

Automatic ROI Recommender for Saw Singulation: Seamless Adaptation for Various Semiconductor Devices

How can we more conveniently generate ROI using deep learning?

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Outline

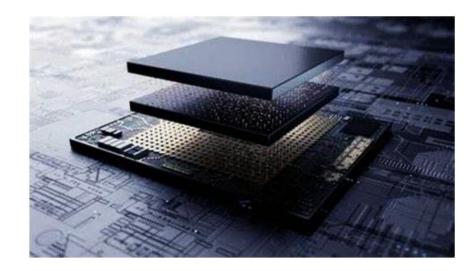
- Introduction
- Related work
- Method
- Experiment & result
- Discussion
- Conclusion



Surging demand for advanced semiconductors.

- Exploding demand for AI & IoT drives HBM growth, with the market expected to exceed \$5 billion by 2027
- Semiconductors are becoming more complex and diverse over time.

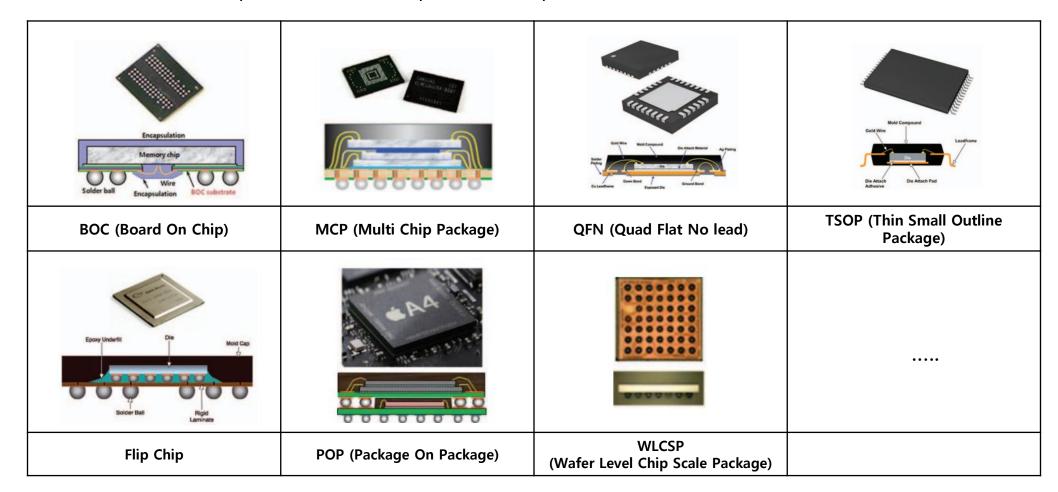






Various types of semiconductor packaging

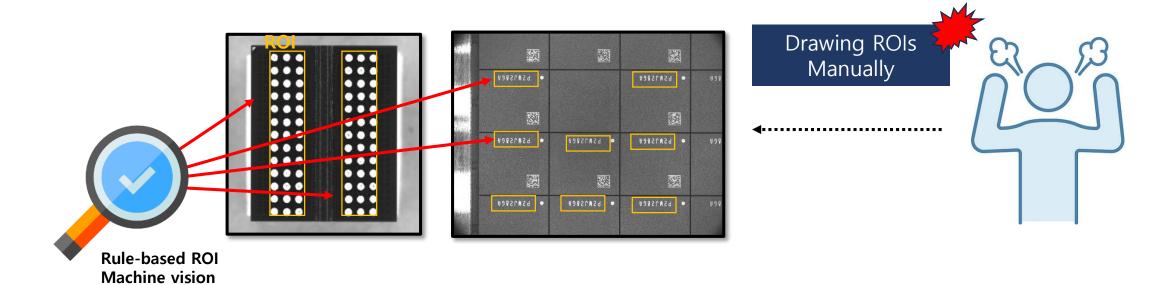
- With the advancement of packaging technology, inspection items have become more diverse, leading to increased complexity.
- As a result, various parameters are required for inspections.





Challenges in creating ROI

- For vision inspection, it is necessary to define the Region of Interest (ROI).
- Although ROI is a key process for determining the inspection area, it must be manually created by the operator for rule-based inspections.
- This process requires significant effort and time



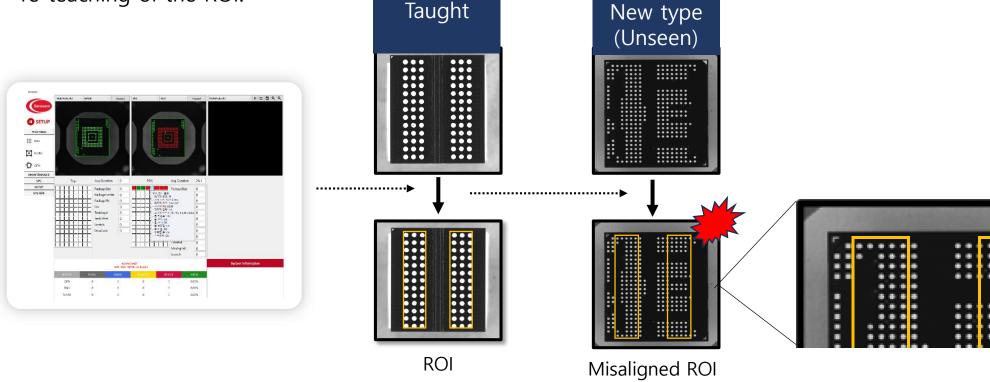


Limitations of rule-based ROI

Machine vision-based inspection programs rely on operators to manually define the ROI,
which is then used to perform inspections based on the same rules for identical package.

However, it is challenging to use the previously taught ROI for new type package, requiring

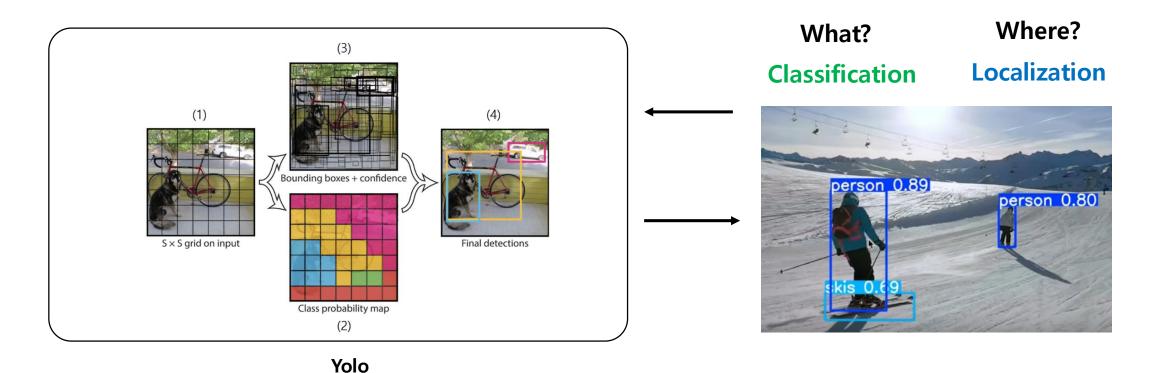
re-teaching of the ROI.





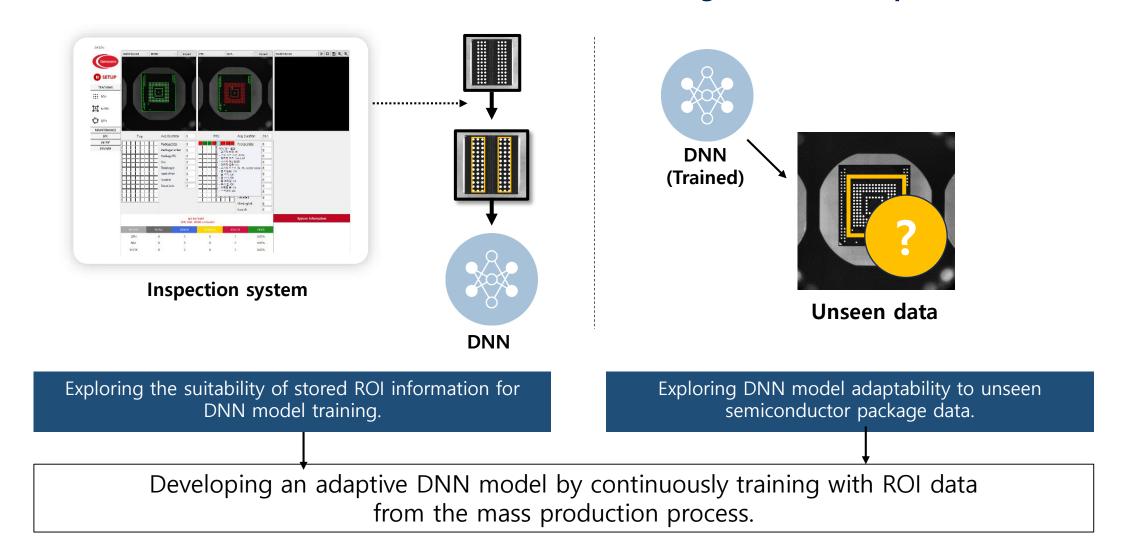
Object detection with Deep Learning

- Object detection identifies objects and their locations in an image.
- Deep learning-based object detection approaches solve the problem by using regression to predict object locations (bounding boxes) and classifications (class probabilities).





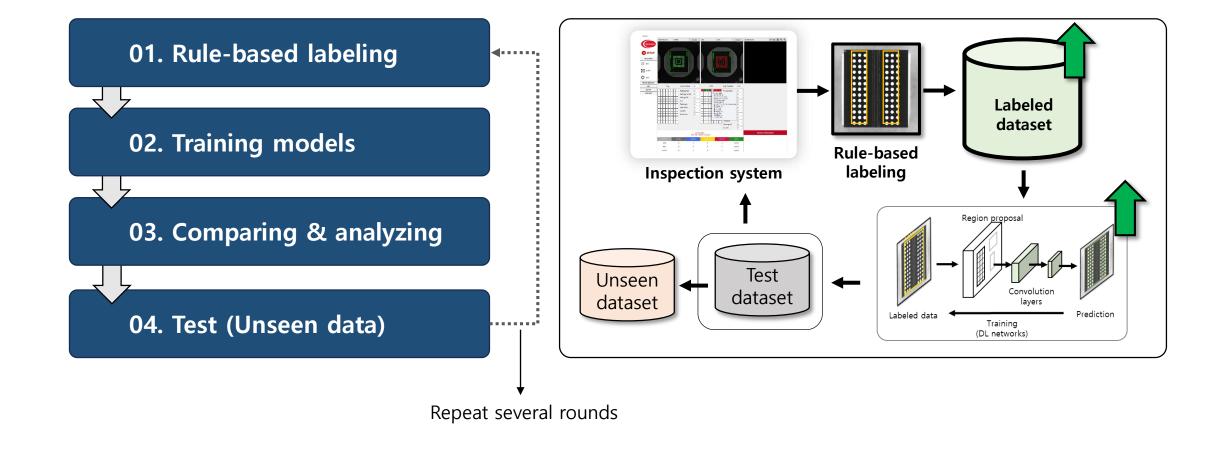
Research on an automatic ROI recommender enabling seamless adaptation





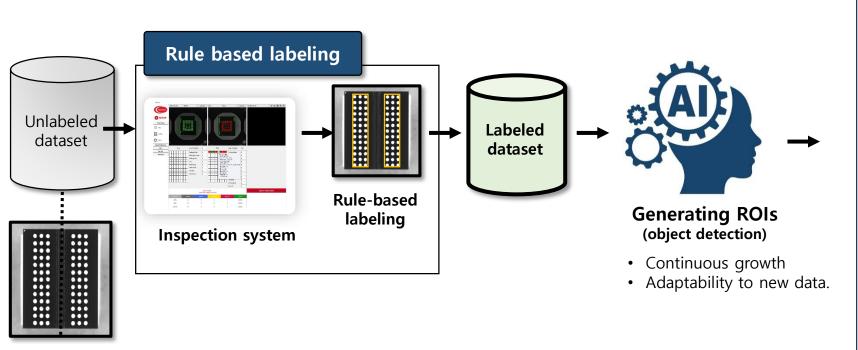
Proposed method - Overview

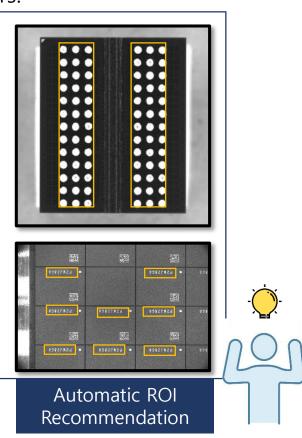
Research on continuous AI improvement using inspection systems.



Solution concept

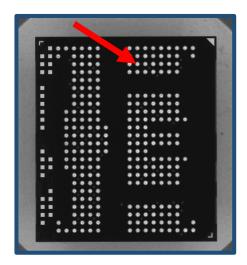
- The vision inspection system stores rule-based ROI labels during operation.
- This system enables continuous training of the DNN model.
- By Training various data, DNN model becomes adaptable to unseen semiconductors.

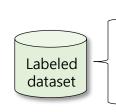






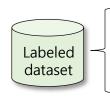
Dataset





Ball	Type 1	Type 2	Unseen
Image			
Round 1	13	90	
Round 2	26 (+13)	180 (+90)	
Round 3	39 (+13)	270 (+90)	
Test dataset	3		
Unseen dataset		42	





Character & 2Dcode	Type 1	Type 2	Unseen
Image	# # # # # # # # # # # # # # # # # # #	### ### ##############################	* \$4.75279442
Round 1	44	23	
Round 2	88 (+44)	46 (+23)	
Round 3	132 (+44)	69 (+23)	
Test dataset	2		
Unseen dataset		16	



Implementation details

No dropout

• Batch size : 2

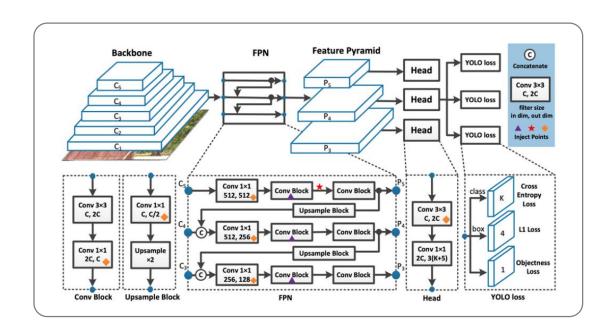
• Epoch : 50

• Optimizer : SGD

• Loss function : BCE (binary cross entropy)

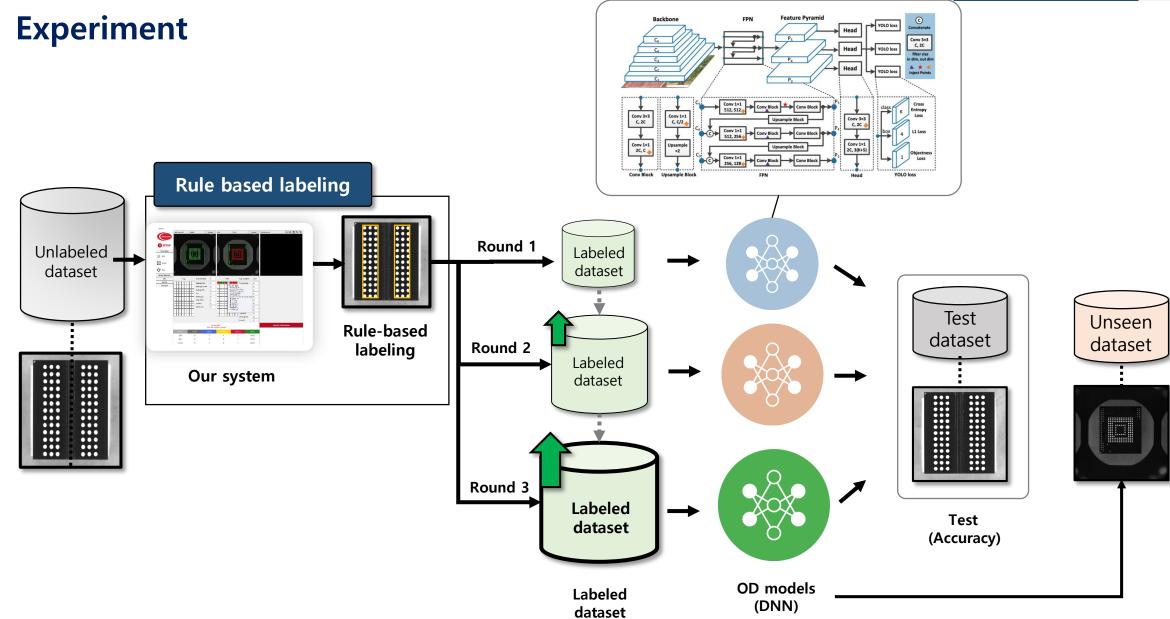
Learning rate: 0.01

Models:



#	DL network	Description
1	Yolo v7	is a real-time computer vision algorithm for object detection that identifies multiple objects in an image or video with a single
2	Yolo v11	pass through a neural network. It is known for its high speed and accuracy, making it widely used in various applications.

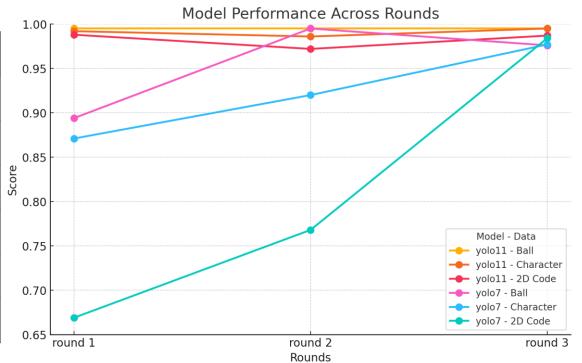






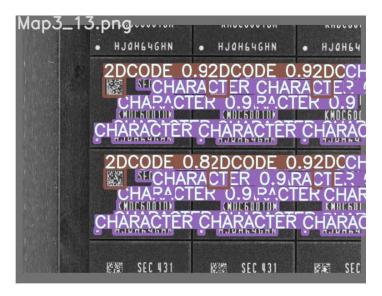
Result 1 – Comparison (test data)

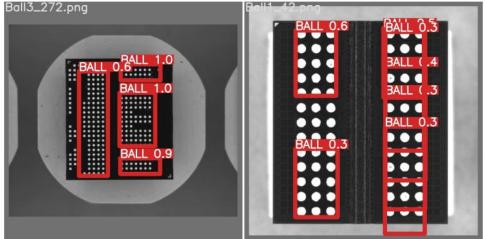
Model	ltem	Round 1	Round 2	Round 3
	Ball	0.894	0.995	0.976
YOLO v7	Character	0.871	0.92	0.977
	2D Code	0.669	0.768	0.984
YOLO v11	Ball	0.995	0.995	0.995
	Character	0.992	0.986	0.995
	2D Code	0.988	0.972	0.987



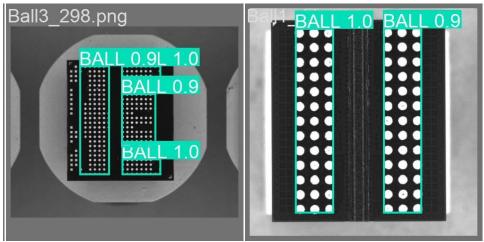


Result 1 – Comparison (test data)





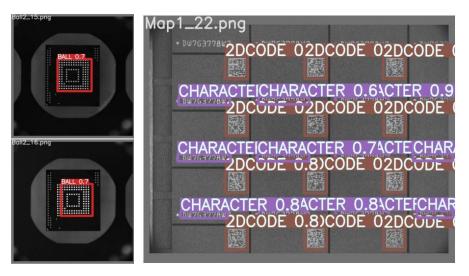


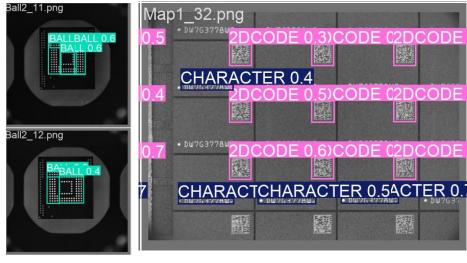


Yolo v7 Yolo v 11



Result 2 - Comparison (Unseen data)





Yolo v7

Yolo v 11

	Ball	Character	2Dcode
Yolo v7	0.195	0.529	0.529
Yolo v11	0.12	0.452	0.452



Discussion

- The vision inspection system generates rule-based ROI labels, proving their value for DNN model training.
- The experimental results showed that YOLO v7 exhibited an increasing performance trend across rounds, achieving an AP of 0.984 for 2D code.
- For Character and 2D code, YOLO v7 demonstrated an AP of 0.529 on unseen data, while YOLO v11 showed an AP of 0.452, confirming the potential of the system as a Seamless Adaptation solution.

Conclusion

- This study explored the effectiveness of training object detection models using vision inspection data. Additionally, by evaluating the performance of the trained model on unseen data, the adaptability to changing semiconductor types was tested.
- Through this exploration, the following contributions are expected:
 - Reduced workload for operators during teaching, enhancing convenience
 - Development of a system capable of continuous performance improvement
 - Confirmation of the potential for creating an ROI recommender adaptable to changes in semiconductor types



Thank you