Research Article

Development of a Laboratory Type Glass Anomaly Detection System

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Abstract

This paper demonstrates the successful design and testing of a prototype glass anomaly detection system developed to improve quality control processes in insulating glass production. This prototype system has demonstrated consistent performance under different test conditions, offering high sensitivity, reliability, and fast scanning capabilities.
Image processing algorithms and machine learning models were used to identify and locate defects on glass surfaces in the manufacturing process. The experiments show that this technology can provide significant advantages to the insulating glass manufacturing industry and prevent the production of defective products by reducing costs.
This study aims to provide guidance to researchers and industry professionals aiming to improve quality control processes. It is also considered that this technology has the potential to be utilized in other industries. Therefore, this study may find a wider industrial application area in the future and has the potential to encourage similar projects.

Keywords: Image Processing, Defect Analysis, Industry 4.0, Insulating Glass, Smart Manufacturing Systems.

1. Introduction

Insulating glass products are now essential in modern construction and enhancing energy efficiency. By saving energy in buildings, well-designed insulating glass plays a crucial role in promoting sustainability and economic efficiency. This underscores the importance of maintaining the quality and integrity of insulating glass, a vital factor in the construction industry and energy conservation.

The widespread use of glass in the construction sector, especially with the use of insulated glass, has increased significantly. These glasses are crucial for energy efficiency, comfort, and environmental sustainability. However, the occurrence of quality errors in glass production has been a significant concern for both manufacturers and end-users. Therefore, the detection and correction of errors in the glass production process emerge as a critical element of quality control processes.

Traditionally, the detection and assessment of errors in glass production have been carried out through visual inspection by the human eye. However, this method can yield variable results due to the influence of the human factor and carries the risk of overlooking some errors. Additionally, this method is time-consuming and may limit production speed.

The rapid advancement of technology presents new opportunities for enhancing quality control processes. Specifically, machine vision systems, known for their high precision and speed, hold significant potential for detecting and analyzing defects in glass production. These systems can precisely identify defects such as scratches, bubbles, cracks, and fractures on the glass surface.

The focal issue addressed in this study pertains to the visual examination of glass emerging from the washing-drying machine in the production lines of insulated glass. Quality control problems arise from the dependence on the human factor in this process. Additionally, there is a circumstance where the visual inspection of insulated glass units, particularly those produced in Jumbo dimensions (3300x6000mm), is not feasible for operators due to the constraints imposed by market demands.

To address this issue, a glass scanning and defect imaging system has been developed that can adapt to different glass dimensions and line heights while aligning with the processes and environment of glass production. As part of the goal of digitizing production, software will be developed to detect and display defects on the glass. This will reduce the impact of the human factor and prevent faulty products from reaching the consumer. Additionally, it will contribute to cost reduction and the preservation of brand value.

This study aims to introduce a glass anomaly detection system developed under laboratory conditions for the purpose of identifying visible defects in the production of insulated glass products. This system aspires to achieve faster, and more accurate results compared to traditional quality control methods. Additionally, it provides manufacturers with the opportunity to prevent the distribution of faulty products to consumers and to reduce costs.

The components utilized in the prototype system of the glass anomaly system to be integrated into the insulated glass production line, along with the hardware communication protocol and image processing technologies, have been detailed. Finally, test results are comprehensively articulated. Through this article, we aim to demonstrate how machine vision systems can play an effective role in quality control in glass production. This study is crafted to provide guidance to researchers and industry professionals seeking to enhance quality control processes in the glass industry. Additionally, we aim to emphasize the importance of these technologies developed to achieve higher quality standards in glass production in the future.

1.1. Literature Research

The problem our study focuses on is the visual inspection and quality control of glass coming out of the washing-drying machine in the insulated glass production line. To address this issue, we reviewed some significant studies in the literature, particularly those exploring the use of image processing and artificial intelligence technologies in glass production.

In 1971, David A. Huffman developed a series of algorithms and techniques used to identify straight lines in images. The Huffman algorithm has a significant impact, particularly in applications such as edge detection and line tracing [1]. In the same year, Adrian J. Clowes researched mathematical and computational methods for detecting objects and edges in images. This study laid the foundation for edge detection and object recognition systems [2].

In 1975, Robert A. Waltz examined symbolic and semantic approaches used for object recognition and image analysis. This study represented a significant advancement in the meaningful identification and determination of objects in images [3].

Additionally, it is noteworthy to mention that studies related to three-dimensional imaging were initiated by Baker in 1977. These studies focused on developing techniques fundamental to the modeling, visualization, and analysis of three-dimensional objects. The works from this period had a significant impact on the fields of computer graphics and image processing, laying the groundwork for advancements in this domain [4].

The glass defect analysis study conducted by Imbert in 1989 marked a significant starting point by employing laser illumination to detect defects on the glass surface. This study made a substantial contribution to the field of detection and analysis of glass surface defects, serving as a crucial resource for subsequent researchers [5].

In the study conducted by Ai and Zhu in 2002, the analysis of defects on glass surfaces was first attempted using the Markov Random Model. In this study, analyses were performed on only three glass surfaces [6].

In the 2006 study conducted by Fezani and Rahmani, the surface analysis of flat glass surfaces was carried out using the energy transformations of wavelet waves. This study demonstrated that background noises could be effectively reduced by utilizing the characteristics of wavelet transformations [7].

In 2007, in a study led by Oh and colleagues, a Model Fitting (MF) predictor was developed to detect low-contrast areas on glass. In this study, the aim was to accurately predict the background model using a modified MF predictor and, as a byproduct, identify stain defects. Light irregularities were modeled as a parabolic function, with the central region being brighter than the surroundings. Zero-mean Gaussian noise was added to real data, and for each simulation, the amount of noise, Gaussian noise standard deviation, and the depth of the actual data in the circle were controlled [8].

In 2007, Perng and colleagues developed two different image processing systems for the automatic inspection of CRT panels. These systems were employed to check for defects on the front surface and side walls of the panels. The goal was to detect errors that could occur on the inner and outer surfaces or in the internal parts of the panels, such as scratches, stains, cracks, bubbles, etc. Panel imaging was facilitated using two different lighting environments. Experimental results indicated that the developed image processing systems could be effectively and efficiently utilized to automatically inspect CRT panels on the production line. In essence, this study demonstrated a successful approach to automate the quality control of CRT panels and the effective application of these systems in the production process [9].

In 2008, Adamo and colleagues presented preliminary results obtained through an experimental automatic and computer-based image inspection technique that proved effective in detecting and classifying production defects in satin glass. They outlined the components of the developed prototype and explained the functions of the image processing system. This system was scalable based on the size of the glass to be analyzed, had processing times suitable for industrial production, and developed distributed computing techniques to handle the increase in computational load. In subsequent studies, they aimed to extend these techniques to other materials such as textiles, leather, and steel sheets [10].

In 2008, the study conducted by Peng and colleagues emphasized that defects present in float glass could dramatically reduce glass quality. In this article, they presented an online defect inspection for float glass using a machine vision-based method and implemented a distributed online defect inspection system for float glass production. This method inspected defects by detecting changes in image gray levels resulting from the optical character difference between glass and defects. They developed a series of image processing algorithms around online inspection system requirements such as analysis reliability, real-time capability, and accuracy. They utilized gradient direction-based image filtering to filter noise and preserve defect source information. Defective and non-defective portions of the glass were obtained using gray range limited thresholding and OTSU algorithms, respectively. A control system based on this method was implemented at the Wuhan glass factory, proving that this inspection method is effective, accurate, and reliable. In summary, the study demonstrated the successful design and implementation of an effective image processing-based approach for online defect inspection in float glass [12].

In 2009, Adamo and colleagues designed a system for a production line quality control system to reproduce real-world issues. This system consisted of a series of CMOS cameras, a controllable roller conveyor, and a PC-based image processing system that also controlled other subsystems. Defect detection was performed using the Canny edge detection method with thresholds selected based on the statistics of processed images [11].

In 2011, Zhao and colleagues proposed a method for sharp edge detection in low-resolution images, thereby enabling the identification of the smallest connected region (rectangle). They ultimately adopted the AdaBoost method for classification. Experiments conducted with 800 bubble images and 240 bubble-free images demonstrated the effectiveness and efficiency of the proposed method in recognizing glass defects such as bubbles and residues [14].

In 2012, Zhang, Hongxi, and their colleagues proposed a defect detection algorithm specifically targeting bubbles, stones, and glass cracks based on Discrete Fourier Transform (DFT) and optimal thresholding methods. The results obtained demonstrated that the proposed detection algorithm provided an application capable of recognizing defect areas with high precision and accurately determining their locations [13].

In 2013, Singh and colleagues briefly discussed various defect types in glass sheets. Different color space techniques were compared and analyzed in terms of performance [15].

The common objective of these studies is the more precise and effective detection and classification of defects in glass production. To achieve this goal, various image processing techniques and algorithms have been employed.

2. Materials and Methods

The glass anomaly detection system will be integrated into insulating glass production lines. The insulating glass production line (IG4.0) is designed and manufactured to make double, triple, or quadruple glass (insulated glass) by washing, drying, and manually matching glass of the declared maximum and minimum dimensions. The operation of the IG 4.0 line manufactured by CMS Machinery includes a series of automated steps used in the production of insulated glass products. The basic operation of the IG 4.0 line is described below:

1. Inlet Conveyor: The production process starts with this conveyor to load the glass sheets to start the manufacturing of insulated glass products. The glass sheets are prepared for loading at this point.

2. Washing and Drying Unit: The washing and drying unit cleans and dries the glass sheets. This step removes dirt and debris from the surface of the glass, thus ensuring better adhesion and insulation.

3. Spacer Assembly Unit: This unit places the spacer frames on the cleaned glass sheets. The spacer frames form the air gap inside the insulated glass product.

4. IG Unit Assembly: After the glass sheets are combined with the spacer frames, they come to the press unit. The press unit compresses the two glass sheets to form the insulated glass product. In this step, gas filling is also carried out into the insulated glass product.

5. Gas Filling: One of the most critical stages of the IG 4.0 line is the gas filling process. In this step, an atmospheric gas such as argon gas is filled into the insulated glass product. Argon gas is used to increase energy efficiency and improve insulation performance.

6. Press Outlet Conveyor: After the products are removed from the press unit, they are directed to the press exit conveyor. Here the products are prepared for packaging or storage.

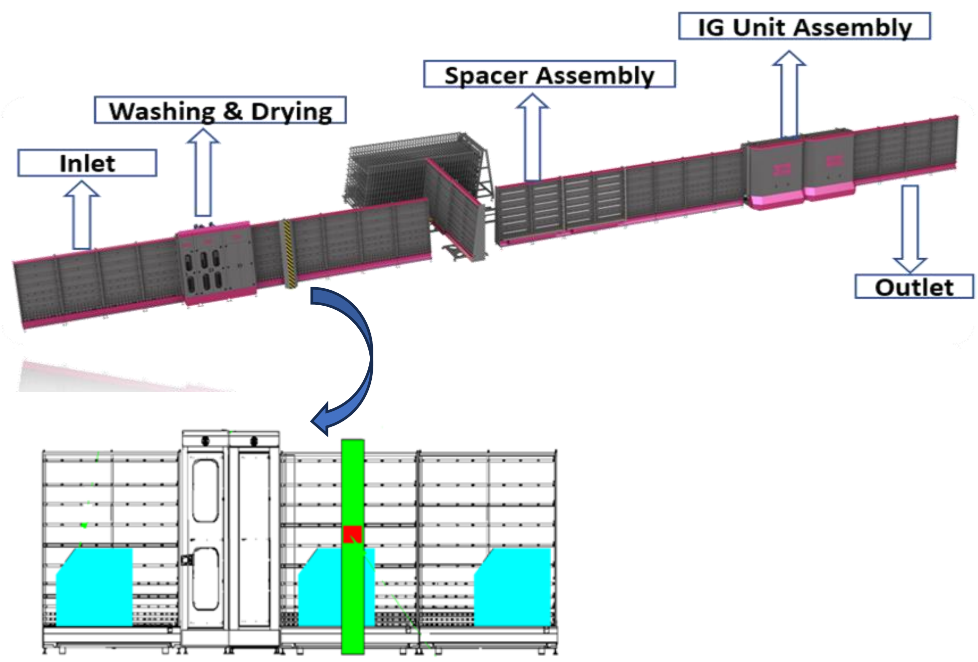

Figure 1: The operation of the insulating glass line is given, and it is shown in which unit the glass anomaly detection system will be used.

2.1. The Proposed Prototype System

Since the glass anomaly detection system has a modular structure, it is possible to develop it on a small scale but with many functions by reducing the number and capacity of the elements that make up the system. For this reason, a prototype has been developed in laboratory conditions where all the functions of the glass anomaly detection system will be created.

The prototype of the system consists of a motion system, an encoder, and a sensor module. A test kit was developed to drive the PLC and the conveyor motor (servo motor). Necessary power supplies were used to energize the sensor.

Motion System: The wheels carrying the glass are controlled by a servo motor under PLC control. The PLC software designed to drive the conveyor, forward - backward speeds, acceleration - deceleration speeds of the conveyor are entered. It allows the glass to move back and forth manually or automatically.

Encoder: It is the part located before the sensor on the prototype. It is placed for test purposes. Length information can be obtained by communicating the encoder with PLC. When working in encoder mode, the conveyor speed information can be obtained from the sensor.

Sensor module: Consists of image acquisition unit, illumination source, image processing units. The Contact Image Sensor is designed for scanning flat surfaces. However, this sensor alone cannot be used for glass surfaces. For this reason, by combining the CIS sensor with various automation product groups, a new sensor system with the capacity and technical specifications required by the sector was created in the laboratory environment. Depending on the camera models, internal or external light sources are used. In the prototype study, a fluorescent lamp was used as an external light source. Contact Image Sensor (CIS) line scan camera and frame grabber are used for image acquisition. Python libraries and machine learning models are used for image processing.

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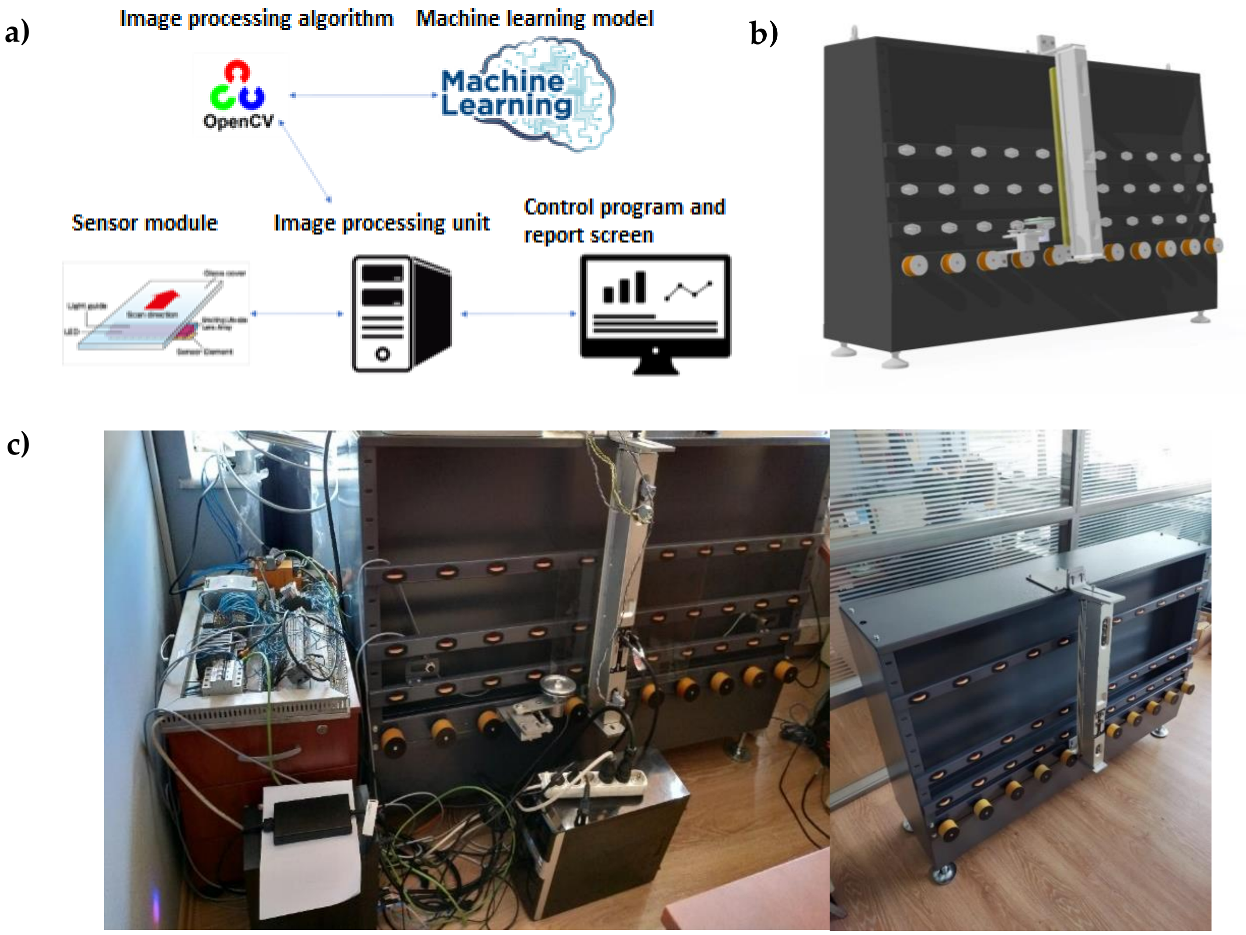

Figure 2: The a) diagram b) 3D design and c) fabricated prototype of the proposed prototype system are given.

2.2. Development of Hardware Communication Protocol

Python libraries and C# software language were used to communicate with the sensor module. A software was produced to adjust the camera's modes and settings such as white-black balance, light control, image acquisition speed. The scanning can be started and stopped through the same software. Images are taken as strips from the sensor and then these glass images are merged and saved in the desired folder.

The software interfaces developed within the scope of the communication protocol are given below:

- Sensor Health Status Display Interface
- Sensor Communication and Tuning Interface
- Os Code Editor
- Image Capture Studio

2.3. Image Processing Application

The image processing application provides information to the user by marking the location of the defect in case of any defect in the images taken.

Communication was provided with Python interfaces and codes. Blurring with Gaussian and filtering using adaptive Threshold is applied, then the presence of glass or defect is detected by counting the counters.

A sheet metal surface database and a deep learning model using TensorFlow, a Python library, were used to train image classification, save the model, and determine which class the trained model and test images belong to.

Images were obtained for the glass database and these images were organized according to the structure required by the deep learning model. Defects that may be found on the glass surface were included in the database structure with their relevant names and then obtained with appropriate deep learning models.

The ImageNet database with 1.4 million images and 1000 classes and the pre-trained MobileNet V2 model were used. VGG Image Annotator was used for labeling.

a. Background Subtraction

Background subtraction is an important image processing technique for separating and detecting the background of objects in a 2D image without depth information. It is defined in the literature as background subtraction or background removal. The reasons for this process are given below:

Counting Objects: Background subtraction is used to detect and count objects in an image. For example, using a security camera or traffic camera, background subtraction can be applied to calculate how many people or vehicles are in a given area.

Capturing and Analyzing Objects in Motion: Background subtraction is important for motion detection. Detection of moving objects is used in many areas such as video surveillance, security monitoring or automation applications. For example, background subtraction can be used to detect a person entering a house and analyze this motion.

Object Recognition: Background subtraction is used in the preprocessing phase of object recognition systems. Object recognition algorithms need background subtraction to separate objects from their background. This is important for the subsequent classification or identification of objects.

Motion Detection: It is used as a key component of motion detection systems. Through this, it can be detected that an object has moved in the field of a camera for a certain period. This is critical for many applications such as security, traffic control or industrial automation.

Background subtraction with OpenCV is done with the absdiff () method, which is included in Core. absdiff performs a subtraction operation between two given matrices, and because of this operation, the changed regions (moving regions) are highlighted. The result of the subtraction is returned as an absolute value.

```
Core.absdiff(src1, src2, dst);
```

b. Noise Filtering with GaussianBlur Method

In the resulting output images, problems such as shifting of some pixels, blurring or incomplete cleaning are common problems in image processing processes. To solve these problems, image filtering is performed. Noise filtering operations are performed before the image thresholding method. There are filtering methods such as Blur, GaussianBlur, Laplace, Sobel. Since only GaussianBlur filter is applied in this study, only this filter is explained.

The GaussianBlur filter is a smoothing operation on the image and the GaussianBlur() method used in the OpenCV library is used to perform this operation. This method takes three main parameters:

Source Image (src): A Mat object representing the initial image to be processed by the GaussianBlur() method.

Result (dst): A Mat object where the blurred image will be stored. This represents the image that will result from the processing.

Kernel Size (kernel size): Refers to the kernel size that will be used for the Gaussian smoothing process. This kernel size is a value used to blur a pixel due to the influence of surrounding pixels. In particular, the kernel size determines how strong or light the process will be.

Kernel Standard Deviation (SigmaX): The Gaussian process has a specific standard deviation value, and determining this value helps control how blur the process generates. A larger SigmaX value produces more blur, while a small value produces less blur.

In summary, the GaussianBlur () method is used to apply a Gaussian smoothing process on the image, and the kernel size and SigmaX parameters can be set to control this process. This filter is important in image processing applications for operations such as noise reduction or edge detection.

```
Imgproc.GaussianBlur(sourceImage, targetImage, new Size (200,200),0);
```

c. Contour Finding

A contour is a sequence of points that express the curve contained in a shape or an image [16]. Image segmentation is important for categorization and segmentation [17]. Contours can be expressed as curves connecting continuous points of the same intensity or color. Contours serve as a useful tool for many applications such as shape inspection, object detection and object recognition.

In OpenCV, contour capture is performed using the findContours function, which takes three basic parameters. The first parameter represents the source image to be processed. The second parameter specifies the contour capture mode and the last one refers to the contour capture method [18].

d. Image Thresholding Method

Image thresholding is a widely used method in the field of image analysis to separate an object from the background [19]. This method is widely used in many fields such as texture analysis, object recognition, fingerprint processing and map analysis [20-21]. In image processing, it converts the received image into a binary image according to the threshold type.

This method is based on determining a threshold value that identifies an object in an image and the following thresholding techniques are generally used:

General Thresholding: General thresholding uses a fixed threshold value to separate the object in the image from the background. This method is easy to use and gives fast results. However, it may not be effective in more complex scenes for non-flat objects.

Local Thresholding: Local thresholding is used to recognize complex objects such as irregular shapes. In this method, the threshold value may vary depending on different regions of the image.

Manual Thresholding: This method is one of the most used methods to highlight the desired objects. The image is converted to gray level, the histogram is extracted, and a threshold value is manually set by the user.

Thresholding with Otsu Method: The Otsu method is a thresholding method used in gray level images. By analyzing the histogram, it divides the image into two classes and calculates the pixel probability densities within these classes.

The thresholding method is important for identifying and processing objects in an image and offers fast results compared to more complex image processing methods. For this reason, it is preferred in many application areas, especially in areas such as object detection, object recognition and image analysis.

e. Convex Field Conversion and Convex Field Filling Operations

Convex area inversion and convex area filling are image processing methods used to create convex covers or outer boundaries that define the boundaries of objects or shapes. Here is more information about these two operations:

Convex Hull: This operation combines the points that represent the boundaries of an object to create the smallest convex hull or outer boundary surrounding that object. The convex hull forms a line or polygon by connecting the outermost points of the object's outer contour. This operation is used to simplify the shape or boundaries of objects, to define objects, and to calculate geometric properties of objects.

Convex Hull Filling: This operation fills in the outer boundaries of an object or shape created by the convex hull, completely covering the object. Once the convex hull forms the boundaries of the object, it can be used to color or mark the inside of the object by filling in the hull. This is useful for analyzing, coloring, or marking the interior space of objects.

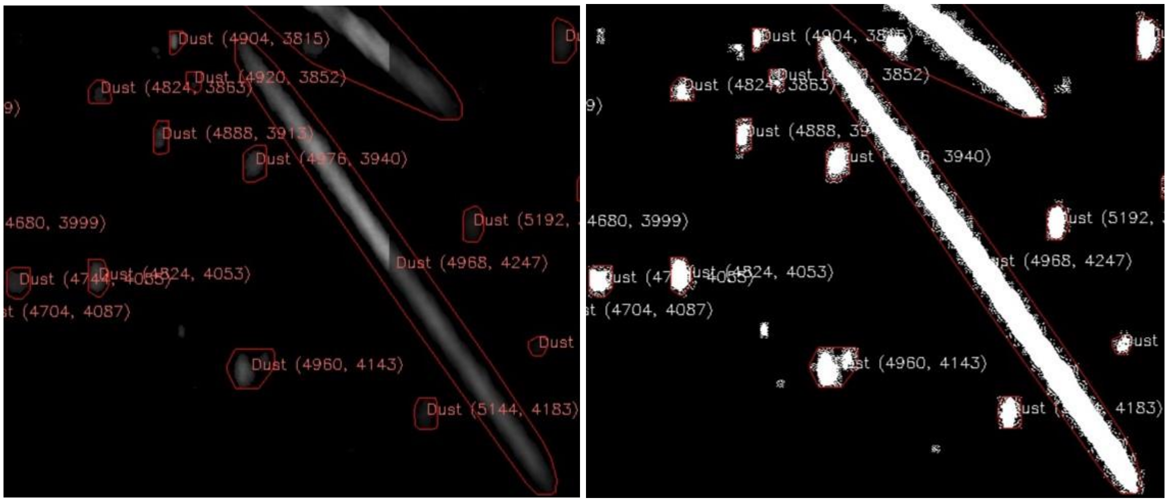

Figure 3: On the left is the real image with convex area filling and on the right is the image with the threshold method applied to it. The red lines indicate that the contours are drawn as convex.

3. Results

Tests were carried out with various power supplies, different collectors, different voltage magnitudes and different cable lengths to prove that the system works statically.

Since the glass product is very sensitive, it is very important to ensure voltage regulation. In the first study, it was tested with 24V, and in the following stages, different voltages were applied to obtain the static operating voltage.

At the beginning of the image acquisition studies, there was a problem in obtaining a clear image. Research and tests were conducted to solve this problem. One of these tests is the use of cables of different thickness. In line with this information, it was determined that image acquisition was successful when a 5V DC 6A power supply was used instead of a 5V DC 5A power supply. Thus, it was determined that the power supply did not meet the desired current value for image acquisition, so the image was not clear.

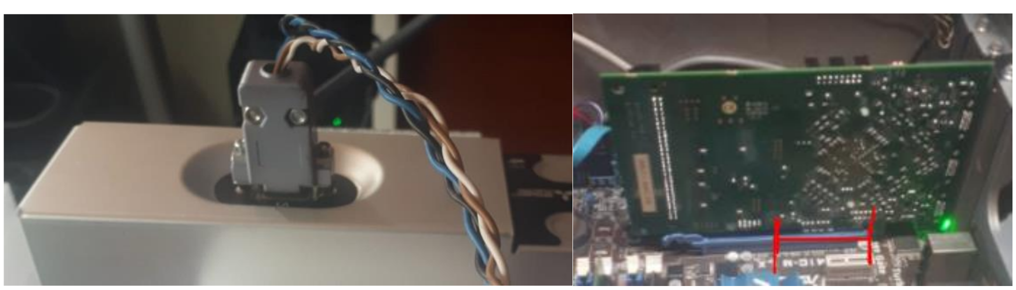

Figure 4: An example of the tests performed to ensure static operation of the system.

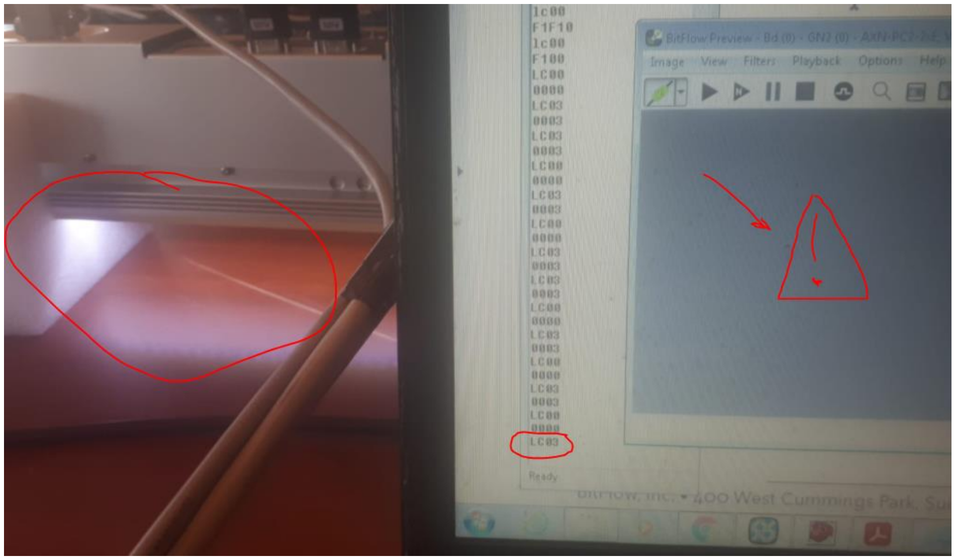

Figure 5: An example of the problems encountered in the first image acquisition studies.

In the study prepared to test the hardware communication protocol, two different operating modes were added as encoder and without encoder and the visualization of the study is shown in Figure 6. A command can be sent manually and when we press the direction button, we switch to the image acquisition protocol. There are two buttons for stopping and restarting image acquisition. There are also options to toggle on and off the features for detecting errors and saving the acquired image. On the right side there is a zoom in and zoom out bar and an area below that area where the image is displayed. In Figure 6, the left side is the Sensor Communication and Tuning Interface, and the right side is where the image is taken and processed.

Figure 6: Hardware communication protocol successfully developed.

For the sensor to detect the glass, different materials were placed behind the glass and the effect was analyzed. As a result of the test:

- When plexi black and blue color is used, the glass is hardly visible. In white color, it gives a darker result than other materials. It reduces the sensitivity of detection.
- A4 paper and cardboard give similar results, but for the long length of the glass more than one material must be used. Transitions between pieces are detected by the sensor.
- It has been observed that fingerprints are a little more obvious with the cable tray cover than others. It offers a more open image. Since the lines on it are vertical, it can offer a more homogeneous background image than other materials when placed correctly behind the dear in the prototype.

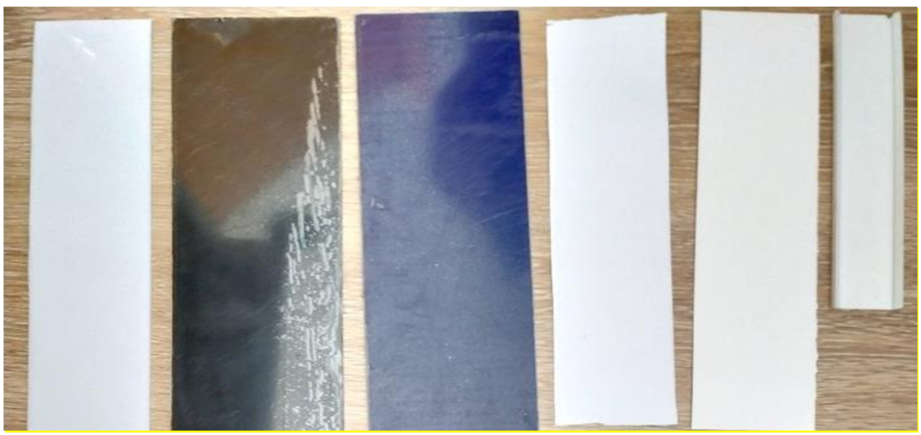

Figure 7: Materials tested: white plexiglass, black plexiglass, blue plexiglass, paper, cardboard, and conduit cover (the shorter one is used as an example).

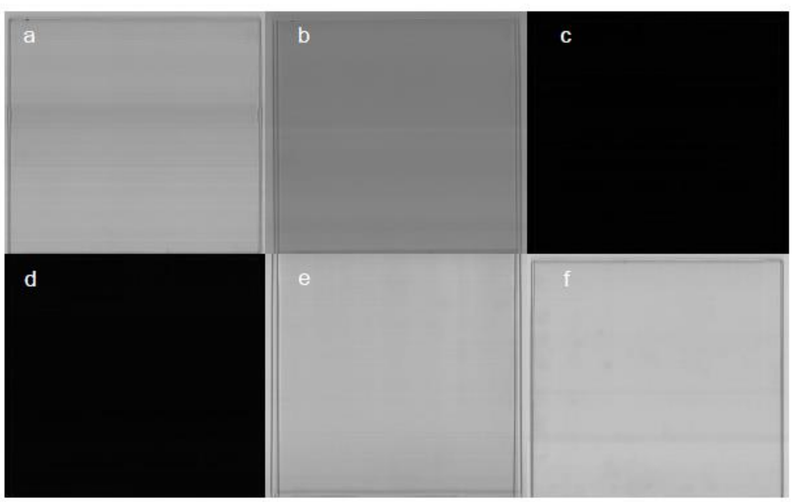

Figure 8: a) A4 paper b) white plexi c) black plexi d) blue plexi e) cardboard f) cable duct was used as background material.

Examples of images obtained in the image processing process are shown in Figure 9.

Figure 9: Examples of image processing process application studies are given.

After various tests, it was found that dust and fingerprints could be detected when an external light source was placed behind the glass instead of a reflective plate. The choice of the type of light source and the repetition rate proved to be important in the tests. The fluorescent light source is both long enough to transmit light to a larger area and has an operating speed of 50Hz, which makes it possible to obtain an image with the camera sensor without any problems.

In the model training and test image, 1093 images and 2 classes (dust and clean) were given. Although approximately 99% training accuracy was achieved, a success rate of 7/10 was achieved when tested.

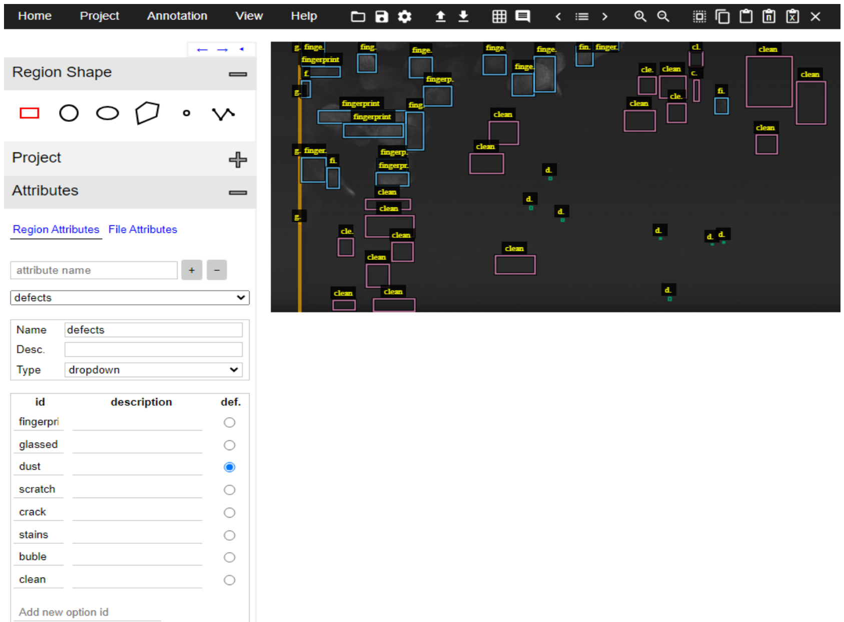

Figure 10: Image labeling on VGG Image Annotator is shown.

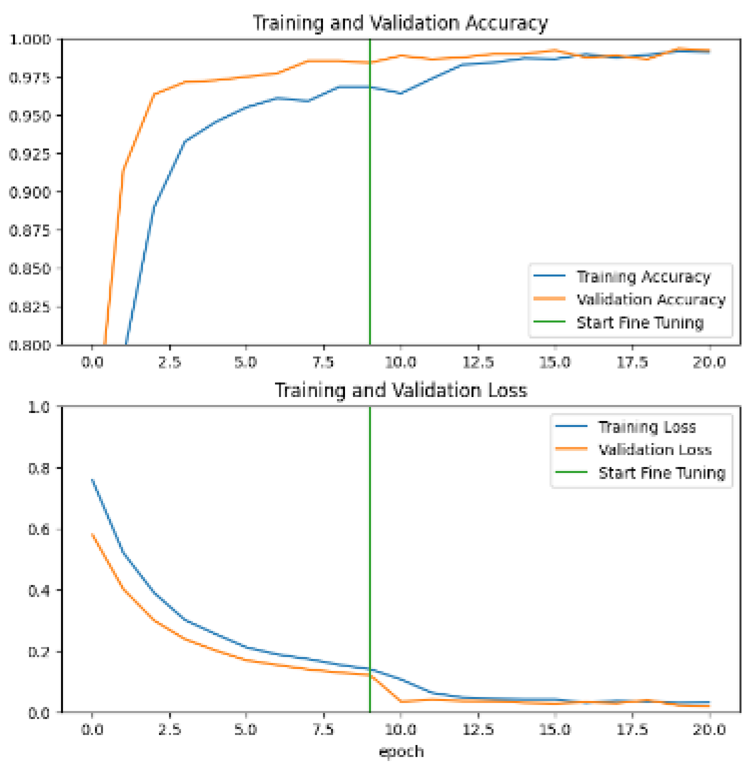

Figure 11: Model training accuracy curve using Tensorflow library, MobileNet V2 model and glass images.

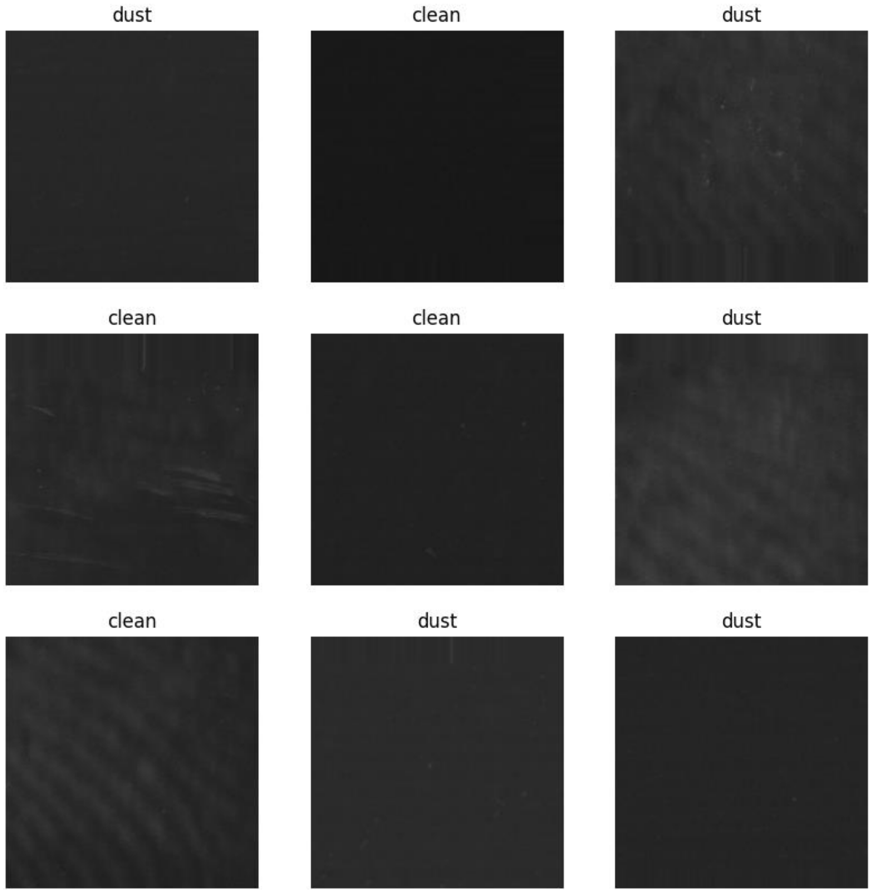

Figure 12: Machine learning outputs.

An algorithm was developed in which objects visible by scanning would be seen more clearly by taking the difference between an image taken when there is no glass and images that continue to be taken in real time, regardless of the use of external or internal light. In the tests, dust and fingerprints were detected with internal light.

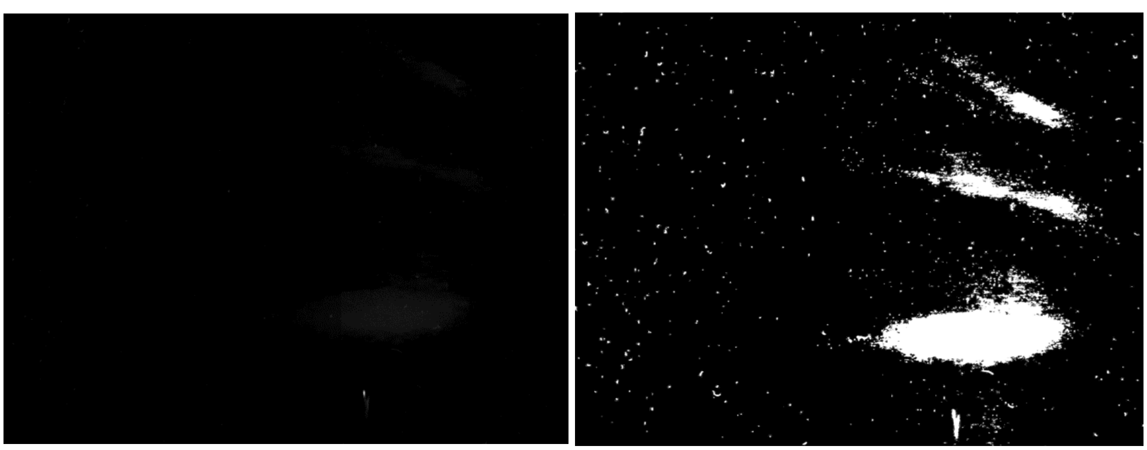

Figure 13: Original image and black and white image obtained.

The location, size and names of the detected defects were drawn on the glass image.

Figure 14: The location, size and names of the defects are plotted in pixels on the acquired glass image.

4. Discussion and Conclusion

This study presents a successful prototype of a glass anomaly detection system aimed at improving quality control processes in insulating glass production. Experiments and tests have confirmed that the developed system has high sensitivity, reliability, and fast scanning capabilities. The prototype system operated consistently under different test conditions and successfully detected defects on glass surfaces.

The image processing algorithm has played a critical role in detecting errors in the acquired images. The filters and counter counting methods used helped us to obtain clear images and provided an effective way of identifying errors that the human eye may not be able to detect under intense light.

The machine learning model achieved high accuracy rates in the training and testing phases and was able to successfully identify dust, fingerprints, and other defects. The database creation process ensured that enough images were available for training the model.

The results of this study show that the developed glass anomaly detection system can provide significant advantages to the insulating glass production industry. By reducing the impact of the human factor, this system can prevent defective products from leaving the production line and reduce costs. In addition, similar technologies have the potential to be used in other industries.

In conclusion, this study aims to inspire researchers and industry professionals who are interested in improving quality control processes in the glass manufacturing industry. In the future, we believe that this technology may find a wider range of industrial applications.

5. Acknowledge

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