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IDENTIFICATION OF DEFECTS IN PRODUCTS USING DEEP LEARNING

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Abstract: In contemporary manufacturing, ensuring product quality is paramount. This project introduces Deep Defect Net, a novel deep learning framework designed for the automated identification of defects in manufactured products. The objective is to revolutionize quality control processes by leveraging the capabilities of deep neural networks to discern and classify defects with unprecedented accuracy and efficiency**.**

Keywords: convolutional neural network (CNN) architectures, Deep learning, Semiconductor,

I. INTRODUCTION

Deep learning represents a subset of machine learning methodologies that draws inspiration from the structure and function of the human brain to enable computers to learn and make decisions. At its core, deep learning leverages artificial neural networks, which are composed of interconnected nodes, or "neurons," organized into layers. The depth of these networks, achieved through multiple hidden layers, distinguishes deep learning from traditional machine learning approaches. In recent decades, electronic devices like computers, tablets, and smartphones have become essential and demand for them is increasing.

Silicon-based integrated circuits, or chips, now squeeze over 10,000 transistors into a few square millimeters. In the majority of semiconductor assemblies, the visual inspection process of the wafer surface depends on manual review by human experts. Since the inspection task requires extreme concentration, the time that an inspector can continue the task is quite limited, and still, it tends to be quite slow and inaccurate. As integrated circuit (IC) feature sizes shrink, semiconductor processes become more complex, and new defect classes become yield limiters. The chip-making process starts on silicon wafers, sliced into chips. Advanced lithography tools are crucial for precise control and defect reduction, increasing manufacturing yield.

II. RELATED WORK

The authors employ an ensemble approach using RetinaNet models with various backbone architectures (such as ResNet and VGGNet). The ensemble strategy combines predictions from multiple models to enhance defect classification and detection accuracy. Denoising SEM Images: SEM (Scanning Electron Microscope) images inherently contain noise due to various factors (e.g., electron beam fluctuations, sample preparation, and imaging conditions). To mitigate noise-induced false positives, the authors apply an unsupervised machine learning model to denoise the SEM images.

The paper aims to improve the classification accuracy of true defects and pseudo defects in electronic circuit boards. It focuses on defect detection using color images and introduces the concept of random sampling combined with Support Vector Machines (SVMs). The proposed method applies random sampling to create multiple subsets of data. Feature selection techniques are then used to find effective combinations of features. These selected feature combinations contribute to accurate defect classification

The authors aimed to tackle the challenging task of classifying a massive dataset of high-resolution images from the ImageNet Large Scale Visual Recognition Challenge (LSVRC-2010). The dataset contains 1.2 million images across 1,000 different classes. The model architecture is designed to handle the immense complexity of object recognition. Non-saturating neurons are used to accelerate training. The authors employ a highly efficient GPU implementation for the convolution operation. To combat overfitting, they introduce a regularization method called “dropout”, which proves to be effective.

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Methodology The primary goal of food analysis is food safety, which is a global health concern for both humans and animals. Consumers increasingly worry about the content and safety of their food supply. Microfluidics and microfluidic analytical devices offer a new approach for rapid and efficient detection of various food contaminants Food samples (e.g., water, milk, juice, or extracts) are introduced into microfluidic channels. Analytes (contaminants) interact with specific reagents or sensors. Detection methods include fluorescence, electrochemical sensing, and optical absorption

The authors investigate the use of CNN-based features for food image retrieval. They take advantage of existing food datasets to build a robust feature representation by using Food524DB, which is the largest publicly available food dataset. The researchers fine-tuned a Residual Network (ResNet-50) using the Food524 Database The last fully connected layer of the ResNet-50 was used as the feature vector for food image indexing and retrieval

III. EXISTING SYSTEM

The existing machine vision system uses machine learning models such as s Support Vector Machines (SVMs) or random forests which do not perform better while detecting tiny particles in the manufacturing of semiconductors.
These systems use cameras and image processing techniques.

Challenges:

Lighting variations: Changes in lighting conditions affect accuracy.
Complex backgrounds: Background noise can interfere with defect detection.
Limited feature extraction: Traditional machine vision cannot extract high-level features.

IV. PROPOSED SYSTEM

The proposed methodology is based on Mask R-CNN which combines the Faster R-CNN and FCN (Fully Connected Network) to get additional mask output other than the class and box outputs. Faster R-CNN is an object detection model consisting of two main components: a region proposal network (RPN) and a detection network. With the help of the above method there are two crucial parameters in the exposure process that can be controlled to get a "good chip", Exposure energy (Energy) and Focal length (Focus)

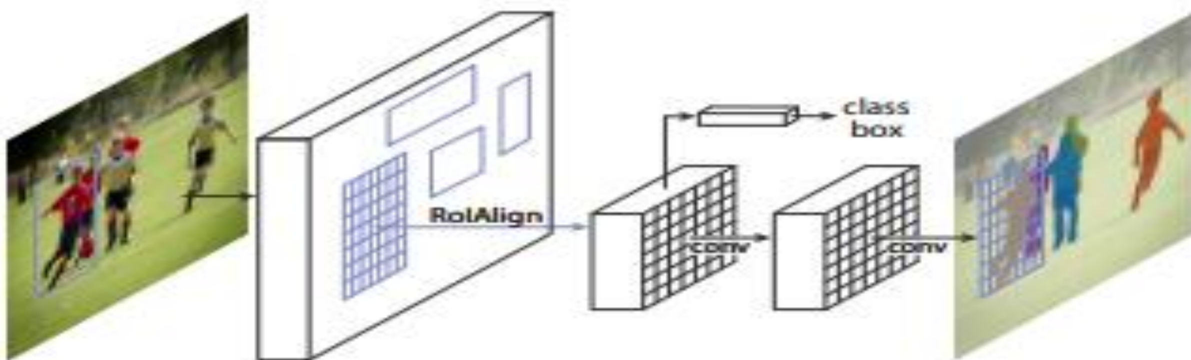

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Figure: System architecture design

V. IMPLEMENTATION

Data Collection and Preprocessing :

The Image Processing Module serves as the initial stage of the defect detection system, responsible for preparing raw images captured from semiconductor manufacturing and food production environments for further analysis. This module employs a series of preprocessing techniques to enhance image quality, standardize formats, and mitigate noise. Upon receiving raw images from the image acquisition component, preprocessing operations such as resizing, normalization, and augmentation are applied using libraries like OpenCV. Resizing ensures uniformity in image dimensions, normalization standardizes pixel values to a common scale, and augmentation generates additional training data by applying transformations like rotation, flipping, or brightness adjustments.

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Semiconductor Data:

Collect High-Resolution Images: Obtain high-resolution images of semiconductor wafers or chips from manufacturing process. These images should cover various defect types (e.g., scratches, cracks, contamination).
Annotation: Annotate the images to label defect regions. Use bounding boxes or pixel-level segmentation masks to mark defects.
Data Augmentation: Augment the dataset by applying transformations (e.g., rotation, scaling, flipping). This increases model robustness and generalization.

Food Product Data:

Collect Diverse Food Product Images: Gather images of different food products (fruits, vegetables, packaged items). Include both normal and defective samples.
Annotation: Annotate the images to identify common defects (e.g., mold, bruises, discoloration). Similar to the semiconductor data, use bounding boxes or masks.
Data Augmentation: Apply data augmentation techniques to the food product dataset as well. Ensure diversity in lighting conditions, angles, and backgrounds.

Deep Learning Model Development

The Deep Learning Model Development Module focuses on the creation and optimization of deep learning models tailored for defect detection in semiconductor manufacturing and food production. This module comprises two sub-modules: one dedicated to semiconductor defect detection utilizing the Mask R-CNN algorithm, and another for food defect detection leveraging the ResNet18 architecture.

Semiconductor Model (Mask R-CNN):
i) Architecture Selection - Mask R-CNN (Mask Region-based Convolutional Neural Network):

Combines Object Detection and Instance Segmentation:
Mask R-CNN extends Faster R-CNN (Region-based Convolutional Neural Network) by adding a segmentation branch. It can simultaneously detect objects (bounding boxes) and segment them at the pixel level. Ideal for scenarios where precise localization and segmentation of object instances are required.

How It Works:
Backbone CNN (e.g., ResNet) extracts features from the input image. Region Proposal Network (RPN) generates candidate object proposals. RoI Align layer aligns features within each proposal. The classification head predicts class labels. The Mask head predicts segmentation masks for each object.

Benefits:
Accurate object localization and segmentation. Handles overlapping instances well. Pre-trained weights provide a good starting point.

ii) Transfer Learning:

Initialize with Pre-trained Weights:
Start with weights learned from a large dataset (e.g., COCO, ImageNet). These pre-trained weights capture general features useful for various tasks.

Fine-Tuning on Semiconductor Data:
Fine-tune the pre-trained Mask R-CNN on your annotated semiconductor dataset. Update the model's weights using backpropagation. Retrain the classification and segmentation heads. The model adapts to semiconductor-specific features.

iii) Hyperparameter Tuning:

Hyperparameter tuning is a critical aspect of training deep learning models, involving the adjustment of parameters that are not directly learned by the model but rather influence its learning process.

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Real-Time Defect Detection and Deployment

The objective of deploying trained models for real-time defect detection during production is achieved through a systematic approach involving deployment, image capture, inference, and action based on detection. Firstly, the trained models are deployed to an edge device, such as an industrial camera system, enabling real-time inference close to the production line. Real-time images of semiconductor wafers and food products are then captured and fed into the deployed models. For semiconductor defect detection, Mask R-CNN is utilized to identify defect regions, such as yield loss or faulty chips, with the overlay of defect masks on the original images for visualization.

Similarly, ResNet-18 is employed for food product defect detection, classifying defects like mold or bruises and labeling them on the images. Based on the detected defects, actions such as rejecting faulty products, triggering alerts for manual inspection, or adjusting production parameters if feasible are taken. This modular approach ensures improved quality assurance by enabling timely intervention, reducing scrap rates, and enhancing product quality. It also enhances efficiency through automated inspection, reducing manual effort, and facilitating faster decision-making during production. Furthermore, the system's adaptability is highlighted as it handles quality assurance for both semiconductor and food products, showcasing its versatility and applicability across diverse production environments and making sure that the model predicts accurately by identifying the defects and give a quality output.

VI. RESULTS AND DISCUSSION

1. Accuracy Metrics:

- Calculate accuracy, precision, recall, F1-score, and Intersection over Union (IoU) for both semiconductor and food defect detection models.
- Evaluate the models' ability to accurately identify and localize defects within images.Compilation and Execution Testing Result.

2. Confusion Matrix:

- Generate confusion matrices to visualize the distribution of true positive, true negative, false positive, and false negative predictions.
- Analyze the confusion matrix to identify common types of misclassifications and areas for improvement.
- Calculate accuracy, precision, recall, F1-score, and Intersection over Union (IoU) for both semiconductor and food defect detection models.
- Evaluate the models' ability to accurately identify and localize defects within images.Compilation and Execution Testing Results

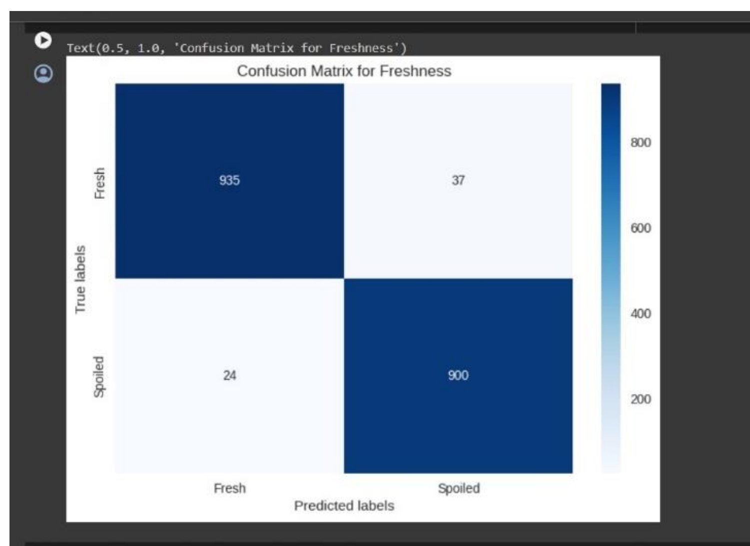

Figure : Confusion Matrix for Food Detection

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3. Visual Inspection:

- Visually inspect images with detected defects to validate the accuracy of the predictions.
- Verify that the detected defects align with ground truth annotations and correspond to actual defects in the images.

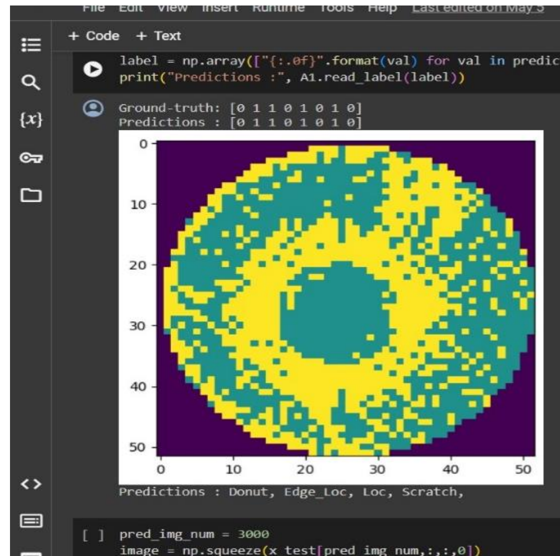

Figure : Visual Inspection for Semiconductor

4. Real-world Testing :

- Conduct real-world testing of the defect detection system in production environments.
- Evaluate the system's performance under varying lighting conditions, image resolutions, and production line speeds.

5. Speed and Efficiency:

- Measure the inference time and throughput of the defect detection system to assess its speed and efficiency.
- Compare the system's performance with specified latency requirements to ensure it meets real-time processing needs.

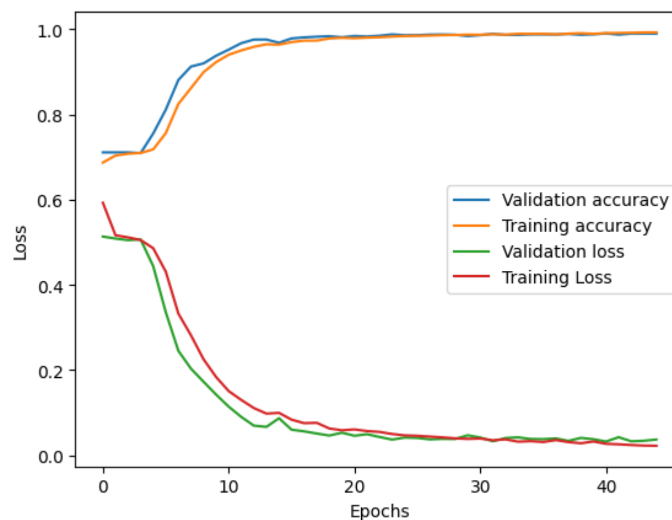

Figure : Accuracy of the Model

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VII. CONCLUSION

In the semiconductor industry, quality control is crucial at various stages, including IC design, wafer fabrication, packaging, and testing. With the help of this defects in tiny chips or particles can be detected.Implementing defect detection models improves productivity, reduces waste, and enhances the overall quality of manufactured products. Whether it's semiconductor chips or food and beverages, this contributes to efficient quality control.

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