LITHOGRAPHY HOTSPOT DETECTION USING VISION TRANSFORMERS

MAJOR PROJECT-II (SPD-602)

Submitted by: Sumedha

M.Tech - S.P.D.D

Roll No.: 2K19/SPD/17

Under the supervision of: Prof. Rajesh Rohilla

Department of Electronics & Communication,
Delhi Technological University

CONTENTS

Topic	Slide Number
• **Aim**	**4**
• **Lithography**	**5 - 6**
• **Literature Review**	**7 - 10**
• Based on methods used for Detecting Hotspots	7 - 9
• Based on Evaluation Parameters	10
• **Transformers**	**11**
• **Vision Transformer**	**12**
• **Dataset Used**	**13**
• **Experiments Performed**	**14 - 17**
• Steps performed for classification using ViT	14 - 15

CONTENTS

Topic	Slide Number
• **Experiments Performed**	**14 - 17**
• Steps performed for classification using CNNs and ANNs	16 - 17
• **Result**	**18 - 19**
• Comparison with other works	18
• Accuracy for all subsets using ViT, CNNs and ANNs	19
• **Conclusion and Future Scope**	**20**
• **Publication**	**21**
• **References**	**22 - 26**

AIM

- In the process of IC design, lithography can be defined as the process of reprinting the pattern of mask on Silicon wafer.
- Lithography is one of the most important steps in this process as it enables Moore's law to be satisfied, for this feature size needs to be decreased every couple of years. This continuous decrease in feature size may lead to printability issues and hence hotspots.

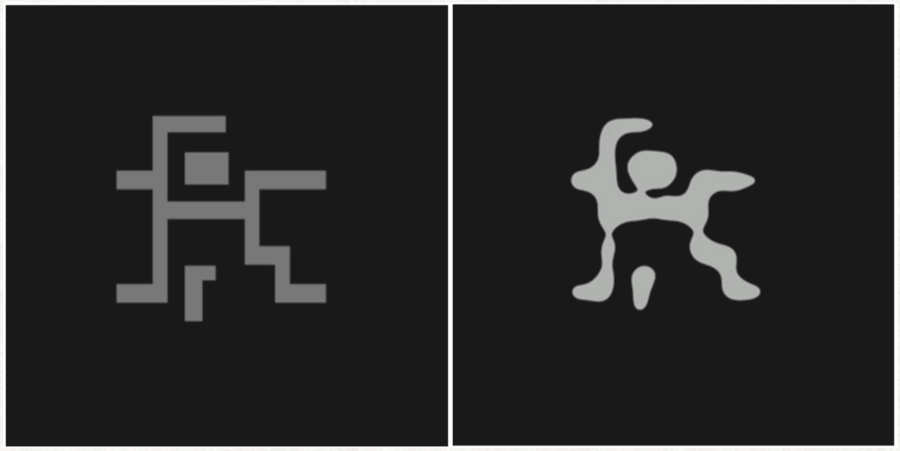

Figure 1 Pattern on mask and Pattern on wafer [36]

- Presence of hotspots can lead to complete failure of the circuit, so it is very important to detect these hotspots with high accuracy. Previously various simulation, machine leaning and deep learning based techniques have been implemented to solve this problem.
- In this work, we propose a method to identify hotspots using Vision Transformers. Along with this, we also use other deep learning techniques such as CNNs and ANNs for comparison purposes.

LITHOGRAPHY

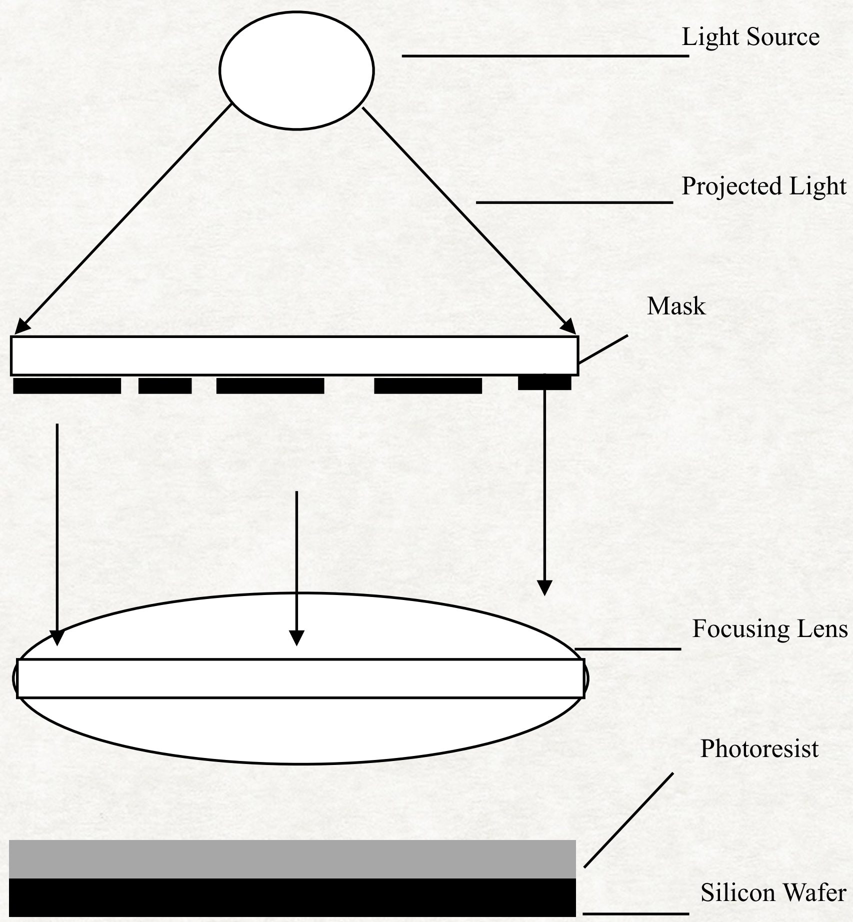

Figure 2 Optical Lithography

- For optical lithography light from a source is projected through a mask via a focussing lens. Mask contains hardcopy of the design that needs to be transferred to photoresist. Focussing lens helps to reduce the size of pattern image falling on Silicon.

- That pattern is then focussed on the photoresist-coated wafer. Photoresist is the light sensitive material which is applied on top of Silicon wafer. Soluble part of the photoresist is rinsed away, leaving an image of the required pattern on the chip.

LITHOGRAPHY

- For the trend of area getting smaller in a cost-effective way to continue, feature size in Lithography process needs to be reduced. Feature size can be defined as: $f = C.\lambda/n$, where, C is Rayleigh constant, λ is the wave length, and n is the numerical aperture. To reduce f, one can increase n or reduce λ.

- To increase n, water or oil can be used as medium instead of air. It is known as **immersion lithography.**

- To reduce λ instead of UV light used in optical lithography, X-rays can be used. It is known as **X-ray lithography.**

  - This technique has various advantages such as smaller throughput, and high resolution. X-rays don't absorb dirt so the risk of contamination is also less.

  - One limitation of this process is blurring of image on the substrate and it depends on the distance between X-ray source and mask and separation of mask and wafer

- Another way of obtaining smaller feature size is by using **electron beam lithography.**

- It provides better depth of focus, resolution and can be easily automated.

  - The time required for this is very high, so it leads to a smaller throughput.

  - Another disadvantage of this lithography technique is that, when electron beam is focussed on substrate, scattering of electrons take place so, they go large distances away from original pattern which may also lead to hotspots.

LITERATURE REVIEW

We divided data into five categories based on methods used for detecting lithography hotspots and into two categories based on evaluation parameters.

These categories are as follows:

BASED ON METHODS USED FOR DETECTING HOTSPOTS

- SIMULATION
- HOTSPOT MITIGATION
- PATTERN MATCHING
- MACHINE LEARNING
- DEEP LEARNING

BASED ON EVALUATION PARAMETERS

- ACCURACY MATRIX
- ROC CURVE

LITERATURE REVIEW

BASED ON METHODS USED FOR DETECTING HOTSPOTS

Table 1 Lithography Hotspot Detection methods

Category	Sub-Categories	Characterstics	Advantages	Disadvantages
Simulation	SAMPLE	• First technique for lithography simulation	Highly Efficient	Expensive in terms of Computational time and complexity
	PROLITH	• Only for Optical Lithography • Available for Personal Computer		
	ProMAX, Monte Carlo, ProBEAM	• Available for e beam Lithography		
Pattern Matching	Graph Based	• Chance of NHS detected as HS is high	Faster than Simulations	Fail to detect previously unseen hotspots
	Template Matching	• Moves accurate pattern over obtained pixel by pixel • High Accuracy • Time taken is high		
	String Search	Efficient		

LITERATURE REVIEW

BASED ON METHODS USED FOR DETECTING HOTSPOTS

Category	Sub-Categories	Characterstics	Advantages	Disadvantages
Lithography Hotspot Mitigation	Lithography Aware Routing and Placement	• Makes use of EPE and Hotspot maps	Reduces risk of hotspots very significantly	Difficult to perform before the whole process has completed
Machine Learning	SVM, Boosting, PCA, Clustering, Semi-supervised technique, Bilinear Classifier, Naive Bayes	• Feature extraction techniques are used before classifying using these techniques	Detects previously unseen hotspots. Accuracy is high.	Chance of NHS detected as HS is a problem
Deep Learning	CNNs, GANs, CNNs with DBSCAN, CNNs with ANNs	• Most of the techniques implemented till now make use of CNNs	High accuracy	Computationall y expensive

LITERATURE REVIEW

BASED ON EVALUATION PARAMETERS

Accuracy Matrix

- Accuracy helps us to determine how many hotspots are correctly identified as hotspots.
- Ideally, a high accuracy is desired.
- Since number of non-hotspots is much larger than the number of hotspots, the dataset is highly imbalanced. A new technique based on Receiver Operating Characteristics (ROC) can be used to handle this dataset imbalance problem

ROC Curve

- For this process, an ROC curve is drawn which shows the relationship between the rate of both true positives and true negatives.
- From this graph AUC score is obtained.
- AUC determines number of times the True Positive Rate (TPR) has higher rank than False Positive Rate (FPR), hence comparing accuracy over entire range.
- This method showed better results as it is spread over whole distribution
- This method proves to be computationally expensive, as there is no inbuilt feature to obtain ROC curve

TRANSFORMER

- Today most of the best performing Natural Language Processing models are Transformer based, but in computer vision based applications, these are not used to much extent.
- A transformer cell consists of encoder and decoders blocks. An encoder converts data to sequences which are fed to the decoder to generate output.
- Transformers work on the self- attention model, this means they don't remember the whole sequence at once, but a perimeter α is assigned. α<1,1> decides how much value the first part of sequence holds while generating the output, similarly α<2,1> decides how much value the second part of sequence holds while generating the output and so on
- Ideally, transformers operate on sequences or sets and applies attention mechanism on the sets. Since attention is a quadratic operation for images, we have to calculate pair-wise inner product between each pair of sets, therefore computations and memory required are very high.
- Images are harder because these are composed of many pixels. In case of transformers image consists are of size 224*224. Every pixel needs to attend every other pixel, so even for a small image we will need ((224)^2)^2 operations. This much computations are not possible to achieve with hardware.

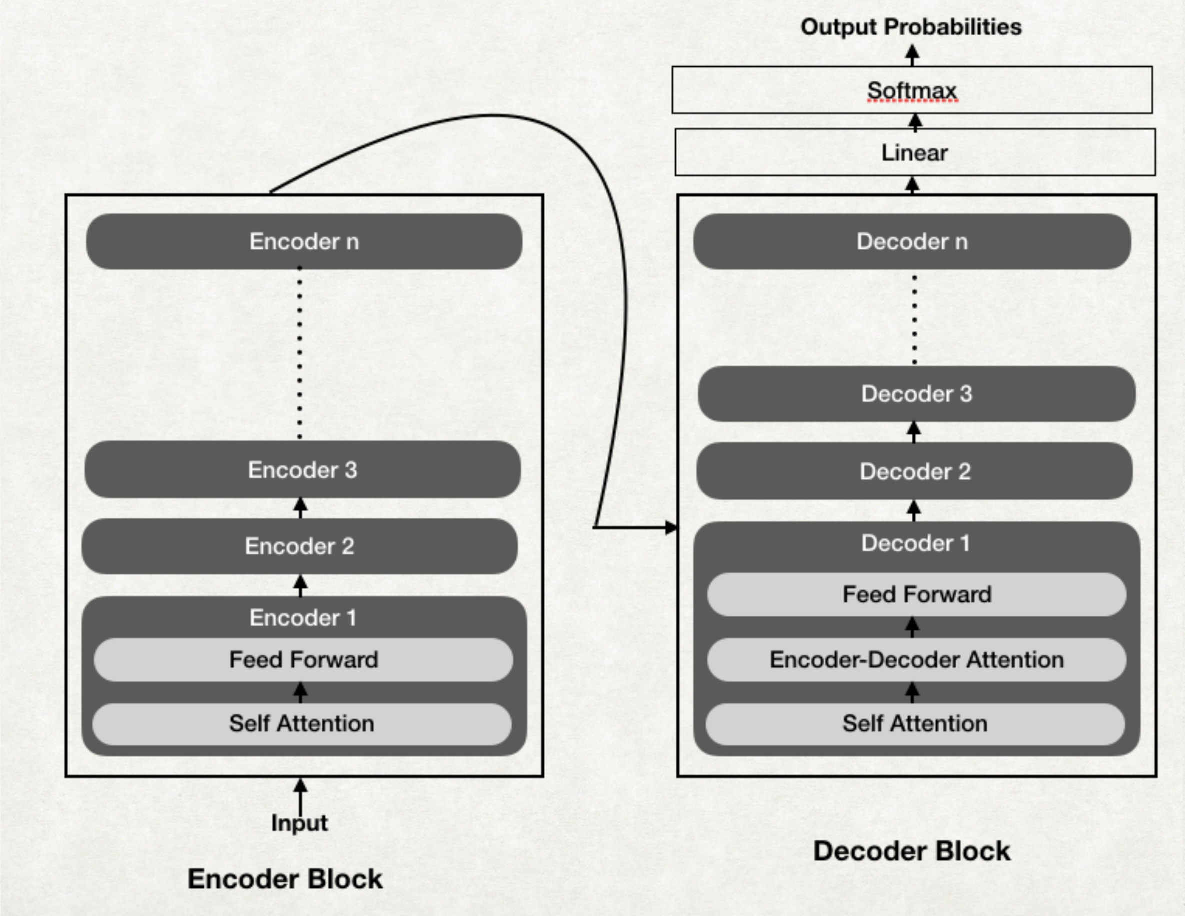

Figure 3 A Transformer cell

VISION TRANSFORMER

- A team at Google Brain modified Transformers by including some extra operations in order to make them usable for Image based applications. This modified version of Transformers is known as Vision Transformer.
- First of all, image is partitioned into patches of same shape.
- Then these patches are vectorized
- Then, positional encoding is added to these patches, because swapping of patches may lead to information loss.
- Other than these CLS token is passed through embedded layer and its output is used to provide classification output.
- All these vectors are passed through Transformer encoder network.
- Its first output is feature vector, which is passed through MLP head, which acts as a classifier and provides image classification output.

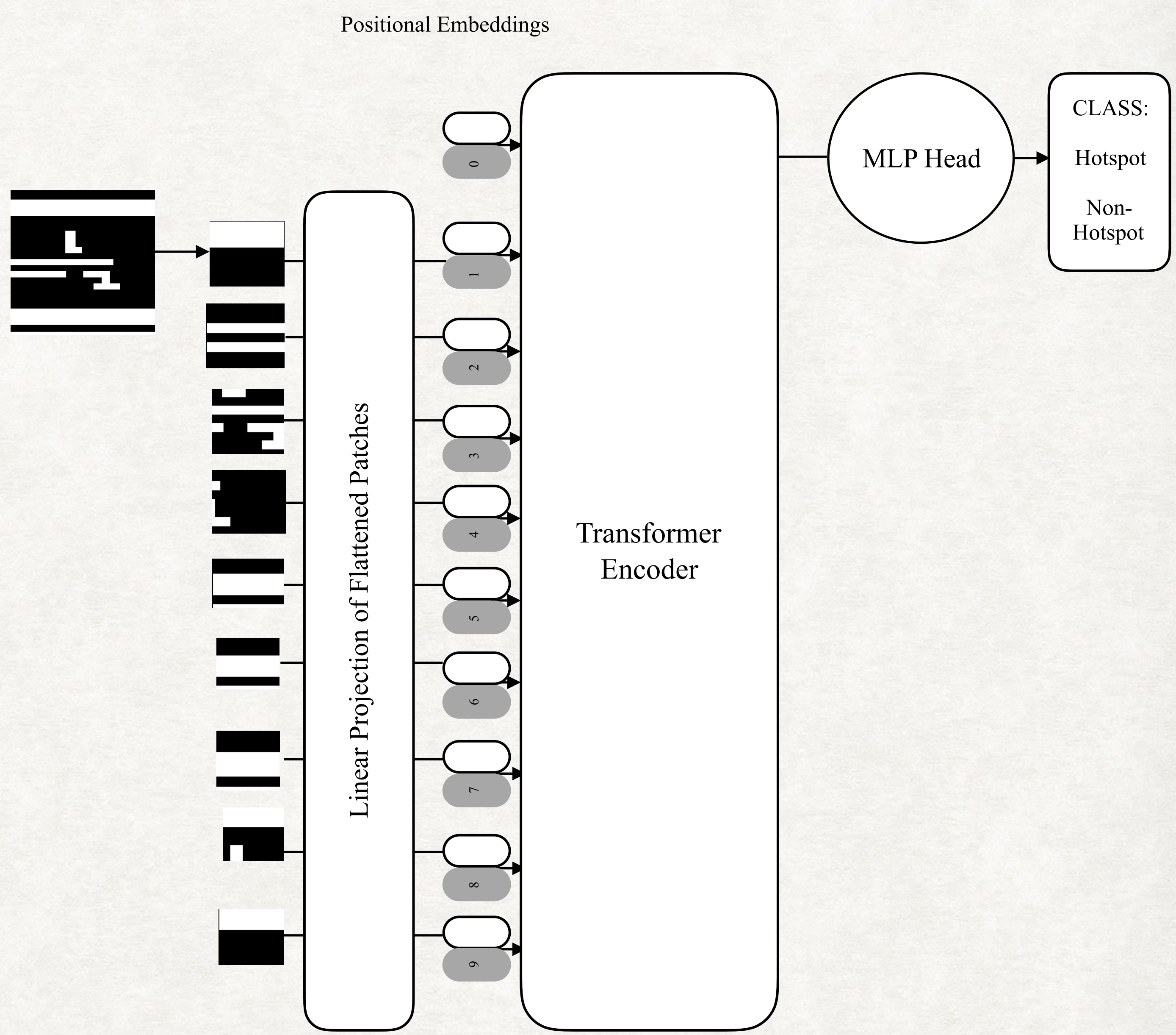

Figure 4 Vision Transformer

DATASETS USED

For this research, we have utilized ICCAD-2012 dataset.

It has five sub data-sets with different types of layouts. First dataset is obtained using 32 nm process and other four have been obtained during 28 nm process.

Table 2 Details of Dataset used

	TRAINING SET			TEST SET		
	Hotspot	Non-Hotspot	Total	Hotspot	Non-Hotspot	Total
Sub-dataset 1	99	340	439	226	3869	4095
Sub-dataset 2	174	5285	5459	498	41298	41796
Sub-dataset 3	909	4643	5552	1808	46333	48141
Sub-dataset 4	95	4452	4547	177	31890	32067
Sub-dataset 5	26	2176	2202	41	19327	19368
TOTAL	1303	16896	18199	2750	142717	145467

EXPERIMENTS PERFORMED

- For this work we detected hotspots using ViT.
- We also identified hotspots using CNNs and ANNs and compared their results to results obtained using ViT
- Along with this, our work has also been compared to previously done works for this problem statement

Steps performed for classification using ViT

IMPORT LIBRARIES

↓

IMPORT DATASET

↓

ANALYSE THE TRAINING SET AND TEST SET

↓

IMPORT PRE-TRAINED MODEL VIT_BASE_PATCH16_224

↓

EXPERIMENTS PERFORMED

Steps performed for classification using ViT

PRE-PROCESS THE DATA

DECIDE VARIOUS HYPER-PARAMETERS

CREATE AND TRAIN THE MODEL

PERFORM IMAGE CLASSIFICATION

CALCULATE TRAINING ACCURACY, TEST ACCURACY, TRAINING LOSS, TEST LOSS

EXPERIMENTS PERFORMED

ViT hyper-parameters used:

Batch_size = 100; Image Size = 224; Learning Rate: 1e-3 for sub-dataset 1, 1e-2 for sub-dataset 2,3 and 4, 5e-2 for sub-dataset 5; Epochs < 5; Patch size = 16x16, optimizer = Adam, loss = cross entropy loss

Steps performed for classification using CNNs and ANNs

- For generating model for CNNs and ANNs Sequential model with a batch size of 64 and Images reshaped to 224*224 resolution have been used.
- For generating model for CNNs 3 Convolution layers with 12 filters and Kernel Size = (3,3) , 2 max-pooling layers with pooling window (2,2) and 2 dense layers give the best results.
- For ANNs best accuracy has been obtained using 9 dense layers and 8 dropout layers with with rate = 0.3.
- Steps performed are same as in case of ViT except that we don’t use pre-trained model for CNNs.
- CNN hyper-parameters used is as follows:

    Model = Sequential; Batch Size = 64; Image Shape = 224; Number of Convolution layers = 3; Number of filters = 12; Kernel Size = (3,3); Activation = relu; Number of Max-Pooling layers = 2; Pooling window = (2,2); Number of dense layers = 2; Number Of Epochs <= 10; Optmizer = Adam; Loss = Sparse Categorical Cross-entropy; Metrics = Accuracy

EXPERIMENTS PERFORMED

Steps performed for classification using CNNs and ANNs

- ANN hyper-parameters used is as follows:

Model = Sequential Batch Size = 64 Image Shape = 224 Number of Dense layers = 9 Activation = relu for first 8 layers and softmax for last layer Number of Dropout layers = 7 Dropout rate = 0.3 Number Of Epochs <= 10 Optmizer = Adam Loss = Sparse Categorical Cross-entropy Metrics = Accuracy

Model: "sequential"

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 222, 222, 12)	336
max_pooling2d (MaxPooling2D)	(None, 111, 111, 12)	0
conv2d_1 (Conv2D)	(None, 109, 109, 12)	1308
max_pooling2d_1 (MaxPooling2	(None, 54, 54, 12)	0
conv2d_2 (Conv2D)	(None, 52, 52, 12)	1308
flatten (Flatten)	(None, 32448)	0
dense (Dense)	(None, 64)	2076736
dense_1 (Dense)	(None, 10)	650

Total params: 2,080,338
Trainable params: 2,080,338
Non-trainable params: 0

Figure 5 Summary of CNN model

Layer (type)	Output Shape	Param #
flatten (Flatten)	(None, 150528)	0
dense (Dense)	(None, 2048)	308283392
dropout (Dropout)	(None, 2048)	0
dense_1 (Dense)	(None, 1024)	2098176
dropout_1 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 512)	524800
dropout_2 (Dropout)	(None, 512)	0
dense_3 (Dense)	(None, 256)	131328
dropout_3 (Dropout)	(None, 256)	0
dense_4 (Dense)	(None, 128)	32896
dropout_4 (Dropout)	(None, 128)	0
dense_5 (Dense)	(None, 56)	7224
dropout_5 (Dropout)	(None, 56)	0
dense_6 (Dense)	(None, 28)	1596
dropout_6 (Dropout)	(None, 28)	0
dense_7 (Dense)	(None, 14)	406
dropout_7 (Dropout)	(None, 14)	0
dense_8 (Dense)	(None, 10)	150

Total params: 311,079,968

Figure 6 Summary of ANN model

RESULT

Accuracy for all subsets using ViT, CNNs and ANNs

Table 3 Accuracy for all subsets using ViT, CNNs and ANNs

Model	Accuracy					Overall Average Accuracy
	Sub-Dataset 1	Sub-Dataset 2	Sub-Dataset 3	Sub-Dataset 4	Sub-Dataset 5	
ViT	95.48	99.37	95.77	99.83	99.80	98.05
CNN	94.37	98.81	90.91	99.45	99.79	96.666
ANN	89.58	97.73	94.58	98.68	99.48	96.01

- From Table 3, We can see that In terms of overall accuracy ViTs give 1.39% better accuracy than CNNs and 2.04% better accuracy than ANNs. For all the Sub-datasets Vit gives the best results. CNNs perform moderately well for sub-datasets 1, 2, 4 and 5 and worst for sub-dataset 3. ANNs perform poorest for sub-datasets 1, 2, 4, 5 and moderately for sub-dataset 3.

RESULT

Comparison with other works

Table 4 Comparison with other works

Model	Accuracy					Overall Average Accuracy
	Sub-Dataset 1	Sub-Dataset 2	Sub-Dataset 3	Sub-Dataset 4	Sub-Dataset 5	
Ours (ViT)	95.48	99.37	95.77	99.83	99.80	98.05
Y.Yu et.al, [9]	93.81	98.2	91.88	85.94	92.86	92.538
H.Yang et.al, [15]	99.6	99.8	97.8	96.4	95.1	97.74
H.Zhang et.al, [35]	100	99.4	97.52	97.74	95.12	97.956
T. Matsunawa et. al [37]	100	98.6	97.2	87.1	92.68	95.116

- Table 4 shows that In terms of overall accuracy ViT model gives the best result. In terms of sub-datasets, for sub-dataset 4 and 5, ViT gives the best accuracy. For sub-dataset 2, accuracy is not the best of all, but it is comparable to best performing models. For sub-dataset 1, H.Zhang and T.Matsunava et.al (Individual feature extraction) provide the best results and for sub-dataset 3, H.Yang et.al gives the best accuracy (data augmentation).

CONCLUSION & FUTURE SCOPE

- From table 3, we can see that in terms of overall accuracy and sub-dataset levels ViT gives the best results
- Table 4 compares our work to already existing works and it is clear from it, that in terms of overall accuracy ViT gives the best results and at sub-dataset level for three out of five, it provides best or comparable results but lags for two sub-datasets.
- From the results we can conclude that although the proposed technique performs better than a lot of already existing state of the art techniques, it fails to supplant all the existing methods for all the sub-datasets. ViTs can be seen as an new and alternate method for the purpose of identifying hotspots in lithography.
- Our aim for future researches remains to improve accuracy for sub-datasets 1 and 3 by improving our model and modifying the dataset using techniques like mirror flipping, upsampling etc. to reduce the imbalance in it and at the same time increasing training data.
- Since the technique is very novel, many improvements lie for it in the coming future. With the improvements in technique, increase in accuracy and lower time can also be expected for our problem statement.

PUBLICATION

- Paper titled “Empirical Laws of Natural Language Processing for Neural Language Generated Text” for published in Springer CCIS 6th ICICCT
- Link : https://link.springer.com/chapter/10.1007%2F978-3-030-88378-2_15
- Indexing: Springer CCIS is abstracted / indexed in Scopus, DBLP, Google Scholar, EI-Compendex, Mathematical Reviews, SCImago.
- Proof of Indexing: https://www.easychair.org/cfp/ICICCT2021


Springer
ccis
ICICCT-2021
jims
Sector - 5, Rohini, Delhi

Certificate of Presentation

Awarded to

Sumedha

for presenting the paper,

Empirical Laws Of Natural Language Processing For Neural Language Generated Text

at 6th International Conference on Information, Communication & Computing Technology (ICICCT - 2021) in collaboration with Springer CCIS and Computer Society of India, held on 8th May 2021 conducted by Jagan Institute of Management Studies (JIMS) Sector-05, Rohini, New Delhi, India. Due to ongoing Corona pandemic the Conference is conducted in live stream mode through Zoom. Selected & presented papers will be published in CCIS Vol. 1417.

Dr. Praveen Arora
Conference Secretariat

Dr. Latika Kharb
Convener

Dr. Deepak Chahal
Convener

REFERENCES

[1]. J. A. Torres, "ICCAD-2012 CAD contest in fuzzy pattern matching for physical verification and benchmark suite," 2012 IEEE/ACM International Conference on Computer- Aided Design (ICCAD), 2012, pp. 349-350.

[2]. S. Gkelios, Y. Boutalis, S.A. Chatzichristofis "Investigating the Vision Transformer Model for Image Retrieval Tasks," 11 Jan 2021, [Online], Available: arXiv:2101.03771v1. [Accessed: June 2021]

[3]. A. Dosovitskiy, L. Beyer, A. Kolesnikov, D.Weissenborn, X. Zhai, T.Unterthiner, M. Dehghani, M. Minderer, G. Heigold, S. Gelly, J. Uszkoreit, N.Houlsby "An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale," 3 Jun 2021, [Online], Available: arXiv:2010.11929v2. [Accessed: June 2021]

[4]. V. Borisov and J. Scheible, "Lithography Hotspots Detection Using Deep Learning," 2018 15th International Conference on Synthesis, Modeling, Analysis and Simulation Methods and Applications to Circuit Design (SMACD), 2018, pp. 145-148, doi: 10.1109/ SMACD.2018.8434561.

[5]. W. Ye , Y. Lin , M.Li , Q. Liu , D.Z. Pan, "LithoROC: lithography hotspot detection with explicit ROC optimization," ASPDAC '19: Proceedings of the 24th Asia and South Pacific Design Automation Conference, January 2019, pp. 292–298, doi.: 10.1145/3287624/3288746.

[6]. B. Yu, J.R. Gao, D. Ding, X. Zeng, D. Z. Pan, "Accurate lithography hotspot detection based on principal component analysis-support vector machine classifier with hierarchical data clustering," J. Micro/Nanolith. MEMS MOEMS, 4 November 2014, doi.: 10.1117/1.JMM.14.1.011003.

[7]. Y. Tomioka, T. Matsunawa, C. Kodama and S. Nojima, "Lithography hotspot detection by two-stage cascade classifier using histogram of oriented light propagation," 2017 !33 22nd Asia and South Pacific Design Automation Conference (ASP-DAC), 2017, pp. 81-86, doi: 10.1109/ASPDAC.2017.7858300.

[8]. W. Wen, J. Li, S. Lin, J. Chen and S. Chang, "A Fuzzy-Matching Model With Grid Reduction for Lithography Hotspot Detection," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 33, no. 11, pp. 1671-1680, Nov. 2014, doi: 10.1109/TCAD.2014.2351273.

REFERENCES

[9]. Y. Yu, G. Lin, I. H. Jiang and C. Chiang, "Machine-Learning-Based Hotspot Detection Using Topological Classification and Critical Feature Extraction," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 34, no. 3, pp. 460-470, March 2015, doi: 10.1109/TCAD.2014.2387858.

[10]. G. Huang, J. Hu, Y. He, J. Liu, M.Ma, Z. Shen, J. Wu, Y. Xu, H. Zhang, K. Zhong, X. Ning, Y. Ma, H. Yang, B.Yu, H. Yang, Y. Wang "Machine Learning for Electronic Design Automation: A Survey," 8 Mar 2021, [Online], Available: arXiv:2102.03357v2arXiv: 2102.03357v2. [Accessed: June 2021]

[11]. G. R. Reddy, C. Xanthopoulos and Y. Makris, "Enhanced hotspot detection through synthetic pattern generation and design of experiments," 2018 IEEE 36th VLSI Test Symposium (VTS), 2018, pp. 1-6, doi: 10.1109/VTS.2018.8368646.

[12]. Y Xiao., X. Huang, and K. Liu, "Transferability from ImageNet to Lithography Hotspot Detection," J Electron Test 37, pp. 141–149, doi.: 10.1007/s10836-021-05925-5. [13]. H. Zhang , F. Zhu , H. Li , E.F.Y. Young, B. Yu "Bilinear Lithography Hotspot Detection Share," ISPD '17: Proceedings of the 2017 ACM on International Symposium on Physical Design, March 2017, Pp. 7–14, doi.: 10.1145/3036669.3036673.

[14]. H. Yang, Y. Lin, B. Yu, E.F. Y. Young, "Lithography Hotspot Detection: From Shallow To Deep Learning", IEEE International System-on-Chip Conference (SOCC), pp. 233–238, Munich, Germany, September 5–8, 2017. !34

[15]. H. Yang, L. Luo, J. Su, C. Lin, B. Yu, "Imbalance Aware Lithography Hotspot Detection: A Deep Learning Approach", SPIE Intl. Symp. Advanced Lithography Conference, San Jose, CA, Feb. 26–Mar. 2, 2017.

[16]. J. A.T. Robles, S. Mostafa, K. Madkour, J.Y. Wuu, "Hotspot Detection Based on Machine Learning," United States Patent Application Publication, 2013,[Online], Available: https://patents.google.com/patent/US20130031522. [Accessed: June 2021]

[17]. Z. XingYu, Y. YouLing "Hotspot Detection of Semiconductor Lithography Circuits Based on Convolutional Neural Network," Journal of Microelectronic Manufacturing, December 2018, pp. 1-8, doi.: 10.33079/jomm.18010205.

[18]. R. Chen, W. Zhong, H. Yang, H. Geng, X. Zeng and B. Yu, "Faster Region-based Hotspot Detection," 2019 56th ACM/IEEE Design Automation Conference (DAC), 2019, pp. 1-6.

[19]. G. R. Reddy, C. Xanthopoulos and Y. Makris, "On Improving Hotspot Detection Through Synthetic Pattern-Based Database Enhancement," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, doi: 10.1109/TCAD. 2021.3049285.

REFERENCES

[20]. W. Ye, M. B. Alawieh, Y. Lin, D.Z. Pan, “LithoGAN: End-to-End Lithography Modeling with Generative Adversarial Networks,” The 56th Annual Design Automation Conference 2019, June 2019, doi.:10.1145/3316781.3317852.

[21]. S. Tamagawa, R. Fujimoto, M. Inagi, S. Nagayama, S. Wakabayashi, “A Hotspot Detection Method Based on Approximate String Search,” CENICS 2016: The Ninth International Conference on Advances in Circuits, Electronics and Micro-electronics, 2016.

[22]. M. Shin, J.H. Lee, "Accurate lithography hotspot detection using deep convolutional neural networks," J. Micro/Nanolith. MEMS MOEMS 15(4), 18 Nov 2016, doi.: 10.1117/1.JMM.15.4.043507.

[23]. H. Yang, J. Su, Y. Zou, Y. Ma, B. Yu and E. F. Y. Young, "Layout Hotspot Detection With Feature Tensor Generation and Deep Biased Learning," in IEEE Transactions on !35 Computer-Aided Design of Integrated Circuits and Systems, vol. 38, no. 6, pp. 1175-1187, June 2019, doi: 10.1109/TCAD.2018.2837078.

[24]. Y. Chen, Y. Lin, T. Gai, Y. Su, Y. Wei and D. Z. Pan, "Semisupervised Hotspot Detection With Self-Paced Multitask Learning," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 39, no. 7, pp. 1511-1523, July 2020, doi: 10.1109/TCAD.2019.2912948.

[25]. Y. Yu, Y. Chan, S. Sinha, I. H. Jiang and C. Chiang, "Accurate process-hotspot detection using critical design rule extraction," DAC Design Automation Conference 2012, 2012, pp. 1163-1168.

[26]. W. Ye, M. B. Alawieh, M. Li, Y. Lin and D. Z. Pan, "Litho-GPA: Gaussian Process Assurance for Lithography Hotspot Detection," 2019 Design, Automation & Test in Europe Conference & Exhibition (DATE), 2019, pp. 54-59, doi: 10.23919/DATE.2019.8714960.

[27]. K. Liu, B. Tan, R. Karri and S. Garg, "Poisoning the (Data) Well in ML-Based CAD: A Case Study of Hiding Lithographic Hotspots," 2020 Design, Automation & Test in Europe Conference & Exhibition (DATE), 2020, pp. 306-309, doi: 10.23919/DATE48585.2020.9116489.

[28]. J. Gao, B. Yu, D. Ding and D. Z. Pan, "Lithography hotspot detection and mitigation in nanometer VLSI," 2013 IEEE 10th International Conference on ASIC, 2013, pp. 1-4, doi: 10.1109/ASICON.2013.6811917. [29]. C.A. Mack, "Thirty years of lithography simulation,” Optical Microlithography XVIII, 12 May 2005, doi.: 10.1117/12.601590.

REFERENCES

[29]. C.A. Mack, "Thirty years of lithography simulation," Optical Microlithography XVIII, 12 May 2005, doi.: 10.1117/12.601590.

[30]. C. Chiang and J. Kawa, "Three DFM Challenges: Random Defects, Thickness Variation, and Printability Variation," APCCAS 2006 - 2006 IEEE Asia Pacific Conference on Circuits and Systems, 2006, pp. 1099-1102, doi: 10.1109/APCCAS.2006.342313.

[31]. J. Xu, S. Sinha and C. C. Chiang, "Accurate detection for process-hotspots with vias and incomplete specification," 2007 IEEE/ACM International Conference on Computer- Aided Design, 2007, pp. 839-846, doi: 10.1109/ICCAD.2007.4397369. !36 [32]. S.K. Kim, J.E. Lee, S.W. Park, H.K. Oh, "Optical lithography simulation for the whole resist process," Current Applied Physics, Volume 6, Issue 1, 2006, pp. 48-53, doi.: 10.1016/j.cap.2004.12.003.

[32]. D.Z. Pan, P.Y. Huazhong, M. Cho, A. Ramalingam, "Design for manufacturing meets advanced process control: A survey," Journal of Process Control, December 2008, doi.: 10.1016/j.jprocont.2008.04.007.

[33]. J. Mitra , P. Yu , D.Z. Pan "RADAR: RET-aware detailed routing using fast lithography simulations," DAC '05: Proceedings of the 42nd annual Design Automation Conference, June 2005, pp. 369–372 doi.: 10.1145/1065579.1065678.

[34]. D. Z. Pan, "Lithography-aware physical design," 2005 6th International Conference on ASIC, 2005, pp. 1172-1173, doi: 10.1109/ICASIC.2005.1611242.

[35]. H. Zhang , B. Yu , E.F. Y. Young, "Enabling online learning in lithography hotspot detection with information-theoretic feature optimization," ICCAD '16: Proceedings of the 35th International Conference on Computer-Aided Design, November 2016, pp. 1–8 doi.: 10.1145/2966986.2967032.

[36] S. Tamagawa, R. Fujimoto, M. Inagi, S. Nagayama, S. Wakabayashi, "ATable Reference-Based Acceleration of a Lithography Hotspot Detection Method Based on Approximate String Search," CENICS 2017: The Tenth International Conference on Advances in Circuits, Electronics and Micro-electronics, 2017.

[37] T. Matsunawa, J.R. Gao, B. Yu, and D. Z. Pan, "A new lithography hotspot detection framework based on AdaBoost classifier and simplified feature extraction," SPIE vol. 9427, 2015.

[38] N. Ma, J.Ghan, S. Mishra, C. Spanos, K. Poolla, N. Rodriguez, L. Capodieci, "Automatic hotspot classification using pattern-based clustering," SPIE Design for Manufacturability through Design-Process Integration II, 4 March 2008, doi.: 10.1117/12.772867. !37

REFERENCES

[39] D. Ding, J. A. Torres and D. Z. Pan, "High Performance Lithography Hotspot Detection With Successively Refined Pattern Identifications and Machine Learning," in IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems, vol. 30, no. 11, pp. 1621-1634, Nov. 2011, doi: 10.1109/TCAD.2011.2164537.

[40] https://nptel.ac.in/courses/117/106/117106093/ [41] J.Ghan, N.Ma, S. Mishra, C. Spanos, K. Poolla, N. Rodriguez, L. Capodieci, "Clustering and pattern matching for an automatic hotspot classification and detection system," SPIE Design for Manufacturability through Design-Process Integration III, 12 March 2009, doi.: 10.1117/12.814328.

[42] Haberfehlner, Georg “3D nanoimaging of semiconductor devices and materials by electron tomography”,2013.

[43] Prof. Nandita Dasgupta “ Lithography Lecture-1 and Lecture-1”, [Online], Available: https://nptel.ac.in/courses/117/106/117106093/. [Accessed: Jully 2021]

[44] Prof. AN Chandokar “ Lecture 16 to 18, Lithography”, [Online], Available:https:// nptel.ac.in/courses/108/101/108101089/. [Accessed: Jully 2021]

[45] Prof. Parasuraman Swaminathan “ Lithography”, [Online], Available: https:// onlinecourses.nptel.ac.in/noc20_mm25/. [Accessed: Jully 2021]

[46] S. Sivakumar, "EUV lithography: Prospects and challenges," 16th Asia and South Pacific Design Automation Conference (ASP-DAC 2011), 2011, pp. 402-402, doi: 10.1109/ ASPDAC.2011.5722221.

THANK YOU !