



Synthetic Defect Data Generation Using Deep Learning Architecture for Improved Wafer Inspection Performance

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Abstract—Wafer defects have become smaller and more complex, increasing the demand for accurate and real-time quality monitoring and control. Wafer surface flaws can be properly inspected to detect defects in the production process faster. Hence, it is essential to have defect checking in the fabrication of the wafer to foster high productivity, cost effectiveness, and ideal performance. This paper provides an efficient wafer defect inspection model based on a Graph Neural Network (GNN) on the Mixed-type Wafer Defect Dataset of Kaggle that comprises some 38,000 wafer maps in 38 different, normal, single-defect, and mixed-defect classes. The wafer maps in the form of 52×52 grids were first processed into matrix normalization, handled labels with label encoder, reshaping, and graph-based representation to maintain the spatial relationships between dies. Stratified sampling was used to divide the dataset into training, validation and testing sets, and data augmentation was used, which included rotation, flipping and cropping to improve robustness and generalization. The suggested GNN has used message-passing and global pooling, which captures complex spatial and relationship defects that are difficult to understand by normal CNN and machine learning methods. The evaluation of the performance was conducted based on accuracy, precision, recall, F1-score, and cross-entropy loss. The experimental results show that the proposed model offers a high classification accuracy of 97.25, a high level of precision (96.70%), recall (96.17%), and F1-score (96.44%). Comparative analysis reveals that the GNN is superior to the MobileNetV1, ResNet50 and SVM models. In general, the findings indicate the strength, consistency, and appropriateness of GNNs in complex multi-defect wafer inspection of semiconductor manufacturing.

Keywords—Wafer defect inspection, Semiconductor manufacturing, Mixed-type defects, Wafer map analysis, Deep learning, Quality control, Defect classification.

I. INTRODUCTION

With the design of semiconductor components for integration, an increasing number of integrated circuit components are being etched onto semiconductor wafers [1]. It is widely used in information and communication, automotive, and aerospace applications. To make electronic products portable and multifunctional, chips must be smaller and tighter, which makes it necessary to accommodate more components on the wafer surface [2][3]. During the manufacturing process [4][5] Cutting wafers can cause chipping and breakage of dies, and dust particles present in the clean room can also cause damage to the dies.

Wafers are the most essential semiconductor materials [6], and therefore is considered to be a major resource in the semiconductor industry [7]. Wafers can be divided into two categories: prime wafers and test wafers. To detect surface defects on wafers, the traditional inspection method is manual inspection, which has a low sampling rate and poor real-time performance, and is highly influenced by experience and subjective factors. In the face of irregularly shaped and weakly imaged defects [8] Traditional algorithms suffer from low performance, high false detection rates, and high noise sensitivity. Computer vision is more effective in detecting defects such as wafer stains, collapses, and cracks, which typically arise from processes such as lithography misalignment, particle contamination, or dicing stress during wafer fabrication [9]. The use of computer vision significantly reduces labor costs and is more suitable for highly integrated wafers. Therefore, some researchers have used deep learning to automatically identify features of interest in images.

Quality assurance [10][11] in manufacturing [12], particularly in injection molding, remains a challenge due to a variety of error types stemming from machine parameters, environmental influences, and batch inconsistencies. As these errors can be expensive to produce in real-world settings, synthetic training data offers a compelling solution for machine learning [13] models tasked with defect detection. The use of synthetic data for deep learning [14][15] has been expanding in various fields in recent years [16], yet the impact of rendering parameters on the quality of this data and the subsequent performance of AI [17][18][19][20] models is not well understood.

Wafer characters are codes comprising numbers, letters, and symbols, and contain production information for each wafer. If an error in a wafer character recognition occurs during production, the information cannot be matched, significantly reducing production efficiency [21]. Therefore, improvement of the accuracy of the wafer character recognition method is significant for improving the production efficiency of the semiconductor industry [22]. Machine learning algorithms [23] can automatically learn the mapping relationship between features and results, and can efficiently complete classification without manual design of classification criteria. In recent years, deep learning algorithms have been used in wafer surface defect detection. Deep learning algorithms [24][25] can automatically extract image features and complete classification and localization, and have a high accuracy. Once the deep learning [26] model is built, detection personnel only need to input wafer images

into the model, without complex image processing steps. The detection method based on deep learning [27] can reduce the difficulty of algorithm development [28], and it has high detection performance, but this kind of method requires a lot of image data to learn the distribution of the defects.

A. Motivation and Contributions

The impetus of the study in question is the growing complexity and miniaturization of semiconductor wafers, which complicate the traditional manual and rule-of-thumb-based inspection technologies, rendering these technologies inefficient, subjective, and incapable of detecting defects in real-time. The currently applied computer vision and deep learning technologies tend not to handle irregular, mixed, and weakly imaged defect patterns and need to be trained on large amounts of high-quality data. In order to overcome these issues, it is highly demanded that advanced models can capture effectively in the complex spatial relationship and enhance better inspection accuracy and minimize the reliance on manual intervention. GNNs provide an exciting way forward as it is a more natural and robust method of modeling wafer structures and encourages their use to the task of inspecting wafer defects in the modern semiconductor manufacturing process with accuracy, automation, and scalability. This research offers certain significant contributions that are discussed below:

- Leveraged the Mixed-type Wafer Defect Dataset directly sourced from Kaggle. The dataset helped properly inspect wafer performance.
- Implemented efficient preprocessing stages like matrix normalization, handling labels with label encoder and image reshaping.
- The dataset underwent the data augmentation strategy to strengthen and generalize the model.
- Implemented the deep learning Graph Neural Network model which effectively works on inspecting the performance of the wafer.
- Measured the performance of the model using accuracy, precision, recall, f1-score and loss function.

B. Novelty and Justification

This study is novel in that it uses graph neural network to simulate mixed-type wafer defects, which effectively predicts the spatial and relationship relationships in wafer maps. This graphical model is more accurate and stronger in classification than other traditional methods, particularly with intricate defects. This work can be explained by the inability of conventional approaches to deal with multifaceted and composite as well as mixed patterns of wafer defects. Graph neural networks allow a better representation of spatial relationships, and the classification of wafer defects is more correct and reliable.

C. Organization of the Study

The study is structured as follows: Section II discusses about the existing studies related to Wafer Inspection performance. Section III details about the proposed methodology consisting of the dataset, preprocessing, model implementation and performance evaluation. Section IV outlines the result analysis and discussion. Lastly, Section V concludes the study and gives the future progress.

II. LITERATURE REVIEW

This part identifies the benchmarking research on performance in wafer inspection in the different fields. Table I highlights the methods, learning type, dataset uses, contributions and architecture.

Mei et al. (2025) suggested a knowledge distillation training strategy is also implemented to equip the lightweight model with the learning capabilities of more complex network models, thus enhancing its mean average precision (mAP) and frames per second (FPS) in inspection tasks. Extensive experimental results demonstrate the effectiveness of their method with data volume robustness, which achieves 88.2% and 88.9% mAP@0.5 on the semiconductor wafer and chip datasets. Moreover, compared to SoTA methods, their framework shows superior performance, achieving a compact model size of only 27 MB and a detection speed of 108.4 FPS [29].

Cheng et al. (2025) proposed that a boundary focal loss (BFLoss) is utilized to constrain the training process. Experiments are carried out on several typical open industrial defect datasets and their own wafer surface defect datasets. The proposed network exhibits a more superior detection performance compared to the other classical traditional counterparts, achieving a high segmentation metric mIoU of 80.71%, 87.05%, 91.23%, and 94.18% on the Kolektor SDD dataset, Magnetic Tile dataset, and two their own wafer surface defect datasets gathered from industrial production lines [30].

Xu et al. (2025) have incorporated and improved a semi-supervised learning approach, Mutex Match, which introduces a dynamic, adaptive and class-wise high-confidence threshold mechanism and achieves excellent classification performance even with extremely scarce annotations-reaching 84.12% accuracy with only one labeled sample per class. It significantly improves pseudo-label utilization and reduces reliance on manual labeling. Experimental results show that MutexMatch outperforms multiple baseline methods in classification accuracy, demonstrating strong robustness and effectiveness [31].

Kumar et al. (2024) proposed a unique approach for semiconductor wafer surface defect inspection using deep convolutional neural networks. Initially, in order to extract features and create feature maps, an innovative structure for feature pyramid networks with atrous convolution (FPNAC) is designed. Secondly, region proposals are generated by feeding the feature plots into the region proposal network (RPN). In order to correctly categorize and segment the flaws, the region recommendations are finally associated to matching size by way of the inputs of a Radial Basis Functional Neural Network (RBFNN), which consists of three branches. The suggested RBFNN produces good overall performance, as evidenced by the experimental findings, which show Mean Intersection over Union (MIoU) of 90.06% and Mean Pixel Accuracy (MPA) of 94.97% [32].

Cheng et al. (2024) suggested a method different from previous methods; only defect-free images are required for the proposed method to achieve defect transfer detection. Experiments on real-world semiconductor wafer production lines show that the proposed method achieves mean intersection over union (mIoU) of 83.49% and 80.12% in defect transfer detection between two background pattern wafers. Furthermore, the excellent performance on other

classical industrial datasets demonstrates that the proposed network has great robustness to various defects and industrial scenarios [33].

Shi et al. (2023) article has studied this problem, and an adaptive coverage path planning (CPP) method for randomly scattering grains using an attention interface is proposed. The proposed randomly scattering waypoints method uses deep reinforcement learning (DRL) for automatic real-time path planning of the second detection. A soft attention interface accelerates the process with a less overlapped check. The experimental results demonstrate the efficiency of the proposed method in terms of less overlapping and fewer steps, and this method learns a better CPP strategy for wafer probing than programmed paths and other RL-based methods [34].

Tziolas et al. (2022) proposed a CNN-based model that utilizes various pre- and post-processing tools and is applied on the public but highly imbalanced industrial dataset WM-811K. To handle imbalance, a methodology of treating each class individually is proposed by applying different processing techniques for down-sampling, splitting and data

augmentation based on the number of samples. The proposed model achieves 95.3% accuracy and 93.78% macro F1-score and outperforms other models in the related literature concerning the identification of the majority of classes [35].

A. Research Gaps

The major gaps are present even though there is an advancement in the inspection of the wafer. The vast majority of approaches are task-specific, and they do not have a common framework that will deal with the efficiency of detection, segmentation, and inspection together. The generalization between various wafer patterns, defects, and production conditions is not well developed. Several techniques use complicated models or customized losses, which lower scalability and applicability in real-time. Such problems as drastic imbalance of classes, latent flaws, and responsiveness to changing industrial conditions are not managed adequately, which is why lightweight, strong, and highly generalizable solutions to inspections are needed.

TABLE I. COMPARISON OF LEARNING PARADIGMS AND NETWORK ARCHITECTURES IN WAFER INSPECTION LITERATURE

| Reference | Proposed Method | Learning Paradigm | Data Type | Key Technical Contributions | Network Architecture |
|-----------------------|--|---|---|--|---|
| Mei et al. (2025) | Lightweight defect detection framework with knowledge distillation | Supervised learning with knowledge distillation | Semiconductor wafer and chip inspection images | Knowledge distillation transfers representation capability from complex teacher models to lightweight student networks, improving mAP and FPS with strong data volume robustness | Lightweight CNN-based detector (teacher-student architecture) |
| Cheng et al. (2025) | Boundary Focal Loss-based defect segmentation network | Supervised learning | Industrial surface defect images and wafer surface datasets | Boundary Focal Loss (BFLoss) constrains boundary learning and improves segmentation accuracy on fine-grained defects | CNN-based segmentation network |
| Xu et al. (2025) | Mutex Match semi-supervised classification framework | Semi-supervised learning | Wafer defect classification data | Dynamic, adaptive, class-wise high-confidence thresholding enhances pseudo-label quality under extremely limited annotations | CNN-based classifier with Mutex Match strategy |
| Kumar et al. (2024) | FPNAC-RBFNN defect detection and segmentation model | Supervised learning | Semiconductor wafer surface images | Atrous convolution-based feature pyramid (FPNAC) improves multi-scale feature extraction; RBFNN enables accurate defect categorization and segmentation | FPN with atrous convolution + RPN + three-branch RBFNN |
| Cheng et al. (2024) | Defect transfer detection using defect-free training images | Unsupervised / One-class learning | Real-world wafer production line images | Requires only defect-free samples; achieves robust defect transfer detection across varying wafer background patterns | CNN-based anomaly detection network |
| Shi et al. (2023) | Attention-based adaptive coverage path planning for wafer probing | Deep reinforcement learning | Wafer probing spatial data | Random waypoint generation with soft attention reduces overlap and improves inspection efficiency in second-stage detection | DRL agent with attention mechanism |
| Tziolas et al. (2022) | CNN-based wafer map defect classification with imbalance handling | Supervised learning | Wafer map images (WM-811K dataset) | Class-wise processing with tailored augmentation and sampling strategies addresses severe class imbalance | CNN with customized pre- and post-processing pipelines |

III. RESEARCH FRAMEWORK

The suggested methodology starts with a mixed type of wafer defect dataset, which is provided by Kaggle and initially undergoes a preprocessing of data. This involves normalization, reshaping and data augmentation in order to enhance the quality of data and model robustness. The data that is processed is then divided into training (70), validation (15) and testing (15) sets. They are proposed and then trained using a graph neural network (GNN) on the training set, where tuning and overfitting are prevented through validation. The performance of the model is tested on the test set based on such metrics as the accuracy, the precision, the recall, the F1-score, and loss, and the analysis of the results is carried out in order to determine the effectiveness of the approach. Figure 1 shows the flowchart of the proposed methodology.

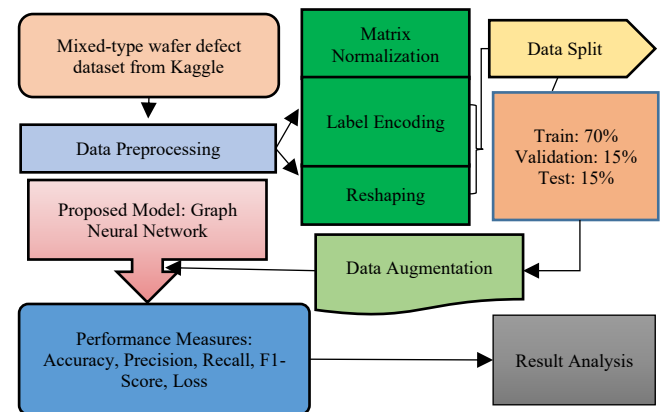


Fig. 1. Flowchart of Wafer Inspection Performance

The proposed methodology is illustrated through a flowchart, and each stage of the workflow is briefly described as follows:

A. Dataset Analysis and Visualization

In this paper, the authors utilize the Mixed-type Wafer Defect Dataset of Kaggle¹, which consists of about 38,000 images of wafer maps in 52×52 grids, and contains 38 classes of wafer map defects such as normal, single-defect, and mixed-defect patterns, which makes it a good dataset to test machine learning models in complex wafer inspection problems.

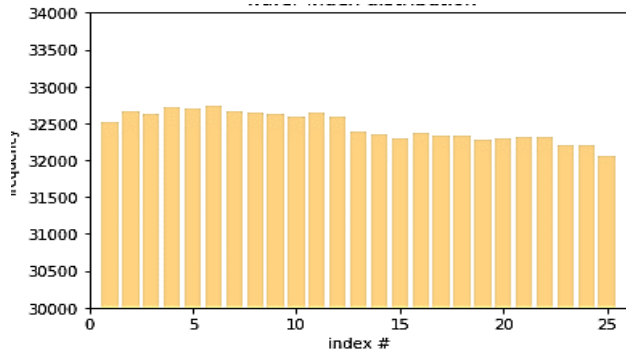


Fig. 2. Wafer Index Distribution

Figure 2 illustrates the number of samples under each defect class and the sample population is mostly even with insignificant differences in the prevalence of the defect classes.

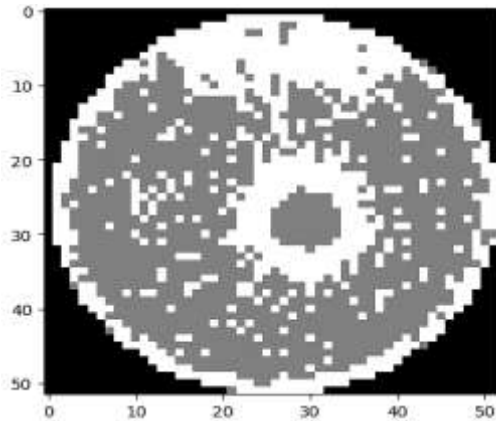


Fig. 3. Sample Wafer Map

The spatial distribution of defects on the wafer surface is shown in Figure 3, which is an example wafer map; the pixel values of the wafer map which are normal die, defective, and blank show the spatial distribution of defects on the wafer.

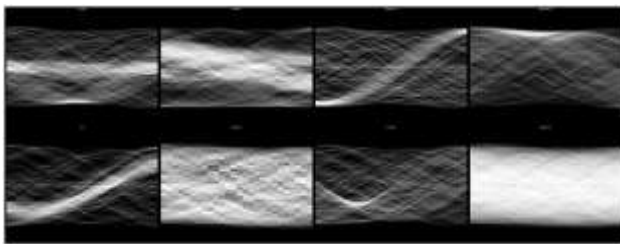


Fig. 4. Failure Type in Wafer

Figure 4 presents examples of typical mixed-type wafer defect patterns, which demonstrate that combined defect structures are complicated and diverse in the dataset.

B. Data Preprocessing

Preprocessing entails converting raw data on wafer maps to a structured and standard form that can be used to train a model. Normalization of wafer map values, resizing to a consistent resolution, and turning wafer maps into graph representations that maintain spatial relations between dies are all part of preprocessing to give it meaningful input to the Graph Neural Network in this study.

- **Matrix Normalization:** The input values were normalized to the range by dividing the value of each pixel in the input by 2 (the highest value in the original data).
- **Handling Labels using Label Encoder:** In multi-label classification problems, each instance can simultaneously have multiple labels. Many implementations convert each label into an 8-dimension one-hot vector.
- **Image Reshaping:** It consists of reshaping, where the 52×52 maps were reshaped to incorporate a dimension of channel, giving it a shape (1, 52, 52) that could be fed to the architecture.

C. Data Splitting

The dataset was split into 70-15-15 for training, validation, and testing, respectively. Since all 38 classes were represented in the split's, stratified sampling was used to ensure that there was a balanced representation of all the classes in the splits.

D. Data Augmentation Strategy

Mixed-type Wafer Defect Dataset already contains GAN-generated samples to counteract the problem of class imbalance, but thus more data augmentation methods were used to further strengthen the models and generalization. Since patterns of wafer defects are geometrical rather than orientational, geometric augmentations have been used but the underlying pattern of defects retained. In particular, the augmentation pipeline consisted of random horizontal and vertical flips, small random rotations in the range of -10 to 10 degrees and small random crops and subsequent resizing to the initial 52×52 resolution. These augmentations do not change defect semantics, but increase the diversity of patterns, allowing the Graph Neural Network to learn a larger set of invariant and discriminative spatial relationships between nodes in the wafer.

These augmentation and pre-processing steps took care of optimum data quality in the model training and maintained the critical features of the defect pattern0073.

E. Model Classification

This study employed the Graph Neural Network to ensure the performance of the wafers. The model is classified below in detail.

Graph Neural Networks (GNNs) [36] have enabled end-to-end learning over relational data due to differentiable loss functions that can be trained with non-linear components like multi-layer perceptrons. Several real-world applications, such as fake news detection, physical simulations, traffic delay

¹ <https://www.kaggle.com/datasets/col1d7era/mixedtype-wafer-defect-datasets>

estimation, and fraudulent transactions prediction, have GNNs as a crucial component. Graph classification is one of the most common downstream graph neural processing applications. While different GNN operators update node-level features via message-passing, the graph-level predictions are done by pooling the member nodes into a single unified representation. This pooling is either done by coarsening functions that gradually reduce the size of the graph or with the help of global pooling methods like average, max, or sum.

The success of GNNs has also led to several attempts toward defining theoretical boundaries of what GNNs can and cannot do. The strengths and weaknesses of graph neural networks have been extensively evaluated in terms of their representation capabilities. Most studies have focused on the capability of message-passing networks using the Weisfeiler-Lehman test, which is constrained by its limitations in distinguishing isomorphic graphs.

Due to the fact that, as we have already mentioned, the graph can be understood as a generalization of an image, the so-called graph convolutional neural networks are usually used. In the classical approach, the convolutional layer performs the convolution operation of a filter, given in the form of a matrix, with the input image. The output of such a convolutional layer can be presented as Equations (1) and (2):

$$\mathbf{x}_{\text{out}} = \sigma \left(\tilde{\mathbf{D}}^{-\frac{1}{2}} \cdot \tilde{\mathbf{A}} \cdot \tilde{\mathbf{D}}^{\frac{1}{2}} \cdot \mathbf{x}_{\text{in}} \cdot \mathbf{w} \right) \quad (1)$$

$$\text{Where } \tilde{D}_{ii} = \sum_j \tilde{A}_{ij} \quad (2)$$

and $\sigma(\cdot)$ stands for activation function, such as rectified linear unit (ReLU).

F. Performance Measures

The study used certain parameters to evaluate the performance of the proposed architecture. A detailed representation of classification outcomes across all the classes, revealing specific patterns of misclassifications. The performance parameters are accuracy, precision, recall, F1-score, and loss function. These parameters are detailed below:

- **Accuracy:** The proportion of correctly classified wafer maps across all classes.
- **Precision:** The proportion of wafer maps classified as a particular defect type that actually belong to that class.
- **Recall:** The proportion of wafer maps of a particular defect type that are correctly classified.
- **F1-score:** The harmonic mean of precision and recall, providing a balanced measure of classification performance.
- **Loss Function:** Cross-entropy loss, which is particularly effective for multi-class classification problems.

Equations (3) to (6) show the mathematical formulation of the parameters.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \quad (3)$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (4)$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (5)$$

$$\text{F1 - Score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \quad (6)$$

IV. RESULTS AND DISCUSSION

The experimental setup utilized a high-performance computing environment consisting of five NVIDIA GeForce GTX 1080 GPUs, each with 8 GB of dedicated memory. The system was supported by 8 GB of DDR4 RAM and powered by an Intel® Core™ i7-8700B processor with 12 MB cache and a maximum clock speed of up to 4.60 GHz.

A. Evaluated Results

Table II summarizes the performance of the proposed Graph Neural Network (GNN) model on the wafer inspection task. The model receives a high classification accuracy of 97.25, which depicts high overall predictive capacity. Besides that, the accuracy of 96.70% shows that the model is effective in identifying the defects with few false positives and the recall of 96.17% shows that the model identifies most of the defected wafers. The resulting F1-score of 96.44% proves a balanced performance of precision and recall, which indicates the strength and validity of the GNN-based method in the inspection of wafer defects.

TABLE II. MODEL PERFORMANCE ON WAFER INSPECTION PERFORMANCE

| Metrics | Graph Neural Network |
|-----------|----------------------|
| Accuracy | 97.25 |
| Precision | 96.70 |
| Recall | 96.17 |
| F1-Score | 96.44 |

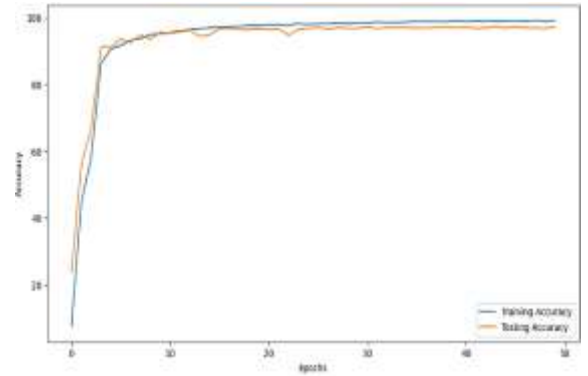


Fig. 5. Training and Testing the Accuracy of the Model

Figure 5 presents the training and testing accuracy of the 50 epochs, and both curves quickly converge towards the beginning stages and reach high accuracy. The similarity in the result of both training and testing shows that the model is highly generalized and there is low overfitting, which shows that the model is stable and useful in inspection of the wafer.

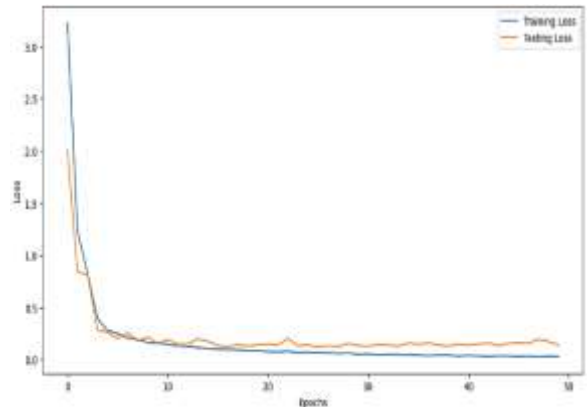


Fig. 6. Training and Testing Loss of the Model

Figure 6 demonstrates that the training and testing loss decreases rapidly at the initial epochs, and the values stabilize at a small level at the end. The nearly parallel relative to each other curves demonstrate that there is no overfitting or significant change in optimization when training the model of wafer inspection.

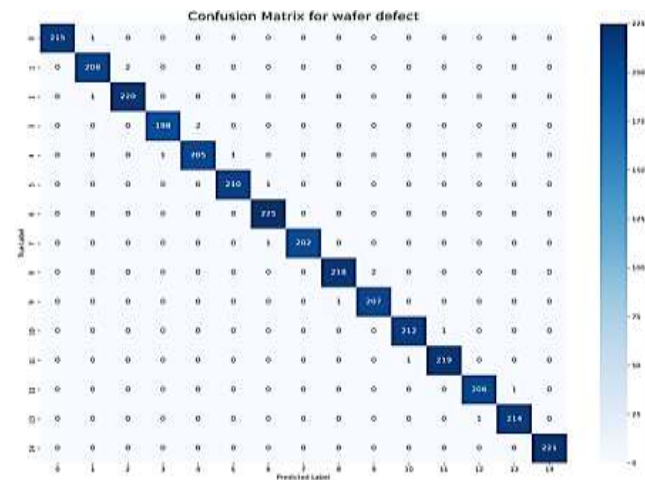


Fig. 7. Confusion Matrix of the Model

Figure 7 features the confusion matrix of classification of the wafer defects and the big diagonal dominance with small misclassifications, which is indicative of good classification and good discrimination between defect classes.

B. Comparative Analysis

This section provides comparisons of the various models with the proposed model. In Table III, a comparative analysis of multiple defect patterns on the use of various models is made on the inspection performance. The GNN proposed has the highest accuracy (97.25%), which is higher than MobileNetV1 and ResNet50, and also much higher than the SVM baseline. MobileNetV1 has a high precision and recall rate, whilst ResNet50 has a leveled performance with the metrics. Conversely, SVM has a considerably lower accuracy and F1-score, which implies that it cannot be used effectively with more complicated patterns of multiple defects. The findings indicate the better and stronger performance of the GNN in inspecting a multi-defect wafer.

TABLE III. COMPARATIVE EVALUATION OF INSPECTION PERFORMANCE OF MULTI-DEFECT PATTERNS

| Metrics | MobileNetV1 [37] | ResNet50 [38] | SVM [39] | GNN |
|---------|------------------|---------------|----------|-------|
| Acc. | 95.7 | 96.92 | 67.97 | 97.25 |
| Pre. | 99.2 | 97.32 | - | 96.70 |
| Rec. | 98.6 | 97.38 | - | 96.17 |
| F1-Sc. | 98.8 | 97.31 | 68.0 | 96.44 |

The achievement of the proposed Graph Neural Network (GNN) in the experimental results indicates that it can be effective and reliable in the inspection of wafer defects. The model has a high accuracy, high precision levels, high recall, and high F1-score, which signify that the model can detect the various defects pattern with high accuracy and minimal misclassification. The training and testing accuracy and loss curves verify that convergence, learning under stability and good generalization with insignificant over-fitting are realized. Additionally, there is good class-wise discrimination as revealed by the confusion matrix. Comparative analysis demonstrates that the GNN is always more effective than CNN-based models and traditional SVM approaches,

underlining the appropriateness to the task of identifying the relationships of multi-defects in complex multi-objectives in the task of wafer inspection.

V. CONCLUSION AND FUTURE PROGRESS

The defects that appear on the wafer surface during the fabrication process of these wafers will seriously affect the wafer product quality and cause huge economic losses. Therefore, it is essential to study the problem of identifying defects on the wafer surface and adjusting the production line in time to improve the manufacturing yield. This paper has managed to illustrate the efficiency of a Graph Neural Network (GNN)-based model to carry out automated inspection of wafer defects with mixed-type wafer map data. The suggested technique is capable of storing important spatial and relational data of dies by modeling wafer maps in the form of graphs, allowing complex single and mixed defect patterns with critical information to be learned. Extensive preprocessing, normalization as well as data augmentation measures have led to better model robustness and generalization. According to the results of the experiment, the proposed GNN demonstrated a high level of performance with an accuracy of 97.25, precision of 96.70, recall of 96.17, and an F1-score of 96.44. It can be said that the GNN is reliable and balanced in its performance in terms of 38 defect classes. The results of the training and testing curves indicate that convergence is stable, and overfitting is minimal, and the confusion matrix indicates high discrimination of classes. The comparison analysis also confirms the effectiveness of the GNN over the CNN-based models like MobileNetV1 and ResNet50, and the traditional SVM solutions, specifically on the multi-defect patterns. In general, the results prove that GNNs can offer a strong and scalable solution to a complicated wafer inspection problem with substantial potential benefits in the context of quality control and yield optimization of semiconductor production.

The future research will aim at applying the proposed GNN structure to real-time inspection of the wafer and large industrial populations. Defect interpretability, scalability and adaptability to the changing semiconductor manufacturing process can be further enhanced by incorporating attention mechanisms, heterogeneous graphs, and explainable AI techniques.

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