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Computer Vision Systems for Defect Detection in Semiconductor Fabrication

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Abstract: The rapid growth of the semiconductor industry continues to push for advances in manufacturing quality assurance capability. Classical human-based visual inspection is becoming increasingly impractical because of high inspection cost and rapid manufacturing throughput, and thus machine vision systems for surface defect detection are becoming common solutions. To facilitate the design and evaluation of such systems, wide-ranging research into computer vision solutions for surface defect detection in semiconductor manufacture is presented. This comprises an overview of semiconductor fabrication processes and defect types, consideration of essential concepts in computer vision, examination of common detection approaches, and the creation of two openly available image datasets. These datasets, designed specifically for semiconductor contexts, are carefully annotated and then employed to assess classical image processing techniques and machine learning detectors.

The general nature of the discussion makes it relevant across numerous manufacturing domains, with emphasis on fundamental computer vision concepts of relevance to any defect detection task. Special focus is given to the preparation of image datasets, and particular attention is placed on design considerations essential for real-world deployment in high-throughput manufacturing environments.

Keywords: Semiconductor fabrication; defect detection; computer vision; image processing; machine learning; dataset; Automated Optical Inspection (AOI); Wafer Defect Detection; Deep Learning-Based Visual Inspection; Semiconductor Manufacturing Yield Analysis; Convolutional Neural Networks (CNNs) for Inspection; Inline Process Monitoring; Submicron Defect Classification; Image-Based Fault Diagnosis; Smart Manufacturing (Industry 4.0); Real-Time Quality Control Systems.

I. INTRODUCTION

The presence of defects in semiconductor components is a major concern for all semiconductor foundries. Defects are hidden, they can have various morphologies, shapes, and sizes, and they can be rare, appearing only in low quantities. Computer vision systems can be effective in reducing the risks associated with defects, provided that these systems have been properly designed, trained, and deployed. An effective vision-based detection system for semiconductors requires a dedicated dataset with annotated images of the defects of interest. Involving foundry industry professionals in the creation and annotation of such datasets improves their quality and subsequently increases the performance of trained systems. Quality control in this phase is important, as high detection performance is crucial for vision-based detection in production environments. Data drift after deployment also needs to be monitored to maintain reliability.

The effect of defect variability is a major challenge. Defect images can differ significantly in size, shape, and color, even for the same underlying process. Moreover, age and environmental variations affect lighting and reflections, resulting in appearances and patterns that are unpredictable and difficult to simulate. The annotation of defects is fragmentary at best, especially for rare defects. An autonomous detection approach, such as deep learning, ideally requires an extensive training dataset. Annotated datasets for semiconductor defects have been proposed, using a range of common computer-vision methods to process the images. Classical machine learning algorithms have also been used for defect detection on foundry images.

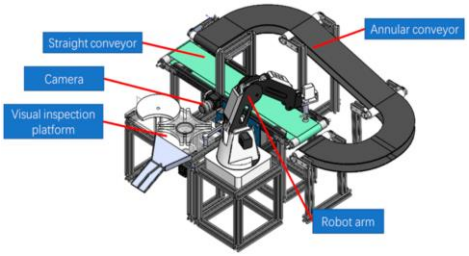

Fig 1: Real-Time Defect Detection for Metal Component

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1.1. Background and Significance

Compliance with stringent product quality requirements and environmental regulations has compelled semiconductor manufacturers to increase defect-sourcing R&D budgets and define detection thresholds for production equipment. Integrated circuits, microsensors, and micromechanical components introduce complex and submicrometric defects that surpass the capabilities of the human eye. To mitigate defects during tech transfer, quality-assurance and metrology systems must locate defects throughout the entire manufacturing process.

Compared with other industrial applications, the use of automatic vision systems for defect detection and classification in semiconductor manufacturing is still in an early stage. These systems have not yet achieved the acceptance of other inspections in fabricating lines. Users are still concerned about the robustness and reliability of the proposed solutions. Research on sensor-based vision systems remains fragmented, concentrated on just a few defect types or categories. No standardized testbed exists, so a broad approach is proposed that includes a representative set of common semiconductor defects. Two system setups have been built, one for ILT/N1 resist masks and another for DUV/WG lithography. Solutions are designed to cope with the challenging conditions of production environments and include requirements for on-line performance, drift compensation, and periodic maintenance.

Equation 1: Convolution (foundation of CNNs + many classical filters)
Let $I[x, y]$ be the image and $K[i, j]$ a kernel of size $(2a + 1) \times (2b + 1)$.
Step 1 (shift kernel over the pixel): center kernel at (x, y).
Step 2 (multiply and sum):

$$(I * K)[x, y] = \sum_{i=-a}^{a} \sum_{j=-b}^{b} K\,[i, j]\; I[x - i, y - j]$$

That's the operation used for blur, sharpening, edge detection, etc.
Why CNN "convolution layers" look similar
A CNN feature map F is computed similarly, but with learned kernels and multiple channels:
If input has channels $c = 1..C$,

$$F_m[x, y] = \sum_{c=1}^{C} \sum_{i=-a}^{a} \sum_{j=-b}^{b} W_{m,c}\,[i, j]\; I_c[x - i, y - j] + b_m$$

Then a nonlinearity (e.g., ReLU):

$$\mathrm{ReLU}(z) = \max(0, z)$$

II. OVERVIEW OF SEMICONDUCTOR FABRICATION AND DEFECT TAXONOMY

Semiconductor manufacturing is responsible for producing the world's most ubiquitous components: integrated circuits (ICs), found in smartphones, tablets, laptops, automobiles, and countless other devices. The fabrication of the individual circuit layers builds on photolithography. Using this technique, a photoresist layer is exposed and developed to define regions where material deposition or etching are subsequently more easily performed. Integrated circuit layers measure in nanometers and the number of layers can count beyond 60. Consequently, the production of ICs requires the careful coordination of several highly complex processes across multiple separation facilities.

A range of fault types can lead to the same functional failure in the final circuit. Such fault types can differ greatly in visual appearance and physical size. Table 1 indicates a taxonomy of faults that may be present on planar, monolithic semiconductor products. These can be categorized based on morphology, size, and origin. Some fault classes are characterized by easily visible external effects, while others are detectable only during specific manufacturing process steps. The variability in external morphology for individual fault types poses the largest challenge for practical computer vision systems.

2.1. Research design

Machine Vision Systems (MVS) are employed for automated quality inspection and defect detection of products. Image-based inspects speed up the detection process, eliminates human inspecting errors and power increasingly within automatic production line setting. Semiconductor (IC) chips are expected to take up high volumes however suffer from a high failure rate on first use. Systematic inspection becomes a necessity for manufacturer. Early detection shorten manufacturing cycle and prevent extensive losses during assembly and package processes. A semiconductor wafer

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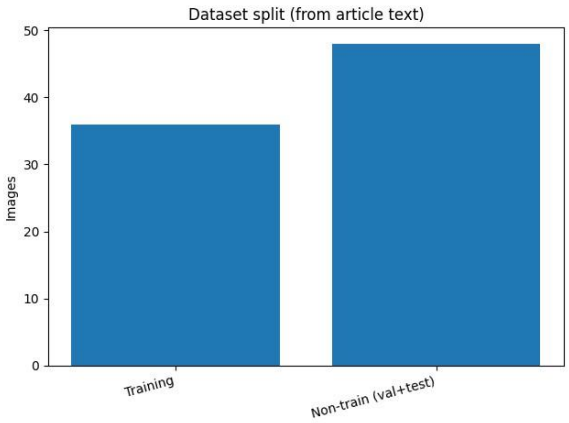
consists of thousands of IC chips, image-based inspection detects defects reside on individual die or in-between circuit patterns.

Majority of the research work focus on detection of cosmetic and non-cosmetic defects on wafers using deep learning approaches. Classifiers based on Convolution Neural Network (CNN) are developed for different defects on wafer. Custom datasets are create to train the classifier models. There are some efforts to built hybrid autoencoder-CNN approach for wafer defect detection. Hybrid deep learning model exploited the best features of both Convolutional Neural Networks (CNN) and Autoencoders, enhanced the detection accuracy and considerably reduced false positives. Various classical methods such as contour, geometric and region properties techniques have been proposed for detecting micro and nano scale pattern defects on wafer surface. Main limitation of machine vision technique for semiconductor application is large number of classes with limited sample size especially minor classes. Copula-based approach is investigated for handling this limitation and validated on semiconductor wafer defect dataset with promising accuracy.



III. FUNDAMENTALS OF COMPUTER VISION IN MANUFACTURING

These systems serve different purposes across production stages, comprising various aspects in their design and fundamental implementation: the preparation of the data for further automatic analysis, the deployment of suitable algorithms to detect the target events, and the appropriate creation and annotation of datasets for the training and validation of machine learning models.

The abundant literature, development, and deployment of computer vision (CV) systems for the inspection and detection of defects and other relevant features in images acquired in semiconductor fabrication processes bears witness to the efficiency and effectiveness of the chosen technologies. These systems serve different purposes across production stages, comprising various aspects in their design and fundamental implementation: the preparation of the data for further automatic analysis, the deployment of suitable algorithms to detect the target events, and the appropriate creation and annotation of datasets for the training and validation of machine learning models.

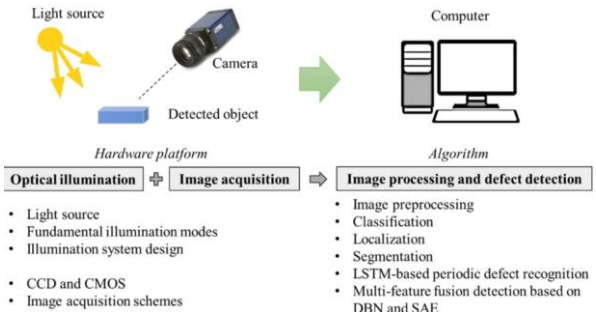


Fig 2: Fundamentals of Computer Vision in Manufacturing

3.1. Image Acquisition and Sensor Modalities

Image acquisition and sensor technology form the fundamental building block of any computer vision installation, with quality of imaging and resolution directly affecting overall detection performance as well as reliability. An ideal computer

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vision defect detection system in semiconductor manufacturing is expected to deliver real-time performance with no latency, or as minimal as possible, with throughput directly proportional to system speed.

Accordingly, the data acquisition system needs to be optimized for speed without compromising on quality. Different imaging modalities, such as non-visible light and multispectral imaging, can also be deployed for enhanced defect detection. Data from different modalities can provide complementary information that makes detection platform more robust; Multispectral imaging detects defects caused due to surface roughness or contamination efficiently, non-visible light hyperspectral imaging is suitable for detecting small defects, while long-wave infrared imaging is suitable for insulation defects. Multispectral and long-wave infrared imaging have also been successfully adopted for surface anomaly detection and fault diagnosis in infrared thermographs of power equipment.

The advantages of underwater computer vision in combination with optical music recognition demonstrate the potential utility of these technologies as complementary systems in the coverage of operational scenarios. State-of-the-art computer vision algorithms based on CNNs, trained on RGB images of music scores, have been integrated with an RGB-D-based underwater computer vision system for underwater combat swims for diving preparation, rescue, and reconnaissance assistance. The integration enables shape, color, and distance perception for a salient color-based algorithm with an RGB-D camera during underwater combat swims.

3.2. Preprocessing and Data Enhancement

A defect-detection process involves several modules that operate in series to achieve a particular output. The operation is termed as non-invertible if new units are not added at each stage, implying a filtering effect. It is non-bijective, being either injective or surjective. In image processing, each operation can be represented using a function, and the overall operation is defined by the composition of these functions. Data preprocessing plays an important role in the defect-detection pipeline, especially with machine-learning-based methods.

The mere collection of a large set of training images is not sufficient for reliable defect detection, especially in a production environment. Defect classifiers based on machine-learning techniques often require a diverse set of defect samples with label information for accurate performance. Unfortunately, it is either difficult to collect a large and diverse set of defect images, or such a diversity may not be present using a single camera setup in a production environment. The need to improve deep-model training with diverse defect samples artificially has gained importance due to the low availability of various defect types.

IV. DEFECT DETECTION APPROACHES

Defect detection in semiconductor fabrication remains a challenging task for vision systems. Proposed solutions can be categorized into three main approaches. The simplest uses classical image processing methods, relying on prior expert knowledge of defect characteristics and heuristics designed to identify them. Equally simple yet more effective is an approach based on trained machine learning classifiers, which support the design of “prototype” or “symbolic” features. Full deep learning solutions, on the other hand, are powerful, scalable, and largely automatic but constrain interpretable pattern formation.

Classical image processing solutions apply methods conceived for other domains, either in their original form or modified to accommodate a semiconductor context. They require expert anatomy knowledge to select feature- or defect-specific detection algorithms; the defects need to be well defined, and ground truth should be available. The best example employs circle detection to identify contamination particles. Methods for anomalies detection in random-structured textured surfaces have also been borrowed from the literature. Shadow classification methods dedicated to automated visual inspection of paving stones are an interesting direction to explore.

4.1. Classical Image Processing Methods

The application of classical image processing techniques is the simplest and most straightforward approach to automating defect detection. Such methods require low or no training effort as they rely on handcrafted features that are tuned based on domain knowledge. Multilayered thresholding, blob detection, or template matching are likely applicable whenever the defect pattern is simple, its expected location known in advance, and sufficient training images available, respectively. Two-color multilayer thresholding makes use of luminance differences between the defect and the substrate and, when suspected defects are known to take the form of blobs, the additional use of hue and saturation permits clearly defining both defect and substrate.

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A more synthetic color-based multilayer thresholding block jointly exploits intensity, chromaticity, saturation, and spatial location for segmenting dirty wafers, defective metal layers, and contamination atop layers. Multiscale sharpening and Gaussian pyramids improve the discrimination of illumination-sensitive fingerprints and scratches, while model-based template matching performs very-well on no-spend layers thanks to the use of rotated templates. Although it did not outperform a machine-learning method based on support vector classifiers, area-perimeter ratio, circularity, moment invariants, and other basic and Zernike descriptors were finally found effective for classifying different kinds of stains on wafers.

Equation 2: Gaussian smoothing and Gaussian pyramid (mentioned as multiscale)
Gaussian kernel

$$G(x, y; \sigma) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right)$$

Smoothed image

$$I_\sigma = I * G(\cdot,\cdot;\sigma)$$

Pyramid levels
A common pyramid uses:

- blur with G
- downsample by factor 2 (denote by $\downarrow 2$)

Level 0: $I_0 = I$
Level 1:

$$I_1 = \downarrow 2(I_0 * G_\sigma)$$

Level 2:

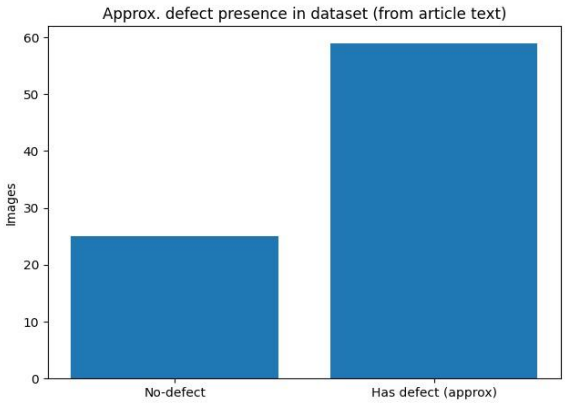
$$I_2 = \downarrow 2(I_1 * G_\sigma)$$

…and so on.
This is the math behind "multiscale sharpening / pyramids."

4.2. Machine Learning-Based Detection

Machine learning (ML) can be used to identify defects in semiconductor fabrication either directly through an image classification pipeline or through the employment of an object detection framework. Image classification systems treat the problem as a supervised learning task, where a network is trained to assign a single label describing the quality of the inspected object. Given its simplicity, it is not surprising that classification has become the dominant approach for semiconductor inspection using ML. In its basic form, an image is fed into a convolutional neural network, and features are automatically learnt from the raw pixel data. Feature extraction can also be achieved by combining a stack of different ML techniques, such as deep feature extraction with a support vector machine. So-called hybrid approaches, which consist of two steps, are also popular. Good feature extraction methods are learned from less data or use synthetic training samples. However, the ability to deal with variations in object orientation is still a limitation of this approach.

Whereas classification represents a global-level analysis of the image, object detection aims to localize and identify all instances of predefined classes within a single image. This is usually achieved by the combination of two separate CNNs, one that proposes candidates for object locations and another that predicts the object category based on the proposed regions. Although typically more computationally demanding than classification, an object-detection-species network architecture still allows for a relatively low inference time. Quasi real-time implementation is also feasible at a higher power cost using a classification-based architecture.



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V. DATASET CREATION, ANNOTATION, AND EVALUATION METRICS

Reflecting the challenging requirements for Computer Vision systems in a manufacturing context, the preparation, annotation, and evaluation of datasets calls for careful attention. Although publicly accessible collections such as the NIST INSPECT image dataset provide useful initial sources, truly effective training, validation, and test datasets must take into account the specific production environment, including defect classes, backgrounds, and imaging configuration. In the context of semiconductor fabrication, special consideration is required to ensure accurate representation and proper labeling of dataset conditions. Additional factors, including development of specific metrics to evaluate model performance, are also crucial.

The, the creation of datasets for specific semiconductor targets must address a number of challenging aspects. The first is undoubtedly the availability of suitable image data from the semiconductor domain, either in public collections or from industrial partners. If unavailable, direct acquisition is necessary, with dedicated illumination, signal-noise ratio, and variability-control protocols. A second consideration concerns the expert-led annotation of the acquired samples, serving to establish the ground truth for subsequent model evaluation. Lastly, each experimental setup contains characteristics not fully visible to the untrained eye but potentially strongly affecting the performance of machine-learning defect-detection approaches. These characteristics must therefore be captured in dedicated scoring functions.

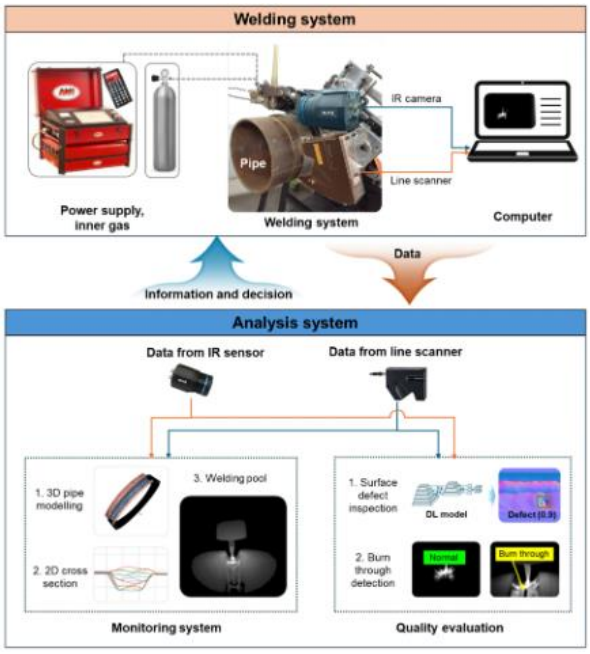

Fig 3: Deep Learning-Based Machine Vision System for Online Monitoring and Quality Evaluation

5.1. Dataset Curation in Semiconductor Context

For detection systems based on machine learning methods, an appropriate training dataset is essential and must be built with training, validation and testing subsets. Although the available dataset is suited for training and evaluation of semantic segmentation methods, it is not appropriate for classification-based approaches for the following reasons: a defect class might be represented by only one or two image instances, some defect classes are very difficult to discriminate even for expert visual inspectors in real-life conditions, there is only a limited number of image instances for some defect classes and most of the defect classes have only very few image instances.

Defect detectors using texture-based features with shallow or no learning typically require a small dataset for training. It is indeed more challenging to define a segmentation rule than a boundary around a defect used for classification. For the common task of detecting defects on semiconductor wafers, a specific small dataset is defined and publicly released for research: it is composed of 10 defect classes distributed on 84 raw semiconductor wafer images. There are at least 20 % of the original images in the dataset for each defect class and around 30 % of the original images do not contain any defect. A set of 43 % of the images is used as the training subset.

5.2. Labeling Protocols and Ground Truth

Careful labeling and definition of ground truth are essential for supervised learning tasks, accommodating the intricacies of the machine-learning approach. Labelling genuine defect signals requires dedicated effort and human involvement,

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which may affect the entire dataset if achieved using a single annotator. Furthermore, the subtlety, severity, and scale of the highlighted defects differ per image and demand separate attention. Therefore, two systems were adopted to label the SEM dataset for training a detection and classification system.

Labeling relies on two categories of defects. The first annotated ground truth set comprises only genuine defect signals. LG is highly sensitive and highlights only severe imperfections. Marked image areas are characterized by boring shapes, and the affectees are generally near-dark regions in the optical signal. Ld defects label the dataset for detection and classification. Ld is practical and recognizes even subtle defects. Marked areas are non-homogeneous, consume a comparatively higher proportion of the task image, and may have a scale difference or a resemblance to the background or surroundings. The second system adopts a multiple-annotator approach to provide an error-aware ground truth without consensus validation by different experts from the respective domain.

VI. SYSTEM DESIGN CONSIDERATIONS FOR PRODUCTION ENVIRONMENTS

In the context of production environments, the feasibility of a defect detection application partly depends on aspects set out at the design stage. Two crucial factors are the response time and the error-free classification rate, with particular emphasis on misclassification (type I and II errors) that may hinder production or generate reprocessing costs. Failure to detect small defects is another kind of misclassification of concern, as it can damage the wafers in later manufacturing steps. A second aspect involves the expected errors over a longer timescale; the practical applicability of a solution is given by the ability to operate reliably for a sufficiently long period of time without requiring recalibration. A longer required recalibration time usually implies a higher cost for the company, and solutions purportedly developed without any drift would be most desirable.

The statistical nature of machine learning classifiers implies that performance is not guaranteed to be unaffected by minor shifts in the distribution of the input data over time. For instance, although contrast stretching and histogram equalisation may help with reusability and provide information-invariant descriptors for the conditions at which they are trained, even tiny changes in the infrared illumination (temperature) would induce variations in the metallisation colour and small inter-modal misalignments may lead to pattern losses in the two infrared images, which can affect the decision-making process. When operating near the detection threshold of the classifier, the cost of misclassification is therefore expected to increase with time, something that can be shown by monitoring its performance using a small validation set."

Equation 3: Classification vs detection (as the article distinguishes)
If model outputs logits z_k for classes $k = 1..K$,

$$p_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

Cross-entropy loss (supervised learning)
If true class is y,

$$\mathcal{L} = -\log(p_y)$$

For one-hot vector y_k:

$$\mathcal{L} = -\sum_{k=1}^{K} y_k \log(p_k)$$

Detection (bounding boxes) — core regression target
A detector predicts a box $b = (x, y, w, h)$. A common regression loss is Smooth L1 on parameters:

$$\mathcal{L}_{box} = \sum_{t \in \{x,y,w,h\}} \text{SmoothL1}\,(\hat{t} - t)$$

6.1. Real-Time Processing and Throughput

In an industrial context, the constraints imposed by production lines often pose an added burden on machine vision systems. These systems typically emphasize detection performance and robustness over real-time throughput. However, in a continuously running production line, defective samples may take time to detect and require the system to process images faster than the production unit can produce them to ensure 100 % sampling. Otherwise, the sampling rate will be lower than the defect rate, causing the production line to become the bottleneck. Such constraints are particularly demanding when using deep learning methods, which need to be both accurate and fast.

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In production environments where the design cycle of a product can be short, the possibility of having a drift in the training data distribution may render an otherwise reliable classifier unstable. The potential presence of shift or drift, together with the possibility of contamination, may attack the system's performance in case it is not regularly updated or kept under control by the user. While constantly retraining a system in production may solve these problems, this solution is not always desirable or possible. The process of retraining the classifier requires time and may even incur the latent cost of no longer providing a service to the production line. Specific data collection strategy protocols can help ease the problem and keep the drift under control.

6.2. Reliability, Drift, and Maintenance

Although the influence of changing illumination on a defect detection system can be mitigated by exploiting multispectral images, the maintenance of trustworthy operation in a production environment also entails scheduling inspections of system performance over time, detecting drift, and assessing potential causes. The features of an inaccurate classifier can change when the underlying process changes or when the data distribution changes while the process remains stable. Such drift can be quantitative (the estimated class probabilities change) or qualitative (the ordering of class probabilities changes), and addressing these issues is vital. Drift detection methods examine the data distribution in the production environment in order to subsequently detect a drift in the classifier features and trigger a re-training of the classifier with recently acquired data.

System maintenance is also crucial, given that a defect detection system typically operates reliably in the long term only when periods of class imbalance in production are avoided. Virtually all defect detection algorithms depend on the integrity of the sensor data they use. Hence, camera calibration and quality control of the illuminations are important regulatory procedures. For systems relying on specific multispectral signatures – such as near-infrared imaging for defect detection – maintenance includes a reliable check of the presence and performance of the near-infrared optical elements.

VII. CHALLENGES AND LIMITATIONS

Defect detection systems are subject to several challenges and limitations. One major concern is the subtlety and variability in defect appearance. Semiconductors are generally clean surfaces, but exhibit various light-fidelity defects. Some defects, such as particles or scratches, have a clear boundary; others, like fogging, are more difficult to distinguish from the nominal pattern. Inspection systems can also fail in reflected-light machines. Several defect categories, for example, powdered fuzz and water stains for droplet-based cleaning, are hard to differentiate; others can become indistinct under certain lighting, such as scratches or stains in shadowed areas. Current models can more accurately detect prominent defects than subtle classifications.

Environmental factors such as illumination, reflection, and contamination also present challenges. Specular reflection off water drops or oil smudges can lead to false alarms, especially in visible domains. Dust on the lens introduces a uniform curtain but can easily evade monitoring. Defect appearance often differs based on the light source and wavelength; using a depth camera helps reduce obscuring caused by the z-axis. Consequently, combinations of sensors with multiple light sources are popular. In semiconductor manufacture, particle detection systems are considered rather mature, but other areas still demand enhancement.

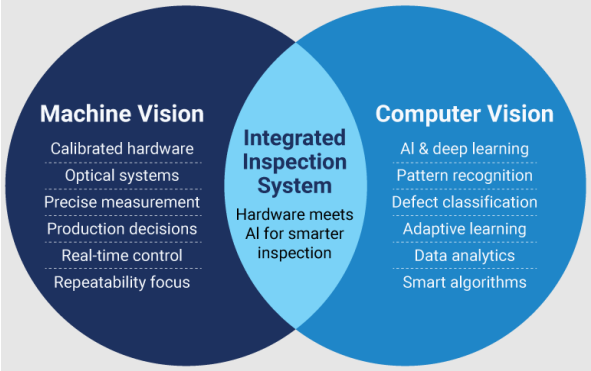

Fig 4: Challenges & Benefits of Machine Vision in Semiconductor

7.1. Variability in Defect Morphology

Focusing on defect appearance may lead to destructive results in all classification systems. Even with the same family defect and same sensor, different morphologies could cause misclassifications. Specification tables generally do not provide information about aliases of the same family defect or defects that may be confused with other family defects.

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For example, despite surface broken not being an alias of surface scratch, they are considered confused defects due to their common characteristics.

In real-world applications, acquiring similar samples for each defect family may not be possible. Consequently, classifiers must be able to detect the alias defects that represent other defect families when a sample is analyzed. A methodology was developed to consider these hidden views based on supervised datasets. Hidden views were automatically generated and mixed up with the real views before being provided to the classifier. When surface broken and surface scratch samples were used in training, the decision tree learned to detect surface scratch and surface broken for the surface scratch family.

7.2. Lighting, Reflection, and Contamination Artifacts Environmental conditions affect all types of manufacturing defects. In particular, contamination can contribute dirt, fabrication residues, or dust. Manufacturing processes can introduce residue deposits on company-owned products. A manufacturing inline product-defect detection system must not be dependent on an external cleaning system. Sensor modalities with different reflectivity properties can see contamination on the sensor that is corroded—i.e., the same product condition for the product.

In defect detection with component images, lighting, reflection, and oxide pattern colour influence the performance of state-of-the-art classification methods. Illumination patterns affect appearance properties—e.g., depth, material colour—or generated optical effects, such as specular reflections. Optical inspection of semiconductor devices is subject to several limitations, such as veiling reflections, and oxide thickness and colour patterns. Specular reflections, in contrast, influence the ability to detect a defect. For quality surface characterization at product level, $\geq 6\%$ of the surface area must contain veiling illumination in testing and validation images.

VIII. CONCLUSION

While Computer Vision offers an acute perception of industrial systems that rivals human observers, it is costly and labor-intensive to implement in practical production settings. Even so, Advances in semiconductor device technologies have led to a strong impact on the growth of the economy in the areas related to the electronics industry. Several defects are introduced at various stages of semiconductor fabrication, resulting in deteriorated performance of semiconductor devices. Conventional defect detection remains a tedious and time-consuming task. With skilled employees retiring from the industry, this problem is expected to worsen in the coming years. Hence, automatic detection of defects during semiconductor fabrication has gained interest in the literature.

The taxonomy of defects can be grouped into various classes based on the type of defect introduced (opens, shorts, misalignments), the causes of the defect (dust particles, equipment failure, scratches, mask defects) and their locations (wafer, die, packaging). However, it is difficult to cover all the types of defects that could occur on semiconductor devices. The complex shape of the device and the requirement of a reliable inspection for any defect on the devices further complicates the development of an automatic detection system.

8.1. Emerging Trends

Recent advances in semiconductor defect classification systems discussed in the previous sections reveal substantial diversity. Decision-making processes may rely on handcrafted rules or conventional computer vision algorithms, while others integrate machine learning algorithms or deep neural networks tailored for image classification. Yet another adopts a YOLO-based approach for instance segmentation. Such variety results from design decisions made in response to unique product attributes, data availability considerations, and the user's objectives. Nonetheless, a few common development patterns may be distilled. For the majority of defect types, the currently implemented systems remain laboratory prototypes rather than industrial implementations. Their application focuses on task-specific quality improvement rather than the real-time, all-in-one inspection establishment typical in semiconductor fabrications. Accordingly, defect differentiation is still performed manually or remains undeployed.

With commercial fabs hosting virtually identical processes and integration techniques employed for product fabrication, the systems should also share similarities. From semiconductor device generation to optical packaging follow Integrated Dev / Fab / Test / Package / System / Module. Among these different division of manufacturing responsibilities, optical packaged die seem common in commercial applications. Semiconductor device vendors often outsource the other divisions to reduce production cost; hence, multi-vendor collaboration remains essential to maintain the quality of whole system performance. As indicated by earlier discussion about defect databases, automotive applications in which SAM rely heavily on multi-vendor cooperation would benefit most from a all-in-one inspection setup. An automatic inspection

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system with ability to precisely localize defects on the optical die surface should able to support the semiconductor device vendor managing the Die Test process in terms of improving yield and quality.

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