The Development Solution for Imbalanced Image Data of Cell Circuit Dents and Film Scratches of AMOLED Mass Production

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Abstract

AMOLED is the core technology in display industry which is made through the glass substrate process. As the AMOLED's resolution becomes higher, the glass becomes thinner, circuit of panel becomes complex and protecting film becomes important. The inspection system for securing the defects of panels and the protecting film process reliability becomes an issue in the manufacturing process. Currently, the inspection is conducted manually on random samples, thus it is impossible to inspect all the defects. for full automatic AI inspection therefor, there is a need for a cutting edge technology and high-performance AI model which has been trained by a balanced training set. However, imbalanced data has been raised as a big issue in the mass production field. This paper proposes the novel solution for the imbalanced image data training model has been developed to automatically classify and determine the defects. , thereby enhancing the detection consistency of the defects. This study applies redesigned DeepSMOTE [1] based on deep learning for an inspection system for the circuits and protection films detection process. This enhanced DeepSMOTE is capable of generating high-quality, synthetic images can enhance minority classes and balance the training set. The effect of this AI model is to solve the imbalanced data and improve the performance of the inspection for the defects of the circuit and the film based on deep learning. Through this paper, the imbalanced image data is solved and the foundation of the solution for imbalanced image data technology applicable to mass production is established. In the test of mass production, finally the AI model got results that 'NG Recall 98%' performance of the model. This paper proposes the enhanced the generating model in the AMOLED mass production.

Author Keywords

Imbalanced data, DeepSMOTE [1], deep learning, oversampling, glass crack, Synthetic image

1. Introduction

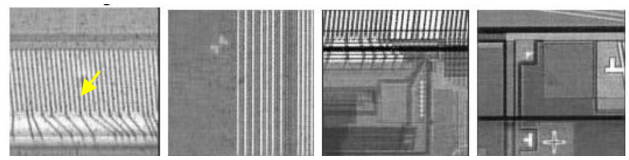
Full autonomous inspection is the core technology of the glass process in manufacturing AMOLED panels. A higher level of detection conditions for dent and scratch is needed as the resolution of products increases, and as the quantity of the AMOLED for production is also increasing, the inspection of the from BP to MOD quality is emerging as the main issue. Therefore, there is a need for a well performing deep learning model and balanced training data set.

However, it is difficult to collect mass records of balanced data in practice and the solution for the imbalanced data applied to manufacturing has not been developed at this time. In this study, the solution for imbalanced data can be applied to the autonomous full inspection and prevent defect leakage of mass production. The solution model has been developed through DeepSMOTE [1] which can be applied to mass production. Our goal is very simple and clear. Adapting Fast and light-weight AI model to the inspection process of AMOLED factory.

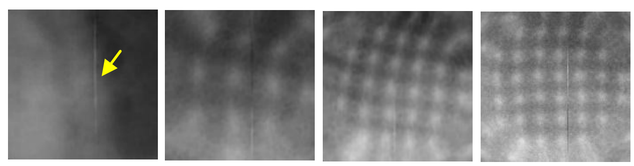
2. Defect images

Dent on the circuit and scratch on the film are main defects **Fig.1**. Compared to standard products, circuit has round shape dent and film has line scratch from top to bottom. The scratch image has grid patterns since inspection light.

The dent and scratch are occurred when mechanical problem of the device arises.



(a) Dent on circuit



(b) Scratch on film

Fig. 1. Dent and Scratch

3. DEEPSMOTE [1]

DeepSMOTE is consisted of an encoder/decoder framework, a SMOTE-based oversampling method, and a loss function with a reconstruction loss and a penalty term. Encoder/decoder framework [3]. The DeepSMOTE backbone is based on the DCGAN architecture, which was established by Radford et al [4]. Radford et al.

The encoder and decoder is trained in an end-to-end fashion. During DeepSMOTE training, an imbalanced dataset is fed to the encoder / decoder in batches. A reconstruction loss is computed on the batched data. All classes are used during training so that the encoder / decoder can learn to reconstruct both majority and minority class images from the imbalanced data. Because there are few minority class examples, majority class examples are used to train the model to learn the basic reconstruction patterns inherent in the data **Fig.2**. This approach is based on the assumption that classes share some similar characteristics (e.g., all classes represent digits or faces). Thus, for example, although the number 9 (minority class) resides in a different class than the number 0 (majority class), the model learns the basic contours of digits.

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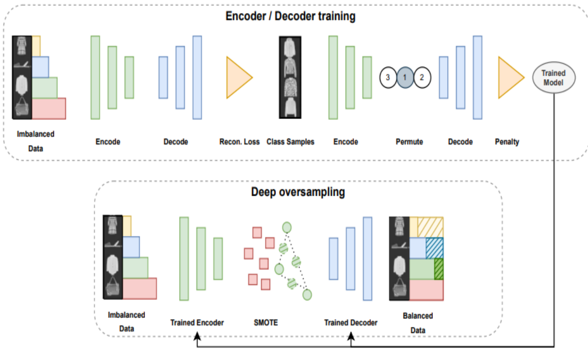


Fig. 2. Illustration of DeepSMOTE implementation.

Algorithm 1: DEEPSMOTE

Data: B: batches of imbalanced training data
$B = \{b_1, b_2, \ldots, b_n\}$
Input: Model parameters: $\Theta = \{\Theta_0, \Theta_1, \ldots, \Theta_j\}$;
Learning Rate: α
Output: Balanced training set.
Train the Encoder / Decoder:
for $e \leftarrow epochs$ **do**
  for $m \leftarrow B$ **do**
    $E_B \leftarrow encode(B)$
    $D_B \leftarrow decode(E_B)$
    $C_D \leftarrow sample(class\ data)$
    $E_S \leftarrow encode(C_D)$
    $P_E \leftarrow permute\_order(E_S)$
    $D_P \leftarrow decode(P_E)$
    $P_L = \frac{1}{n}\sum_{i=1}^{n}(D_Pi - C_{Di})^2$
    $\mathrm{T}_L = R_L + P_L$
    $\Theta := \Theta - \alpha\frac{\partial T_L}{\partial \Theta}$
Generate Samples:
for $i \leftarrow number\ of\ minority\ classes$ **do**
  $C \leftarrow select(class\ data)$
  $E \leftarrow encode(C)$
  $G \leftarrow SMOTE(E)$
  $S \leftarrow decode(G)$

4. Synthetic image generation

The model trained defect images and generated synthetic images. It has been implemented for learning minority class and generating the minority classes. We developed two Encoder-decoder frame work for the proof of the performance. Below is the described cases of the experiences process step by step and the results of split condition tests.

4-1 200*200 dent on circuit images generating

For the first time, the original circuit images (7000*2000) are too big size to train the model. Therefore, for the better performance we crop the dent images to 200*200. The generation model trained 100 dent images and generated 200 synthetic images. It has been implemented for learning minority class and generating the minority classes. We implemented and tuned the data of AMOLED mass production. Encoder/decoder of DeepSMOTE has the Convolution-Neural-Network (CNN) which has 7-layers **Fig.3**.

After the model has been learned, the DeepSMOTE generates the synthetic images **Fig.4**. They are high resolution. Fortunately, the features of the defects are generated well. It took more than 8 hours (1000 epochs) for the training.

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 8, 100, 100]	128
LeakyReLU-2	[-1, 8, 100, 100]	0
Conv2d-3	[-1, 16, 50, 50]	2,048
BatchNorm2d-4	[-1, 16, 50, 50]	32
LeakyReLU-5	[-1, 16, 50, 50]	0
Conv2d-6	[-1, 32, 25, 25]	8,192
BatchNorm2d-7	[-1, 32, 25, 25]	64
LeakyReLU-8	[-1, 32, 25, 25]	0
Conv2d-9	[-1, 64, 13, 13]	18,432
BatchNorm2d-10	[-1, 64, 13, 13]	128
LeakyReLU-11	[-1, 64, 13, 13]	0
Conv2d-12	[-1, 128, 7, 7]	73,728
BatchNorm2d-13	[-1, 128, 7, 7]	256
LeakyReLU-14	[-1, 128, 7, 7]	0
Conv2d-15	[-1, 256, 4, 4]	294,912
BatchNorm2d-16	[-1, 256, 4, 4]	512
LeakyReLU-17	[-1, 256, 4, 4]	0
Conv2d-18	[-1, 512, 1, 1]	2,097,152
BatchNorm2d-19	[-1, 512, 1, 1]	1,024
LeakyReLU-20	[-1, 512, 1, 1]	0
Linear-21	[-1, 512]	262,656
Total params	2,759,264	
Trainable params	2,759,264	
Non-trainable params	0	

(a) Encoder

Layer (type)	Output Shape	Param #
Linear-1	[-1, 1, 512]	262,656
ReLU-2	[-1, 1, 512]	0
ConvTranspose2d-3	[-1, 256, 4, 4]	2,097,408
BatchNorm2d-4	[-1, 256, 4, 4]	512
ReLU-5	[-1, 256, 4, 4]	0
ConvTranspose2d-6	[-1, 128, 7, 7]	524,416
BatchNorm2d-7	[-1, 128, 7, 7]	256
ReLU-8	[-1, 128, 7, 7]	0
ConvTranspose2d-9	[-1, 64, 13, 13]	73,792
BatchNorm2d-10	[-1, 64, 13, 13]	128
ReLU-11	[-1, 64, 13, 13]	0
ConvTranspose2d-12	[-1, 32, 25, 25]	18,464
BatchNorm2d-13	[-1, 32, 25, 25]	64
ReLU-14	[-1, 32, 25, 25]	0
ConvTranspose2d-15	[-1, 16, 50, 50]	8,208
BatchNorm2d-16	[-1, 16, 50, 50]	32
ReLU-17	[-1, 16, 50, 50]	0
ConvTranspose2d-18	[-1, 8, 100, 100]	2,056
BatchNorm2d-19	[-1, 8, 100, 100]	16
ReLU-20	[-1, 8, 100, 100]	0
ConvTranspose2d-21	[-1, 3, 200, 200]	387
Tanh-22	[-1, 3, 200, 200]	0
Total params	2,988,395	
Trainable params	2,988,395	
Non-trainable params	0	

(b) Decoder

Fig. 3. Model summary (learning rate: 0.0002, epoch: 1000, latent space: 1024)

(a) Generated synthetic dent image

Fig.4. Synthetic images dataset (200*200)

4-2 396*396 Scratch on film images generating

The generation model trained 272 line defect images and generated 2000 synthetic images. Encoder/decoder of DeepSMOTE has the Convolution-Neural-Network (CNN) which has 8-layers **Fig.5**. After the model has been learned, the DeepSMOTE generates the synthetic images **Fig.6**.

Layer (type)	Output Shape	Param #
Conv2d-1	[-1, 8, 198, 198]	128
LeakyReLU-2	[-1, 8, 198, 198]	0
Conv2d-3	[-1, 16, 99, 99]	2,048
BatchNorm2d-4	[-1, 16, 99, 99]	32
LeakyReLU-5	[-1, 16, 99, 99]	0
Conv2d-6	[-1, 32, 50, 50]	4,608
BatchNorm2d-7	[-1, 32, 50, 50]	64
LeakyReLU-8	[-1, 32, 50, 50]	0
Conv2d-9	[-1, 64, 25, 25]	32,768
BatchNorm2d-10	[-1, 64, 25, 25]	128
LeakyReLU-11	[-1, 64, 25, 25]	0
Conv2d-12	[-1, 128, 13, 13]	73,728
BatchNorm2d-13	[-1, 128, 13, 13]	256
LeakyReLU-14	[-1, 128, 13, 13]	0
Conv2d-15	[-1, 256, 7, 7]	294,912
BatchNorm2d-16	[-1, 256, 7, 7]	512
LeakyReLU-17	[-1, 256, 7, 7]	0
Conv2d-18	[-1, 512, 4, 4]	1,179,648
BatchNorm2d-19	[-1, 512, 4, 4]	1,024
LeakyReLU-20	[-1, 512, 4, 4]	0
Conv2d-21	[-1, 1024, 1, 1]	8,388,608
BatchNorm2d-22	[-1, 1024, 1, 1]	2,048
LeakyReLU-23	[-1, 1024, 1, 1]	0
Linear-24	[-1, 1024]	1,049,600
Total params:	11,030,112	
Trainable params:	11,030,112	
Non-trainable params:	0	

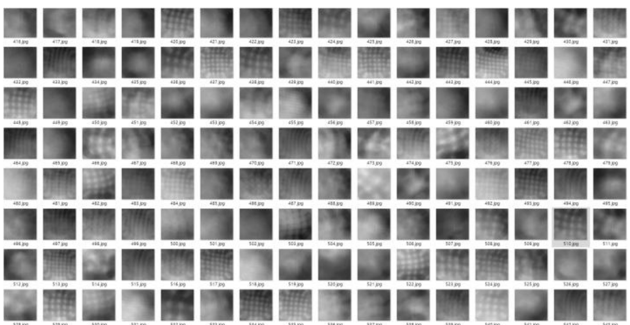
(a) Encoder

Layer (type)	Output Shape	Param #
Linear-1	[-1, 1, 1024]	1,049,600
ReLU-2	[-1, 1, 1024]	0
ConvTranspose2d-3	[-1, 512, 4, 4]	8,389,120
BatchNorm2d-4	[-1, 512, 4, 4]	1,024
ReLU-5	[-1, 512, 4, 4]	0
ConvTranspose2d-6	[-1, 256, 7, 7]	1,179,904
BatchNorm2d-7	[-1, 256, 7, 7]	512
ReLU-8	[-1, 256, 7, 7]	0
ConvTranspose2d-9	[-1, 128, 13, 13]	295,040
BatchNorm2d-10	[-1, 128, 13, 13]	256
ReLU-11	[-1, 128, 13, 13]	0
ConvTranspose2d-12	[-1, 64, 25, 25]	73,792
BatchNorm2d-13	[-1, 64, 25, 25]	128
ReLU-14	[-1, 64, 25, 25]	0
ConvTranspose2d-15	[-1, 32, 50, 50]	32,800
BatchNorm2d-16	[-1, 32, 50, 50]	64
ReLU-17	[-1, 32, 50, 50]	0
ConvTranspose2d-18	[-1, 16, 99, 99]	4,624
BatchNorm2d-19	[-1, 16, 99, 99]	32
ReLU-20	[-1, 16, 99, 99]	0
ConvTranspose2d-21	[-1, 8, 198, 198]	2,056
BatchNorm2d-22	[-1, 8, 198, 198]	16
ReLU-23	[-1, 8, 198, 198]	0
ConvTranspose2d-24	[-1, 1, 396, 396]	129
Tanh-25	[-1, 1, 396, 396]	0
Total params:	11,029,097	
Trainable params:	11,029,097	
Non-trainable params:	0	

(b) Decoder

Fig. 5. Model summary (learning rate: 0.0002, epoch: 1000, latent space: 1024)

As the image size increased, the resolution also improved.



(a) Generated synthetic scratch images

Fig. 6. Synthetic images dataset (396*396)

5. Classification model test

During the test, we used the Testset (OK: 2724, NG: 949) with some classification models. The most highly evaluated indicator is recall. In factories, leakage is a top priority and is a major factor-affecting yield, so it was tested based on recall. In the test, InceptionV3 performed best so it selected as the best classification model **TABLE 1**.

TABLE 1. Result of the Classification models

Testset#1	**Inception V3**		ResNet50		EfficientNetB5		XCeption	
Actual / Predict	OK	NG	OK	NG	OK	NG	OK	NG
OK	2457	267	2538	186	2378	346	2487	237
NG	22	927	119	830	60	889	29	920
Accuracy	92.13%		91.70%		88.95%		92.76%	
Precision	90.20%		93.17%		87.30%		91.30%	
Recall	**99.11%**		95.52%		97.54%		98.85%	
F1-score	94.46%		94.33%		92.13%		94.92%	

6. Result of InceptionV3 with synthetics

For a clearer result, the model has tested another test set. We secured new testset images. This is from another process line and the model has never trained even a single image of the line data set. It proves that the model trained with synthetic images is state-of-the-art class and is optimized for mass production since there is less leakage of NG image.

Table 2. Result of the InceptionV3 trained with synthetics

Testset#2	**Trained only trainset**		**Trained trainset+synthetics**	
Actual / Predict	OK	NG	NG	OK
OK	65	213	273	5
NG	12	216	21	207
Accuracy	55.53%		94.86%	
Precision	23.38%		98.20%	
Recall	84.42%		**92.86%**	
F1-score	36.62%		95.45%	

8. Conclusion

The solution for imbalanced data is essential to be able to apply deep learning model of high performance. This is because mass production is still suffering from imbalanced data. The good performance model needs a balanced data set to train. In practice, gathering balanced data is impossible since no defected data is acceptable to the production line. If it was, the line would not be operating.

In this paper, we are focus about imbalanced data in the mass production field. Through this study, it is possible to get balanced data. For the training of the model, balanced data is one of the most important requirements. Thus, we studied how to solve the matter and developed the solution. It will be helpful to get a balanced dataset for the process engineers. We propose the solution for imbalanced data in the manufacturing of AMOLED mass production. It makes it possible to stabilize the yield, automatically fully inspect to prevent leakage of cracked and broken glasses, and enables full automation logistics in the factory. Through this study, the solution for imbalanced data has established the standard cutting edge technology of the smart factory.

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