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A New Prototype That Performs Real-Time Error Detection in Glass Products

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Abstract

Due to their economical, ergonomic, and processing power capabilities, unique designs and software development applications based on embedded systems are becoming more common every day in detecting errors in product output in quality control processes. In this study, an automated control system based on embedded system was performed to detect errors on the surfaces of products purchased from a glass factory that performed quality control manually by eye. A prototype consisting of the conveyor band and micro drive and camera embedded system was designed for the realization of this system. The embedded system has an open source software that works with morphological image processing techniques and makes boundary determination by gaussian method. The success rate of the system was found by classifying it with Support Vector Machine, Quadratics Discriminant and Medium Tree classifiers. The application of the system has been tested in a glass factory, and as a result of the test process, the system has achieved a high success rate of defect detection in glass products. The system detects all faulty glass products and 93.8% of the faults in the faulty glass products.

Key Words

"Glass defects, Morphological image processing, Classification, Embedded systems"

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1. Introduction

Glass, which is a versatile substance, is used as a complementary accessory in many products as it is used in packaging of many products due to its transparency, its shape does not deteriorate, it does not give out smell and taste. Since the extraction of raw materials used in glass production causes the consumption of natural resources, it damages the environment. This makes it necessary to minimize the margin of error in glass production and processing. Therefore, it is of great importance that any defects which may occur should be detected before they are released (Nishu and Agrawal, 2011).

During glass production, the risk of imperfection of glass arises in many ways. It may have the same defect structure but comes from different mechanism sources (Zhao et all. 2011), (Singh et all. 2013). The types of defects that occur in glass products generally appear as surface point defects and scratch surface defects. Surface point defects are circular-shaped, while scratch surface defects are rectangular-shaped scratch-looking defects. The types of defects that occur in glass are given in Table 1.

Tablo 1. Type of glass defects (Rosli et all. 2018)

Name of defects	Description
Foreign Material	Opaque material embedded in the glass.
Low-Contrast Defect regions	Contain of elements or regions (dark and /or bright) that are relatively contrast against the background.
Scratches and spots	Mark or irregular patches on the surface.
Bubbles and inclusions	Contain an air bubble like material trapped inside a glass.
Hole and dirt	Major problem for manufacturers, particularly when production process includes a surface treatment stage.

Defects in glass products are more commonly detected by the eye, which is called the traditional method. This method directly affects error detection due to the decrease in sensitivity in vision due to fatigue and the negative effects in environmental environment such as low contrast, dust, dirty floor. As a result of this, time, raw materials, energy loss and consequently the product quality decreases.

Finding and correctly evaluating defects is the goal of the automatic quality control system. Automatic quality control system has been used to correct defects in many industrial products such as steel industry (Spinola et all. 2011), fabric (Qu et all. 2016), optic cable (Chen et all. 2016), Ceramic (Cabral and Araújo, 2012), (Keser et all. 2010), (Hocenski et all. 2006), (Elbehiery et all. 2005), LCD (Chao et all. 2006), (Liu and Chen, 2011). Because glass surfaces are reflective, it is not so easy for the system to find the error (Kumar and Kaur, 2013). Special methods are used for this. In these systems, images taken from cameras can detect defects in a very short time and with a high success rate thanks to machine vision systems and this method is used in many industrial areas today (Öztürk and Akdemir, 2018).

Machine vision systems are systems that can instantly detect defects in industrial production systems, simplifying the architecture of the system in which they are used. Error detection in these systems begins by taking pictures of the products on the conveyor belt using the camera. The captured image is then processed by image processing algorithms. Finally, the quality of the product is determined. many methods are used in machine vision systems for error detection such as color space transformation (Nishu and Agrawal, 2011), (Singh et all. 2013), edge detection (Keser et all. 2010), (Öztürk and Akdemir, 2018), (Öztürk and Akdemir, 2015), Fourier analysis, threshold (Cabral and Araújo, 2012), clustering, Anisotropic invasion model (Chao et all. 2006) and the Sobel operator (Kumar and Kaur, 2013).

When we examine the studies in the past, basic defects were detected on the glass product. The first identified defects were tried to find out by taking advantage of feature extraction and image processing techniques. While performing this operation, boundary detection in defects, canny, sobel, fuzzy logic, the methods were used. Defects which were determined their boundaries were determined by various them of machine learning methods (neural networks, fuzzy logic, the average of neighboring pixels, etc... subject) and divided into the types of defects according to the threshold value. When the software system was completed and the prototype stage was reached, it was seen that the computer-based prototype of a design were done. In our study we conducted a study to diagnose point defects and scratches on the glass. We used gaussian method which is method with a high success rate same plane in 2-variable systems and we made the determination the boundaries of system bugs. In the next step, after boundary detection we divided the types of defects on the glass by morphological image processing techniques. In the last step, through the design phase of the prototype, open source coded embedded design of a system were made and we established real-time error detection system.

In the proposed system, a prototype was designed suitable for real production systems that detect defects on glass surfaces. The prototype used in the system consists of conveyor belt, micro drive, camera and software. First, glass products were washed to remove environmental factors (dust and dirt). Then real-time images were taken by the camera unit. 100 lumen light source was applied in closed environment while the image was taken. In the third step, morphological image processing techniques (on, off, expansion, etching) were applied to these images taken in real time and the defects were determined. Finally, the system decided that the error was a submerged or scratch error by taking into account the pixel numbers in the defects due to the threshold value. Classification was made to determine the success rate of the system.

Section 2 describes the structure of the designed prototype. Section 3, morphological image processing and software of the system has provided. In Section 4, the system which determines the success rate of the classification process is described. In Section 5, we finalize this article.

2. The Structure of Prototype

The prototype is designed according to the properties of the glass material to be processed. Material properties can be size, color, and shape. The purpose of creating the prototype is to detect unwanted defects on the processed product with a high success rate. In prototype design, parameters such as reflective glass product surfaces, lighting system, camera features play an important role. In addition, the size of the prototype should be greater than the size of the glass products which we examined. The built-in glass products we use are 90x10 cm2 or 60x10 cm2 in size.

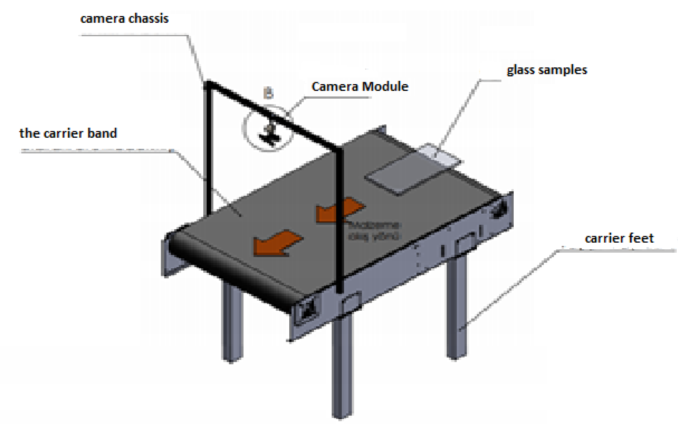


Figure 1. Overall image of the prototype

Figure 2. Actual image of the prototype

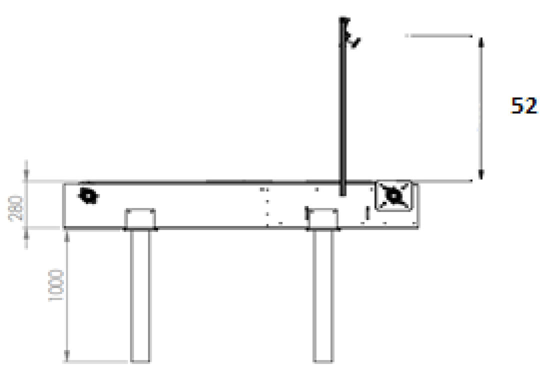


Figure 3. Side perspective of the prototype

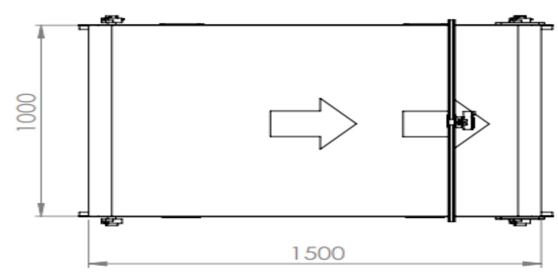


Figure 4. Top perspective of the prototype

Fig. 1 shows the overall image of the prototype and Fig. 2 shows the actual image of the prototype. Fig. 3 is the side perspective of the designed prototype, while Fig. 4 is the top perspective. In the belt design, a conveyor belt design consisting of 12V 55rpm motor, rubber strip and gears was made.

The camera should be placed in a position where you can see exactly the glass product to be measured (Adelson and Wang, 1992). The following equation was used to determine the location of the camera.

$$\frac{1}{d} = \frac{h}{v}\left(\frac{1}{f} - \frac{1}{D}\right) + \frac{1}{D} \quad \text{Camera Position} \tag{1}$$

The variables in the equation above refer to
d: camera height,
D: change in the image of object
h: displacement of object's image in sensor plane
v: change in space distance
f: the focal length of the lens.

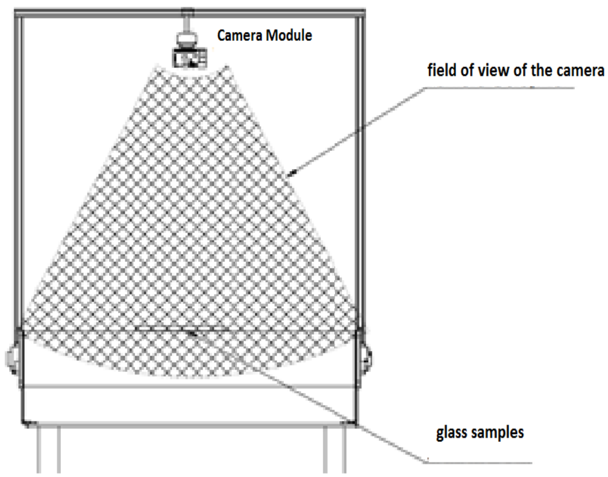


Figure 5. Field of view of the camera

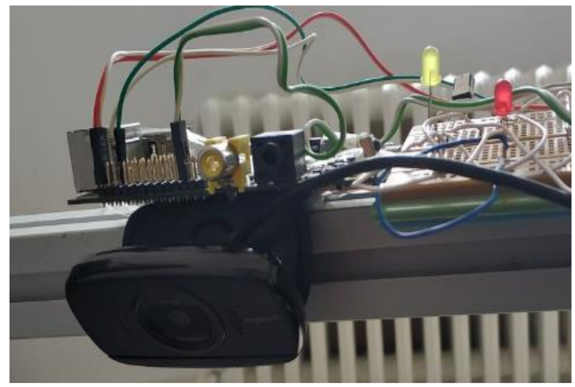
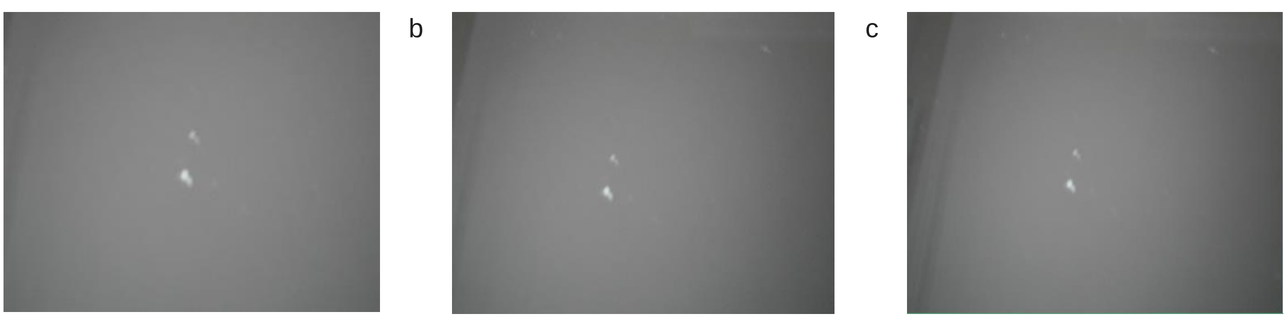


Figure 6. Embedded System

Fig. 5 shows the field of view of the camera used in the prototype. Fig. 6 shows the actual image of the embedded system used in the generated system.

The camera used in the prototype is CMOS (Complementary Metal-Oxidized Semiconductor), its lens is 16 mm and its resolution is 5MP, HD 720p (1280 x 720).



(a) (b) (c)

Figure 7. Camera images of different heights

Fig. 7. Experimental camera images taken from three different heights are given (a) 45 cm, (b) 50 cm, (c) 52 cm high. The result obtained from Equation 1 was also proved experimentally. Another important issue with the camera is the speed at which the camera captures images. In real-time systems, the speed of image capture should be faster than the speed of the conveyor belt. In this study, the camera was selected to take 30 fps (frames per second images) to remove blurring in the image. With a 30 fps fixed camera, the most basic way of detecting the change in the environment through image processing is to determine whether the absolute difference of the images captured in succession, the ratio of the image to the total number of pixels that occur, exceeds a certain threshold. This situation is mathematically,

$$AFD(t) = \frac{1}{w * h} \sum_{x=1}^{w} \sum_{y=1}^{h} |I_t(x,y) - I_{t-1}(x,y)| > E_1 \tag{2}$$

It can be expressed as. Here, the AFD means the average frame difference
It: the current captured frame;
It-1: the previous frame;
w: is the horizontal pixel size of the captured image;
h: is the vertical pixel size;

(x, y): shows the location of the corresponding pixel and,
E1: shows the threshold value. The value specified by the threshold value is the rotation speed of the conveyor belt, our conveyor belt moves at a speed of 5.75cm / sec. In the image obtained at the values below the threshold value, the image was blurred, and the number of errors detected was less than the number of errors in the images obtained at the values above the threshold value. This affects the success rate of the system in finding faults. This is clearly seen in the images taken above and below the threshold value below (Figure 8).

(a) (b)

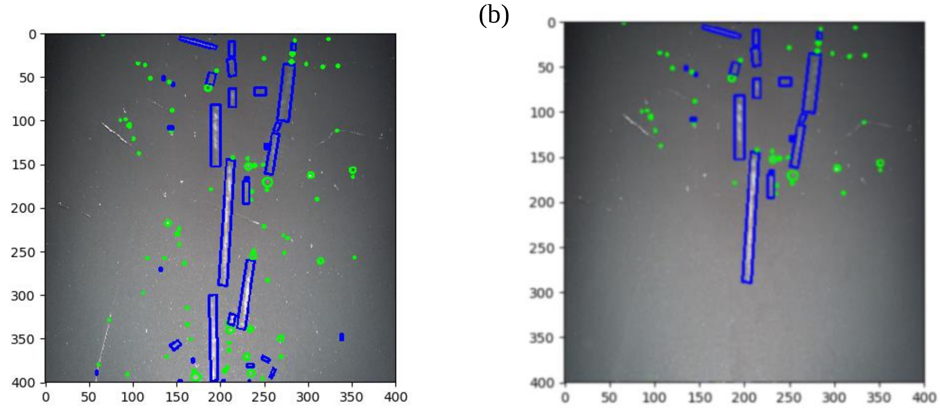


Figure 8. Threshold value a) E_1>1 b) E_1<5

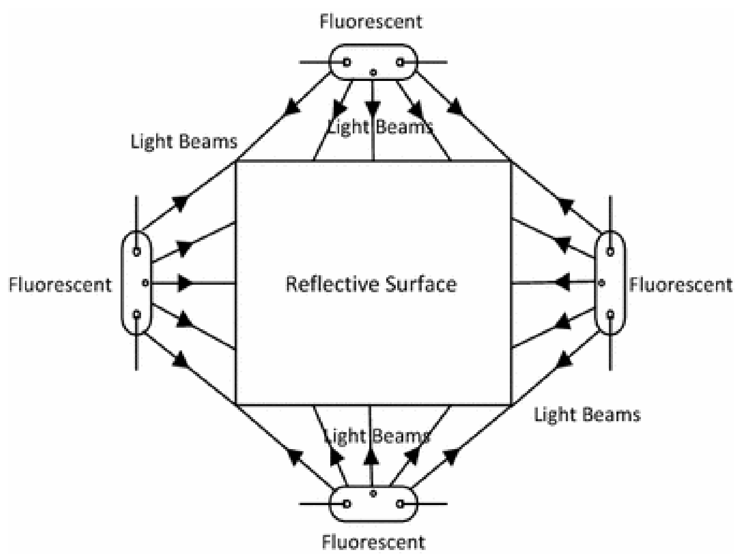


Figure 9. Homogeneous light source (Öztürk and Akdemir, 2018).

The rays reflected from the glass surface are perceived by the camera as intense brightness, which causes the image to be distorted (Öztürk and Akdemir, 2018). Homogeneous light source should be used to prevent reflections on the surface of glass products. In the prototype, homogenous lighting of the environment was provided by fluorescent lamps while glass products were flowing on the conveyor belt. As shown in Fig. 9, the working environment is homogeneous illuminated.

Table 2. Mikro-drive characteristics

Processor	A20 ARM Cortex-A7 dual-core processor
GPU	ARM Mali400MP2 OpenGL ES 2.0 / 1.1
RAM	1GB DDR3
Memory	External tf card
Network	10/100/1000 Mbit / s Ethernet
Video Output	HDMI
Audio Output	3.5mm & HDMI

USB Connect	2 x USB 2.0 connect port
GPIO	Power (+ 5V, + 3.3V ve GND) UART, I2C, SPI & PWM
Power Input	Micro USB (5V / 2A)
Size	92x60mm, 48g

Table 2 shows the micro-drive and its features used in the prototype.

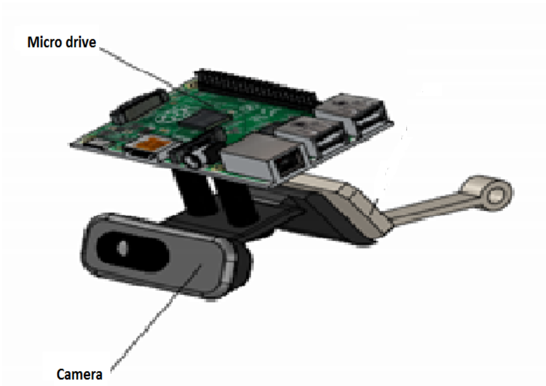


Figure 10. Embedded system design

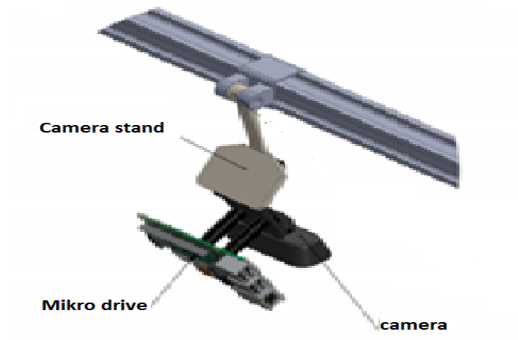


Figure 11. Stand of embedded system

In Figure 10 and 11, the embedded system design (micro drive and camera) used in the prototype is given.

3. Software

The Phyton programming language was used in the software for the designed prototype. The Phyton language is open source software. The algorithm of the software installed on the micro drive is given as follows. Fig.12 shows the flow diagram of the software.

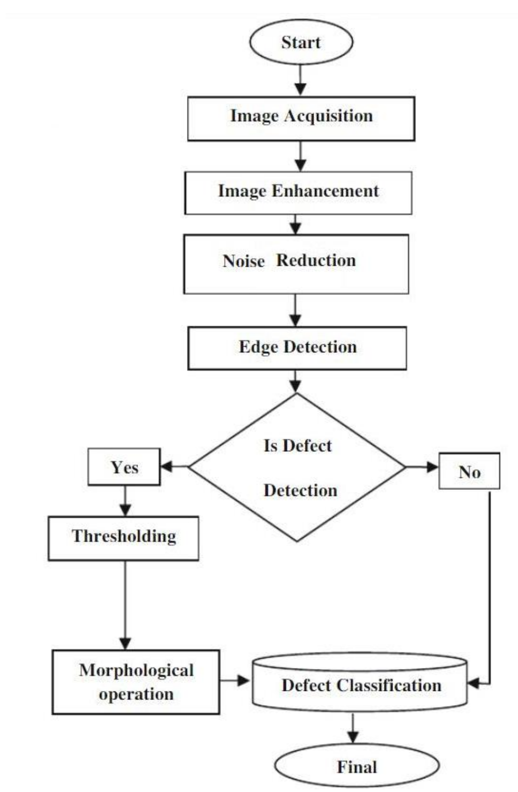


Figure 12. Flow diagram

The processing steps of the algorithm are:
1) Image acquisition /capture (image acquisition)
2) Image enhancement by making the image gray transform
3) Making the image more visible by eliminating unwanted pixels in the image (Noise Reduction))
4) Determining the boundaries of the objects on the image (edge detection)
5) Defect detection (yes/no)
6) Terminating the software by going to error classification if there are no defects (no), (Defect Classification and Final)
7) If an error is detected, error determination based on the boundary value (threshold)
8) Creating the type of error that is determined by The Shape of the error morphologically (Morphological Operation),
9) Classifying the error on the last step (Defect Classification) and (Final) to terminate the software.

Figure 13. Original glass image

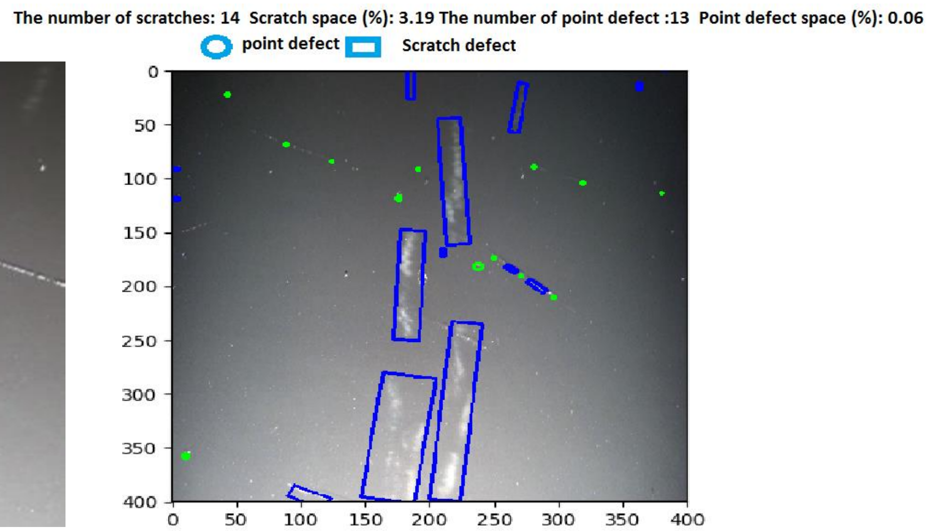


Figure 14. Software screen

The original image of the glass sample is given in Fig. 13, in Fig. 14, a screenshot showing the lines that appear by software is given.

4. Classification

Classification is a process that makes use of known examples to make comments about a new example (Adem and Orhan, 2013). The defects on the glass in this study are on two types and one plane. That's why Quadratics Discriminant, SVM (Support Vector Machine) and Medium Tree classification are used.

A dataset consisting of 30 solid glass images, 30-point defect glass images, and 30 scratch error glass images were used for classification.

Quadratics Discriminant; â ≠ 0, 2. finds roots in an equation of degree 1 unknown. These roots are x1 and x2. To calculate the roots, first the delta value is calculated in the equation. Δ (delta) is expressed as: Δ (Delta) = Delta value is calculated after the comparison process and roots are calculated.

$\Delta > 0$; a positive discriminant indicates that the quadratic has two distinct real number solutions.

$$X_1, X_2 = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \tag{3}$$

$\Delta = 0$; a discriminant of zero indicates that the quadratic has a repeated real number solution.

$$X_1 = X_2 = \frac{-b}{2a'} \tag{4}$$

$\Delta < 0$; a negative discriminant indicates that neither of the solutions are real numbers.

SVM is a theory of machine learning in statistical structure. The purpose of this method is to predict the optimal decision function. By distinguishing the two classes from the data studied, the optimal hyperplane is determined by the decision function, so that one can distinguish the educational data. The equations of the support vectors in SVM are given to be used (SVM-1).

$$\begin{aligned} wx + b &= +1, y = +1 \\ wx + b &= -1, y = -1 \end{aligned}, \text{(SVM-1)} \tag{5}$$

In a linearly differentiable binary classification problem, when "y" is the class label, "w" is the weight vector, and "b" is the approximate value. To increase the value of M, it is necessary to minimize the value of W, as shown in the value of optimal plane intervals (SWM-2).

$$m = \frac{2}{\sqrt{ww}},\ f_{\min}(\mathrm{w}) = \frac{ww}{2}, \qquad \text{(SVM-2)} \tag{6}$$

$$y_i(wx_i + b) - 1 \geq 0$$

$$\mathrm{L}(\mathrm{w,b,a}) = \frac{w^2}{s} - \sum_{i=1}^{k} a_i y_i (wxi + b) + \sum_{i=1}^{k} a_i \qquad \text{(SVM-3)} \tag{7}$$

The resulting equation is solved by the LaGrande method. The LaGrande method Is the decision function of the equation for binary classification (SWM-4).

$$f(x) = sign(\sum_{i=1}^{k\Sigma} a_i y_i (xxi) + b \qquad \text{(SWM-4)} \tag{8}$$

Medium Tree Classification: The main idea in decision trees is to divide the elements of the data set into groups. The aim is to continue the process until all elements of the group have the same label. It is used to create a decision tree from the dataset and determine what to do in certain situations. Entropy, known as the uncertainty measure of a random variable in the medium Tree classification, is the expected value of information contained by all examples for a process. Information is a measure of information about the occurrence of a random event. Equal probability situations represent high uncertainty. The formula for the entropy value is below.

$$H(X) = \sum_{i=1}^{2} p_i \, log \, 2 \, p_i = -(0.5 \, log_2 \, 0\,.\,5 + 0.5 \, log_2 \, 0\,.\,5) = 1 \tag{9}$$

The term entropy (H) is a value that depends on the Pi probabilities of all its belonging States. The threshold value for the classifiers identified above is 0.63. Data in the classification 5 iteration did not reach the result. Since the process of repeating what the machine learned after 5 iterations started, the correct iteration number was determined as 5. The results of the classifier are as indicated below.

Validity criteria: the values given below are calculated to see the success of the classification.
Number of point defect (BS): The number of pixels in glass products containing ship point defect error.
Number of scratches (CS): The number of pixels in glass products that contain scratch defects.
Total surface pixel count (TP): The total number of pixels on the glass product surface.
Point defect rate (BO): The ratio of the total pixel number of point defect faults to the number of pixels on the entire surface. This ratio determines if there is fault tolerance by finding out how much space the fault occupies on the surface.
Scratch rate (CO): The ratio of each scratch defect to the entire surface. This ratio determines if there is fault tolerance by finding out how much space the fault occupies on the surface.
Robust product (SU): Product with error pixeline below a certain threshold.
Total error (TH): Incorrect pixel count on a product.

TH=(BS+CS)/TP   BO=BS/TP   CO=CS/TP

The total error parameter (sensitivity) is the value that is valid for finding the threshold value pixels of the glass product that we must separate the defective or solid products from each other. The value that enables the determination of whether the product whose point defect rate is determined is above the point defect threshold value after the incorrect solid separation is made. The number of scratch defects (CS) is the value in determining the scratch error, which is likewise called the second type of defect. Point defect rate (BO) and scratch rate (CO) is the total pixel ratio of the number of point defect and scratch defects. This is the value used to make the decision whether mistakes can be ignored.

The results of the confusion matrix resulting from the classifiers used in the classification, FFA- Medium Tree, FFA-SVM and FFA - Quadratics Discriminant content are given below.

Table 3. The results of the confusion matrix resulting from the classifiers used in the classification, FFA- Medium Tree, FFA-SVM and FFA - Quadratics Discriminant

CLASS	POINT DEFECT	SCRATCH DEFECT
POINT DEFECT	26	3
SCRATCH DEFECT	3	27

FFA- Medium Tree

CLASS	POINT DEFECT	SCRATCH DEFECT
POINT DEFECT	27	3
SCRATCH DEFECT	4	26

FFA-SVM

CLASS	POINT DEFECT	SCRATCH DEFECT
POINT DEFECT	28	2
SCRATCH DEFECT	3	27

FFA - Quadratics Discriminant

Classification by iterative thresholds was done in Medium Tree, SVM, and Quadratics discriminant-based classifiers as indicated in the table. A total of 30 scratch defects in the medium Tree classification resulted in 27 scratches and 2 point defects. In total, 30 point defects were classified as 27 point defect faults and 3 scratch faults. The point defects were classified as scratch defects because of the similarities between point defect and scratch defects. Scratch defects one error according to the number of pixels classified as solid. In the classification made by SVM based iterative threshing, 26 scratch and 4 point defect defects were classified in a total of 30 scratch defects, 27 point defect and 3 scratch defects were detected in a total of 30 point defects. The similarity of scratch and point defects in classification defects decreased the percentage of accuracy. In the Quadratics Discriminant-based classifier, 27 scratch defects and 2-point defects were classified in the same data collection, while 28-point defects and 2 scratch defects were classified in the point defects. Here, too, it has reduced the success rate due to the similarities of scratch defects to point defects. The results show the highest success rate in the 3 different models used. The products included in the classification are the ones that are found to be solid, submerged, faulty, and scratch-off; the pixel numbers of these products are determined and the classification is made.

5. Results and Evaluation

In this paper, an error detection system is proposed on a dataset consisting of built-in glass products. This dataset consists of 90 glass products for testing in total and consists of 3 classes as solid, submerged and scratched. Examination of glass surfaces is very difficult due to reflection and transparency. For this reason, an open source prototype was developed using morphological image processing techniques. This prototype is a software system that uses a camera on a micro drive to determine the products flowing on the conveyor belt as solid, submerged and scratched, and works with a high success rate of 93.8%. The manual control showed a success rate of approximately 50%. The study will give direction to the work in the future in the detection error of reflective surfaces.

References

Adelson, E. H. & Wang, J. Y. A., (1992). "Single Lens Stereo with a Plenoptic Camera," IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 14, no. 2. pp. 99–106, 1992.

Adem, K., & Orhan, U. "Imaging processing-based quality control of transversal seams in Tetra Brik Aseptic cartons," 2013 21st Signal Process. Commun. Appl. Conf., pp. 1–4, 2013.

Cabral, J. D. D., & Araújo, S. A., (2012). "Computer Vision System for Automatic Quality Inspection of Glass Products Used for Food Packaging," Int. Conf. Ind. Eng. Oper. Manag., pp. 1–10, 2012.

Chao, S. M., Tsai, D. M., Tseng, Y. H. & Jhang, Y. R., (2006). "Defect detection in low-contrast glass substrates using anisotropic diffusion," Proc. - Int. Conf. Pattern Recognit., vol. 1, pp. 654–657, 2006.

Chen, X., Liu, N., You, B., & Xiao, B., (2016). "A novel method for surface defect inspection of optic cable with short-wave infrared illuminance," Infrared Phys. Technol., vol. 77, pp. 456–463, 2016.

Elbehiery, H., Hefnawy, A., & Elewa, M., (2005). "Surface defects detection for ceramic tiles using image processing and morphological techniques," Proc. - WEC'05 3rd World Enformatika Conf., vol. 5, no. 5, pp. 158–162, 2005.

Hocenski, Z., Vasili, S., & Hocenski, V., (2006). "Improved canny edge detector in ceramic tiles defect detection," IECON Proc. (Industrial Electron. Conf., pp. 3328–3331, 2006.

Keser, T. Hocenski, Z., & Hocenski V., (2010). "Intelligent machine vision system for automated quality control in ceramic tiles industry," Strojarstvo, vol. 52, no. 2, pp. 105–114, 2010.

Kumar, N., & Kaur N., (2013). "Detection of Defects in Glass Using Edge Detection with Adaptive Histogram Equalization," Int. J. Innov. Res. Comput. Commun. Eng., vol.1, Issue 6, pp. 1321–1327, 2013.

Liu, Y. H. & Chen, Y. J. (2011). "Automatic defect detection for TFT-LCD array process using quasiconformal kernel support vector data description," Int. J. Mol. Sci., vol. 12, no. 9, pp. 5762–5781, 2011.

Nishu & S. Agrawal (2011). "Glass Defect Detection Techniques using Digital Image Processing–A Review," Spec. issues IP Multimed. Commun., vol. 1, pp. 65–67, 2011.

Öztürk, Ş. & Akdemir, B., (2018). "Fuzzy logic-based segmentation of manufacturing defects on reflective surfaces," Neural Comput. Appl., vol. 29, no. 8, pp. 107–116, 2018.

Öztürk, Ş. & Akdemir, B., (2015). "Comparison of Edge Detection Algorithms for Texture Analysis on Glass Production," Procedia - Soc. Behav. Sci., vol. 195, pp. 2675–2682, 2015.

Qu, T., Zou, L., Zhang, Q. X., Chen, & C. Fan, (2016). "Defect detection on the fabric with complex texture via dual-scale over-complete dictionary," J. Text. Inst., vol. 107, no. 6, pp. 743–756, 2016.

Rosli, N. S., Fauadi, M. H. F. M., Awang, N. F., & Noor, A. Z. M. (2018). "Vision-based defects detection for glass production based on improved image processing method," J. Adv. Manuf. Technol., vol. 12, no. Special issue1, pp. 203–212, 2018.

Singh, T., Lal Dua R., Agrawal, S. & Acharya, A. (2013). "Detection of Defects in Glass Sheet using C. S. C based Segmentation Method," Int. J. Comput. Appl., vol. 68, no. 14, pp. 29–32, 2013.

Spinola, C., Canero,G. J. G., Moreno-Aranda, J. M. Bonelo, & M. Martin-Vazquez, (2011). "Real-time image processing for edge inspection and defect detection in stainless steel production lines," 2011 IEEE Int. Conf. Imaging Syst. Tech. IST 2011 - Proc., no. May, pp. 170–175, 2011.

Zhao, J. Q. J. Kong, Zhao, X., J. Liu, & Y. Liu, (2011). "A method for detection and classification of glass defects in low resolution images," Proc. - 6th Int. Conf. Image Graph. ICIG 2011, pp. 642–647, 2011.