DigWise Technology Corporation, LTD.

DTCO.VS GAN-VS™ User Guide

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1. Introduction

The GAN-VS™ utilizes a Generative Adversarial Network (GAN) as its core framework for wafer-level virtual data generation. Through a training process involving the generator and discriminator, the model learns to create high-dimensional synthetic images that accurately represent key wafer characteristics. This approach enables realistic data augmentation and simulation, aiding process optimization and parameter exploration within semiconductor manufacturing.

2. Virtual Silicon Data Format

To ensure seamless integration and analysis within the GAN-VS™, it is essential to understand the required data format for Chip Probing (CP) and Wafer Acceptance Test (WAT) data. The following sections outline the expected structures for data type:

- **File Type**: ZIP and CSV.
- **Required Columns**:
  - **LWID**: A distinctive identifier assigned to each generated wafer for tracking and analysis. (Lot Id. + Wafer No.)
  - **X**: Represents the horizontal coordinate, uniquely identifying the chip's position on the generated wafer.
  - **Y**: Represents the vertical coordinate, uniquely identifying the chip's position on the generated wafer.
  - **Features**: Measurement parameters (refer to TABLE I and Fig. 1).

TABLE I: Generated virtual silicon features in the dataset.

Feature	Description	Unit
CP1	Leakage current	µA
CP2	Chip speed	Hz
CP3	Functional accuracy at 300MHz	%
CP4	Functional accuracy at 400MHz	%
CP5	Functional accuracy at 500MHz	%
CP6	Functional accuracy at 600MHz	%
WAT1	Gate threshold voltage of the low threshold NMOS	V
WAT2	Gate threshold voltage of the low threshold PMOS	V
WAT3	Gate threshold voltage of the ultra-low threshold NMOS	V
WAT4	Gate threshold voltage of the ultra-low threshold PMOS	V
WAT5	Drain current of the low threshold NMOS	mA
WAT6	Drain current of the low threshold PMOS	mA
WAT7	Drain current of the ultra-low threshold NMOS	mA
WAT8	Drain current of the ultra-low threshold PMOS	mA

LWID	X	Y	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	CP11	CP12	CP13	CP14	CP15	WAT1	WAT2	WAT3	WAT4	WAT5	WAT6	WAT7	WAT8
genData-1	40	1	2.278975	606.5499	635.3969	559.3203	408.7622	607.1519	630.7541	632.8522	626.9127	541.1194	708.7959	343.1524	586.4268	612.101	85.94261	201.9283	327.8782	0.241161	0.242123	3965.865	3568.198	0.165054	0.171641
genData-1	41	1	2.134723	625.7311	613.7444	582.3254	465.2362	662.9866	636.1604	630.6859	618.3936	579.8528	701.7642	341.4895	553.2333	648.2996	76.43232	183.1382	304.7937	0.244644	0.241681	3059.856	3668.839	0.164317	0.173019
genData-1	42	1	1.7152	634.4235	659.6755	529.7715	426.2163	672.5837	651.2987	650.7822	604.0487	508.9424	698.6339	324.716	595.3189	632.0618	62.78581	190.1719	339.6315	0.243973	0.238843	3307.246	3474.117	0.165485	0.172718
genData-1	32	2	1.978955	632.9401	611.1257	583.5493	334.3385	646.7486	636.4955	612.9314	614.0333	573.3686	728.6314	335.2638	610.8349	636.7879	242.8402	207.521	339.9277	0.245076	0.23986	3233.272	4007.761	0.16441	0.174742
genData-1	33	2	2.090456	666.2777	654.6711	664.5424	540.7428	606.8378	651.7916	661.6203	662.7089	660.93	841.5173	386.9765	713.354	719.8051	91.55892	182.0438	314.4982	0.244736	0.241928	3679.207	3677.264	0.165945	0.170521
genData-1	34	2	2.276103	690.2176	650.4465	669.0796	647.0334	629.3972	661.6108	676.0566	690.8859	676.1803	851.8647	425.4778	679.9696	761.5731	107.2787	185.9172	305.8875	0.244948	0.24121	3768.169	3689.797	0.164986	0.172418
genData-1	35	2	2.783077	568.9532	681.2278	677.779	672.7677	601.4663	690.8456	689.1133	696.6234	701.1541	888.9571	422.8423	750.7193	777.7618	105.7357	172.4236	275.8443	0.243645	0.241422	3580.025	3570.515	0.162532	0.17159
genData-1	36	2	2.678269	631.0665	695.9177	690.328	687.0961	613.4429	684.7401	690.9114	699.1147	702.7372	912.2399	465.578	777.4813	802.225	115.7319	184.6545	312.0474	0.245704	0.240001	4239.256	3854.25	0.167796	0.17368
genData-1	37	2	3.337587	683.1279	702.2633	705.8648	708	610.8021	668.3956	695.9814	702.4533	708.1999	919.6882	469.4406	782.9693	810.336	112.7986	200.8487	334.2412	0.245273	0.242707	3920.832	3759.749	0.165816	0.174258
genData-1	38	2	3.24663	655.8797	654.8351	688.8464	705.0971	652.1343	678.3757	708.0118	696.8067	700.5202	918.0143	449.2233	764.3081	835.1689	148.1062	180.9373	307.484	0.244544	0.242649	3805.644	3542.647	0.162751	0.173189
genData-1	39	2	3.72497	628.5428	684.4878	684.2183	670.3632	616.9798	675.1467	691.2282	699.9357	699.1425	920.9996	460.4248	816.5801	822.7846	186.2881	185.6036	335.1658	0.245224	0.241728	3228.196	3865.204	0.16232	0.174011
genData-1	40	2	3.0807	643.231	687.09	699.8585	697.1997	647.5907	682.7025	687.7859	700.834	698.8849	929.966	451.7168	779.5165	838.7102	191.4804	192.2096	341.066	0.246622	0.24193	3382.019	3290.426	0.164586	0.174189
genData-1	41	2	4.055163	624.3344	652.7922	686.0345	665.4265	576.2171	666.759	696.7407	703.6597	699.4816	943.8719	450.0276	818.5866	835.7317	151.5683	174.1684	358.5423	0.241338	0.241387	3375.862	3840.648	0.165299	0.173292
genData-1	42	2	4.011644	609.1054	663.049	704.5247	698.6374	598.8808	679.0995	697.8108	702.0218	702.3262	956.2959	461.777	812.4771	809.1787	122.6518	180.5063	326.8213	0.243725	0.240266	2938.59	3567.704	0.160879	0.173101
genData-1	43	2	2.725966	577.6885	653.8688	694.8362	667.3454	584.3152	695.421	684.682	695.4957	698.1248	944.0977	485.7281	820.4938	819.9998	133.4823	198.873	340.1791	0.244565	0.243665	3927.845	3823.848	0.164162	0.17167
genData-1	44	2	3.481142	636.216	687.407	699.7151	662.5197	636.4946	681.268	693.6212	696.5013	700.7693	923.3197	454.2425	825.7902	796.2756	155.7876	176.5312	296.869	0.242734	0.24218	3560.704	3662.445	0.160594	0.173495
genData-1	45	2	3.37472	657.3715	699.9957	698.8177	670.4709	665.9219	690.3673	690.9702	701.5191	705.4705	899.235	453.3985	844.6734	780.0702	140.3053	196.0275	300.2036	0.244774	0.244874	3408.27	3883.581	0.163719	0.173229
genData-1	46	2	2.710373	629.2116	698.4384	705.0092	697.0528	600.5399	679.0911	692.8084	699.4172	704.1115	910.9553	432.2372	824.1324	776.8236	122.2343	181.5315	312.1264	0.244998	0.242556	3573.044	3586.629	0.167995	0.171466
genData-1	47	2	2.560055	686.1339	676.2798	698.1616	708	664.0854	687.7727	684.1022	698.2462	706.2691	884.9473	435.3209	791.3465	801.6642	123.9188	167.6312	362.2683	0.243204	0.239784	3162.264	3659.913	0.165553	0.172623
genData-1	48	2	2.627258	623.0101	685.7596	694.0972	696.6509	608.8845	695.6712	690.1954	699.9047	699.6639	848.5004	403.7912	679.6329	764.3695	111.3017	208.6429	321.9962	0.244358	0.243525	2888.299	3487.011	0.164803	0.171846
genData-1	49	2	2.196778	677.1159	696.407	691.661	621.9879	652.683	697.8732	694.268	700.9285	696.1099	826.785	392.6404	683.9425	719.5722	102.3523	183.9215	333.0307	0.243283	0.243045	3544.734	3330.949	0.164102	0.171418
genData-1	50	2	2.170113	686.515	675.5395	592.0668	406.1339	677.4817	694.6334	687.0104	658.8393	561.7248	759.075	353.848	638.0635	686.252	72.9549	189.0113	350.2529	0.243274	0.243448	3796.953	3918.608	0.166922	0.173099
genData-1	29	3	2.643449	689.3152	673.5674	692.2635	666.8034	631.3584	706.6794	697.6342	698.58	703.1384	813.4386	392.1484	684.3214	716.6789	89.43584	199.5023	319.8031	0.243856	0.242969	3783.422	3832.352	0.163251	0.173464
genData-1	30	3	2.626087	611.6005	642.0643	697.8935	681.1611	698.958	677.7819	700.792	696.7557	697.3076	861.9257	455.3832	794.7408	775.624	98.91451	187.7892	298.4243	0.246804	0.244138	3587.496	3734.797	0.165336	0.172402
genData-1	31	3	3.34973	658.7009	689.4821	678.7529	701.3848	611.0576	659.47	684.1402	696.7804	701.7046	947.0569	456.4821	839.0124	840.7366	164.4688	182.5708	328.3803	0.245098	0.2414	3051.598	3586.654	0.16273	0.172633
genData-1	32	3	3.349411	628.2497	679.7629	704.1441	704.0461	640.2209	670.3092	680.6617	698.6601	705.6399	970.3211	470.2498	834.557	914.1172	128.3199	181.1467	330.7221	0.24479	0.238502	3697.551	3711.096	0.166503	0.172181
genData-1	33	3	3.546763	625.5706	685.3016	698.849	669.9547	609.7304	679.5933	697.1977	702.2618	698.4055	1007.245	495.0844	846.0891	907.2994	154.4214	191.3178	292.904	0.246398	0.24429	4096.241	3593.368	0.162311	0.172726
genData-1	34	3	3.528721	608.0423	682.3565	705.5056	684.6813	572.9803	629.3703	697.5512	699.4916	702.0965	1020.511	499.435	854.5005	902.0099	148.1072	193.6286	304.3504	0.242421	0.243873	3739.692	3632.196	0.165183	0.17249
genData-1	35	3	4.092679	537.2963	638.6273	695.9977	702.0821	561.9177	648.6008	687.1685	702.5234	702.568	1059.697	512.0128	895.6016	862.2019	140.8537	180.1264	321.6879	0.245666	0.239659	3343.137	3628.755	0.166223	0.171948
genData-1	36	3	4.010819	584.6219	645.1451	687.1689	704.8496	557.897	690.4469	680.0621	697.1758	702.6858	1050.969	522.8312	900.7278	867.7139	169.0404	183.3154	317.892	0.245397	0.242083	3020.642	3723.161	0.167677	0.17197

Fig. 1 CP + WAT Virtual Silicon Data Format

3. Dataset Conversion

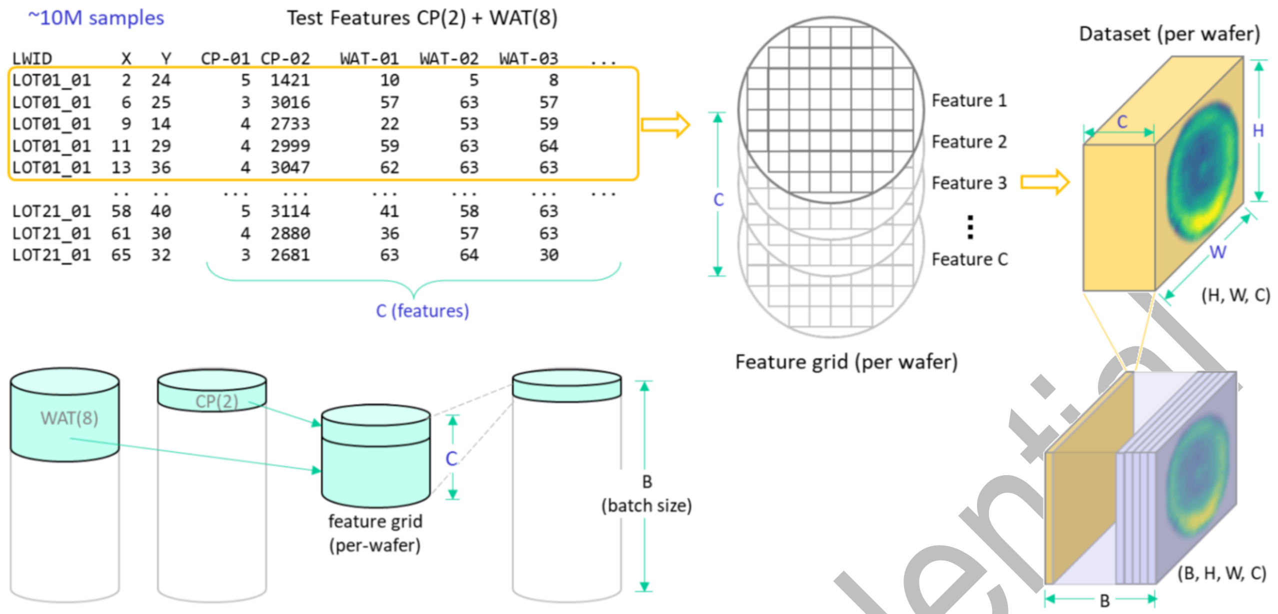

Fig. 2 Dataset Conversion

As shown in Fig. 2, the figure illustrates converting wafer data into a multi-channel image format. The original CP and WAT test data are transformed into 2D images with multiple feature dimensions (parameter C). The size of C is directly related to model size, and training time increases non-linearly with C. The dataset in the legend includes 8 WAT measurements and 2 CP measurements, totaling 10 dimensions (C=10). Notably, the wafer is circular, but the data is represented in a rectangular format, with data outside the wafer boundary filtered using a mask to maintain analysis accuracy.

To further augment the training set, slight angle rotations are applied, especially useful when data is limited during early mass production. This method increases data diversity and enhances model stability. By simulating potential rotational defects and process parameter distributions, as shown in Fig. 3, we can capture key features of the chip manufacturing process, improving the model's training effectiveness.

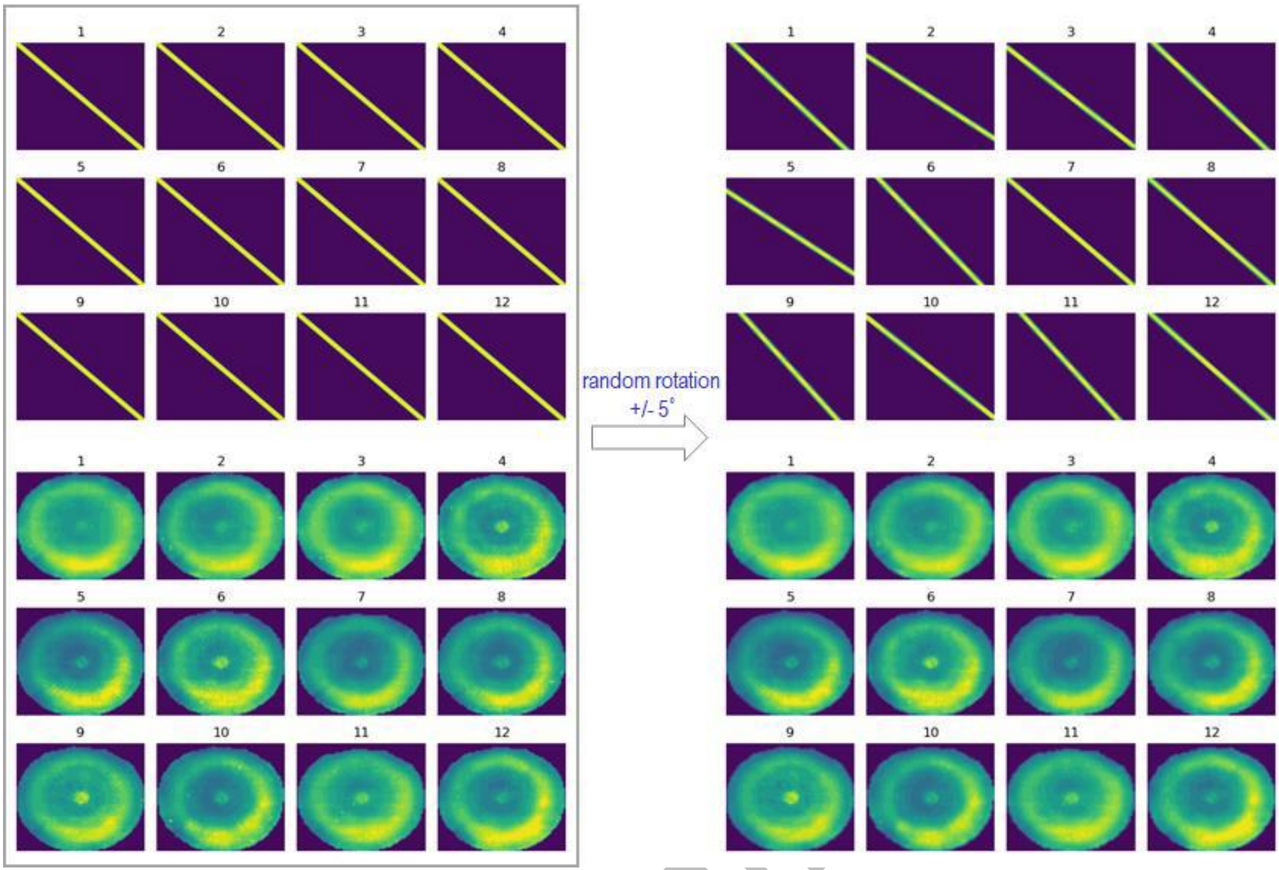

Fig. 3 Data Augmentation

4. GAN-based Virtual Silicon (GAN-VS)

This section explains how the GAN model is used to model multi-dimensional test data from the chip manufacturing process, covering chip performance, wafer process characteristics, and potential defects, to accurately capture process defects and parameter uniformity.

4.1. GAN Model

As shown in Fig. 4, the generator consists of convolutional layers and outputs multi-dimensional images through a Tanh layer to simulate chip images. The discriminator uses convolutional layers and a Sigmoid layer to assess the authenticity of the chip data. The two components work together to generate high-quality chip data.

During training, we use BCE Loss and minimize the difference between generated and real chips through gradient descent. To enhance training stability, Batch Normalization and LeakyReLU activation are applied. The Adam optimizer is used with an initial learning rate of 0.001, decaying by 0.9 every 100 epochs. Training runs for 10,000 epochs with a batch size of 20. Ultimately, the GAN model generates realistic chip data, including chip location, wafer flatness, and process defects, forming a reliable foundation for simulating and analyzing the manufacturing process.

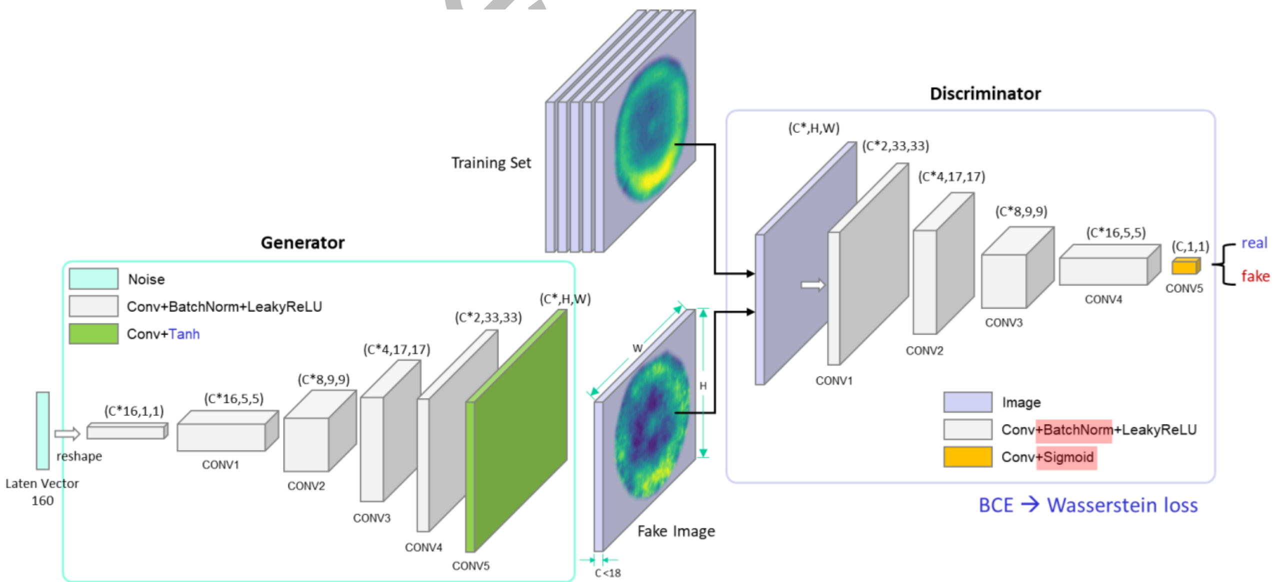

Fig. 4 GAN Modeling

4.2. GAN Model Performance Evaluation

We evaluate the GAN model by plotting 2D scatter plots of generated and real samples, with feature combinations as axes. Ideally, the scatter plots should overlap, ensuring that the generated data aligns with the real data in both individual and joint feature distributions, as shown in Fig. 5.

Additionally, we use quantitative metrics, such as Jensen-Shannon divergence (JS Divergence) to compare the probability distributions of the generated and real data, and the KDE metric to assess the differences between feature distributions, ensuring the reliability and accuracy of the generated chip data.

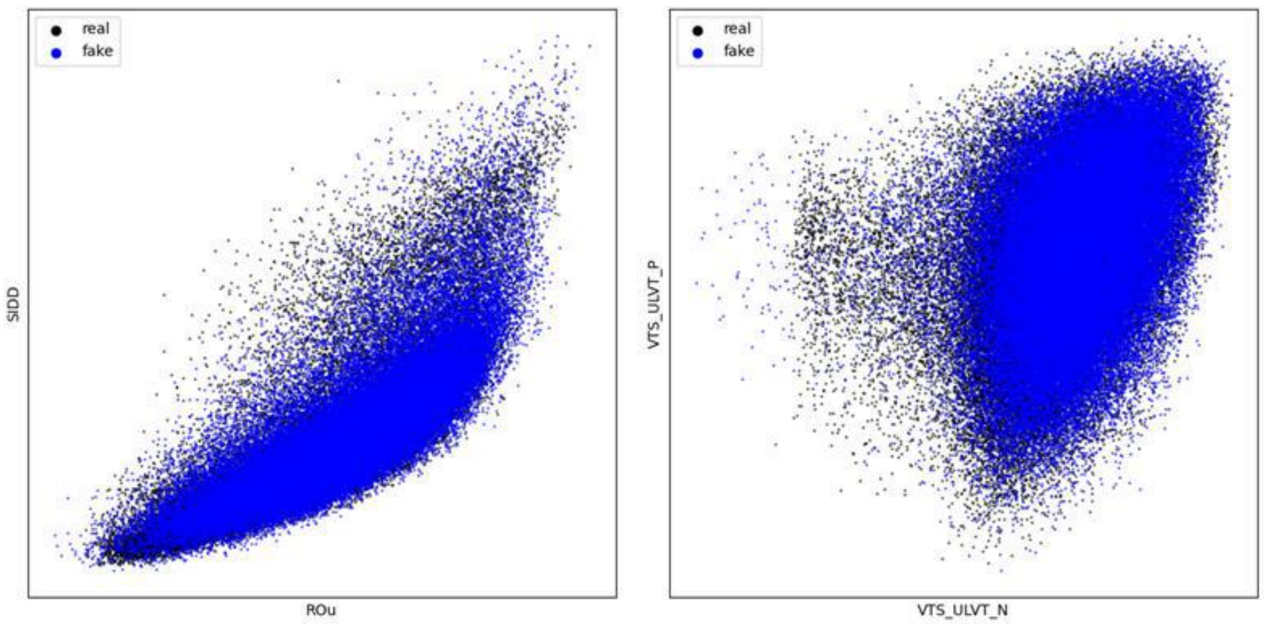

Fig. 5 Feature Scatter Plot for GAN Model Similarity

We evaluate the similarity between real data and GAN-generated samples by comparing their feature distributions. Using Jensen-Shannon (JS) divergence, lower values indicate greater similarity between the generated and real samples. The JS divergence between the real distribution P and generated distribution Q is defined as follows:

$$D_{JS}(P||Q) = \frac{1}{2}D_{KL}(P||M) + \frac{1}{2}D_{KL}(Q||M) \tag{1}$$

The Kullback-Leibler divergence DKL(P||M) can be calculated using the following formula:

$$D_{KL}(P||M) = \sum_{x \in X} P(x) \log \frac{P(x)}{M(x)} \quad (2)$$

where M represents the mixed distribution of P and Q, defined as:

$$M = \frac{1}{2}(P + Q) \quad (3)$$

Since the JS divergence between the two distributions ranges from 0 to 1, the similarity of the JS divergence between P and Q is defined as:

$$Similarity = 1 - D_{JS}(P||Q) \quad (4)$$

JS divergence similarity analysis (Similarity = 1 - JS) shows that the probability distributions of the model-generated virtual chip data closely match real data in each dimension, with values ranging from 0.98 to 1.0. Additionally, the model exhibits strong robustness and generalization performance for anomalous datasets. See Fig. 6 for details.

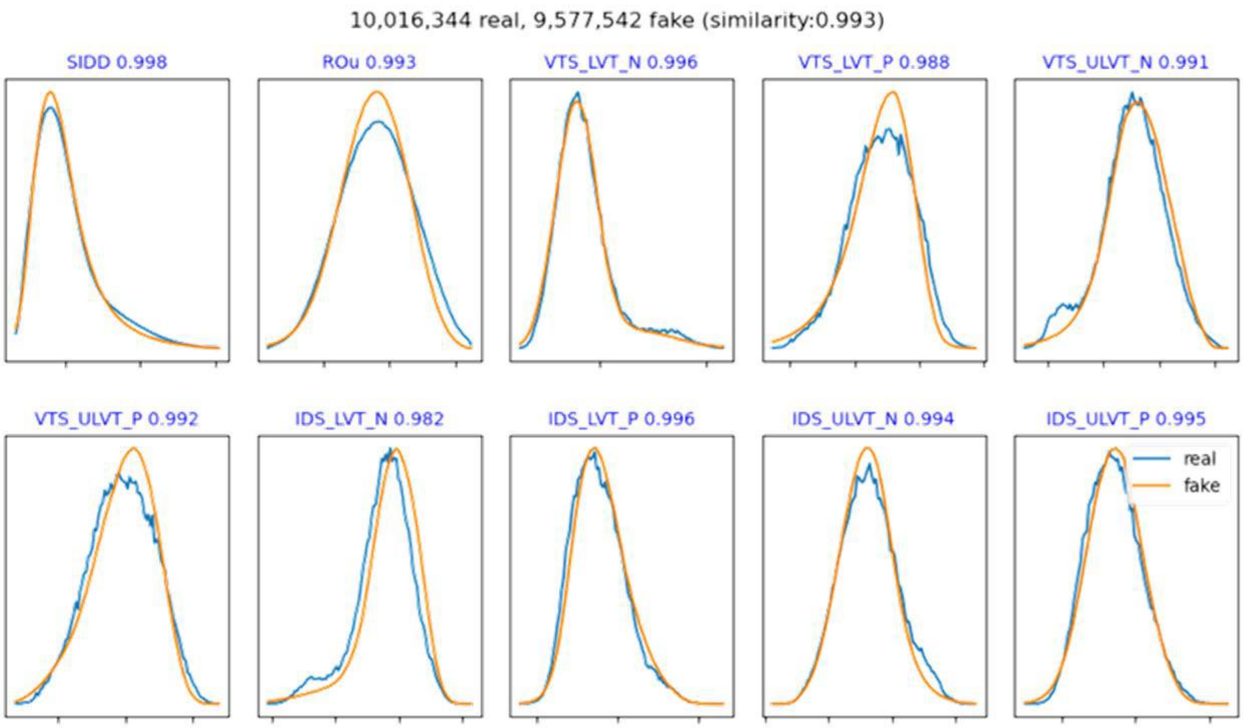

Fig. 6 Feature Distribution Similarity

As shown in Fig. 7, experimental results reveal that the GAN model's high-dimensional chip data closely matches real chip data in scatter plots between any two features. The model successfully captures process variability during process adjustments, marked by yellow, green, and blue circles. In high-dimensional space, the relationships between features and their joint distributions remain consistent with the original data.

To enhance the model, we can exclude data irrelevant to mass production, such as intentionally skewed wafers, to avoid learning anomalies from early process adjustments. Unlike traditional methods, the GAN model effectively learns nonlinear relationships in the chip manufacturing process, capturing subtle details and fitting the real data distribution more precisely. Further analysis confirms that the GAN model accurately captures parameter distributions, wafer-level uniformity, and manufacturing process details, reflecting more realistic wafer defects, as seen in Fig. 8.

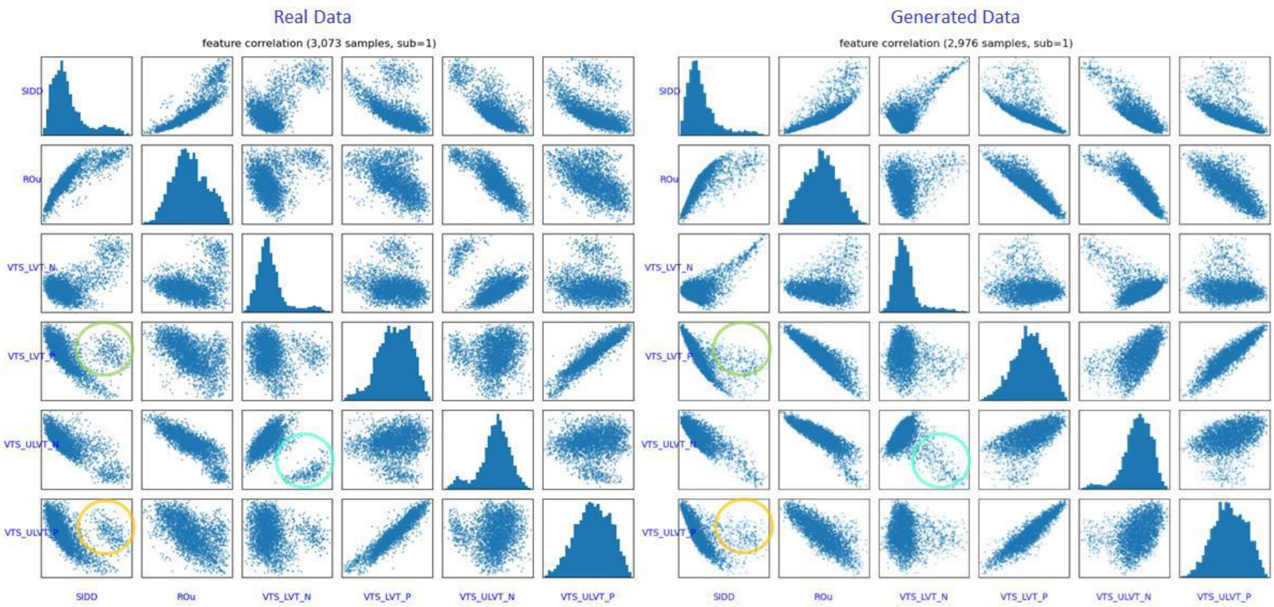

Fig. 7 Feature Correlation Matrix between Generated and Real Silicon

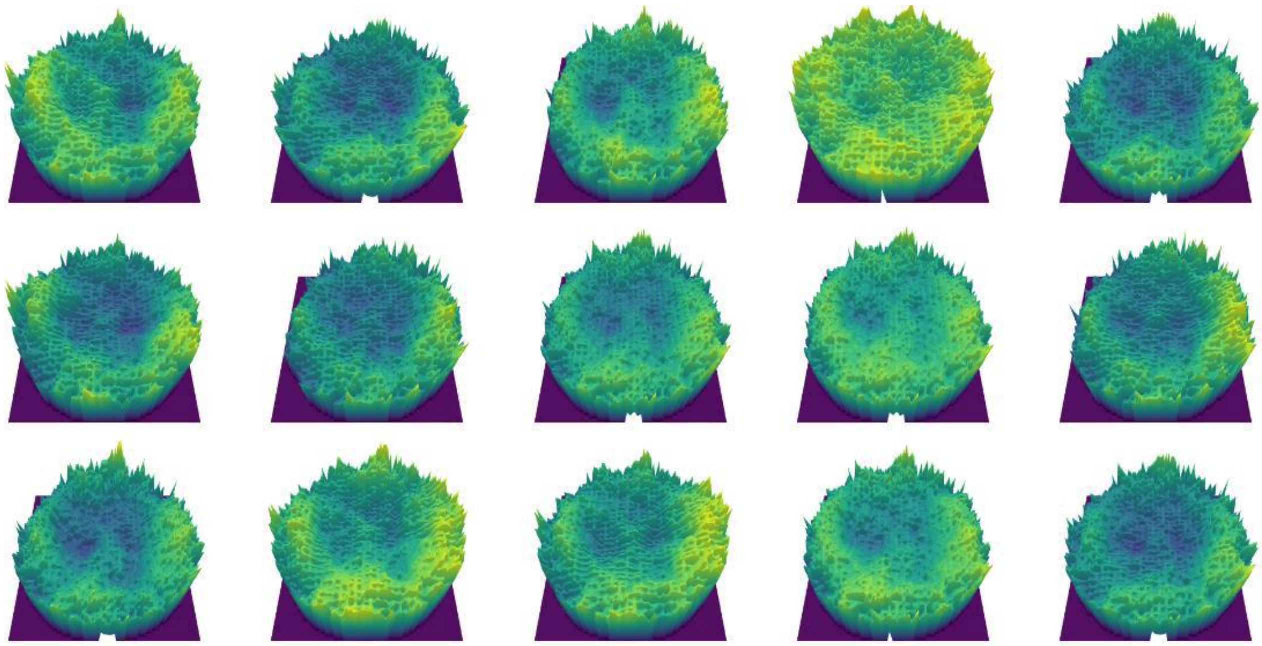

Fig. 8 Wafer-level Feature Uniformity of Generated Silicon

GAN-based methods often face challenges in convergence and instability. While the improved WGAN (using Wasserstein Loss and removing BatchNorm and Sigmoid layers, as shown in Fig. 10-3) enhances performance, it still struggles with data distributions that have multiple peaks. Additionally, chip functional accuracy (e.g., frequency-dependent features like CP3-CP6) typically follows non-Gaussian distributions, such as bimodal, skew-normal, log, or cosh forms. As multi-core chip performance is highly influenced by operating frequency, GANs face difficulties in handling such tasks. The next section will explore how diffusion models can address these challenges.

5. Virtual Silicon Data Visualization

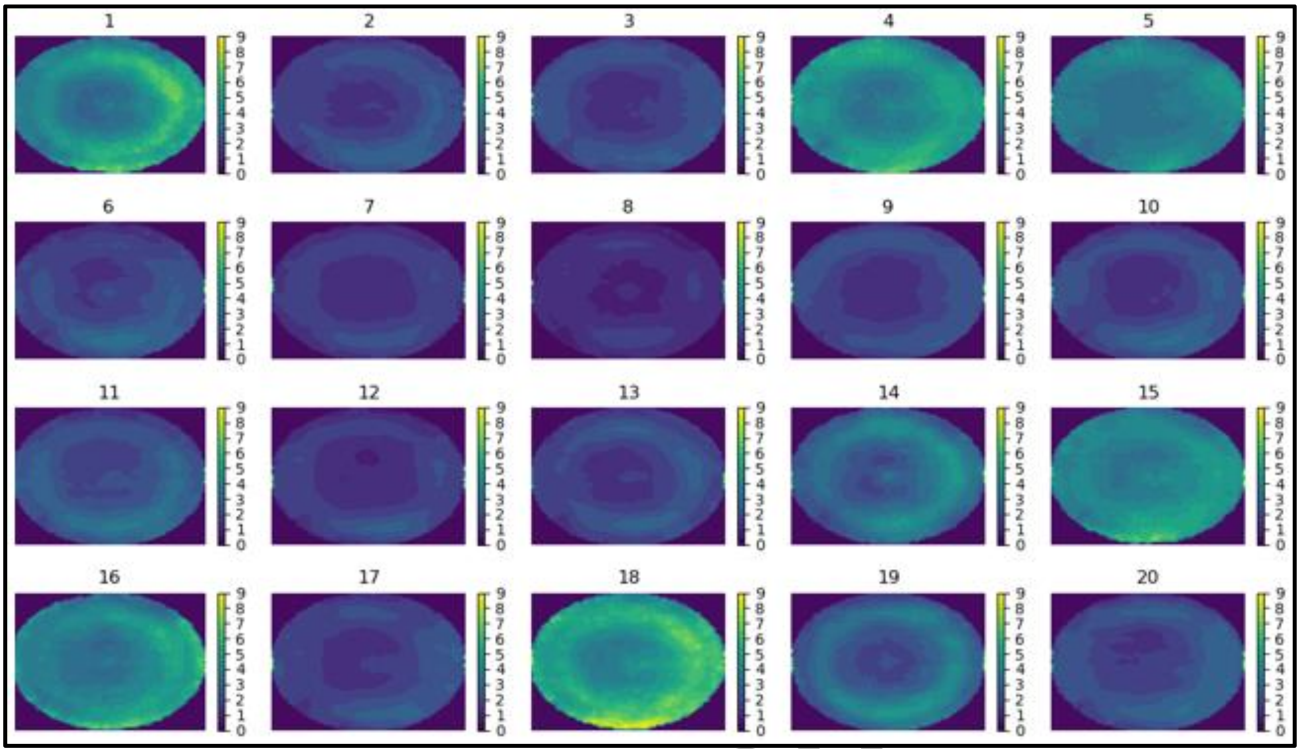

Fig. 9 Demonstrations of 20 pre-wafer samples with CP1 generated by GAN

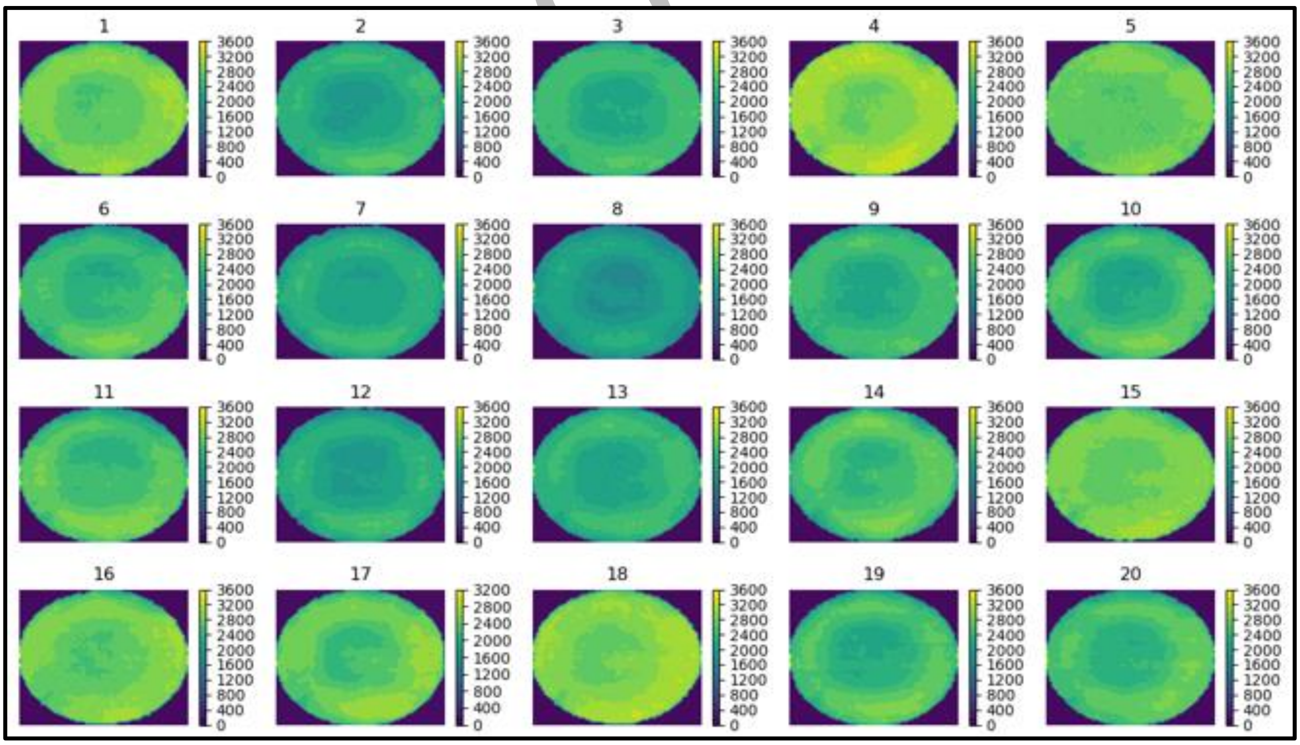

Fig. 10 Demonstrations of 20 pre-wafer samples with CP2 generated by GAN

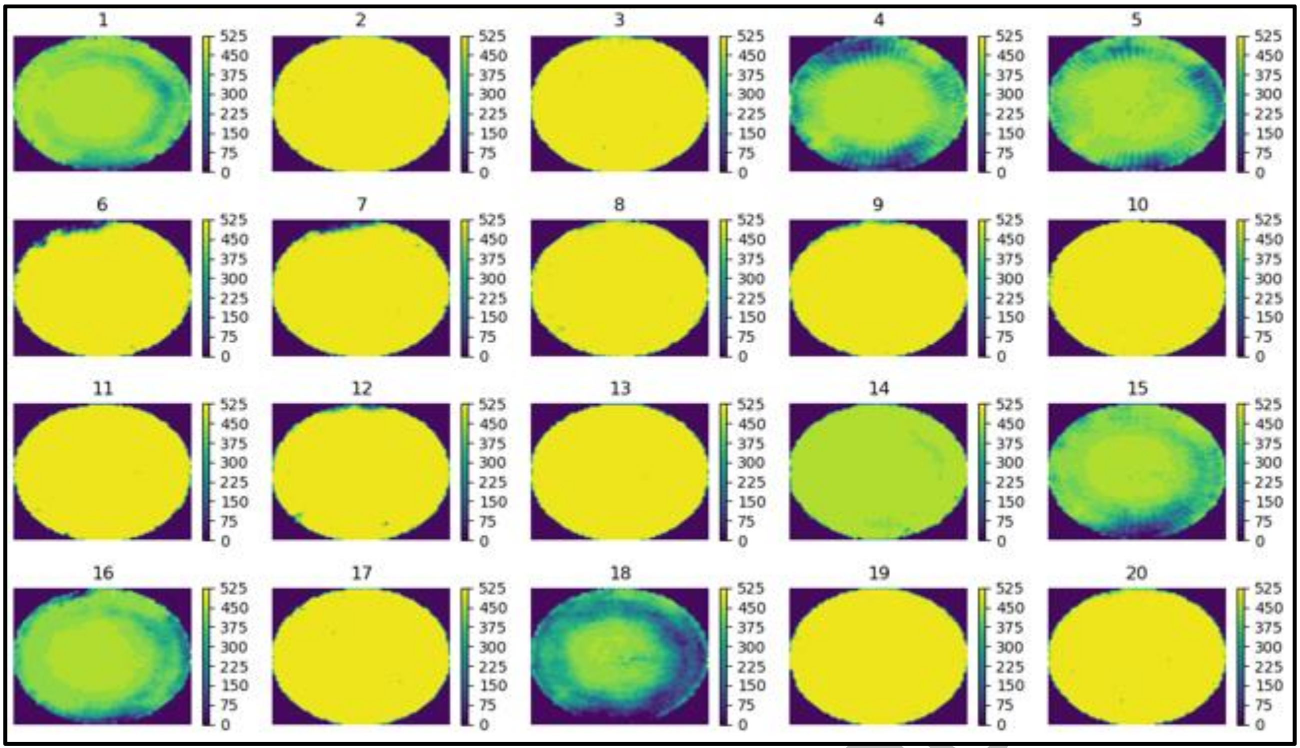

Fig. 11 Demonstrations of 20 pre-wafer samples with CP3 generated by GAN

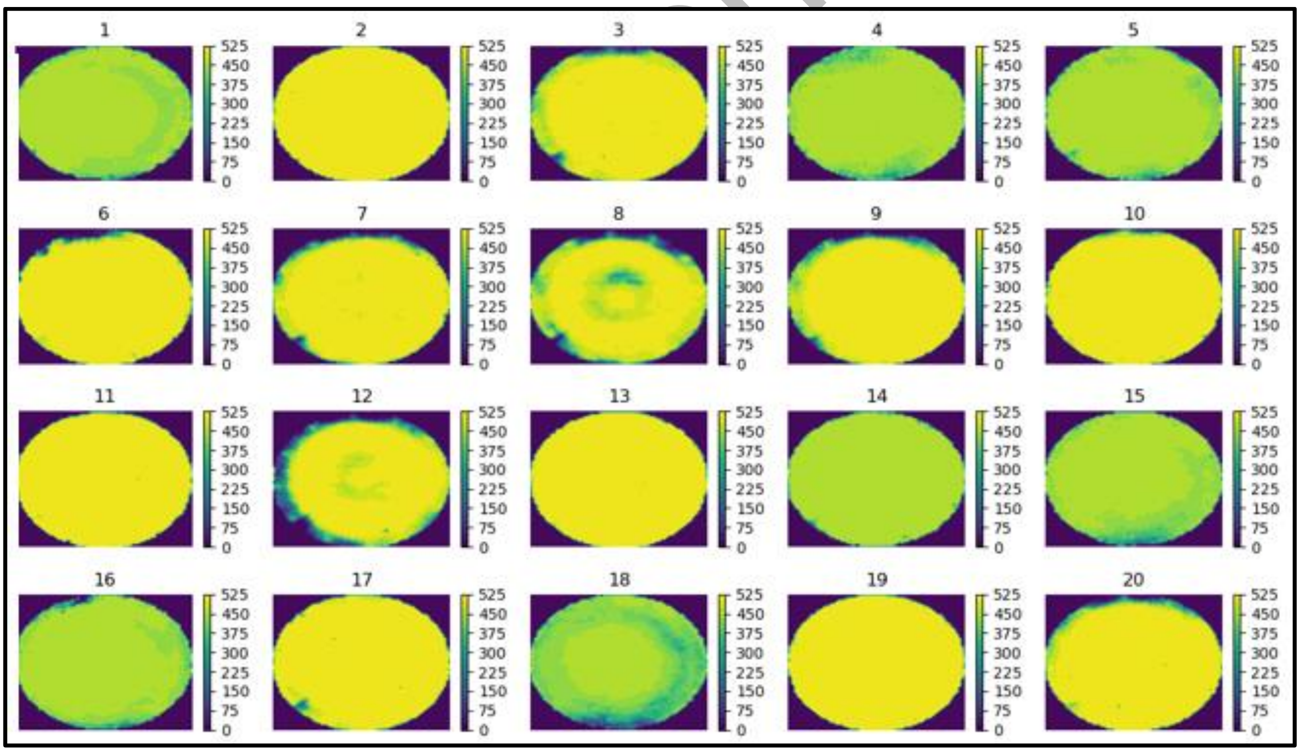

Fig. 12 Demonstrations of 20 pre-wafer samples with CP4 generated by GAN

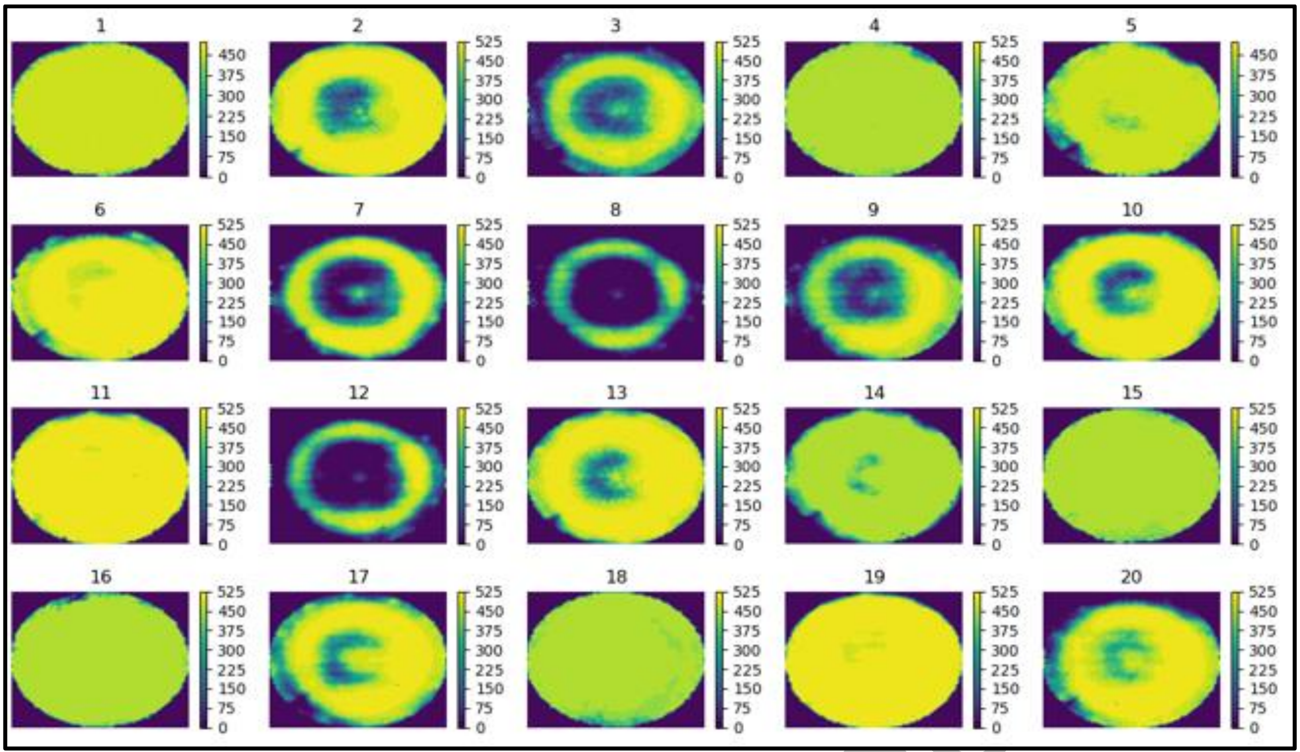

Fig. 13 Demonstrations of 20 pre-wafer samples with CP5 generated by GAN

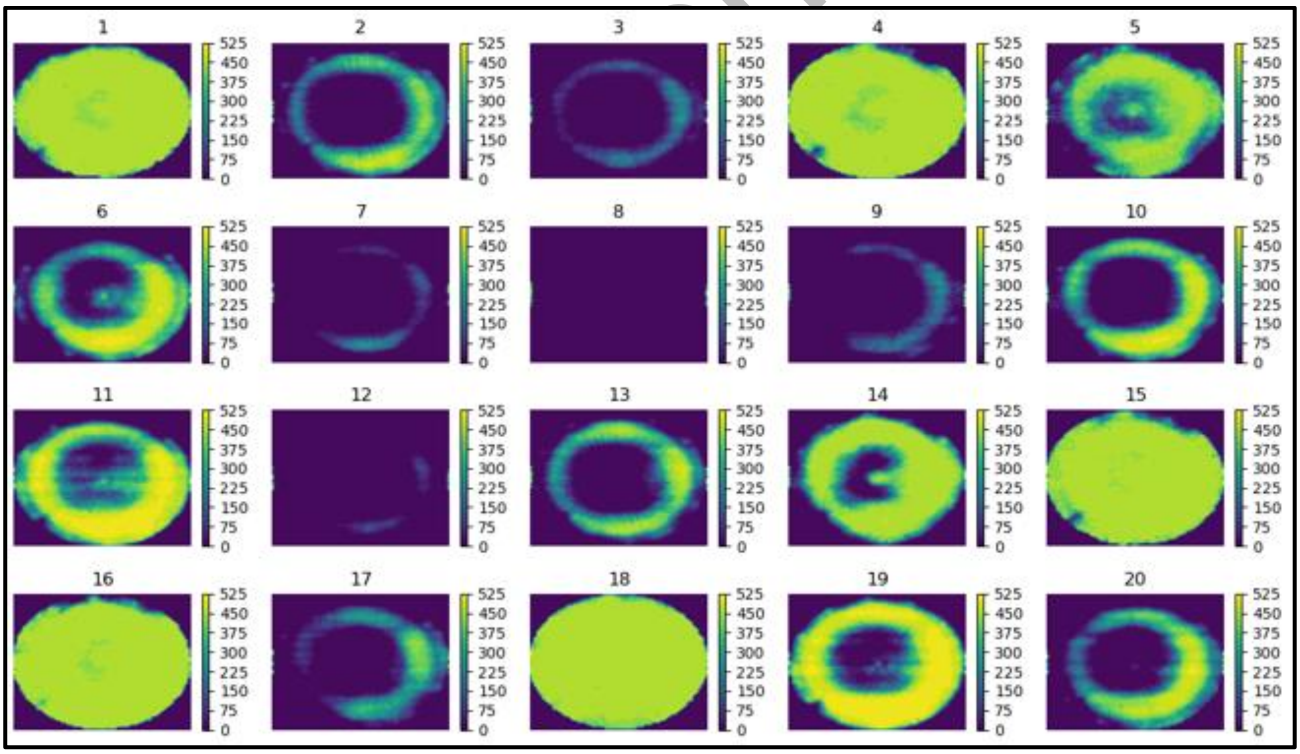

Fig. 14 Demonstrations of 20 pre-wafer samples with CP6 generated by GAN

6. Getting Started

6.1. Beginner Users

Access: Free download of one suitable sample from the website.

Purpose: To explore and familiarize themselves with the system or product.

6.2. Advanced Users

Access: Option to download 5 or 10 samples based on the chosen subscription plan.

Purpose: To gain deeper insights or leverage additional resources for professional use.

6.3. Custom Users

Access: Users requiring more samples are encouraged to contact us directly for customized solutions.

7. Customer Support and Assistance

For further assistance or to report any issues you may encounter, please reach out to our dedicated support team. Our team is committed to providing timely solutions and ensuring your experience with our system is seamless.

Contact Information:

- **AnswerXpert QA Forum:** http://172.17.20.61/post_message4.php
- **Operating Hours:** Monday to Friday, 9:00 AM - 6:00 PM (GMT)

Feel free to contact us with any questions, feedback, or concerns. We value your input and are here to help you resolve any challenges effectively.