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Using automatic defect classification to reduce the escape rate of defects

By: Bryce Chi,
Onto Innovation

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Automated optical inspection (AOI) is a cornerstone in semiconductor manufacturing, assembly and testing facilities, and as such, it plays a crucial role in yield management and process control. Traditionally, AOI generates millions of defect images, all of which are manually reviewed by operators. This process is not only time-consuming but error prone due to human involvement and fatigue, which can negatively impact the quality and reliability of the review.

In the Industry 4.0 era, the integration of a deep learning-based automatic defect classification (ADC) software solution marks a significant advancement in manufacturing automation. For one, ADC solutions reduce manual workload – meaning less chance of human error and higher accuracy – and, two, they are poised to lower the costs associated with high-volume manufacturing (HVM).

Deep learning, a branch of machine learning based on artificial neural networks, is at the core of these ADC solutions. It mimics the human brain's ability to learn and make decisions; this enables the system to recognize complex patterns in data without explicit programming. Compared to traditional methods, this approach offers a significant leap in processing efficiency and accuracy.

In the last two decades, the surge in processing power and data availability has made deep learning and machine learning algorithms increasingly practical and effective. Deep learning also has shown exceptional capabilities in finding, through self-learning, hidden patterns within large data sets, making it a suitable fit for ADC applications.

An ADC solution can be integrated with AOI tools to develop a robust ADC library, a library which can use a combination of machine learning algorithms, such as K-nearest neighbors (KNN) and convolutional neural networks (CNN) models, to improve accuracy but reduce the escape rate of defects. ADC supports both inline, or tool centric ADC, and offline applications, making it adaptable for various AOI machines across the HVM spectrum.

The primary function of ADC is to automatically classify defect codes. This is crucial for quality control in semiconductor manufacturing. By automating the classification process, ADC systems effectively streamline the inspection process, addressing common defects like scratches and pad defects with higher precision and reliability.

For our study, we employed an ADC approach using two sophisticated machine learning algorithms to ensure precise and efficient defect classification:

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K-Nearest Neighbors (KNN): This supervised learning algorithm excels in pattern recognition tasks such as handwriting and image recognition. KNN operates by identifying the closest data points (a.k.a., neighbors) in a feature space to classify unknown inputs with high precision and accuracy. The KNN algorithm evaluates the similarity based on the proximity of data points, refining the classification process (Table 1).

Manual/ADC	198	201	202	203	209	210	213	1	254	Total	Classified	Accuracy
198	133	5		37				6	8	189	95.8%	73.5%
201		169						4	2	175	98.9%	97.7%
202	30		211	4					8	253	96.8%	86.1%
203	13	12	6	219				8	20	278	92.8%	84.9%
209		16			212				12	240	95.0%	93.0%
210		10		8		148		6	15	187	92.0%	86.0%
213				8		13	154			175	100.0%	88.0%
1								178	12	190	93.7%	100%
Total	176	212	217	276	212	161	154	202	77	1687	95.4%	88.4%
Purity	75.6%	79.7%	97.2%	79.3%	100%	91.9%	100%	88.1%	0.0%			

Table 1. The performance matrix result of KNN model

Convolutional Neural Networks (CNN): A cornerstone of deep learning techniques, CNN is instrumental in image processing tasks, including classification, segmentation and object detection. It utilizes multiple convolutional layers to automatically extract and learn features from images. This process involves the analysis of each image to discern intricate patterns; this is crucial for accurate defect identification in semiconductor manufacturing (Table 2).

Manual/ADC	198	201	202	203	209	210	213	1	254	Total	Classified	Accuracy
198	178	3		4					4	189	97.9%	96.2%
201		168		1					6	175	96.6%	99.4%
202			253							253	100.0%	100%
203	3	1	2	250		2	3	3	14	278	95.0%	94.7%
209					230				10	240	95.8%	100%
210				2		180		1	4	187	97.9%	98.4%
213				2		3	170			175	100.0%	97.1%
1				1				171	18	190	90.5%	99.4%
Total	181	172	255	260	230	185	173	175	56	1687	96.7%	98.1%
Purity	98.3%	97.7%	99.2%	96.2%	100%	97.3%	98%	97.7%	0.0%			

Table 2. The performance matrix result of CNN only

By combining the robust feature analysis of KNN with the advanced pattern recognition capabilities of CNN, the ADC method employed in our study was able to achieve significant accuracy in classifying a wide range of defect types. This dual approach not only enhances the overall classification process but also adapts to the intricate and varied nature of defects encountered in semiconductor assembly.

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Manual/ADC	198	201	202	203	209	210	213	1	254	Total	Classified	Accuracy
198	130			2					57	189	69.8%	98.5%
201		150							25	175	85.7%	100%
202			198						55	253	78.3%	100%
203	2			201				2	73	278	73.7%	98.0%
209					228				12	240	95.0%	100%
210				1		148			38	187	79.7%	99.3%
213							154		21	175	88.0%	100%
1								168	22	190	88.4%	100%
Total	132	150	198	204	228	148	154	170	303	1687	82.0%	99.5%
Purity	98.5%	100%	100%	98.5%	100%	100.0%	100%	98.8%	0.0%			

Table 3. The performance matrix result of KNN+CNN

Our study determined that a multi-engine ADC process demonstrates a breakthrough in defect classification performance, leveraging advanced AI engines like CNN and KNN. This approach not only meets but often exceeds industry standards, with significant achievements including:

- Attaining an accept/pass/classify rate of approximately 99%.
- Reducing the defect escape rate to about 0.2%.
- Lowering the overkill rate to around 0.2%.

The integration of different models, particularly KNN and CNN, with our study's inline ADC system provides a robust solution for AOI tools. This integration ensures high accuracy in classifying defects and reduces the risk of misclassification. Meanwhile, an offline ADC variant is able to focus solely on deep learning for defect image analysis.

Our findings show that while CNN-based models alone offer substantial accuracy, the incorporation of KNN significantly minimizes the likelihood of defect misclassification. This dual-model strategy, particularly effective in inline ADC applications, ensures reliable and precise defect classification across various manufacturing scenarios.

About the author

Bryce Chi is an application and integration engineer at Onto Innovation.