Identification of Defects in Semiconductors using various Machine Learning Techniques

Vinay Chavhan

Abstract— In this modern world, we all know how technology is developing and bringing evaluation every day. Semiconductors played a pivotal role in this. The first semiconductor was developed in 1947 in the USA and from then as technology is evaluating the size of the transistor on the chips is shrinking and increasing in numbers. These semiconductors are used in various electronic devices you can imagine. The manufacturing of semiconductors involves many process operations which might create some defects in them which is not good for the end product. In this paper, we present a machine-learning module that can detect nine types of defects in semiconductors. The paper begins with a discussion of semiconductor defects, followed by a comprehensive visualization and various machine-learning techniques in python. It was discovered that similarly organized procedures could be used for many processing steps, allowing for the acceptance of this technology as a standard data processing method.

Index Terms— Chips, Semiconductors manufacturing process, data classification

1 Introduction

In this present world, technology is changing how we live and work. From electrical devices in our pockets to huge and magnificent vehicles and vast data centers, pacemakers to weather predicting systems – every one of them has semiconductor chips that are involved to make the product feasible for humans. One of the most capital- and technology-intensive market segments is the semiconductor one. Semiconductor devices are extremely crucial to perform and automating a process or a system. There are many types of semiconductor chips – memory chips, microprocessors, GPUs, ICs, analog chips, and Mixed Circuit Semiconductors / Digital chips.

A process with hundreds of steps, semiconductor fabrication [1][2] is extremely complex. Even though there are many semiconductor chips, the base lies in the preparation of the transistors which are manufactured with the help of semiconductor wafers made of silicon. These semiconductor wafers are also called silicon wafers and undergo 500 stages on average to produce the required design and configuration of the transistors, and the amount of monitoring data generated throughout the entire production process is enormous. Although there are many process operations involved, some of the prominent ones are Lithography, Diffusion, Etching, Ion Implantation, Chip Cutting, etc. These process operations produce defects unconsciously due to many parameters and surrounding conditions. If the process isn't rectified or corrected, defective wafers are generated which decreases the productivity of the manufacturing plant. Effective fault prediction in equipment is required to prevent sudden equipment failure and is also advantageous to increase production, lower costs, and speed up repair times. To reduce the defective wafers generation, the wafers need to be scanned at appropriate locations and the images are appropriately assessed to take corrective actions in the corresponding processes.

In this paper, we aim to investigate various image recognition – machine learning techniques to identify the type of defect in the silicon wafer effectively and compare the effectiveness between various machine learning techniques that would be identified. The dataset is donated by Ashadullah S [Num] on Kaggle and is publicly available for re-experimentation. The research objectives (RO) of the paper are like this RO 1: To describe the trends within the semiconductor images on how many defective images are in each type of defect. There are a total of 9 types of defects. RO 2: To predict the type of defect out of 9 defects on each image and label it. RO 3: To defend the model for performing the predictions in RO2 we check the accuracy of the model on testing data. We have divided the total dataset into 80-20, 80% for training, and 20% for testing.RO 4: To evaluate the relationship implied by the model prediction and locate the defect on the image.

The organization of this paper is as follows. The review of related work to fault detection in silicon wafers is presented in Section 1.1. Then the Exploratory data analysis is explained in section 2. The proposed predictive model for the detection of silicon wafer defects using various machine learning techniques and visualizations is explained and demonstrated in Section 3.

A series of experiments and results are presented in Section 4. Finally, Section 5 concludes the paper with a discussion of our future research direction.

1.1 Related Work

Cost, quality, and delivery time are crucial considerations for businesses to achieve long-term competition in the majority of manufacturing operations. Process engineers must keep an eye on production processes and ascertain the distinctive traits of anomalous products as soon as feasible [1], [6], [7], [15]. Process control is essential for the semiconductor industries, which run multistage manufacturing processes on a smaller 300-nanometer product size [18]. Pham and Afify [35] studied manufacturing-related machine-learning approaches. They assessed the various machine learning methods and looked at the use cases where they have been put to good use.

The previous papers have identified the type of the defects and here I can observe the gap in research that they did not mark where in that image the defect is present. As a part of this paper and research, we are generating new Knowledge that we aim to identify the defect and mark on the image where the defect is present exactly.

Identifying the defect is the classification problem which is solved by different machine learning algorithms but marking the defect on the image is a different problem which is one of the research objectives of this paper. This research objective will enhance the productivity of semiconductor manufacturers. We can identify what type of defect is occurring more and where in the image it is frequent. By collecting the information, we can deduce the parameters which might be affecting those defects and based on we can make changes in the manufacturing process to make it more optimal.

2 Exploratory Data Analysis

The dataset used in this project is pickle datatype, which is available on the Kaggle website. The dataset contains wafer maps(which are images) and the type of defect it has in the label column. 811,457 wafer maps collected from 46,393 lots in real-world fabrication. It contains nine types of defects mostly which are Center, Donut, Edge-Loc, Edge-Ring, Loc, Random, Scratch, Near-full, and none. One can download the dataset from the given link: https://www.kaggle.com/code/shawon10/wafer-defect-classification-by-deep-learning

The dataset contains a total of six columns which are wafer map, die size, lot name, water index, trianTestLabel, and failure type. We will require only a wafer map, trainTestLabel, and failure type. The dataset is very large containing a total of 811457 entries, the original file size is 2.1GB. The main attribute here is the image, from the image we will predict what defect it has. The images are of different sizes and we will need to preprocess them before going further.

During preprocessing steps, we observed that there are no missing values in the dataset. We dropped some columns which are not needed for further analysis which are, die size, lot name, and waferIndex. We categorized the data with defects and the data without defects. We saw that the total labeled data is 172950 rows Data with defects is 25519 rows and Data without defects are 147431 rows. We observed that images having the none type defects are way more which is not good for our analysis. We reduced the size of none type label data. For the next step, We first analyzed the size of images and the most frequent size in the dataset and then concluded that the most suitable size would be 26 widths and 26 heights would be correct for all images, we then converted the required images to that format. This step takes longer to run cause we are working on each image resize in the database.

We then visualized the data to get an understanding of it. Fig 2.1 shows the frequency of all types of defects in the vertical bar chart and the pie chart shows the categorization of labels with a pattern, labels without a pattern, and non type labels. The next higher frequency of images with defects is Edge-Ring after None-type. Near full has the least amount of images in the dataset for our analysis.

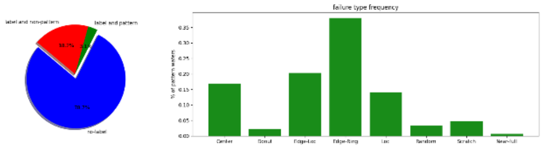

Fig 2.1 Failure Type Frequency

Now we have the images with a fixed size. We now convert the images to RGB color code. Fig 2.2 shows the color-coded image of the image containing each type of defect.

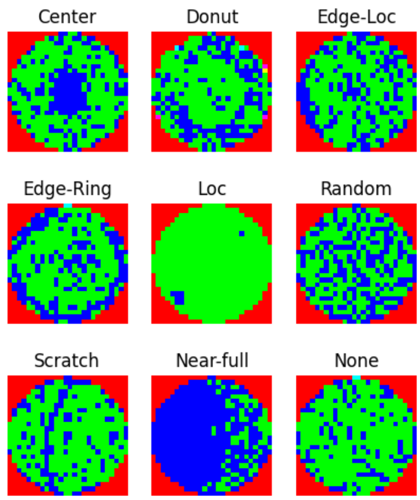

Fig 2.2 Type of defects

One of the trends in the dataset we saw is that the non-type of images data is higher which means that it's good that we observed the defects in the dataset are lower. This leads us the correct the dataset and reduces the non-type of data from the dataset. Another trend we saw in the dataset is to defect center and Edge-loc is almost the same it almost seems like they are co-related to each other, but we can't say that surely. We got the final data with 46581 rows for further analysis.

3 Methodology

We observed many different machine learning techniques to apply to this classification problem and applied the below techniques. We changed the shape of image for different algorithms as requires.

1. Support vector machine classification (SVC)
2. Decision Tree
3. Random Forest
4. AdaBoost
5. Gradient Boosting
6. BAGGING ENSEMBLE MODEL
7. K means
8. XGBoost
9. K- Nearest Neighbor (KNN)
10. Convolution Neural Network (CNN)

We compared the accuracy and confusion matrix for each algorithm and decided to go ahead with the CNN as our final algorithm image detection which showed 88 % accuracy with a 4-Fold method. We calculated the accuracy and val-accuracy with respect to each Epoch for the finalized CNN model.

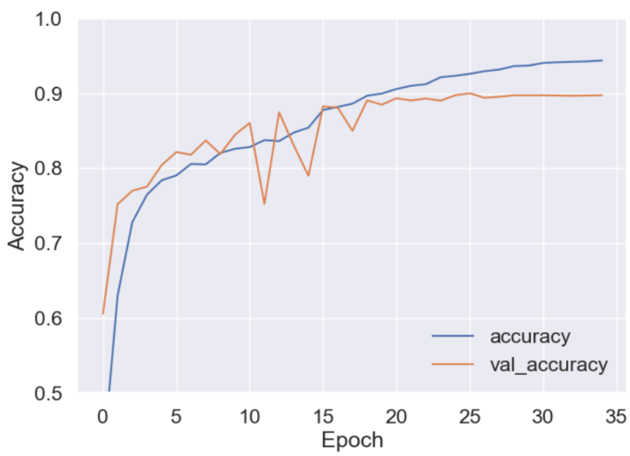

Fig 3.1 Accuracy with respect to each Epoch for CNN

The dataset is then divided into training and testing data in the ratio of 80:20. The model is built on the training dataset using different algorithms. After this, the trained model is applied to the testing dataset and different evaluation matrices are calculated to check the accuracy of our model.

4 Results and Discussion

For the assessment of the created models, usually, goodness-of-fit metrics are used to review the prediction capability of the model. Accuracy is the main measure that we used to decide on the experiment. We also used the confusion matrix, F1 score, and Root means squared error to determine the outcome of the different experiments. We applied a total of 10 models and found the aforementioned measures. When we tried giving the data which has the none type label images in a higher percentage, we got higher accuracy. This was overfitting the models and was not giving the correct accuracy. Later we updated the data processing technique and reduced the none type of label images from the dataset. After applying the models to new data, we got the result that is not overfitting. The accuracy of the model was reduced but that's what we expected.

After applying all the models, we saw that CNN is giving the right accuracy and we applied the 4-Fold technique to that and got an accuracy of around 89%. After that XGBoost gave 85% accuracy and so on. The feasibility of the models seems right, even if we have new features added to the dataset in the future the accuracy of the models should not get impacted that much. Even if we get the new data altogether with new image collection in the future, the models should perform better and give appropriate results. The research objectives have been accomplished by this paper and we can classify the image defects with given technique.

5 Conclusion

The manufacturing of semiconductors is one of the most capital intensive and competitive industry. Optimization in the manufacturing process has received significant attention since it has started. There are many challenges and opportunities for the engineers and researchers to develop the model for this growing industry. A good classification model is very necessary for the predication of the defect and enhancing the semiconductor manufacturing industry. Most silicon wafers are very complex and produced the different types of defects which is contributed by hundreds of parameters. For such large amount of measurement data, authentic analysis technique is very needed.

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