Machine vision-based cutting process for LCD glass defect detection system

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Abstract
In this research, the automatic optical detection system is developed for detecting the sectional profile and the surface of the thin-film transistor liquid crystal display (TFT-LCD) panels after being treated through the cutting process. Traditional image processing inspection relying on pre-determined thresholding cannot achieve ideal results in slight defects in glass substrates. The proposed image pre-processing process was integrated with the deep learning technique to further enhance the detection process of inconspicuous defects in glass substrates. In addition, the photoelastic reflection lighting technique was used to highlight subtle defects in low-contrast surface images of glass substrates. When tested with the sectional profile photodetector, uniformed lighting effect is achieved by combining the concentrated light source of the inner coaxial lens with the line light source in order to test the surface coarseness-related characteristics of the glass sectional profile so as to indicate the defect while intensifying the contrast effect of the sectional profile background. When detecting the sectional profile defect, Auto Encoder network model of the deep learning is used to learn the background picture retrieved from the original picture through the linear regression process. As a next step, the model is used again to predict the result by subtracting the background picture from the original picture, and then the defect position is highlighted; as a result, 98% accuracy is achieved. When detecting the model acceleration, it is conducted by revising the model weighting data format. In terms of U-Net Model, the reading time has been shortened for 4.28 s; in individual picture, the prediction time has been shortened for 0.29 s; in Auto Encoder, the model reading time has been shortened for 19.23 s; and the individual picture prediction time has been shortened for 0.94 s. As for the surface detection, the circular polariscope is developed. During the detection, the photoelastic reflection theory is employed by projecting the circularly polarized light vertically onto the panel surface in order to produce the interfering halo at the deformed area surrounding the denting defect, and the resulting features are referenced to identify the denting defect. By screening the mean luminance value of the sliding window and the discrete value, 90% detection accuracy can be achieved. In the meantime, it can also be used to pinpoint the denting defect that is over 3° in average angle change as seen on the normal line surrounding the defect.

Keywords Feature detection · Defect detection · Deep learning · Model acceleration · Reflective photoelasticity method

1 Preface

1.1 Introduction
In recent years, the demand for the TFT-LCD is soaring along with the rapid development of consumer electronic products [1]. Nowadays, the panel industry is gradually putting their focus on lighter, thinner, and curving panel [2] that the defect resulting from the panel cutting would pose greater influence to the success of panel packaging. Due to this reason, the panel defect detection after cutting has become one of the key items in panel manufacturing process [3] in recent years. The following two factors are the main reasons that will cause the panel fracturing during the packaging process [4]. The first is the panel cutting quality where defect is easily formed at the sectional profile during the panel cutting process due to poorer cutting parameters of the cutter wheel, damage of the cutter wheel, and the

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panel moving actions. Another reason is the surface denting defect, and it is mainly caused during the panel moving and cleaning process where the surface crashing and scratching damage would be easily created by the debris produced during the panel cutting process. The aforesaid factors are the reasons causing the weakening of panel strength that will lead to the fracturing failure during the subsequent bending test and packaging. Currently, the production line is detected mainly by manual random inspection method. Such method will easily invite higher cost, lower efficiency, and higher omission issues. Because the cutting will be executed by individual lot type, it may result in massive loss of materials when detecting the defective test piece as to affect the panel output.

During the cutting processes of glass substrates that may produce the sectional profile and surface defects in TFT-LCD [5]. In terms of sectional profile photodetector design, the research conducted by Lin in 2002 [6] is referenced, and it is learned that in the modern automated optical inspection (AOI) system design, the line scan camera has been applied in a variety of high-efficient process detection. To achieve high-efficient detection, the line scan camera is used in the detection system of this research as the detection camera. As for the implementation of light source, just a few panel sectional profile-related detection articles can be found. Although the glass sectional profile belongs to higher reflective source, it is coarse in surface features. From the research conducted by Lu et al., as conducted in 2018 [7], it is learned that the coarse surface materials are suitable for bright field lighting where uniform light sources (inner coaxial, ring-type light sources, etc.) are applied to indicate the defect position according to the specific defect reflection phenomenon. In aspect of TFT-LCD cutting process, the research conducted by Imai [8] for the TFT-LCD glass cutting process in 2019 indicated that the conditions of cutter wheel can be judged according to the rib mark presented on the penal sectional profile. According to the research conducted by Pan in 2008 [9], it is also learned that the panel cutting process will be divided into upper and lower cutter wheel cutting for both panels. Therefore, the damage status of upper and lower cutter wheel can be judged according to the rib marks presented on the upper and lower panels. In terms of feature separation, reference has been made to the research conducted by Ronneberger et al., in 2015 [10]. Under fewer dataset condition, the U-net architecture proposed in the research is applied, and its success rate can be up to 92% in the cell feature separation case. Based on the research result proposed by Lin in 2020 [11], regarding the separation of medical image, the supervised U-Net and the non-supervised U-Net are quoted for comparison by which, the DSC (Dice similarity coefficient) is applied in calculating the area intersection ratio between the separated image and the positive sample image for using as the similarity coefficient of both images. In addition, such coefficient is also used as the accuracy indicator of feature separation. Based on statistical results, it is learned that the U-Net Model is more superior in feature separation accuracy with its 92% accuracy. In terms of defect detection, the method proposed by Jo in 2019 [12] is quoted in this research. During the research, the background pictures presenting varied luminance values are obtained through Auto Encoder network regression method, and then the defect position is therefore separated (Figs. 1, 2, 3, and 4). It is also applied to the defect presenting different depth such as light spot, line scratches, and Mura defect, as per Fig. 5.

Fig. 2 Analyzed sectional profile detect: a impurities defect, b rib mark damage defect, c crashing defect, d omission damage defect, and e cracking defect

![Substrate-A](image1)

Translucent conductive film (ITO) Glass substrate BM(Black Matrix) Liquid crystal

Substrate-B Color optical filter (R.G.B.)

**Fig. 1** Internal construction of test piece for TFT-LCD panel detection

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Further, we also referenced the research conducted by Xu et al., in 2017 [13] by which, the Auto Encoder network model is applied to output the finally added convolutional neural network (i.e., CNN) layer for carrying out the screening; as a result, it is learned that the generality of the feature learning can be reinforced through such method. In aspect of model acceleration, the research conducted by Vanhoucke in 2011 [14] indicated that the model computation speed can be positively increased by applying fixed data in the weighting data when compared to the float data. Taking the vocabulary voice identification as the example, when using CPU to calculate the lot amount, the CPU speed can be accelerated for over 4 times when using the fixed computation method in the weighting data, as compared to the float method, and the model prediction accuracy has dropped for 2% only. As for the surface detection, the research conducted by Lawn et al. in 1975 [15] proved that the deformation features are presented near around the microcracks of the glass substrate surface, and such deformation will create the interfering value during the optical imaging process. Such interfering value is critical to the glass fracturing, and it can be used as the stress indicator when predicting the glass fracturing. Based on the research conducted by Shin et al. in 2011 [16], it proved that the reflective circular polariscope can be used to take the picture of interfering marks around the glass surface cracks more effectively. In the research conducted by Chen, His-Chao et al. in 2017 [17], they explained that when the glass object is crashed by external force, the internal molecular structure of such object will be squeezed and dragged and then present refractive rate distribution on each direction. In this way, the interfering marks can be created with the circular polariscope through the photoelastic reflection method in order to achieve the total field stress measuring effect when observing the macroarea field. Summing up the aforesaid literatures, the challenges of the automatic surface inspection in a glass substrate are the low-contrast images by the non-uniformity of the varied fracturing phenomenon resulting in the intensities of defects, and glass substrates are hardly identified. Therefore, it is troublesome to detect slight defects [18] in glass substrates using traditional image processing methods such as the pre-determined threshold method and blob inspection.

During the research, the inspected panel is divided into sectional profile and surface for carrying out the detection. In terms of sectional profile, there will be slight height...
difference at the section area because the glass may present varied fracturing phenomenon after being cut. Due to this reason, uneven luminance issue may present in the retrieved picture that it would be difficult to set up the fixed threshold value for executing the detection by conventional image processing method. Therefore, the deep learning model is selected for this research to carry out the detection. To reduce the system development cost to acquire the intended edge computation effect, the embedded control system is used to execute the control while considering about the embedding system computation burden issues. Lower system computation burden is achieved by changing the model weighting format. In terms of panel surface, the panel surface retardation image is retrieved by using the circular polariscope with the photoelastic reflection method. In the meantime, the research also used the features of the interfering halo that has been produced by the residual stress resulting from the deformation around the denting defect, as being indicated in the retardation image. In this research, the aforesaid features are used as the detection basis in determining the denting defect. The novel defect detection system is developed for this research in order to detect the TFT-LCD panel after being cut. The main purpose of this system is to find out the defects that will affect the packaging and cause the panel cracking. For this purpose, a set of photodetector system is designed for the sectional profile and the surface of the panel respectively. In terms of detecting the sectional profile, the U-Net Model is used to separate the rib mark features that will affect the panel strength in order to calculate the percentile of depth value. In the meantime, the Auto Encoder Model is also used to predict the background picture in order to find out the defect position at the middle area of the sectional profile by subtracting it from the original picture, and then it is highlighted. In terms of network acceleration, to meet the required production line efficiency, the network weighting data format is revised in order to provide quicker model network reading and prediction time. When executing the surface detection, the reflective circular polariscope technology is employed to produce the interfering halo surrounding the denting defect. As a
next step, the denting defect is separated through the mean luminance value and the dispersion in order to find out the denting defect that has caused the panel cracking.

The research method developed for this system is mainly divided into the following 5 sectors:

1. Design of the corresponding detection system by collecting and analyzing the defect features of the panel sectional profile and the reflection characteristics of the surface coating material
2. Sectional profile rib mark features detection process
3. Sectional profile defect detection process
4. Network model acceleration process
5. Surface denting defect detection process

2 Research method and experimental framework

2.1 Introduction of test piece

The size of the test piece used in this research is about 100 × 100mm², as per the internal construction indicated in Fig. 1. When executing the glass surface detection, it will be required to consider about the bottom layer material of the glass surface at upper and lower sides of the panel. When detecting glass substrate-A, the research result [17] indicated that the residual stress response between the ITO film and the glass substrate can be effectively observed through the photoelastic reflection effect of the circular polariscope. As for glass substrate-B, its bottom side is covered with BM plating layer in order to prevent the internal light from leaking during the panel conveying process to prevent it from mixing with the internal RGB light source. Based on the research result [19], it is learned that such protection effect is achieved by coating the surface with chromium material.

From the Material Reflectance Report [20], it is learned that when projected under 500~700 nm wave length of visible light, 60~70% of material reflectance can be achieved on the chromium layer. Therefore, the 634 nm red point light source is selected for the surface detection in order to carry out the panel surface detection.

2.2 Introduction of defect type

In aspect of sectional profile defect, not so many cases have been executed in the current market for studying the defects on the cut-apart section of the TFT-LCD panel. Therefore, the defect of this part will be defined according to the type of defect being photographed on the test piece and the type of defect being discussed with the vendor. Indicated in Fig. 2 are the resulting defect types. Currently, the size of the sectional profile defect defined by the vendor is over 100μm², and it will be used for making the judgment.

In terms of surface defect, the main reason affecting the panel strength is the denting type of defect. During the imaging process, impurities staining and crashing damage defect are presenting black color features; but the variation of defect features between both of them is not so obvious, as per Fig. 3. Therefore, they cannot be effectively classified simply from the area size aspect. Based on the research result [21], it is learned that the defect with lower gray level value obtained during the imaging process will lead to incorrect result when using the defect area classification method. In this research, the photoelastic reflection effect of the circular polariscope is employed for projecting the light onto the surface of the test piece. Based on the change surrounding the surface defect, different retardation variations will be presented when covered by the circularly polarized light, and the interfering halo feature is therefore produced. During the research, such feature is used to differentiate the denting and staining defects.

2.3 System framework and detection process

Based on the defects presented in different positions on the panel, the sectional profile and the surface detection systems are designed. In terms of sectional profile detection system framework, the inner coaxial light source is employed to increase the concave and convex variation on the surface in order to intensify the edge contour of the Test Piece by combining with uniformed lighting effect of the line light source. As for surface detection system framework, the circularly polarized light is produced through the circular polariscope. As a next step, the photoelastic reflection method is employed by projecting the light vertically onto the panel surface through the inner coaxial telecentric lens. Finally, the polarized camera is used to take the image from the corresponding phase angle. Indicated in Fig. 4 are the frameworks designed for the sectional profile and the surface, respectively.

2.4 Sectional profile detection process

When executing the sectional profile detection, the NVIDIA AGX Xavier embedded system is used for the detection system to carry out the intended control. The moving pictures of the test piece are taken by controlling the detection platform through Modbus communication. Next, the sensing signal of the light blocking sensor is used as the image retrieving signal in order to trigger the camera to take the picture. In the meantime, the background screening is also conducted for the retrieved sectional profile pictures. Further, the pictures are brought to the rib mark feature detection process
for separating the rib mark features, calculating the depth percentage, and separating the intermediate images of the test piece. Following that, the sectional profile defects are retrieved through the defect detection process. Finally, the pictures are exported for the defect detection result. Indicated in Fig. 5 is the overall detection process.

2.5 Background screening

During the research, the sectional profile image-related information of the test piece is retrieved through the background screening method. Based on the background luminance, the threshold value “120” is set for carrying out the binarization process in order to search these four corner points, i.e., $P_1$, $P_2$, $P_3$, and $P_4$ on the marginal edge of the sectional profile at upper, lower, left, and right sides of the image. Next, the corner point coordinates are used to calculate the upper width $\delta_{up}$ and lower width $\delta_{down}$ that are located on the sectional profile of the panel, and then the calculation result is employed to determine if the aforesaid width values are compatible with 184 pixels of estimated panel length. Through such process, the serious damage types of omission and rib mark defects are screened. Through the positions of corner point coordinates, the outer contour margins of the test piece are connected. Based on the outer contour margin positions, the image-related information of the sectional profile can be exported, as per the overall flow chart indicated in Fig. 6, 7, and 8.

2.6 Rib mark feature detection

As described in the research result [8], the panel strength will be weakened if the percentage of rib mark depth is bigger than 20%. Therefore, the U-Net Model is used in this research for carrying out the separation of rib mark features. When using the training pictures, the masking method is employed to cover up the intermediate portion of the imported image so that the rib mark will remain for taking the feature picture. To increase the data of the training picture, the width is based for dividing the sectional profile

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**Fig. 6** Sectional profile detection process-related pictures: a original picture, b sectional profile picture, c rib mark feature detection result, and d sectional profile defect detection result.

**Fig. 7** Background screening flow chart.

**Fig. 8** Output sectional profile diagram (c).

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pictures into 204 copies of pictures with each of them occupying 184 × 184 pixels to start the model training. Indicated in Fig. 9 are the data-related pictures.

In this research, the U-Net framework proposed by the research [10] is revised. To minimize the weighting quantity of the model in order to reduce the speed predicted for the model, the upper and lower sampling layers are changed to two layers for carrying out the training. When executing the convolution process for each layer, the overfitting problem encountered during the training process is mitigated through the excitation function “Relu.” When executing the lower side sampling for each layer, key features are remained through the “max pooling” process. Finally, the excitation function “sigmoid” is employed to carry out the feature classification on the output picture and feature picture. Indicated in Fig. 10 is the overall network framework. Table 1 shows the U-Net parameters for the experiment. Due to the limitations of the number of samples, the batch size used in this article is 5. For the experiments, the Adam optimizer with an initial learning rate of $1 \times 10^{-4}$ was used. The number of epochs is 150.

### 2.7 Rib mark feature classification and depth calculation

After predicting the distribution positions of the rib mark features through the model, the marking lines are drafted according to the gray-white distribution of the rib mark features as indicated in the predicted image, and then it is mapped to the input picture from which $I_{1,x}$ and $I_{2,x}$ are obtained to represent the depth values of left and right rib mark features of the test piece, respectively. Based on the method indicated in Formulas (1) to (2), the rib mark depth percentage ($D_{1}$, $D_{2}$) is calculated in order to determine if the depth of $D_{1}$ and $D_{2}$ features are within 20%. Finally, the marking line coordinates are used to separate the intermediate sector of the sectional profile for the convenience of executing the sectional profile defect detection in the future. Indicated in Fig. 11 and 12 are the entire process.

$I$ means overall panel thickness; $I_{x}$ means glass substrate thickness.

\[ I_{x} = \frac{I}{2} \]  

“I_{1,2,x}” means rib mark depth of upper and lower glass substrates. “$D_{1,2}$” means rib mark depth percentage of upper and lower glass substrates.

\[ D_{i=1,2} = \left( \frac{I_{i}}{I_{x}} \right) \times 100 \]  

### 2.8 Sectional profile defect detection

At the intermediate sector of the sectional profile, varied dimness will present on the background due to different glass fracturing condition. Although the difference with background can be observed according to different defect depth at the sectional profile, there is not any fixed gray-level value. Indicated in Fig. 13 is the defect at the intermediate sector of the sectional profile.

When detecting the sectional profile defect, the linear regression method is proposed for this research in order to calculate the background picture. The resulting background picture is used for training the Auto Encoder network model with which, the image subtraction is conducted through the model prediction picture and the original picture. Next, the Gaussian filter rated at “3 × 3 Kernel” in size is also used to eliminate the noise signal indicated in the subtraction picture. Finally, the binary value is used to acquire the defect area size, and then the defect is highlighted. Indicated in Fig. 14 is the overall process.

When executing the linear regression, the marginal corner points coordinates $P_{1}, P_{2}, \ldots P_{4}$ are obtained by inputting the image in which coordinates $P1$ and $P2$ are
connected for using as the regression path; in the meantime, the point-based pixel value of $Y$-axis path is also treated as the independent variable $x_i$ during the regression process. Next, regression coefficients $a$ and $b$ are deduced by resolving the pixel values presented on the path in Formulas (4) to (5). After completing the regression of all pixels on $Y$-axis path, the pixel histogram in Fig. 15c is observed in which the red line refers to the point-based pixel value along the scanning path and gray line represents the point-based pixel value $Y_t$ after the regression. The result proves that such method is able to retain the background information through the defect screening process. Finally, such regression method is also employed to scan $Y$-axis line by line starting from the right-hand side in order to complete the regression process, and then the background picture is obtained. Indicated in Fig. 15a is the entire regression process.

Indicated in Formula (3) is the linear regression formula where $Y_t$ means the pixel value after the regression, $x_i$ means the point-based pixel value along the scanning path, $a$ refers to regression line slope, and $b$ represents regression line intercept.

$$Y_t = ax_i + b$$

By scanning the summated pixel $n$, the point-based pixel position $X_i$ and the point-based pixel value $Y_i$ along the path, the slope of regression line is calculated for the aforesaid three values, as per Formula (4):

$$a = \frac{n \cdot \sum_{i=1}^{n} X_i Y_i - \sum_{i=0}^{n} X_i \sum_{i=0}^{n} Y_i}{n \cdot \sum_{i=0}^{n} X_i^2 - (\sum_{i=0}^{n} X_i)^2}$$  \hspace{1cm} (4)

The values are resolved in the Formula (5) through $a$, and the regression line intercept $b$ is obtained:

$$b = \frac{\sum_{i=1}^{n} Y_i}{n} - a \frac{\sum_{i=1}^{n} X_i}{n}$$  \hspace{1cm} (5)

After acquiring $a$ and $b$ parameters by scanning all of the pixel values along the path, the point-based regression pixel value $Y_t$ on $Y$-axis scan path can be acquired with Formula (3).

In aspect of Auto Encoder network architecture, the model training is conducted by using 204 copies of original pictures and regression pictures, and the network architecture used in the research indicated in is also referenced [12]. Based on the Auto Encoder network architecture, the down-sampling compression is conducted for the imported original picture through the strides. By retaining the features of the original picture, the up-sampling is conducted, and then the picture is restored to its original size. After completing the input, the regression picture and the imported picture are used to carry out the concatenate feature fusion. At the same time, quicker model convergence is also achieved by means of Relu. Finally, 3 layers of CNNs are added to minimize the variation between the pictures obtained after the sampling and the input picture in order to intensify the model learning effect (Table 2). Indicated in Fig. 16 is the overall framework.

### 2.9 Model acceleration process

To achieve higher model prediction and reading speed for the embedded system, the “1080 Ti server” is used in this research for carrying out the model training. During the training, the Tensor RT function is employed to analyze the architecture of the training model. In the meantime, the weighting data format is also modified by changing the floating-point
number (Float32) to integer (INT8) in order to create the inference engine required for the model optimization. The model weighting format is also changed by combining the model in the inference engine. Through the aforesaid method, the INT8 type of weighting model is obtained, and then it is combined in the NVIDIA AGX Xavier System for carrying out the image prediction in order to reduce the model prediction and reading speed. Indicated in Fig. 17 is the entire process.

2.10 Surface detection process

The research is also conducted by using the Circular Polariscope together with the photoelastic reflection method. By combining the polarizer and the λ/4 wave plate, the incident circular polarized light thus created is projected onto the panel surface. Based on the research result obtained from [22], it is learned that the tip-point of the denting defect is where maximum deformation is located and that the glass is also affected by the deformation being developed around the aforesaid tip-point. In result, tensile stress is produced inside the glass that has led to the subsequent damage. Based on the tensile stress retardation level created inside the deformation area surrounding the denting defect, the circular polarscope is used to create the halo feature according to the photoelastic reflection theory, and then the halo is used as the feature indicator for identifying the denting defect. Based on the research result obtained from [23], it is also learned that the LED light source can effectively prevent the laser Speckle when using the interferometer; therefore, the LED spot is applied as the light source to

![Diagram](image-url)
take pictures. From the discourse concluded by the research in [24], it is also learned that the photodetector installation and the test piece are photographed by vertical projection method, and the result indicated that the best interfering effect has been achieved for the scratch defect. Indicated in Fig. 18 is the detection framework schematic.

During the research, the polarized camera is also used to take the images from varied polarizing angles, and they are expressed as $I_\alpha$ ($\alpha = 0^\circ, 45^\circ, 90^\circ, \text{and} 135^\circ$). In the meantime, the Stokes Vector proposed by Stokes is also applied to describe the polarizing status of the object [25].

The Stokes Vector $S$ is presented in “$4 \times 1$” matrix structure, as per Formula (6):

$$
S = \begin{bmatrix}
S_0 \\
S_1 \\
S_2 \\
S_3
\end{bmatrix} = \begin{bmatrix}
I_0 + I_{90} \\
I_0 - I_{90} \\
I_{45} - I_{135} \\
I_L - I_R
\end{bmatrix}
$$

In Stokes Vector, $I_L$ and $I_R$ represent the left and right circularly polarized light, respectively. $S_0$ refers to the total light enhanced image, $S_1$ and $S_2$ refer to the linearly polarized image formed by the orthogonal effect between the polarized angles, and $S_3$ means the circular polarized light.
image. In this research, the polarizing status of the object is expressed through the aforesaid four parameters. Further, the Mueller Matrix is also applied to execute the transitional derivation [26] for the optical component. The aforesaid is also applied to perform the process derivation through the photoelastic reflection method with the circular polariscope, as per Formula (7).

\[
\begin{bmatrix}
S_0 \\
S_1 \\
S_2 \\
S_3
\end{bmatrix} =
\begin{bmatrix}
m_{00} & m_{01} & m_{02} & m_{03} \\
m_{10} & m_{11} & m_{12} & m_{13} \\
m_{20} & m_{21} & m_{22} & m_{23} \\
m_{30} & m_{31} & m_{32} & m_{33}
\end{bmatrix}
\begin{bmatrix}
S_0 \\
S_1 \\
S_2 \\
S_3
\end{bmatrix}
\]

(7)

Indicated in Formula (7) is the Stokes Vector calculated for the initial polarized incident light (vertically) of the framework:

Table 2 Auto Encoder network-related parameters

| Parameter type     | Parameter value       |
|--------------------|-----------------------|
| Kernel_size        | 3×3 pixels            |
| Batch size         | 10                    |
| Epoch              | 150                   |
| Loss               | MSE                   |
| Optimizer          | Adam                  |
| Learning rate      | 1e−5                  |
The λ/4 wave plate retardation is set at 90°. When the transmission axis is projecting at 45° onto the fast axis, its Mueller Matrix is expressed as per Formula (9):

\[
\begin{bmatrix}
1 & 0 & 0 \\
0 & 0 & 1 \\
0 & 1 & 0 \\
\end{bmatrix}
\]

By combining the aforesaid Formulas (8) and (9), the polarizing status of the circularly polarized light is obtained and expressed as \(M_1\), as per Formula (10):

\[
M_1 = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix} \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix} = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 \\
\end{bmatrix}
\]

In the Mueller Matrix, the test piece is mainly composed by rotation angle \(M_a\) matrix and retardation \(M_\delta\) matrix, as per Formulas (11) and (12):

\[
M_a = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & \cos 2\alpha & \sin 2\alpha & 0 \\
0 & -\sin 2\alpha & \cos 2\alpha & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

\[
M_\delta = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & \cos \delta & 0 & -\sin \delta \\
0 & 0 & 0 & 0 \\
0 & \sin \delta & 0 & \cos \delta \\
\end{bmatrix}
\]

Therefore, the derivation process relating to the incident and reflection of the test piece is expressed as \(M_2\), as per Formula (14):

\[
M_2 = M_{af} \cdot M_a^\delta \cdot M_a \cdot M_\delta
\]

The process by reflecting the circularly polarized light to the polarizer is expressed as \(M_3\), as per Formula (15):

\[
M_3 = 0.5 \cdot \begin{bmatrix}
1 & 0 & 0 & 0 \\
1 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

By combining process \(M_1\), \(M_2\), and \(M_3\) in the derivation, the image information retrieved by the polarized camera is expressed as the object retardation status \(\delta\), as per Formula (16):

\[
M_3 \cdot M_2 \cdot M_1 = \begin{bmatrix}
0.5 (\sin \delta)^2 \\
0.5 (\sin \delta)^2 \\
0 \\
0 \\
\end{bmatrix}
\]

Because the reflection direction is contradictory to the incident direction, the rotation angle \(M_{af}\) matrix is selected for the reflection direction, as per Formula (13):

\[
M_{af} = \begin{bmatrix}
1 & 0 & 0 & 0 \\
0 & \cos 2\alpha & -\sin 2\alpha & 0 \\
0 & \sin 2\alpha & \cos 2\alpha & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]

Through Formulas (17) and (18), it is learned that when the circularly polarized light is projected onto the test piece surface, the derivation result indicated that the retardation resulting from the deformation of the object is assumed at 90°. After projecting the circularly polarized light, the derived result is obtained as the Mueller matrix:

\[
\begin{bmatrix}
1 & 1 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & 1 & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}
\]
polarized light onto the material, as learned from the Stokes Vector parameters, the original circular polarization-related component information will be distributed to the linearly polarized component after going through the deformation process.

The resulting $\gamma_1$ is obtained by assuming that the deformation retardation of the Test Piece is under $90^\circ$ status, as per Formula (17):

$$\gamma_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(90^\circ) & 0 & -\sin(90^\circ) \\ 0 & 0 & 1 & 0 \\ 0 & \sin(90^\circ) & 0 & \cos(90^\circ) \end{bmatrix} (17)$$

The information of incident circularly polarized light source derived from $M_I$ is used to multiply with $\gamma_1$. From the result, it is learned that the component of circularly polarized light information will be converted to the linearly polarized component, as per Formula (18):

$$S' = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & \cos(90^\circ) & 0 & -\sin(90^\circ) \\ 0 & 0 & 1 & 0 \\ 0 & \sin(90^\circ) & 0 & \cos(90^\circ) \end{bmatrix} \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 0 \\ 0 \\ 0 \end{bmatrix} (18)$$

Through the derivation process as indicated in the formula above, it is learned that the retardation information acquired from the framework applied in this research can be used to effectively identify the retardation variation caused by the internal stress of the deformed glass surface.

The test result indicated that the stress ripples can be observed from the imaging result after applying the stress on the glass substrate. It justifies that the internal stress can be observed by the photodetector more effectively, as per Fig. 19.

From Fig. 20, the interfering halo created by the retardation variation cannot be seen on the impurities stained panel. However, such feature can be observed from the panel where...
the surface is damaged. On this basis, the detection is conducted during the research.

After retrieving the image, it is treated through the normalization process in order to present the interfering halo more clearly. Next, the Otsu computation method is applied to calculate its luminance threshold value $\delta_1$. Based on such threshold value, the average luminance is calculated for the “80 × 80 sliding window in order to single out the image luminance block. Indicated in Fig. 21 is the entire process.

After acquiring the illuminating area, the luminance dispersion value is calculated for the picture according to Formula (19) (Fig. 22). As indicated in Fig. 23, it is learned that the luminance dispersion value containing the halo features is mostly over 60. Therefore, such indicator is used by this research as the interfering feature screening conditions. In the formula, $\delta_4$ means the dimness dispersion of the image; $N$ means the total pixel number in the sliding window block, $Pix_i$ refers to the point-based pixel value of the sliding window, and $\delta_2$ represents the mean luminance value of the sliding window.

$$\delta_4 = \frac{\sqrt{\sum_{i=0}^{N}(Pix_i - \delta_2)^2}}{N}$$  \hfill (19)

Finally, the calculation result indicated that the dispersion value in the window block is mostly over 50, and it is concluded as having the interfering area features. In the meantime, it can be used to accurately highlight the area presenting the halo interfering features. Indicated in Fig. 24 is the highlighting result.

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**Fig. 18** Circular polariscope detection architecture schematic

**Fig. 19** Retardation imaging after applying stress on the glass substrate

**Fig. 20** Comparison between the defect retardation images: a impurity stains; b surface damage
3 Result and discussions

3.1 Experiment evaluation indicator

During the research, the confusion matrix is applied to calculate the accuracy of the respective function in the detection system. The calculation is executed by inputting positive-category pictures (defect picture) and negative-category pictures (defect-free pictures) for comparing with the result retrieved from the detection system. In result, the following four parameters are obtained, and they are $TP$ (true positive), $TN$ (true negative), $FP$ (false positive), and $FN$ (false negative). Provided in Table 3 is the confusion matrix statistical table.
Based on the TP, FP, FN, and TN parameters acquired from the confusion matrix statistical process, the accuracy, precision, and recall are calculated for using as the referential indicator of rendering the detection result. In this respect, recall serves as the percentage of the defect result being judged by the detection system for all of true defects, and it can also be regarded as the reverse indicator for determining the omission factor. In the meantime, precision represents the percentage of true defect as being judged by the detection system according to the defect picture, and it can be regarded as the false positive rate indicator. Described in Formulas (20) to (22) is the calculation procedure of the respective indicator.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + TN + FN} \tag{20}
\]

Detection Results of the interfering area features

Detection Results of the non-interfering area features

Fig. 23 Statistical dispersion value of sliding block

Fig. 24 Interfering feature highlighting result
3.2 Experiment result and discussions for rib mark detection

In this research, the sample pictures are grouped into separable rib mark feature pictures and inseparable rib mark feature pictures. Separable pictures are used as the positive-category pictures and major damage pictures, and inseparable rib mark feature pictures are used as the negative-category pictures. In the meantime, 25 copies are selected from each of them for carrying out the statistical calculation, and these pictures will also be transmitted to the detection system. Based on the statistical result in Table 4, it is learned that negative-category pictures can be completely screened off before sending to the detection system for further processing. The result also indicated that the U-Net Model will not be affected by the background dimness and the defect that the rib mark features can be completely separated in achieving 100% accuracy without omission and false detection issues. The average detection time of such process lasts about 0.92 s. Indicated in Fig. 25a is the separation result. This study also compared YOLO v5 [27] with Rib mark detection training. The results exhibited in Table 5 show that this model is not conducive to detecting dim and varying luminous rib marks. According to the detection results using YOLO v5 shown in Fig. 25b, it can be observed that discontinuous or dim edges have poor prediction performance.

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (21)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (22)
\]

3.3 Experiment result and discussions for sectional profile defect detection

In view that the major damage category defect has been removed from the rib mark detection process, the target to be studied will be the sectional profile detection result. During the research, the detection and judgment are conducted for the rest of fracturing, crashing, and impurity defects for which the non-defect sectional profile pictures are used as the negative-category pictures. To execute the detection, 50 copies of 128×128 pixel sample pictures are selected from each of them for carrying out the statistical calculation. As indicated in Table 6, the non-defect pictures can be accurately classified. The defect detection result indicated that 96% accuracy can be achieved while maintaining 100% for the recall indicator. As such, it is learned that false detection is the main reason leading to the false judgment. Indicated in Fig. 26 is the detection result, and the average time required for completing the sectional profile detection is 1.24 s.

3.4 Result and discussions for model acceleration experiment

During the research, the data statistical method is applied to read and predict the speed for U-Net and Auto Encoder before and after the acceleration. In the meantime, the effect on the detection and the feature separation accuracy after the acceleration is also compared. In this research, 50 copies of non-training pictures are selected. Based on the statistical chart indicated in Fig. 27, it is learned that the model reading time has been shortened for 4.28 s when using the U-Net Model. As indicated in the statistical chart in Fig. 28, the model reading time has been shortened for 19.23 s when using the Auto Encoder. Based on the statistical result in Table 7, we see that the average prediction time has been shortened for 0.29 s when using the U-Net Model. As for the Auto Encoder, the average prediction time has been shortened for 0.94 s. As such, it is learned that the faster the speed, the bigger the layer number of model network and the more obvious in shortening the reading and prediction time. Because prominent image features are predicted for this research, the statistical detection result indicated that there is not any accuracy reducing issues after being accelerated.

3.5 Result and discussions for surface detection experiment

During the research, 10 pictures presenting the surface damage defect and the staining defect are selected separately for...
carrying out the statistical calculation. Based on the statistical data in Table 8, we see the staining picture can be judged as non-damage that 90% of detection accuracy can be achieved. Based on 80% of recall indicated, it is learned that the main false reason is due to the reflectance at BM and polarizer and false judgment is made for the surface damage picture. Other detection result is indicated in Fig. 29, and it shows that the average process detection time lasts for 0.9 s.

To deal with the false detection of the damage defect not being highlighted, the Keyence VK-X3000 Laser Confocal is used in this research to perform the 3D scanning on the TFT-LCD panel. The result indicated that the surface deformation is the main reason creating the interfering halo feature on the damage defect, as per Fig. 30. The verification result also

| Table 5 | Statistical result of YOLO v5 for rib mark feature detection |
|---------|-------------------------------------------------------------|
|         | True | Separable rib mark picture | Inseparable picture |
| Feature separation | 22 (TP) | 7 (FP) |
| Major defect screening | 3 (FN) | 18 (TN) |
| Accuracy | 80% |
| Precision | 76% |
| Recall | 88% |

| Table 6 | Statistical result for sectional profile defect detection |
|---------|-------------------------------------------------------------|
|         | True | Defect pictures | Non-defect pictures |
| Judged as defect | 50 (TP) | 2 (FP) |
| Judged as non-defect | 0 (FN) | 48 (TN) |
| Accuracy | 98% |
| Precision | 100% |
| Recall | 100% |
supported the result described in [28] research. It reveals that the stronger the glass surface loading stress, the larger the plastic deformation on the surface.

During the research, the quantitative indicators of surface deformation are calculated. After acquiring the Point Cloud File with Keyence VK-X3000 Laser Confocal, it is converted to depth chart for carrying out the calculation of Normal Line Chart. After acquiring the point-based depth normal line vector, vertical coordinate axis is created for calculating the included angle for the point-based depth normal line vector for using as the deformation quantitative indicator of the depth at each individual point. When calculating the area deformation, the KAM (kernel average misorientation map)

Table 7 Average prediction time and accuracy for both models

|                     | Average prediction time | Detection accuracy |
|---------------------|-------------------------|--------------------|
| Before acceleration for U-Net | 0.41 s                   | 100%               |
| After acceleration for U-Net  | 0.12 s                   | 100%               |
| Before acceleration for Auto Encoder | 0.96 s                 | 98%                |
| After acceleration for Auto Encoder | 0.02 s                 | 98%                |

Table 8 Surface detection statistical result

| Detected   | True | Surface damage picture | Surface staining picture |
|------------|------|-------------------------|--------------------------|
| Judged as damage | 8 (TP) | 0 (FP)                 |
| Judged as non-damage | 2 (FN) | 10 (TN)            |
| Accuracy   |      | 90%                     |
| Precision  |      | 100%                    |
| Recall     |      | 80%                     |

Fig. 26 Sectional profile defect detection result: a fracturing defect and false detection highlighting result; b impurities defect detection result; c crashing defect detection result

Fig. 27 Reading and prediction statistical time before and after the acceleration for U-Net Model

Fig. 28 Reading and prediction statistical time before and after the acceleration for the Auto Encoder Model
Fig. 29  Surface detection result pictures: a and b Interfering halo defect highlighting result; c and d detection error result picture

Fig. 30  TFT-LCD surface 3D scanning result: a surface scanning result for non-interfering halo defect; b surface scanning result for interfering halo defect
measuring method proposed by research is referenced [29] by setting the $40 \times 40$ pixels searching area to find out the maximum included angle changing point surrounding the defect scope, and the result is used as the center point $\theta_0$. Next, the $3 \times 3$ KAM matrix is utilized to calculate the average normal line changing angle. With the average normal line changing angle obtained, the average normal line changing angles obtained for the damage defect with and without the interfering features are put into statistical comparison, as per Fig. 31. It is learned that when the average normal line changing angle is over 3°, the interfering halo feature can be created with the circular polariscope used in this research.

4 Conclusions

When conducting the sectional profile detection, the background screening method is used in the image pre-processing in order to remove the rib mark damage and the debris defect. Next, the rib mark feature depth is also detected through the U-Net Network Model for which its detection accuracy is up to 100% and the average detection time is about 0.92 s. In the meantime, the Auto Encoder is also used to predict the background regression picture, and the defects are highlighted by subtracting it from the original picture in order to complete the impurities, crashing and fracturing defect detection. As a result, it achieves 98% of detection accuracy, and the average detection time lasts for about 1.24 s. In the meantime, the Auto Encoder is also used to predict the background regression picture, and the defects are highlighted by subtracting it from the original picture in order to complete the impurities, crashing and fracturing defect detection. As a result, it achieves 98% of detection accuracy, and the average detection time lasts for about 1.24 s. During the detection process, the detection efficiency of the production line is also considered. During the research, the acceleration of model reading and prediction time is also conducted by modifying the model weighting data format. In the aspect of the U-Net Model, the reading time has been shortened for 4.88 s, and the prediction time has been shortened for 0.29 s. As for the Auto Encoder Model, the reading time has been shortened for 19.23 s, and the prediction time has been shortened for 0.94 s. Through the aforesaid method, a highly efficient and more accurate detection effect is achieved for the sectional profile of TFT-LCD panel. In terms of surface detection, the category of denting defect and staining impurities defect is studied during the research in which circular polariscope together with the photoelastic reflection method are applied for detecting the surface of TFT-LCD panel. The experiment result proves that it can detect the surface denting defect rated over 3° of average normal line value. Through average luminance value and screening the dispersion conditions, it will be easy to highlight the interfering halo features produced by circular polariscope for which its accuracy is up to 90% and the detection time is about 0.9 s. As such, the surface denting defect categorization can be achieved with the method proposed by this research.

Author contribution Chao-Ching Ho conceived and designed the experiments; Hao-Ping Wang performed the experiments; Chao-Ching Ho and Hao-Ping Wang analyzed the data; Yuan-Cheng Chiao and Hao-Ping Wang contributed deep learning implementations; Chao-Ching Ho wrote the paper.

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Declarations

Ethical approval This article does not contain any studies with human participants performed by any of the authors.

Consent to participate Informed consent was obtained from all individual participants included in the study.

Consent for publication The participant has consented to the submission of the case report to the journal.

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