SAKARYA ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ DERGİSİ

Sakarya University Journal of Science
SAUJS

ISSN 1301-4048 e-ISSN 2147-835X Period Bimonthly Founded 1997 Publisher Sakarya University
http://www.saujs.sakarya.edu.tr/

Title: A Novel Deep Learning Method for Detecting Defects in Mobile Phone Screen Surface Based on Machine Vision

Authors: İsmail AKGÜL

Recieved: 2022-12-19 00:00:00

Accepted: 2023-02-06 00:00:00

Article Type: Research Article

Volume: 27
Issue: 2
Month: April
Year: 2023
Pages: 442-451

How to cite
İsmail AKGÜL; (2023), A Novel Deep Learning Method for Detecting Defects in Mobile Phone Screen Surface Based on Machine Vision . Sakarya University Journal of Science, 27(2), 442-451, DOI: 10.16984/saufenbilder.1221346
Access link
https://dergipark.org.tr/en/pub/saufenbilder/issue/76551/1221346

Sakarya University Journal of Science 27(2), 442-451, 2023

A Novel Deep Learning Method for Detecting Defects in Mobile Phone Screen Surface Based on Machine Vision

İsmail AKGÜL*[1]

Abstract

With the innovations in technology, the interest in the use of mobile devices is increasing day by day. Any defect that may occur during the production of smart mobile phones, which is among mobile devices, causes significant damage to both the manufacturer and the user. The careful detection of defects that may occur on the screen glass, which is one of the most striking defects among these defects, with the human eye significantly affects the workforce cost. Therefore, it is important to detect defects with the help of software. In recent years, many methods based on machine vision have been developed for the detection of any object or difference in the image.

In this study, a new model structure called Yolo-MSD, based on machine vision and the Yolo-v3 deep learning model, which detects and classifies oil, scratch, and stain defect types on the glass on the touch screen surface used in the design of smart mobile phones, is proposed. The proposed model structure (Yolo-MSD) is obtained by reducing the number of blocks in the Darknet-53 network structure developed in Yolo-v3. As a result of the training, a success rate of 98.50% with the Yolo-v3 model and 98.72% with the Yolo-MSD model was achieved in detecting and classifying defect types. Therefore, it has been observed that the Yolo-MSD model structure is better than the Yolo-v3 model structure by making better feature extraction from the types of defects on the screen glass since it is both faster and has less complexity.

Keywords: Machine vision, deep learning, Yolo-v3, Yolo-MSD, defect detection

1. INTRODUCTION

The use of mobile devices, which play an important role in the development of the world, is increasing day by day with the development of technology. The development of smart mobile phones, which is among mobile devices, and which is one of the most important inventions of our age, has greatly facilitated human life. The development of touch screens in the design of smart mobile phones has provided convenience for all users, and has increased the use, efficiency, and interaction of smart mobile phones, providing a more convenient and faster workflow. The quality and flawlessness of the screen glass in the touch screen design play an important role in the production process of smart mobile phones [1]. Therefore, the slightest defect that may occur on the touch screen surface during the production of smartphones causes more

* Corresponding author: iakgul@erzincan.edu.tr
[1] Erzincan Binali Yıldırım University, Department of Computer Engineering
ORCID: https://orcid.org/0000-0003-2689-8675

defects or damages during the use of smartphones [2].

For this reason, it is necessary to carefully examine the screen surface with the human eye to detect any defects that may occur on the touch screen surface during the production of smart mobile phones [3-5]. This situation causes both loss of time and slower production for industrial organizations producing smart mobile phones [6-8]. Therefore, a machine vision system is needed to detect the defects in the glass on the touch screen surface of smart mobile phones efficiently and quickly.

Machine vision is a set of systems that reduce the defects in many application processes performed by machines and, accordingly, have the ability to make quick decisions [9-11]. In recent years, in parallel with the developments in the field of technology, many artificial intelligence-based methods for defect detection in the industry have been developed and successful results have been obtained [12-15].

In this study, a new model structure (Yolo-MSD) based on machine vision and Yolo-v3 deep learning is proposed to detect the defects on the glass on the touch screen surface used in the design of smart mobile phones. Yolo-v3 and proposed Yolo-MSD deep learning methods were trained separately using a dataset containing 3 types of screen surface defects (oil, scratch, and stain), and the defects occurring on the smart mobile phone surface were detected and classified. The remainder of the study is organized as follows. In Chapter 2, studies on the detection of defects on the surface of smart mobile phones are examined and discussed. Materials and methods related to the study are presented in Chapter 3, and experimental results and discussions are presented in detail in Chapter 4. In Chapter 5, information about the results of the study and future studies is given.

2. RELATED WORKS

In this section, the studies carried out in recent years in detecting the defects on the surface of mobile phones are examined in detail.

Jian et al. developed an improved fuzzy c-means cluster algorithm to detect defects in mobile phone screen glass. Thanks to the developed algorithm, defects on the screen glass of the mobile phone were detected in 1.6601 seconds, with success rates of 94% sensitivity and 97.33% specificity [1]. In their study, Park & Kweon proposed a multi-class classification model to classify the defects on the screen panel surface used in smartphones. In the proposed model, a new filter method that was successful under various conditions was used and successful results were obtained [16].

Wang et al. proposed a deep learning model based on Faster R-CNN to detect defects on the mobile phone surface. In the proposed model, the feature pyramid network and the ResNet-101 model are combined to detect smaller defects. However, to reduce the quantization deviation, the RoI Pooling layer was replaced with the RoI Align layer and a 99.43% mAP success rate was achieved in detecting defects [17]. Li et al., in their study, proposed a new algorithm to detect and classify mobile phone screen defects. Successful results were obtained by proposing a clustering algorithm to prevent false detection and a classification algorithm that combines multi-layer perceptron and deep learning for classification [18].

Zhang et al., in their study, proposed a method called FDSNet to detect defects on the mobile phone screen in real-time. The proposed method has shown successful results in detecting defects on the mobile phone screen [19].

Wang et al. obtained successful results by using many methods including morphological filter, gamma grayscale, threshold segmentation, and binary tree classifier to classify defects (scratch, bruise, pit, and blister) on the mobile phone screen [20]. Jianguo et al., on the other hand, proposed a method based on machine vision to detect scratches on the mobile phone screen and achieved a success rate of 98.7% [21].

3. MATERIALS AND METHODS

3.1. Dataset and Preprocessing

In the study, a Mobile phone screen Surface Defect (MSD) dataset containing 3 types of surface defects (oil, scratch, and stain) was used to detect and classify the defects on the screen surfaces of smart mobile phones. In this dataset, there are 1200 images in total, 400 images with 1920×1080×3 pixel size for each defect type [19, 22]. 960 images in the Train-Val in the dataset were combined and used for the train, and 240 images in the Test were used for the test. Example images of each defect type in the data set are shown in Figure 1.

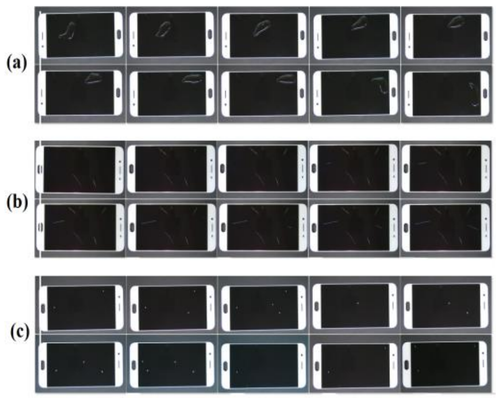


Figure 1 Sample images of defect types in the dataset (a) oil, (b) scratch, (c) stain

The pixel size of each defect type image in the dataset was preprocessed by reducing it by ¼ in a way that the width and height ratio was maintained. As a result of preprocessing, each defect type image is reduced to 480×270×3 pixels. In addition, to train the Yolo models, the coordinates of each defect type were labeled manually with the help of the LabelImg [23] program. The number of labels obtained for each defect type as a result of labeling is given in Table 1.

Table 1 Number of labels for each type of defect in the dataset

Types of defects	Number of defect type labels in the dataset		
	Train	**Test**	**Total**
Oil	441	115	556
Scratch	1096	288	1384
Stain	879	247	1126
Total	**2416**	**650**	**3066**

3.2. Yolo-MSD Model Structure

In the study, Yolo-v3 [24] deep learning model is based on to successfully detecting and classifying oil, scratch, and stain defects in the dataset. By changing this model structure, a new model structure (Yolo-MSD) based on Yolo-v3 has been proposed for better feature extraction in defect types. Layer structures used in Yolo-v3 and Yolo-MSD architectures are given in detail in Table 2

When Table 2 is examined, the number of layers is reduced by reducing the number of 7th Block ×4, 9th Block ×4 and 11th Block ×2 repetitions in the Darknet-53 network structure of the proposed Yolo-MSD model. The Yolo-v3 model structure, which has 106 layers, was reduced to 76 layers and the Yolo-MSD model structure was created.

Therefore, by using fewer layers in the Yolo-MSD model, its complexity is reduced compared to the Yolo-v3 model. In this way, both better feature extraction has been achieved and a model structure has been created that can be trained faster.

Table 2 Yolo-v3 and Yolo-MSD model structures

Blok	Type	Filters	Size/Stride	Output	Repeat Yolo-v3	Repeat Yolo-MSD
1	Convolutional	32	3×3/1	416×416×32		
2	Convolutional	64	3×3/2	208×208×64		
3	Convolutional Convolutional Residual	32 64	1×1/1 3×3/1	208×208×32 208×208×32 208×208×64	×1	×1
4	Convolutional	128	3×3/2	104×104×128		
5	Convolutional Convolutional Residual	64 128	1×1/1 3×3/1	104×104×64 104×104×128 104×104×128	×2	×2
6	Convolutional	256	3×3/2	52×52×256		
7	Convolutional Convolutional Residual	128 256	1×1/1 3×3/1	52×52×128 52×52×256 52×52×256	×8	×4
8	Convolutional	512	3×3/2	26×26×512		
9	Convolutional Convolutional Residual	256 512	1×1/1 3×3/1	26×26×256 26×26×512 26×26×512	×8	×4
10	Convolutional	1024	3×3/2	13×13×1024		
11	Convolutional Convolutional Residual	512 1024	1×1/1 3×3/1	13×13×512 13×13×1024 13×13×1024	×4	×2
	Detection Layers				82 94 106	52 64 76

The training and analysis of the Yolo-v3 and Yolo-MSD model structures were carried out in the Python programming language using the TensorFlow library in the Google Colaboratory [25] environment. Thus, the success of Yolo-v3 and Yolo-MSD models were compared using images containing 3 different defect types in the dataset. To compare the models, the train-test parameters given in Table 3 were used in both models.

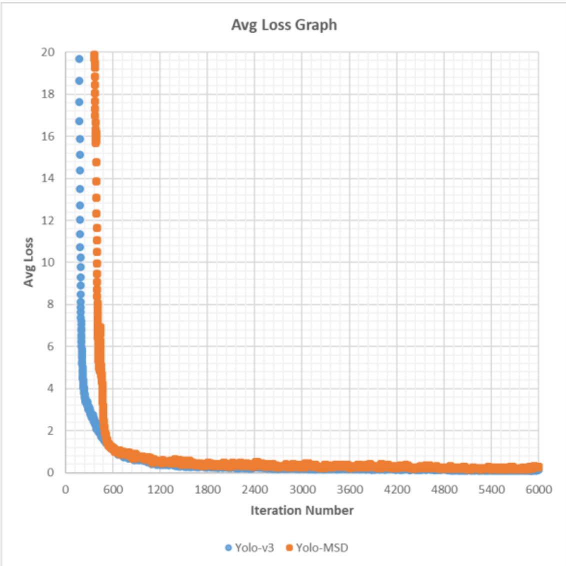
4. RESULTS AND DISCUSSION

In the study, Yolo-v3 and the proposed Yolo-MSD deep learning methods were trained and tested using the parameters given in Table 3 to efficiently detect and classify the defects on the glass on the screen surface of smart mobile phones. To determine the validity of the training and testing results of the Yolo-v3 and Yolo-MSD model structures, each model was trained 5 times separately. As a result of training and testing, the Yolo-v3 model showed a learning success between 98.38% and 98.50%. The Yolo-MSD model, on the other hand, achieved a learning success between 98.45% and 98.72%. Average Loss, mAP@0.50, and Average IoU graphs of the best training and

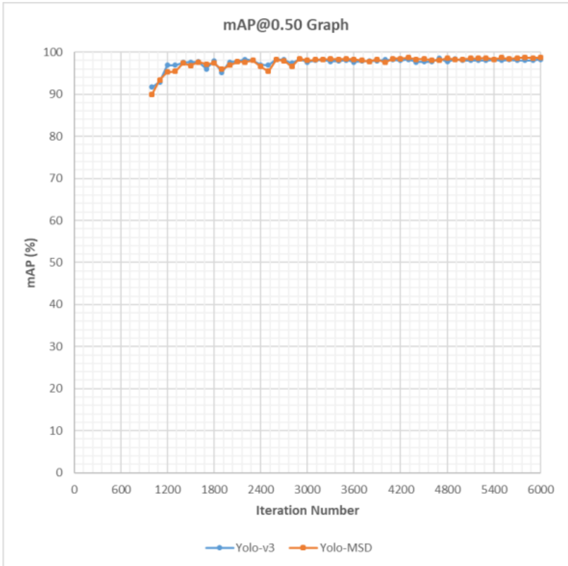
Table 3 Parameters used in training Yolo-v3 and Yolo-MSD model structures

Parameters	Values
Batch	64
Subdivisions	16
Mini Batch Size	4
Width	416
Height	416
Channels	3
Momentum	0.9
Decay	0.0005
Angle	0
Saturation	1.5
Exposure	1.5
Hue	0.1
Learning Rate	0.001
Burn In	1000
Max Batches	6000
Steps	4800, 5400
Activation Function	Leaky

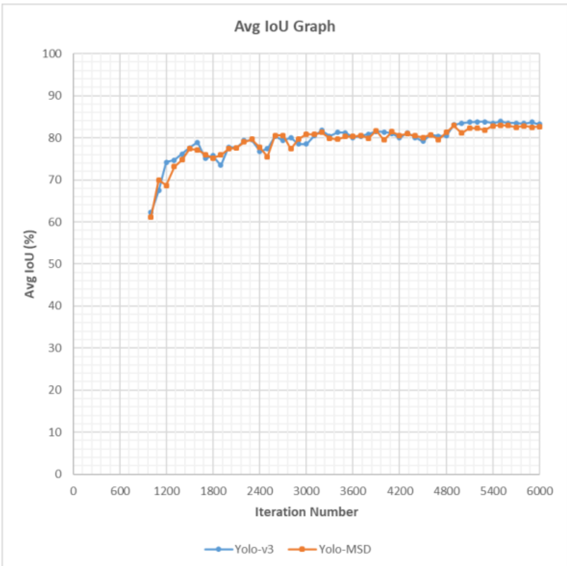
test result obtained by running 5 times are given in Figure 2. The model was recorded in the epoch with the best result from the training and testing process carried out during 6000 epochs. All analyzes and performance tests were performed according to the best-recorded model and all metric measures obtained are given in Table 4 comparatively.



(a)



(b)



(c)

Figure 2 Comparative graphics obtained as a result of training and testing the Yolo-v3 and Yolo-MSD model structures (a) Average Loss, (b) mAP@0.50, (c) Average IoU

Table 4 Metric criteria obtained as a result of training and testing Yolo-v3 and Yolo-MSD model structures

Metric Criteria	Models	
	Yolo-v3	**Yolo-MSD**
Best Epoch	4700	4300
Average Loss	0,145222	0,272315
mAP@0.50	98.50	98.72
Average IoU	80.34	80.93
Precision	1.00	0.99
Recall	0.98	0.98
F1-Score	0.99	0.99
Total Training Time	34,433.124 sec.	26,391.039 sec.
Support	650	650

According to the results obtained in Figure 2 and Table 4, the Yolo-v3 model achieved success values of 98.50% mAP, 80.34% Average IoU, and 0.145222 Average Loss as a result of 4700 epochs. The proposed Yolo-MSD model, on the other hand, achieved success values of 98.72% mAP, 80.93% Average IoU, and 0.272315 Average Loss as a result of 4300 epochs. According to the results obtained, the proposed Yolo-MSD model achieved more successful results as a result of fewer epochs. It is seen that the proposed model is better than the Yolo-v3 model as a result of training and testing.

Therefore, with the proposed Yolo-MSD model, a more advantageous model structure has been obtained compared to the Yolo-v3 model due to its speed and low complexity of the model structure, depending on the number of layers used in training and testing the defect types.

Table 5 Classification rates by defect type as a result of training and testing Yolo-v3 and Yolo-MSD models (AP: Average Precision, mAP: Mean Average Precision)

Dataset Classes	AP	
	Yolo-v3	**Yolo-MSD**
Oil	98.15%	98.06%
Scratch	98.61%	98.94%
Stain	98.74%	99.16%
mAP@0.50	**98.50%**	**98.72%**

In addition, as a result of the training and testing of the Yolo-v3 and Yolo-MSD models, the classification rates according to the defect type were obtained to determine the rate at which each defect type was classified, and the details are given in Table 5.

4.1. Performance Testing of Yolo-v3 and Yolo-MSD Models

Performance tests were conducted for each model structure to test the validity of the Yolo-v3 and Yolo-MSD models discussed in the study on real-life performance. As a result of the performance tests, sample images of oil, scratch, and stain defect types on the screen glass surface of smart mobile phones are given in Figure 3.

In addition, the proposed Yolo-MSD method for detecting and classifying the defects on the screen surface of smart mobile phones has been compared with different methods in the literature, and the comparison results are given in Table 6 in detail. In the study, it is seen that the proposed Yolo-MSD model structure gives better results than many different model structures when the successful results obtained in the training, testing, and performance testing stages are taken into consideration

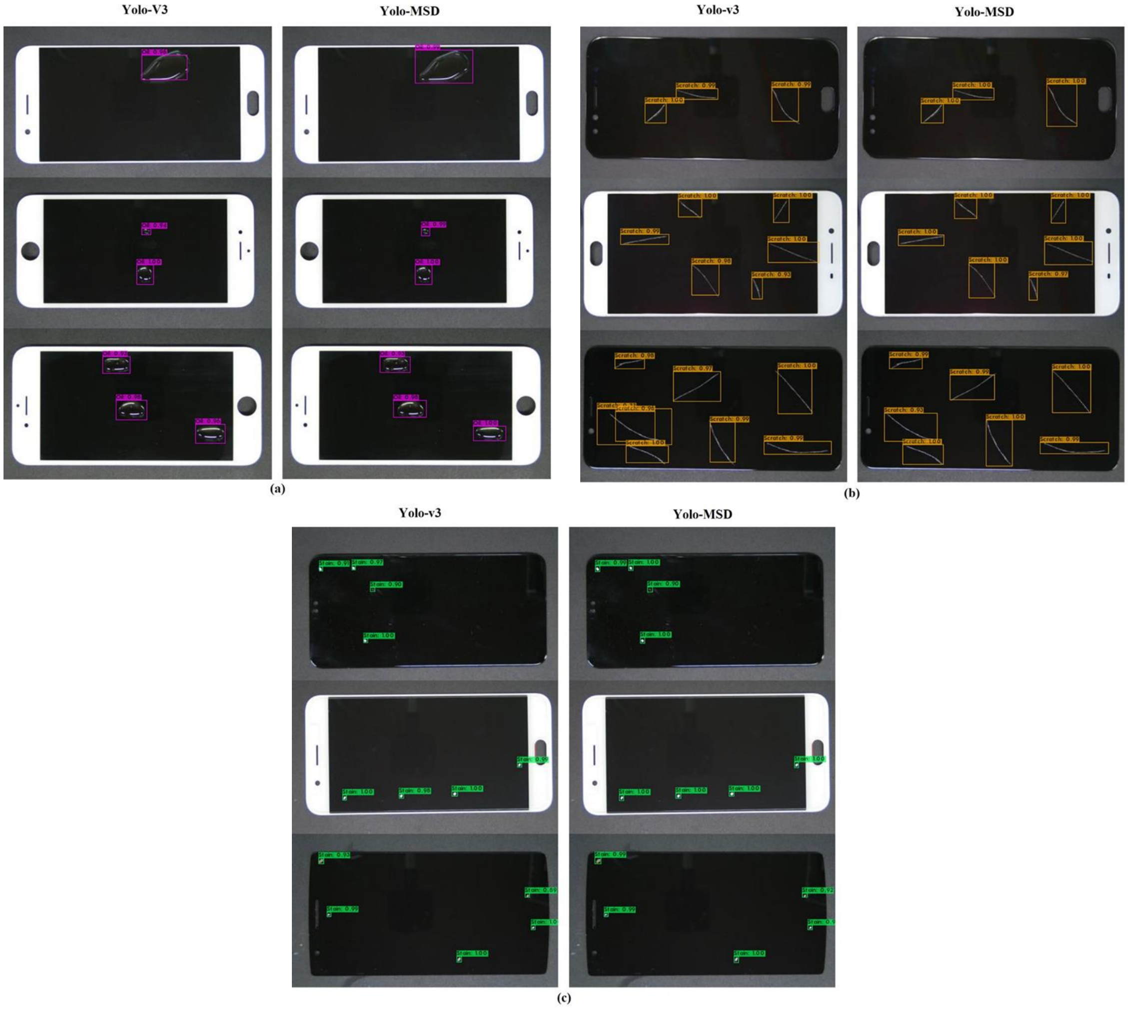


Figure 3 Sample images of performance test results of Yolo-v3 and Yolo-MSD models (a) oil, (b) scratch, (c) stain

Table 6 Comparison of the proposed method with different methods for detecting defects on the screen surface of smart mobile phones

Ref.	Models	Dataset	Success Rate
[7]	HMFCA-Net	MPSSD DAGM	83.75% 98.41%
[8]	EU-Net	Dataset consists of scratches and bubbles	70.2%
[13]	GoogLeNet	Dataset consists of the positive sample, point defect, and linear defect	98%
[17]	Faster R-CNN (ResNet101)	Dataset consists of screen scratches, edge defects, point defects, and stripe dents	99.43%
[19]	FDSNet	Magnetic-tile-defect-datasets NEU-Seg MSD	63.90% 78.80% 90.20%
The proposed method	**Yolo-MSD**	**MSD**	**98.72%**

5. CONCLUSION

In this study, a new Yolo-MSD model based on machine vision and Yolo-v3 deep learning model has been developed to detect and classify defects on the glass on the touch screen surface used in the design of smart mobile phones. Yolo-v3 and the developed Yolo-MSD deep learning methods were compared by training-testing 5 times using the same parameters. As a result of the comparisons, the Yolo-v3 model showed a learning success between 98.38% and 98.50%, and the Yolo-MSD model showed a learning success between 98.45% and 98.72%. However, it has been observed that the developed Yolo-MSD model is both faster and less complex than the Yolo-v3 model.

According to the experimental results obtained, Yolo-MSD is the method that detects and classifies the types of oil, scratch, and stain defects that occur on the surface of the smart mobile phone with a success rate of 98.72%. Therefore, it is thought that the Yolo-MSD deep learning method developed in the study provides successful results in detecting and classifying the defects on the surface of smart mobile phones, and accordingly, it will help industrial organizations produce smart mobile phones in terms of both time and higher quality production. It is expected that a real-time method will be realized by using different methods and different datasets for the detection and classification of different types of defects that will occur on the smartphone surface in the future.

Funding

The author has no received any financial support for the research, authorship or publication of this study.

The Declaration of Conflict of Interest/ Common Interest

No conflict of interest or common interest has been declared by the author.

The Declaration of Ethics Committee Approval

This study does not require ethics committee permission or any special permission.

The Declaration of Research and Publication Ethics

The author of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication envirnment other than Sakarya University Journal of Science.

REFERENCES

[1] C. Jian, J. Gao, Y. Ao, “Automatic surface defect detection for mobile phone screen glass based on machine vision,” Applied Soft Computing, vol. 52, pp. 348-358, 2017.

[2] L. Meiju, Z. Rui, G. Xifeng, Z. Junrui, “Application of improved Otsu threshold segmentation algorithm in mobile phone screen defect detection,” In 2020 Chinese Control And Decision Conference (CCDC), Hefei, 2020, pp. 4919-4924.

[3] L. Yuan, Z. Zhang, X. Tao, “The development and prospect of surface defect detection based on vision measurement method,” In 2016 12th World Congress on Intelligent Control and Automation (WCICA), Guilin, 2016, pp. 1382-1387.

[4] Z. C. Yuan, Z. T. Zhang, H. Su, L. Zhang, F. Shen, F. Zhang, “Vision-based defect detection for mobile phone cover glass using deep neural networks,” International Journal of

Precision Engineering and Manufacturing, vol. 19, no. 6, 2018.

[5] Y. Lv, L. Ma, H. Jiang, “A mobile phone screen cover glass defect detection model based on small samples learning,” In 2019 IEEE 4th International Conference on Signal and Image Processing (ICSIP), Wuxi, 2019, pp. 1055-1059.

[6] J. Jiang, P. Cao, Z. Lu, W. Lou, Y. Yang, “Surface defect detection for mobile phone back glass based on symmetric convolutional neural network deep learning,” Applied Sciences, vol. 10, no. 10, pp. 1-13, 2020.

[7] Y. Zhu, R. Ding, W. Huang, P. Wei, G. Yang, Y. Wang, “HMFCA-Net: Hierarchical multi-frequency based Channel attention net for mobile phone surface defect detection,” Pattern Recognition Letters, vol.153, pp. 118-125, 2022.

[8] J. Pan, D. Zeng, Q. Tan, Z. Wu, Z. Ren, “EU-Net: A novel semantic segmentation architecture for surface defect detection of mobile phone screens,” IET Image Processing, vol. 6, pp. 2568–2576, 2022.

[9] J. Zhang, Y. Li, C. Zuo, M. Xing, “Defect detection of mobile phone screen based on improved difference image method,” In 2019 International Conference on Intelligent Informatics and Biomedical Sciences (ICIIBMS), Shanghai, 2019, pp. 86-92.

[10] Z. Ren, F. Fang, N. Yan, Y. Wu, “State of the art in defect detection based on machine vision,” International Journal of Precision Engineering and Manufacturing-Green Technology, vol. *9*, pp. 661–691, 2021.

[11] M. Eshkevari, M. J. Rezaee, M. Zarinbal, H. Izadbakhsh, “Automatic dimensional defect detection for glass vials based on machine vision: A heuristic segmentation method,” Journal of Manufacturing Processes, vol. 68, pp. 973-989, 2021.

[12] C., Jian, J. Gao, Y. Ao, “Imbalanced defect classification for mobile phone screen glass using multifractal features and a new sampling method,” Multimedia Tools and Applications, vol. 76, no. 22, 24413-24434, 2017.

[13] H. Chen, “CNN-based surface defect detection of smartphone protective screen,” 3rd International Symposium on Big Data and Applied Statistics, Kunming, China, 2020, pp. 1-7.

[14] S. Qi, J. Yang, Z. Zhong, “A review on industrial surface defect detection based on deep learning technology,” In 2020 the 3rd international conference on machine learning and machine intelligence, Hangzhou, China, 2020, pp. 24-30.

[15] W. Huang, C. Zhang, X. Wu, J. Shen, Y. Li, “The detection of defects in ceramic cell phone backplane with embedded system,” Measurement, vol. 181 no. 2021, pp. 1-7, 2021.

[16] Y. Park, I. S. Kweon, “Ambiguous surface defect image classification of AMOLED displays in smartphones,” IEEE Transactions on Industrial Informatics, vol. 12, no. 2, pp. 597-607, 2016.

[17] T. Wang, C. Zhang, R. Ding, G. Yang, “Mobile phone surface defect detection based on improved faster r-cnn,” In 2020 25th International Conference on Pattern Recognition (ICPR), Milan, 2021, pp. 9371-9377.

[18] C. Li, X. Zhang, Y. Huang, C. Tang, S. Fatikow, "A novel algorithm for defect extraction and classification of mobile phone screen based on machine vision," Computers & Industrial Engineering, vol. 146, no. 2020, pp. 1-14, 2020.

[19] J. Zhang, R. Ding, M. Ban, T. Guo, "FDSNeT: An Accurate Real-Time Surface Defect Segmentation Network," In ICASSP 2022-2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP), Singapore, 2022, pp. 3803-3807

[20] C. Wang, C. Li, Y. Huang, X. Zhang, "Surface defect inspection and classification for glass screen of mobile phone," In Tenth International Conference on Graphics and Image Processing (ICGIP 2018), Chengdu, 2019, pp. 527-536.

[21] Z. Jianguo, L. Ying, Q. Jiakun, J. Tiantian, L. Jun, "Surface scratch detection of mobile phone screen based on machine vision," Journal of Applied Optics, vol. 41, no. 5, pp. 984-989, 2020.

[22] "Github", Nov. 02, 2022. [Online]. Available:https://github.com/jianzhang96/MSD

[23] D. Tzutalin, "LabelImg", Nov. 8, 2022. [Online]. Available: https://github.com/tzutalin/labelImg

[24] J. Redmon, A. Farhadi, "Yolov3: An incremental improvement," arXiv preprint, pp. 1-6, 2018.

[25] Google Colaboratory, "Colab", Nov. 11, 2022. [Online]. Available: https://colab.research.google.com