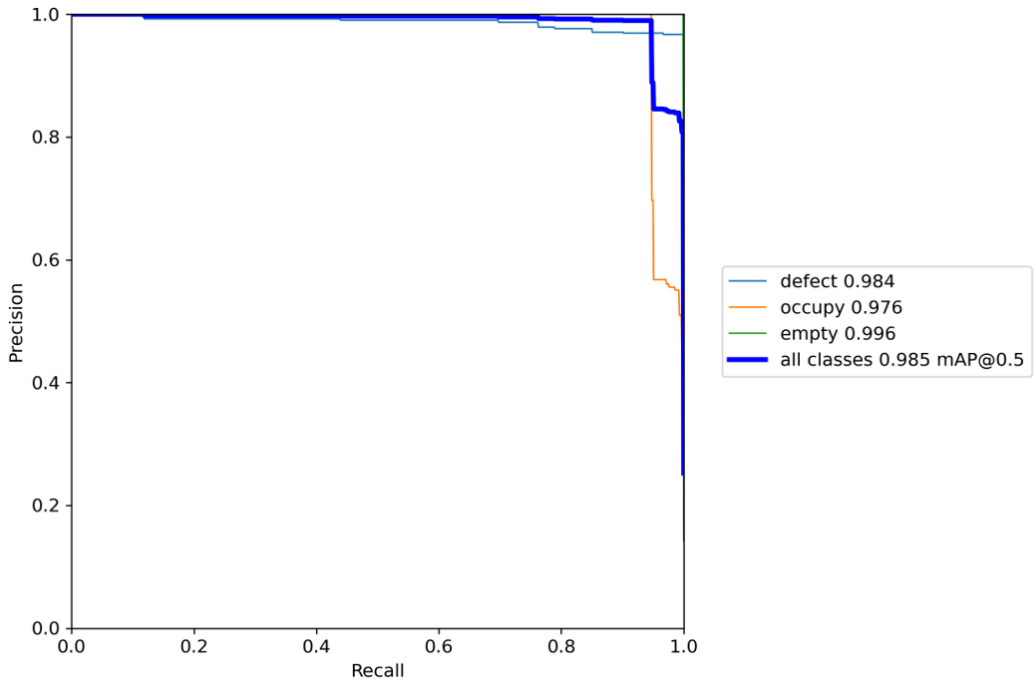


Figure 10. Line chart of mAP with traditional YOLOv5

3.3 On-site image sensing and recognition

After completing the training model, a well-trained model can identify pictures, videos, and real-time streaming images. Therefore, we transplants the trained model to an embedded platform, Jetson Xavier NX, for object detection [24] applications. Jetson Xavier NX is a product of NVIDIA with artificial intelligence, and designed for high-speed image recognition, as shown in Figure 11. Once Jetson Xavier NX has completed the object detection, it will also output the image identification result in time, as shown in Figure 12. According to the image identification result, we will evaluate how good the embedded platform is in the execution performance.

Figure 11. An embedded platform — Jetson Xavier NX

(a) defective condition

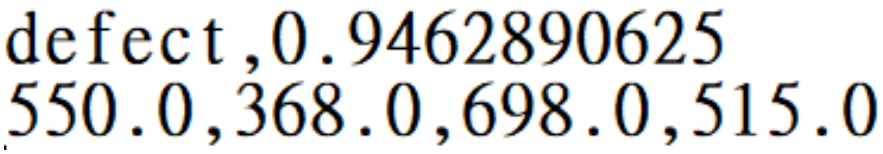
(b) empty condition

(c) occupied condition

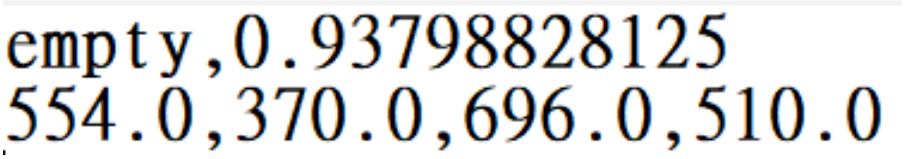
Figure 12. Chip detection showing results

3.4 Spatial location and identification accuracy

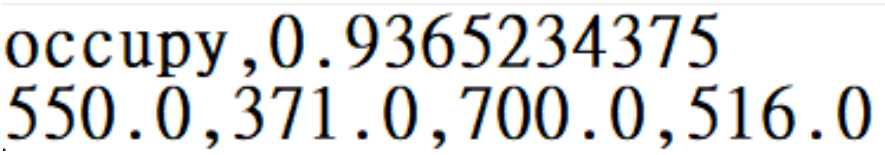
This part describes the identification results of chip detection. These results include the type of object to be identified, the accuracy of identified object, and the spatial location of the object, as shown in Figure 13. It is noted that how to deal with the situation of detecting any defective chip at the specified spital location of a chip slot. Once any defective chip has been detected and given a warning message to monitors, people can shutdown or pause the production line operation immediately to avoid the damage of the followed chip put into the same spital location next time. Operators have to learn the guidline of this procedure so as to maintain the production lines secured and operative machines safely.



(a) defective case



(b) empty case



(c) occupied case

Figure 13. Spatial location and the accuracy of identified objects

3.5 On-site detection of chip contour

This section utilizes the information about the chip detection in detail to establish a warning system for people. As the detection of any defective chip has occurred, people must stop the operative machine immediately to avoid the unexpected loss. With the assistance of chip inspection, the system can detects any defective chip at once and automatically send a warning message to monitor, as shown in Figure 14. The notebook records the information about the defective chip, and its corresponding actual spactial position as indicated in the box marked by color red. For the convenience, we number the chip slots initially. The way of numbering slots is from left to right and top to bottom, as shown in Figure 15. Technically speaking, system set the file name of notebook to the current timestamp to let people inuitively understand when the case happened and which chip slot has a defective one, as shown in Figure 16. This way is not only to show the timestamp directly for peolpe, but it also saves a lot of time for checking which chip slot.

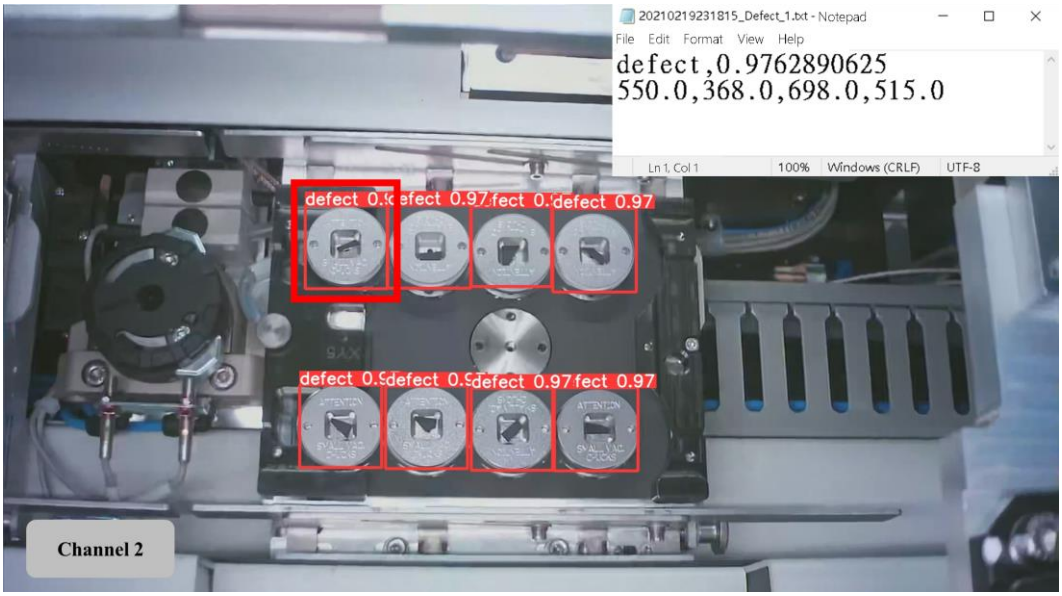


Figure 14. Display information about the exact location

Figure 15. Number all the chip slots

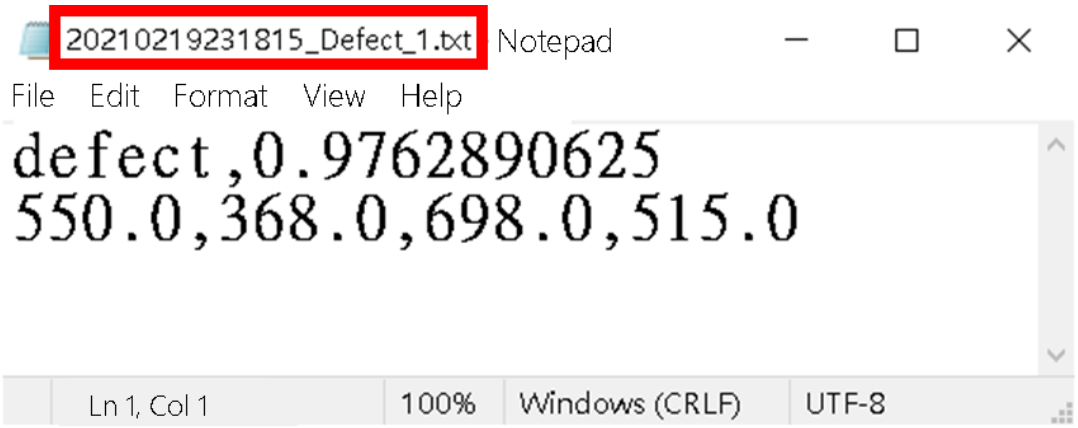


Figure 16. Provide timestamps and slot numbers of all the chip slots

3.6 Modification of the YOLOv5 network architecture

The YOLOv5 network architecture significantly reduces the number of computations implementing feature extraction and generates valuable features. The main modules use the backbone of MobileNetV3 [18] and the attention mechanism of SENet [20] to replace the whole traditional backbone and call it M3-YOLOv5 model, as shown in Figure 17 to Figure 19. The prediction structure of the M3-YOLOv5 is the same as Figure 4.

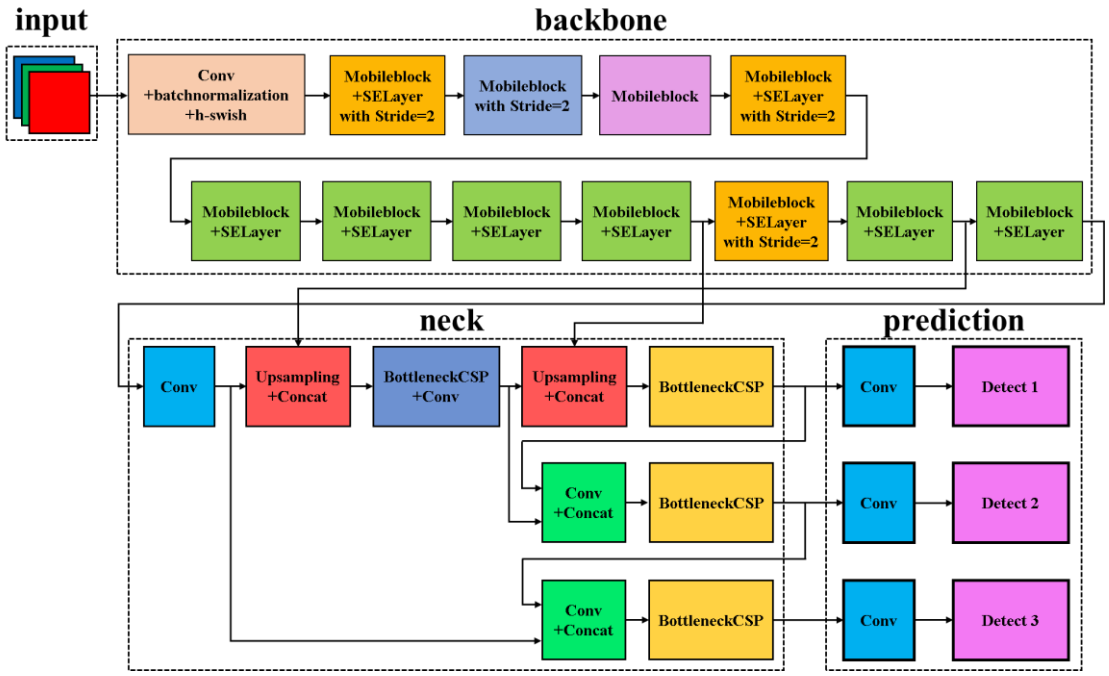


Figure 17. The architecture of the M3-YOLOv5 model

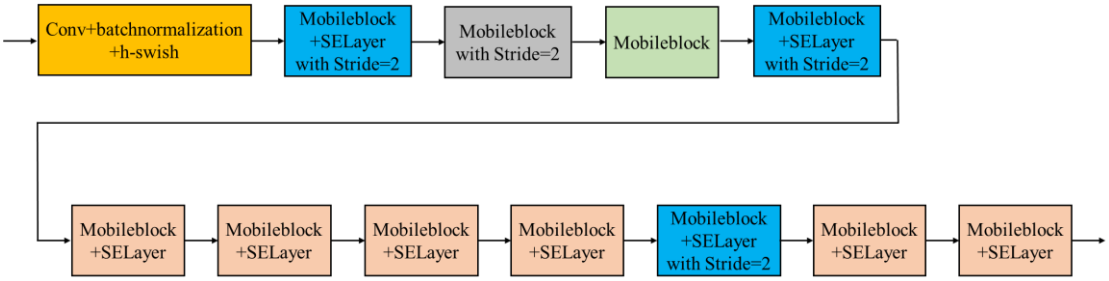


Figure 18. The backbone structure of the M3-YOLOv5 model

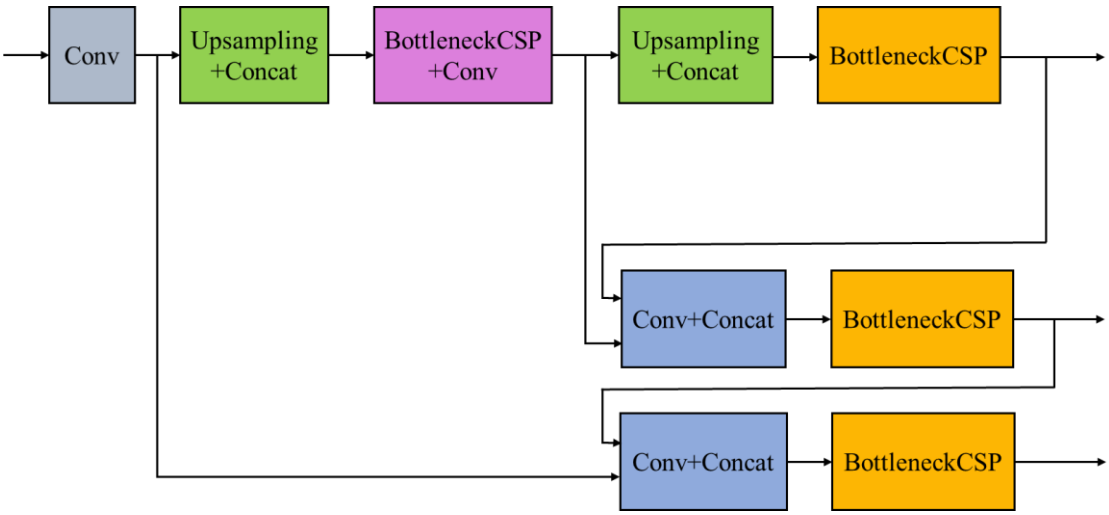


Figure 19. The neck structure of the M3-YOLOv5 model

3.7 Average accuracy of M3-YOLOv5 model

After completing the training of the improved M3-YOLOv5 model, implement the performance evaluation, and the mAP is shown in Figure 20.

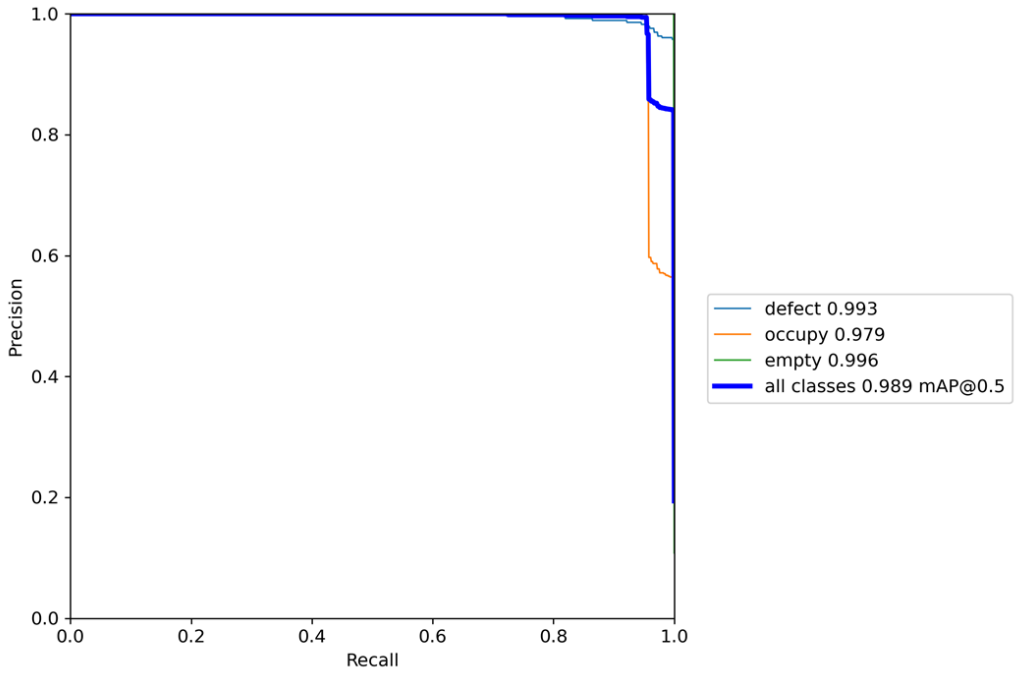


Figure 20. Line chart of mean average precision of M3-YOLOv5

Chapter 4. Experimental Results and Discussion

4.1 Experimental environment

The training environment is mainly implemented in Workstation, and the test environment is based on the Jetson Xavier NX embedded platform, as shown in Table 1. The software copyright is shown in Table 2.

Table 1. Hardware specifications

Resource	Workstation	Jetson Xavier NX
GPU	NVIDIA GeForce RTX 2080 Ti	384-core NVIDIA Volta™ GPU with 48 Tensor Cores
CPU	Intel (R) Core(TM) i9-7900X CPU @ 3.30GHz	6-core NVIDIA Carmel ARM®v8.2 64-bit CPU 6MB L2 + 4MB L3
Memory	96GB	8 GB 128-bit LPDDR4x @ 1600 MHz 51.2GB/s
Storage	256GB*1(SSD) 2TB*1(HDD)	16 GB eMMC 5.1

Table 2. Software copyright

Software	Version
LabelImg	1.8
Anaconda® Individual Edition	4.9.2
Jupyter Notebook	6.1.4
PyTorch	1.6
JetPack	4.4

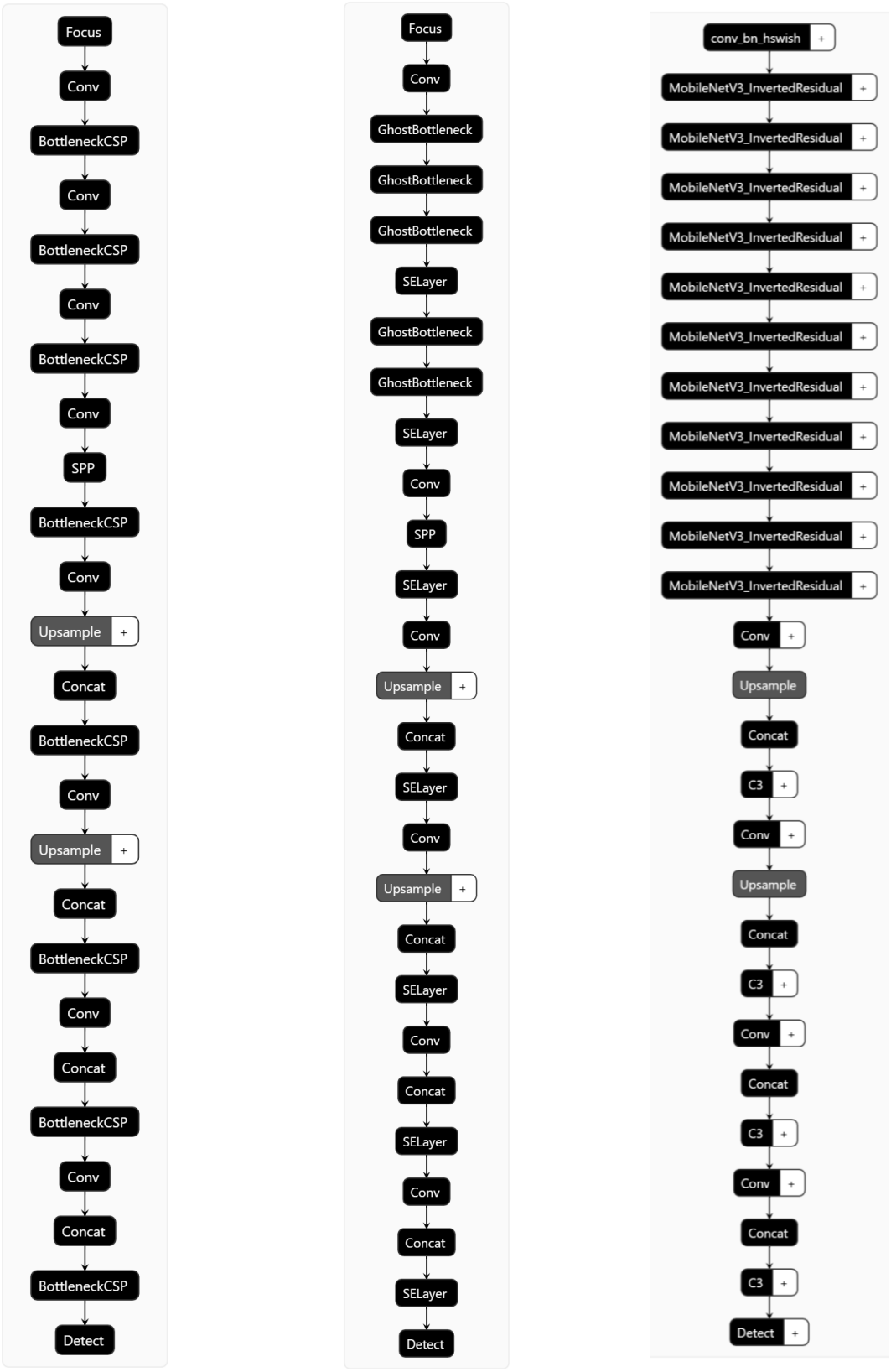
4.2 Experimental design

We performed two experiments of the object detection effect, and the operating speed of the trained YOLOv5 model on the embedded platform, Jetson Xavier NX in this section. Then, we compared the performance of the two improved lightweight YOLOv5 models and the traditional YOLOv5 model.

4.3 Experimental results

4.3.1 Demonstrating the three YOLOv5-related architectures

Here shown the different feature extraction function between the traditional YOLOv5 model and the backbone of MobileNetV3 published in 2019 proposed as a key feature extraction. We have demonstrated the differences among the three YOLOv5-related architectures, the traditional YOLOv5, the improved GSEH-YOLOv5, and the improved M3-YOLOv5 as shown in Figure 21. The biggest difference between the three YOLOv5-related models is that they refer to different network architectures for feature extraction. The traditional YOLOv5 model refers to the CSPNet architecture, GSEH-YOLOv5 refers to the GhostNet architecture, and M3-YOLOv5 refers to the MobileNet architecture.



(a) Traditional YOLOv5 (b) GSEH-YOLOv5 (c) M3-YOLOv5

Figure 21. Architectures of three YOLOv5-related models

4.3.2 Estimation of model training time and video inference time

With the Jetson Xavier NX embedded platform, here mainly estimated the time-consuming of training the traditional YOLOv5 model and the modified M3-YOLOv5 model given the same training data set. The test of a video with 1805 testing data proceeded to record the time taken for object detection and image recognition for each testing data. Eq. (1) Calculate the Average Inference Time (AIT) of three different YOLOv5 models for each image under the same test video. In Eq. (1), VIT_{ijk} represents the time to infer the use of the test video, and FN represents the total number of frames of the test video.

$$AIT_{ijk} = \frac{VIT_{ijk}}{FN}, where\ i = 1,2,\ldots,l, j = 1,2,\ldots,m, k = 1,2,\ldots,n \quad (1)$$

Technically speaking, we set the parameters of training model as follows: the input image size 416x416, the batch size 64, and the number of iterations 300. After the experiment, the estimated results are listed in Table 3. In Table 3, the first row represents the training time for three different YOLOv5 models based on the same parameter settings. The second row stands for the time consuming of object detection and image recognition according to the total of 1805 image frames. The third row is the average time of object detection and image recognition for each frame.

Table 3. Training and inference times (unit: second)

Method	YOLOv5	GSEH-YOLOv5	M3-YOLOv5
Training	4167.7	4136.4	2224.8
Inference	199.528	179.541	206.088
Average	0.0321	0.0256	0.0365

4.3.3 Real-time detection speed and recognition accuracy

The performance of real-time object detection relies on the number of captured and computable frames per second and the accuracy of image recognition. Eq. (2) is used to calculate the frames per second of three YOLOv5-related models for detecting

objects in real time, where $RAIT_{ijk}$ is the time required for each image in 480-pixel height and 640-pixel width real-time images. Eq. (3) is used to calculate the accuracy of the three YOLOv5-related models, where c_{ijk} represents the identified categories and APc_{ijk} represents the accuracy of each class.

$$FPS_{ijk} = \frac{1}{RAIT_{ijk}}, where\ i = 1,2,\ldots,l, j = 1,2,\ldots,m, k = 1,2,\ldots,n \quad (2)$$

$$mAP_{ijk} = \frac{APc_{ijk}}{c_{ijk}}, where\ i = 1,2,\ldots,l, j = 1,2,\ldots,m, k = 1,2,\ldots,n \quad (3)$$

Eq. (2) is used to calculate the speed in the real-time object detection with the Jetson Xavier NX embedded platform. After that, Eq. (3) is used to calculate the average accuracy of the three YOLOv5-related models after training with the same parameters, as shown in Table 4.

Table 4. Speed and accuracy of models

Method	YOLOv5	GSEH-YOLOv5	M3-YOLOv5
Speed (fps)	22.222	27.397	25
Accuracy (%)	98.5	97.5	98.9

4.3.4 Operational cost

From the experimental results in Table 4 and Table 5, it can be known that execution speed can be effectively improved by greatly reducing the number of parameters and FLOPs.

Table 5. Numbers of parameters and FLOPs of models

Method	YOLOv5	GSEH-YOLOv5	M3-YOLOv5
Parameters (#)	7251912	4182136	3205296
FLOPs (GFLOPs)	16.8	6.9	6.0

4.4 Discussion

The model size of the traditional YOLOv5 is about 14.4 MB. The experimental results show that the traditional YOLOv5 model can perform real-time object detection

in an embedded platform Jetson Xavier NX at the speed of 22.222 fps and obtain the image recognition accuracy of 98.5%. On the other hand, the model size of the GSEH-YOLOv5 is 8.3 MB that is 42.4% less than that of the traditional YOLOv5 model, and it can perform real-time object detection in an embedded platform Jetson Xavier NX at the speed of 27.397 fps that is 23.3% higher than that of the traditional YOLOv5 model did. However, its image recognition accuracy is 97.5% that is 1% lower than that of the traditional YOLOv5 model. Our proposed approach, the M3-YOLOv5 model, with the model size of 6.5 MB that is 54.9% less than that of the traditional YOLOv5 model, and it can carry out real-time object detection in an embedded platform Jetson Xavier NX at the speed of 25 fps that is 12.6% higher than that of the traditional YOLOv5 model. It's image recognition accuracy is 98.9% that is 0.4% higher than that of the traditional YOLOv5 model.

Chapter 5. Conclusion

In this paper, the object detection algorithm with the improved M3-YOLOv5 is used to perform real-time recognition of a chip contour and detect whether it is defective. This study evaluated the performance about the recognition accuracy and detection speed between the proposed approach, GSEH-YOLOv5, and the traditional one. When compared with GSEH-YOLOv5, the proposed approach is little efficient in speed because it sacrifices the accuracy to increase its detection speed. For real-time object detection and image recognition using Jetson Xavier NX embedded platform, the experiments show that the proposed approach achieves better recognition accuracy and detection speed than that of the traditional one. Therefore, using the proposed approach can effectively help A semiconductor company in Taiwan to reduce the number of damaged chips and greatly enhance its competitiveness with other companies.

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