IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Optimizing Semiconductor Yield: A Focus On Wafer Fault Detection And Prediction

[1]T. Raghavendra Gupta, [2]Naga Tanusri Nukala, [3]R. Rishikesh Reddy, [4]Neha Basvoju, [5]V. Sandeep Kumar
[1]Associate Professor, [2]Student, [3]Student, [4]Student, [5]Student
[1]Computer Science & Engineering,
[1]Hyderabad Institute of Technology and Management, Hyderabad, India.

Abstract: A wafer, a thin semiconductor slices crucial for microelectronic devices, notably in integrated circuits (ICs), plays a fundamental role in various industries, such as computing, solar cells, and optics. We created a machine learning model utilizing Python, Flask, and PyCharm, as well as Random Forest and XG Boost Classifiers to anticipate the need to replace wafers based on sensor inputs. Wafer fault detection is essential in semiconductor production, enhancing fabrication yield by identifying non-functioning wafers. The dataset includes wafer names and 590 sensor value columns, with the last column indicating "Good/Bad" status, transmitted in batches for analysis. The two classes, +1 and -1, signify the working condition and the need for replacement, respectively, ensuring efficient identification and prediction of faulty wafers without impacting other resources.

***Index Terms* -** wafer, integrated circuits, computing, machine learning model, fault detection, sensor inputs, classification, replacement.

1.INTRODUCTION

Wafers constitute a fundamental element in the realm of integrated circuit (IC) manufacturing, serving as crucial carriers in the intricate processes of microelectronics and semiconductor production. In this dynamic industry, engineers face perpetual challenges arising from the inherent complexity of manufacturing processes and the continuous evolution of technology. To remain competitive, a primary emphasis on yield enhancement becomes imperative. The semiconductor sector strives to meet the escalating demand for devices by embracing efficient manufacturing automation practices, underscoring the critical need to address factors limiting yield.

Wafers, essential for creating electronic ICs and silicon-based photovoltaic cells, play a pivotal role as substrates in these designs. Engineers employ processes such as doping, implantation, and etching to meticulously construct integrated circuits, highlighting the indispensability of wafers in the semiconductor manufacturing landscape.

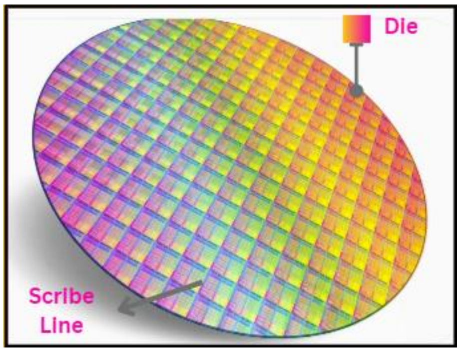

Figure 1: Silicon Wafer

Wafer fault detection emerges as a crucial component in semiconductor manufacturing, aimed at identifying defects and elevating fabrication yield. This becomes particularly essential in navigating the complexities of manufacturing processes and staying abreast of technological advancements. The strategic implementation of wafer fault detection is pivotal for semiconductor fabrication companies, as it allows for a proactive approach in addressing yield-limiting factors and ensures maximum productivity. Through the filtration of defective chips, wafer fault detection transforms raw wafer space data into a comprehensive Wafer Warehouse map (WBM).

Defect patterns in wafer manufacturing refer to the recurring formations or distributions of defects on the wafer surface. These patterns, which include random, cluster, edge, patterned, and uniform defects, serve as crucial indicators of potential manufacturing challenges. Random defects manifest unpredictably across the wafer, posing challenges for accurate predictions. Cluster defects are concentrated in specific areas, affecting the localized yield and requiring targeted solutions. Edge flaws raise the possibility of wafer breaking during subsequent production processes. Patterned defects may suggest systematic issues in the manufacturing process, thereby allowing for focused improvements. Uniform flaws have far-reaching consequences that lower the overall wafer performance. Analyzing and categorizing these patterns is essential for implementing effective quality control measures, improving the manufacturing processes, and ultimately enhancing the yield and reliability of semiconductor devices. To achieve this, advanced inspection and metrology techniques are systematically employed during wafer fabrication.

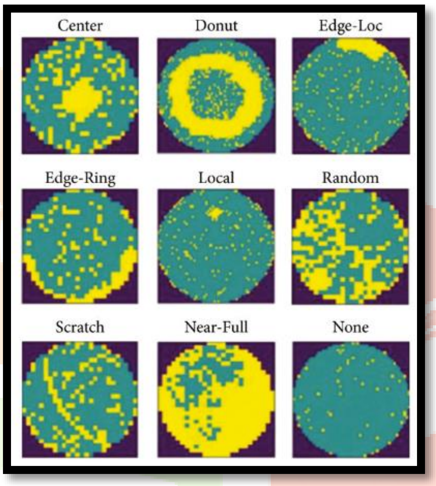

Figure 2: Common Defect Patterns in Wafers

The proposed research is significant because of its ability to use machine learning for wafer defect identification, providing a forward-thinking method for identifying non-functioning wafers. This innovation holds promise for applications in optimizing semiconductor production, ensuring the production of high-quality ICs, and ultimately contributing to the overall efficiency and competitiveness of the semiconductor industry. Machine learning integration into wafer flaw detection gives a chance to improve the precision and efficacy of this crucial part of semiconductor production, supporting technological improvements and fulfilling the expectations of an ever-changing market.

2.LITERATURE SURVEY

Wafers are used as carriers in the fabrication of integrated circuits. Manufacturing difficulties might result in distinct fault patterns on wafer maps. Recent technical advances have enabled wafer testing to evaluate chip electrical performance. Defective chips are recognized and filtered away, yielding the wafer Warehouse map (WBM) [1]. Common defect cluster patterns include Center, Edge-Loc, Edge-Ring, Loc, Scratch Random, and None patterns.

Kim et al. [2] used batch training to handle imbalanced data with an equal mix of either good and bad wafers in each batch. They categorized wafers into defective (patterned) and regular (non-patterned) classes, employing binary classifiers in related studies They proposed a neural network-based approach for bin coloring as well as a compact four-layered CNN to detect excellent from poor wafers in their study. However, further work is needed to classify bad wafers into specific defect types for a detailed defect analysis.

Effective defect monitoring approaches are critical in defect analysis and a fabrication facility's total output. Conventional approaches to defect monitoring traditionally involve manual inspections by domain experts [3], yet these methods lack accuracy and efficiency. The expense of labor is a significant concern. Additionally, the continuous reduction in chip sizes makes human intervention and manual defect monitoring impractical. The field of semiconductors industry has continually used cutting-edge technical methods to reduce production costs while improving precision and efficacy.

In their approach outlined by Nakata et al. [4], To track production data daily, a combination of data mining and machine learning approaches was used. They developed a CNN (Convolutional Neural Network), particularly for the long-term monitoring of recurring failures in defect patterns. This CNN functioned as a single-class classifier comprising five layers, and its parameters were determined empirically. The training process involved using unlabeled images to detect the reappearance of frequently occurring defect patterns.

2.1 Problem

In the realm of wafer manufacturing, the intricate interplay of environmental conditions and process parameters gives rise to defects on the wafer surface, directly impacting overall production yield. Recognizing and accurately detecting these faults is crucial not only for quickly identifying anomalies in the production process, but also for making appropriate modifications. The inadequacies in this process contribute to diminished production efficiency and heightened scrap rates, posing a substantial challenge to the overall quality of semiconductor manufacturing.

Traditional approaches to the early detection of wafer surface defects heavily lean on manual inspection carried out by seasoned professionals. However, this time-honored method encounters formidable challenges, characterized by inefficiencies, compromised accuracy, elevated operational costs, and inherent subjectivity. As industrial products become increasingly sophisticated, the reliance on manual inspection proves insufficient in meeting the stringent standards and efficiency requirements of contemporary manufacturing. This creates a pressing problem, demanding innovative solutions to enhance the precision and efficiency of defect detection in wafer manufacturing processes.

2.2 Existing System and its Limitations

Prior efforts in fault detection methods have primarily focused on addressing process control challenges using a limited set of features derived from tool-state and process-state measurement data. Recent advancements have extended these methods to incorporate machine learning, particularly deep learning, utilizing deep convolutional neural networks for the analysis of wafer maps. However, the existing system still faces challenges in terms of scalability, adaptability, and handling the complexity of modern semiconductor manufacturing.

2.3 Existing System and its Limitations

The proposed system leverages contemporary semiconductor manufacturing technology, enabling real-time process control through data obtained from equipment sensors and final electrical tests. With the substantial volume of data generated throughout the production process, the manual application of traditional process control methodologies, such as univariate and multivariate control charts, proves inefficient. Instead, the proposed system introduces an automatic and advanced process control method. The key phases include Data Cleaning, Feature Selection, Boosting, and Model Building. This approach aims to create a robust and accurate model capable of detecting faults within highly imbalanced data featuring numerous features. By doing so, it addresses the limitations of manual inspection and traditional control methods, promising improved efficiency and adaptability in semiconductor manufacturing processes.

3.METHODOLOGY

3.1 Application Flowchart

The application flow chart of wafer fault detection that you provided shows the following steps:

- Start: The procedure begins with data collecting from the wafer. These data may be gathered using a variety of techniques, including optical examination, electrical testing, and mechanical probing.
- Data validation: Once the data is collected, it is validated to ensure that it is complete and accurate.
- Data transformation: The data is then transformed into a format that can be processed by the fault detection system. This may involve cleaning the data, removing noise, and converting it to a consistent format.
- Data insertion in DB: The transformed data is then inserted into a database. This database stores the data for future analysis and reporting.
- Export the required data to CSV for training: A subset of the given data is exported to a CSV file for training the fault detection model.

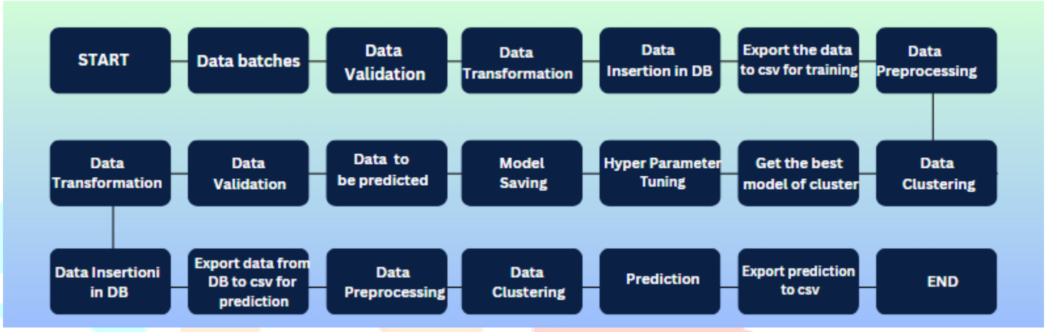

Figure 3: Application Flowchart of Wafer Fault Detection

- Model saving: The trained model is saved in order to detect flaws in fresh wafers.
- Data preprocessing: The new wafer data is preprocessed to prepare it for fault detection. This may involve cleaning the data, removing noise, and converting it to a consistent format.
- Data prediction: The preprocessed data is then passed to the fault detection model for prediction. The model forecasts the chance of a defect forming in each wafer position.
- Data clustering: The predicted fault data is then clustered to identify groups of related faults. This helps to identify patterns in the fault data and to understand the root causes of faults.
- Export prediction to CSV: The displayed fault data is transferred to a CSV file to further investigation and reporting.
- End: The process ends with generation of a report that summarizes the fault detection results.

The figure also shows the following key components:

- ✓ Data collection: This section collects data from the wafer using a variety of techniques, including optical inspection, electrical testing, and mechanical probing.
- ✓ Data preprocessing: This component prepares the collected data for fault detection. This may involve cleaning the data, removing noise, and converting it to a consistent format.
- ✓ Fault detection: This model was trained on historical wafer data to predict the likelihood of a fault occurring at each location on the wafer.
- ✓ Data clustering: This component groups the predicted fault data into clusters to identify patterns of the fault data and to understand the root causes of faults.
- ✓ Reporting: This component generates a report that summarizes the fault detection results.

This application flow chart would be used to implement a wafer fault detection system in a variety of ways. The specific implementation will depend on the specific needs of the application and the available resources.

3.2 PyCharm & Flask

The collaboration between PyCharm and Flask in wafer fault detection is crucial for developing an efficient web application that integrates machine learning models. PyCharm's Python IDE streamlines coding, while Flask's micro web framework enables a user-friendly interface. This synergy facilitates real-time fault detection, enhancing accuracy and efficiency in semiconductor manufacturing. The system's predictive capabilities, driven by machine learning models, contribute to timely decision-making, optimizing production yield, and reducing scrap rates. This integrated solution represents a shift from manual to automated inspection, addressing inefficiencies and elevating product quality and competitiveness in the semiconductor industry.

3.3 Datasets

Periodically, the client will send data file batches to a designated location. These files will encompass wafer details, featuring names and 590 columns with diverse sensor readings. The conclusive column in each file will denote the wafer's status, labeled as either "Good" (+1) or "Bad" (-1). Alongside the data files, the client is required to supply a crucial "schema" file. This file is essential because it contains important details about the training files, such as the names of the files, the length of the date and time values in the file names, the counts of the columns, the names of the columns, and the data types of each column. The methodical processing and training of the machine learning model for efficient wafer fault detection is ensured by this combined data and schema approach.

3.4 Data Ingestion

The system is built to create a database with the specified name that the client provides during the data ingestion phase. A connection is made to an existing database if one has one. Concurrently, the database creates a table called "Good_Data" to hold the files from the "Good_Data_Folder." The column names and datatypes listed in the schema file were used to define the table structure. Both new and old files can be seamlessly trained with this method. After that, files from the assigned folder are added to the table, and any files that have incorrect data types in any of their columns are sent to the "Bad_Data_Folder".

3.5 Data Validation

The subsequent data validation step involves several checks to ensure the integrity and adherence to specified criteria. This includes checking the length of both date and time values in the file names. If these values meet the specified requirements, the files are moved to the "Good_Data_Folder"; otherwise, they are redirected to the "Bad_Data_Folder."

Further validation steps include confirming the correct number of columns in each file and verifying that their names match those specified in the schema file. Any discrepancies result in the file being moved to the "Bad_Data_Folder.". If any datatype mismatches are detected, the respective file is moved to the "Bad_Data_Folder." Lastly, files with all NULL or missing values in any column are discarded and redirected to the "Bad_Data_Folder."

3.6 Data Preprocessing

The subsequent data preprocessing phase is a fundamental step in machine learning-based wafer fault detection. This stage involves enhancing data quality through various techniques, including handling missing data, outlier detection, noise reduction, feature engineering, and normalization. Dimensionality reduction techniques, such as Principal Component Analysis (PCA), are also employed to retain essential information while mitigating the curse of dimensionality.

3.7 Database Operations

In terms of database functions, the system includes a wide range of functions that are essential for effective fault finding. Data intake, storage, preprocessing, retrieval, indexing, analysis, model training, visualization, reporting, security, backup, and archiving are some of these operations. To manage and analyze data during the fault-detection process, each operation is essential.

3.8 Clustering

The K-Means Clustering algorithm was used as an Unsupervised Learning method in the last stage of data clustering. Based on their similarities, this algorithm clusters the unlabeled datasets. Reducing the distances between the data points and the clusters they corresponded with was the main goal. An elbow plot was used to determine the ideal number of clusters, and the "Knee Locator" function made dynamic cluster selection easier. By using these clustering techniques, observations with similar characteristics can be automatically categorized, which offers important insights into the dataset's underlying structure.

4.ALGORITHMS

Two potent machine learning algorithms used in wafer fault detection are Random Forest and XG Boost. Each has specific benefits that add to the overall efficacy of the detection procedure.

a. Random Forest:

With the use of multiple decision trees constructed during training, Random Forest is an ensemble learning technique that produces the mean prediction for regression problems or the mode of classes for classification problems. Random Forest provides various advantages when it comes to wafer fault detection.

- Robust against Overfitting: When compared to individual decision trees, Random Forest is less susceptible to overfitting. This is important for wafer fault detection, where the model must separate the noise in the sensor data from real patterns. Random Forest's ensemble nature aids in preserving a balance between overfitting and accuracy.
- Importance of Features: Random Forest is able to evaluate the significance of various features within the dataset. This is important for wafer fault detection because it shows which parameters or sensors are most important in classifying wafers as defective or good. Comprehending the significance of features facilitates the interpretation of the model's decision-making procedure.
- High generalization and accuracy: Random Forest builds several decision trees and combines their results to produce predictions that are typically highly accurate. With the help of this ensemble approach, the model's robustness for a range of wafer fault scenarios is increased and its ability to generalize well to new data is enhanced.

b. XG Boost:

Another ensemble learning algorithm that builds a strong predictive model by combining the capabilities of several weak learners is called XG Boost, or eXtreme Gradient Boosting. These are some of its unique advantages in wafer fault detection.

- Gradient Boosting Technique: By reducing the errors of the prior iterations, XG Boost uses a gradient boosting framework to improve the model's performance over time. This leads to an extremely precise and flexible model that works well with intricate wafer-fault patterns.
- Handling Imbalanced Data: Databases for wafer fault detection frequently show class imbalance, meaning that there are significantly fewer defective wafers than there are good wafers. In order to prevent the model from being biased towards the majority class and to provide a balanced approach to learning from both classes, XG Boost handles imbalanced data well.
- Regularization Techniques: L1 and L2 regularization are two regularization techniques that XG Boost uses to help control the complexity of the model. In wafer fault detection, this is crucial to keep the model from getting overly complex and possibly overfitting the training set.

In summary, Random Forest and XG Boost contribute significantly to wafer fault detection by offering high accuracy, robustness, feature importance analysis, and effective handling of imbalanced data. Their ensemble nature and sophisticated algorithms make them well-suited for the complexities of semiconductor manufacturing processes.

5.RESULTS AND DISCUSSION

The wafer fault detection project proved that machine learning could be used to identify flaws in silicon wafers. On a held-out test set, the model demonstrated high accuracy, indicating that it can be applied to new data. The model can be applied in a number of ways to raise the standard of semiconductor production. It can be implemented for various instances.

- Examine wafers at different points during the manufacturing process in order to find defects early.
- Remove wafers that have a higher likelihood of being defective from the manufacturing process.
- Offer input to the production process in order to assist in locating and removing the main sources of errors.

Wafer fault detection has made a significant impact on the semiconductor manufacturing industry. Potentially, it could raise the standard.

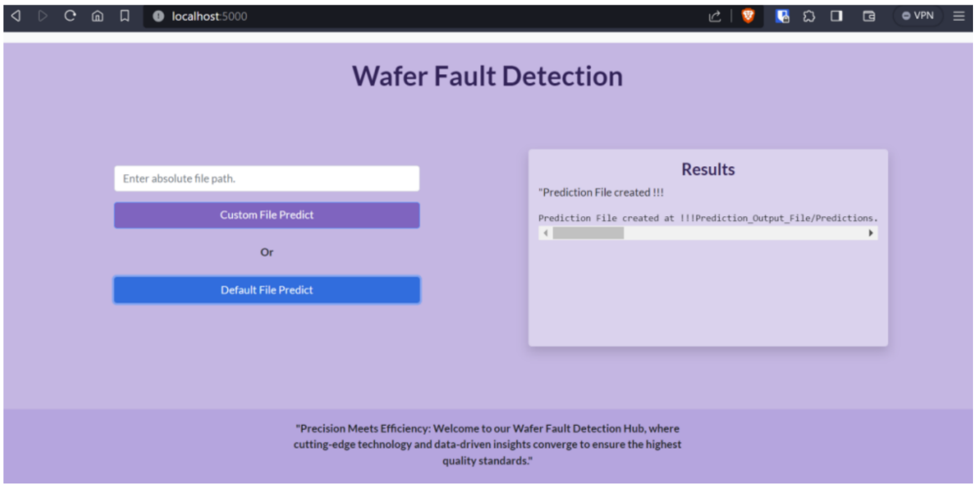

Figure 4: Default File Prediction in Wafer Fault Detection.

The goal of this user interface's design was to make it simple and easy to use. It has an easy-to-use interface with instructions that are clear. Users can now enter the wafer fault-detection code. The color purple, which is frequently connected to wafer fault detection, is used in this code. Custom file prediction and default file prediction are the two formats in which the results are presented. While the default file prediction option uses predefined code, the custom file prediction option lets users upload their own wafer fault detection code. Additionally, a brief explanation of the wafer fault detection procedure is given. Those who are unfamiliar with wafer-fault detection may find this explanation useful.

REFERENCES

[1]] Shankar N G., Zhong Z W. (2005) Defect detection on semiconductor wafer surfaces[J]. Microelectronic Engineering, 77(3/4): 337-346.

[2] J. Kim, H. Kim, J. Park, K. Mo, and P. Kang, "Bin2Vec: A better wafer bin map coloring scheme for comprehensible visualization and effective bad wafer classification," Appl. Sci., vol. 9, no. 3, 2019

[3] C. Y. Hsu, W. J. Chen, and J. C. Chien, "Similarity matching of wafer bin maps for manufacturing intelligence to empower Industry 3.5 for semiconductor manufacturing," Comput. Ind. Eng., vol. 142, p. 106358, Apr. 2020.

[4] K. Nakata, R. Orihara, Y. Mizuoka, and K. Takagi, "A Comprehensive BigData-Based Monitoring System for Yield Enhancement in Semiconductor Manufacturing," IEEE Trans. Semicond. Manuf., vol. 30, no. 4, pp. 339– 344, 2017.