Photolithography Hotspot Detection Based on Deep Learning LHD Model

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***Abstract*—Raising pattern density on the integrated circuit layout enables reduction of the chip size and cost, while fabrication becomes more difficult. Both number and type of hotspot are increasing during the scaling down. Hotspot detection usually relies on photolithography simulation, that consumes large number of massive computational resource and often takes a long time. To address these limitations, we propose a lightweight hotspot detection model, the Lithography Hotspot Detection (LHD) model, based on deep learning technology. In order to enhance the training of the model, we employed Mentor Calibre's SONR tool to sample the hotspot and non-hotspot graphics and prepare the input dataset. Experimental results show that the hotspot detection accuracy of the LHD model reaches 95.25%, which is 5.07% higher than that of the traditional classification model Convnext.**

Keywords—Deep learning, Hotspot, LHD, Convnext, Convolutional neural network

I. INTRODUCTION

As the production process nodes of integrated circuits continue to shrink, the mismatch between the imaging size of the photolithographic mask pattern and the wavelength of the light source can lead to the appearance of optical proximity effects, which directly affect the imaging accuracy of the photolithographic mask pattern. In the process of lithographic manufacturing layout, manufacturing defects such as short circuits or open circuits often exist in the layout area due to the optical proximity effect, forming photolithographic hotspots. Therefore, it is important to study and improve the detection technology of photolithographic hotspots to improve the quality and reliability of integrated circuit manufacturing [1].

Photolithographic hotspot is a potential circuit risk for chips, which seriously threatens the stability and safety of chips, and thus reduces the yield of chips. Therefore, how to effectively detect photolithographic hotspots has become a key concern in the industry. Traditional hotspot detection methods based on photolithography simulation [2] require a lot of time and computational resources, and are generally characterized by false alarms and missed graphics. And with the development of integrated circuits, the lithography simulation model and layout are becoming more and more complex, and the traditional methods have been difficult to meet the demand. In contrast, traditional machine learning [3] and pattern matching [4] based methods have some advantages in lithographic hotspot detection, but their performance decreases with the complexity of transistor layout patterns and the increase of sample size. Therefore, new methods need to be explored to solve the photolithography hotspot detection problem.

Aiming at the above problems, in this paper, we propose a lightweight hotspot detection model, called the LHD model, which has low structural complexity, a small number of parameters, and excellent hotspot detection performance. We realize the lightweight network structure by establishing a new join of convolutional, pooling and fully connected layers, and obtain a new network adapted to classify hotspot and non-hotspot images after learning and training. In addition, the comparison with the classical hotspot detection model Convnext highlights the superiority of the LHD model in various metrics. The method has high adaptability and accuracy, and can effectively solve the problems of time-consuming detection of lithography simulation and the inability of pattern matching to recognize unknown hotspots. Meanwhile, since the deep learning model [5] can automatically extract image features, the method in this paper eliminates the manual extraction process, simplifies the training process, and improves the detection effect. The

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method has obvious advantages and can provide a new solution idea for lithography hotspot detection.

II. DEEP LEARNING HOTSPOT DETECTION

The supervised deep learning algorithm in pytorch is used in the hotspot detection method in this paper, and the main process is as follows:

1) The graphical crop of poly target layer is converted into image as a dataset, which is labeled as 5 classes of hotspots and 1 class of non-hotspots according to the simulation results;

2) A lightweight hotspot detection model LHD model is proposed, where 80% of the data is used as input to train the model and 20% of the data is used as test to predict the hotspot type;

3) Enhance the hotspot detection effect by algorithm optimization and model improvement, and compare with the existing network Convnext.

Convolutional neural network takes image as input, realizes image feature extraction by convolutional kernel of convolutional layer, and combines the extracted features to get the corresponding output. The layout data can be represented as graphical data, and the convolutional neural network is suitable for hotspot detection [5]. The principle of hotspot detection method based on convolutional neural network is shown in Fig. 1, where the preparation of the input dataset is done by the SONR tool. The SONR extracted feature classifications are used as labels to label the dataset, and 80% of the training graphs are used for training, and the structure and parameters of the LHD model are continuously optimized and adjusted during the training process, and the predicted results of the 20% of the test graphs are observed to make them optimal. The trained LHD model has simple structure, few parameters and good hotspot detection performance.

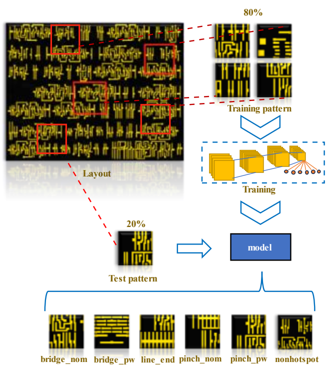

Fig. 1. The hotspot detection technology flow.

After a series of convolution, pooling and full connection layer operations, a probability value is finally obtained, and according to this probability threshold, it is determined whether there is a hotspot in the image and what kind of hotspot it belongs to.

A. Network Structure

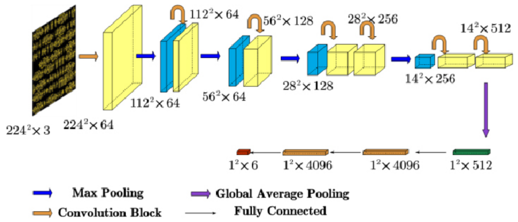

Fig. 2. The structure of the LHD model.

The described lightweight lithography hotspot detection model LHD is composed of a 10-layer network, which includes seven convolutional layers and three fully connected layers as shown in Fig. 2. The convolution kernels of the first to seventh convolutional layers are 64, 64, 128, 256, 256, 512, 512, respectively. Between each of the two layers, there is a pooling layer with a 2×2 pooling matrix (maximum pooling) and a move with a step size of two. After convolution the feature map is spread into $1 \times 1 \times 512$ feature vectors through the average pooling layer, and finally mapped to a $1 \times 1 \times 6$ output layer through three fully connected layers. The number of layers of convolutional layers in the five convolutional blocks is 1, 1, 1, 1, 2, 2, for a total of 7 convolutional layers, and repeated experiments prove that this structure has the best detection effect while keeping the convergence stable.

B. Evaluation Function

In deep learning classification models, the commonly used evaluation metrics include Accuracy, Recall, Precision and F1 score. In this paper, these four evaluation functions are used to evaluate the performance of the LHD model on hotspot detection and to conduct comparison experiments with the traditional classification model Convnext.

The results of hotspot detection are categorized as follows: True positive (TP): the hotspot graph is recognized as a hotspot graph. True negative (TN): recognizes non-hotspot graphs as non-hotspot graphs. False positive (FP): recognizes a non-hot graph as a hot graph. False negative (FN): identifies a hot graph as a non-hot graph. Then, the definition of accuracy, recall, precision and F1 score are as follows:

$$accuracy=(TP+TN)/(TP+TN+FP+FN) \tag{1}$$

$$recall=TP/(TP+TN) \tag{2}$$

$$precision=TP/(TP+FP) \tag{3}$$

$$F1=(2recall\times precision)/(precision + recall) \tag{4}$$

The accuracy rate indicates the ratio between the number of hotspot areas correctly predicted by the model and the total number of samples. The recall rate is the ratio between the number of hotspot areas correctly predicted by the model and the actual number of hotspot areas. The precision rate represents the ratio between the number of hotspots correctly predicted by the model and the total number of hotspots predicted by the model. The F1 score is the reconciled mean of the accuracy rate and the accuracy rate. The values of accuracy, recall, precision and F1 score are all between 0 and 1, and the larger the value, the better the performance of the model.

The lithography hotspot detection model LHD proposed in this paper uses the binary cross entropy loss function as the loss function of the model. Its formula is shown as follows:

$$BCELoss = -\,(ylog(p(x)) + (1 - y)log(1 - p(x))) \qquad (5)$$

where y denotes the true label (0 or 1), p(x) denotes the predicted probability value of the model for the sample. In this paper, the parameters of the model are updated according to the value of the binary cross-entropy loss function by back-propagation algorithm and optimization method in order to improve the performance and prediction accuracy of the model.

III. EXPERIMENT AND RESULTS

A. Dataset Preparation

In the chip fabrication process, lithographic hotspot detection is crucial to ensure the quality of chips, especially in the hotspot detection of the silicon gate layer, which has an important impact on the yield of chips. For model training and evaluation, we collected 3064 poly layer layout data from a 12-inch 55nm fab as the dataset for this experiment as shown in Fig. 3, with the resolution of 224 × 224 for each image and the ratio of the training set to the test set as 8:2. In order to ensure the accuracy of the test results, we ensured that there is no overlap between the test set and the training set, which allows us to better evaluate the generalization ability of the model. In these data, 680 hotspot maps and 2384 non-hotspot maps are included, of which the hotspot set includes the following five categories: BRIDGE NOM, BRIDGE PW, LINE END, NH, PINCH NOM, and PINCH PW, with the numbers of 63, 16, 201, 200, 200, and 2384, in that order.

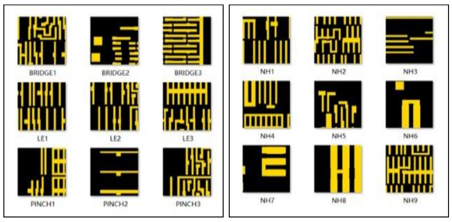

Fig. 3. Dataset Input: (a)Hotspot (b)Non-hotspot.

B. Experiment Results

This experiment was conducted using an NVIDIA GeForce RTX4090, Linux operating system, with the network model coded in Python 3.8, using Pytorch as our deep learning framework. The network was run for 200 iterations using the SGD optimizer with an initial learning rate of 0.001, weight decay of 0.0001, and momentum of 0.9. In order to visually assess the effectiveness of the LHD network in detecting hotspot and non-hotspot graphs of each type, a confusion matrix in tabular form was produced for this experiment, the values on the table represent the probability values for the model to recognize the real type as the predicted type, and the diagonal elements show that the LHD model achieved accuracy on the experimental dataset. The results in Fig. 4 show that the LHD model performs well and achieves more than 90% accuracy in BRIDGE NOM, BRIDGE PW, LE and NH types. The accuracy is slightly lower in the two types PINCH NOM and PINCH PW, as they are extremely similar, with only minor differences given to the conditions, but the accuracy can be more than 70%.

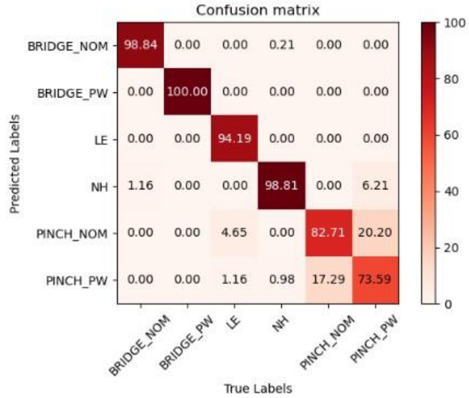

Fig. 4. Accuracy confusion matrix.

The designers of Convnext model have made it stand out among the advanced CNN classification models such as Resnet and Transformer through the macro-design of the stage computation ratio and the backbone Patchify, as well as the micro-design of the reduction of the activation function and the normalization layer. Through clever design, the accuracy of Convnext in Imagenet data set is 82.0%, which is about 0.7% higher than that of Swin Transformer network [6]. Convnext has the best balance of accuracy and computation capacity but with a simpler design, which is very suitable for classification and detection tasks, so Convnext model is used in this paper as a reference comparison.

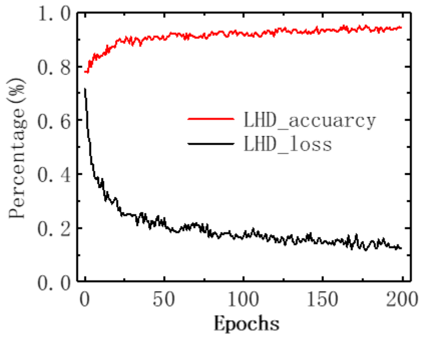

Fig. 5. Accuracy loss and function curve.

Figure 5 shows the variation of LHD's loss and accuracy on the test set. The experiments show that the accuracy and evaluation loss of LHD converge after about 100 epochs, and the accuracy of the model can reach 95.25% after convergence, which is excellent. We compared the performance of the LHD model and the classical classification model Convnext as shown in Figure 6. The results show that Convnext network is used in hotspot detection scenarios the accuracy starts to converge only after 133 epochs and the converged accuracy is 90.18%, which is 5.07% higher compared to Convnext for LHD network, reflecting a higher performance.

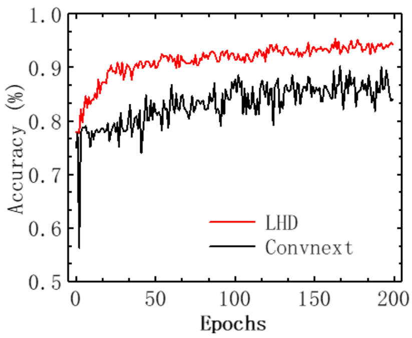

Fig. 6. Model accuracy comparison.

Comparison of the number of parameters in Fig. 7 shows that the LHD model is excellent in lightness, and separately calculating the number of parameters of the two models yields that the number of parameters of the LHD model is 2.21×10^7, and the number of parameters of the Convnext model is 1.98×10^8, and the model of LHD is more streamlined, and the number of parameters is relatively reduced by 88.8%.

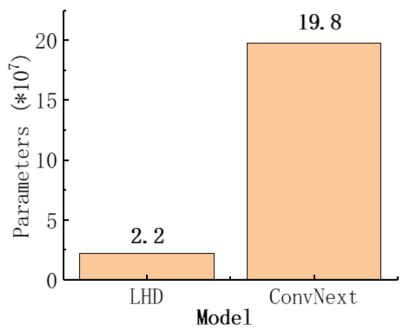

Fig. 7. Model parameters comparison.

In addition to the accuracy metrics, we also compare the two checking the full rate, checking the accuracy rate and the F1 score as shown in Fig. 8. It can be seen that no matter which evaluation function is used, LHD achieves higher function values than Convnext, and the detection rate can even be 44.4% higher on the PINCH NOM type, which again shows that the LHD proposed in this paper can achieve better detection results while realizing model lightweighting.

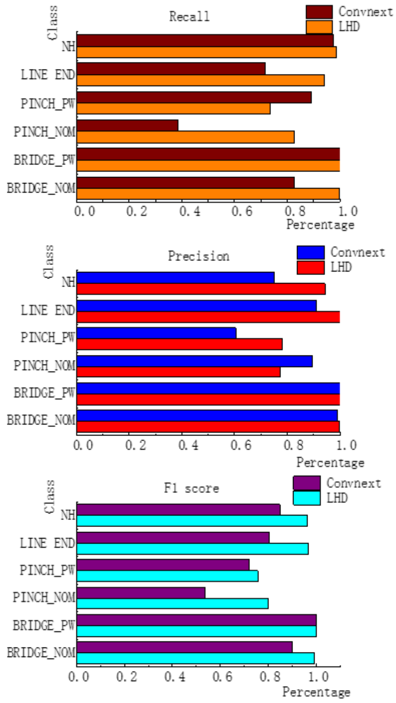

Fig. 8. Evaluation function comparison.

IV. CONCLUSION AND DISCUSSION

In this paper, for the subject of lithographic hotspots before the optical proximity effect correction session of chip manufacturing, a hotspot graphic detection method based on LHD is proposed. The trained LHD model possesses a simple structure, few parameters, and outstanding hotspot detection performance, making it achieve an accuracy of 95.25%, surpassing the recently proposed Convnext model by 5.07%. The experiments show that the accuracy and estimated loss of LHD converge after about 100 epochs, which is faster than Convnext's 133 epochs while the parameters of the former are 88.8% lower than the latter. All the data show that the model is excellent for hotspot detection in the lithography segment of chip manufacturing, with high accuracy, good convergence and low parameter count.

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