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Early Stage Detection of Crack in Glasses by Hybrid CNN Transformation Approach

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Abstract

Recently, glass crack detection methods have been emerging in Artificial intelligence programming. The early detection of the crack in glass could save many lives. Glass fractures can be detected automatically using machine vision. However, this has not been extensively researched. As a result, a detection algorithm is a benefit to study the mechanics of glass cracking. To test the algorithm, benchmark data are used and analysed. According to the first findings, the algorithm is capable of figuring out the screen more or less correctly and identifying the main fracture structures with sufficient efficiency required for majority of the applications. This research article has addressed the early detection of glass cracks by using edge detection, which delivers excellent accuracy in fracture identification. Following the pre-processing stage, the CNN technique extracts additional characteristics from the input pictures that have been provided due to dense feature extraction. The "Adam" optimizer is used to update the bias weights of networks in a cost-effective manner. Early identification is achievable with high accuracy metrics when using these approaches, as shown in the findings and discussion part of this paper.

Keywords: CNN, sobel operator, edge detection, image denoising, glass crack, feature extraction

1. Introduction

It is a goal of the glass industry's automated inspections to improve the quality of the product while increasing production rates. Therefore, false positives and negatives must be minimized to replace human reviews with new technology. This research is of particular interest because scientists and engineers who work with glass are keen to know how it fractures. Forensic scientists, for example, are interested in modelling the formation of fractures. It is a common practice for researchers to examine images of damage by hand to construct physical

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models that estimate the location of a projectile. The enormous digitalized datasets on fractured glass might be used in other domains, such as material science [1-3]. The future iPhone's display may, for example, benefit from engineering data on fractures collected from real-world use. Figure 1 shows various crack types in glass.

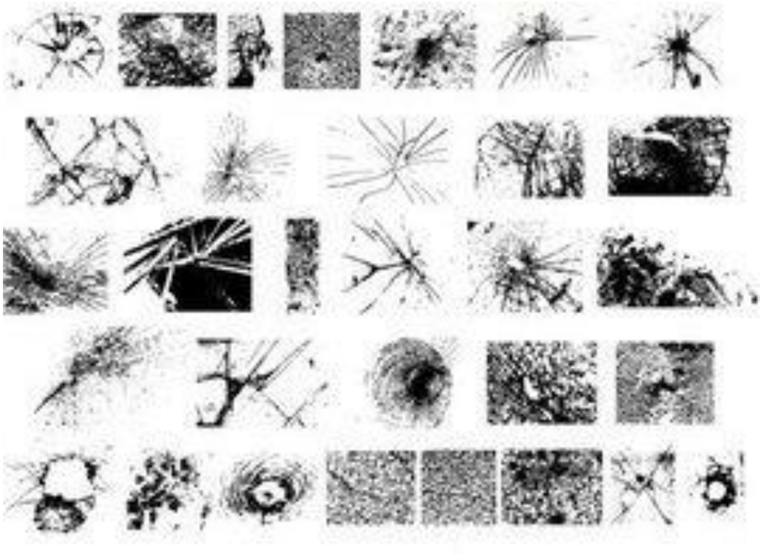

Figure 1. Various cracks of glass database [30] [31]

A common difficulty with traditional concrete is that it deteriorates with time, resulting in construction structures like bridges, dams, and buildings. Maintaining and monitoring the facilities regularly is the best way to prevent the deterioration by age. The old manual inspection approach cannot satisfy the considerable road pavement inspection needs. Cracks are now detected using a variety of computer vision techniques [4-8].

Breaks in glass caused by traffic accidents have a distinctive expression that differs from the healing process, thus minimizing the need for specialized expertise and making it more accessible to everyone. After the deep neural network was created, the technology for understanding the features of the cracked glass, it has made a considerable progress in studying road traffic accidents [9]. It has a strong generalization capacity and can extract the distinctive expression of shattered glass and other damages in car accidents, improving artificial intelligence in many applications. In general, laminated glass is more substantial than flat glass, and four-frame support glass has more extraordinary ability to withstand impact than four-point support glass. The flat glass specimen was subjected to fragment analysis. Radial cracks in flat glass with four frames are the most common breakage, and the sharp dagger-shaped pieces they produce are most common. There are also dagger-shaped components and the limit of four-point support plate glass [10-15].

This research paper has been written with several sections containing past research works about glass crack detection methods; section 3 discusses the glass crack detection method with image segmentation approach; section 4 delivers experimental test results and its discussion by the proposed method. Finally, a conclusion with future enhancement has been discussed.

2. Literature Survey

The robustness of the HOG (Histogram of Oriented Gradients) approach for producing picture characteristics functions well for object identification. Based on this theory, a picture is described by its local intensity gradients or edge directions. In order to compute HOG for a given picture, cells are used to divide it into smaller, more manageable chunks. Then, in a histogram, the pixel gradient directions in each cell are displayed as bars. When Dalal and Triggs overlapped these cells in their study and demonstrated improved performance [16].

Oliveira et al. developed a model to identify cracks by determining gap damages using a sample. For unsupervised training of system pictures under the sampling paradigm, a subset of the available image databases is automatically picked. Based on the categorization of non-overlapping picture chunks, operations are defined. Following that, the crack's width is estimated using the detected crack block. A new dynamic programming-based crack detection system has been suggested [17].

The algorithm is a faster computation time, but it's also inaccurate. Gabor filters are used to identify cracks, which have an extraordinary impact on detecting surface fractures but not recommended to detect complicated cracks. This crack detection method by Zhang et al. used a four-layer CNN with an accuracy of 87% that has to be improved. This is the final approach presented by Zhang et al. which does not work well when identifying minor and distributed road fractures [18] [19].

An object's coordinates were deduced using the convolutional neural network's knowledge of the properties of shattered glass and fractures in car accidents as input to a regression network. In road traffic collision scenarios, the convolutional network learns about the features of broken glass, including categorization information and information about the object's size and position. The regression classifier was used to replace Alex Net's softmax classifier, and the objective regression function was reset to identify targets [19].

2.1 Research Gap

Several studies aimed at discovering cracks on glasses but fail to detect them early with the assistance of initial damages like dirt and other extraneous elements like photographs accessible in benchmark databases on the Internet. There are no other works found thus far like the present proposal.

3. Proposed Method

3.1 Early Glass Crack Detection Set-up

3.1.1 Algorithm Pre-processing Procedure

The initial processes in locating picture fractures are grayscale conversion, adding Gaussian blur, performing edge detection, eliminating noise dilatation, and eroding edges. Figure 2 depicts the findings at each stage of this approach. As previously stated, to evaluate the success of this step, corners are manually picked when the first step processes are unsuccessful. An advanced machine learning technique was then utilized to finish the edge features [20].

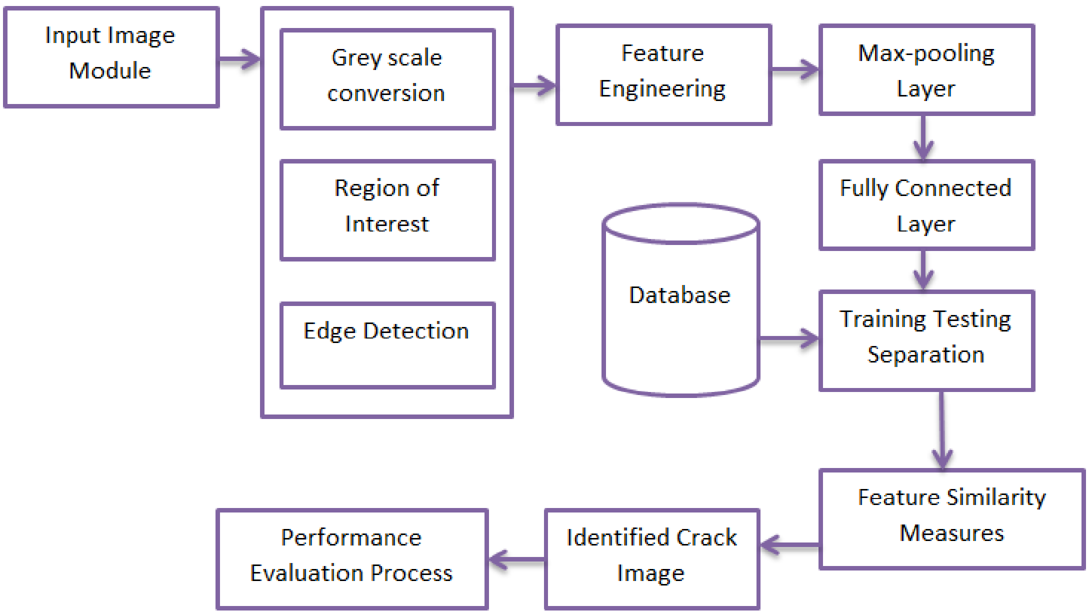

Figure 2. Proposed framework for early detection of glass crack

Step 1: Crack identification

The candidate coordinates for this object detection are compiled using a sliding window of glasses that skips 10 pixels. The candidate that receives the most excellent score for each corner is designated as that corner's coordinates in the final results. Aside from a few instances of poor performance, the corner detection was typically reliable. For this reason, a manually produced database is employed to test the performance of crack detection by CNN in corners.

Step 2: Image edge detection

Glass cracks may be seen as picture edges. In many machine vision applications, edge detection is a critical component and the subject of much study which is shown in the figure 2 as the proposed framework. The gradient of picture pixel intensities is generated using the Gaussian filter's derivative. First, the technique uses a Gaussian filter to decrease the image's aforementioned noise. Then, in order to retain the local maximum pixels in a certain sequence, algorithms take the gradient in many directions and scan the input supplied picture. Lastly, the Sobel detector has a high and low threshold to categorise pixels [21, 22].

Step 3: Crack identification by neural network

Training a multi-class CNN feature extraction on the pictures is both training and testing method, which is accomplished by creating a training set and manually building the testing set using a testing process that developed 100 pixels around each of the spots in the picture shown. Using this tool, 12 samples of each corner type and 200 examples of non-screen corner objects are extracted and identified. Each of the four corner kinds is represented by a patch in this image. In addition, there are instances of images of screens without corners and models of corners that were not screened in the non-screen corner items. At least a few cases in the proposed data set improved due to these two adjustments.

3.1.2 Loss calculation

Modelling the classification issue to predict how likely an example is to fall into one of the classes is an option when trying to transfer input variables to a classification label. A binary classification task, for example, might have two classes to predict whether the standard belongs to the first class. It can anticipate the chance of an example falling into each category when using multiple-class categorization.

3.2 Neural Network Construction

A biological structure modelled after the human nervous system is called a neural network. Because of its capacity to learn from data and create a network model for categorization, pattern recognition, and forecasting, neural networks are extensively employed in various fields. The neural network's most promising aspect is that it helps stimulate the neural network and produce a model that can be utilized further and applied to new data that hasn't previously been exposed to the network. Other classification approaches lack this characteristic [23-27].

A CNN is a neural network modelling method used to extract additional characteristics from pictures that have already been processed. The CNN tool trains and evaluates a neural network model for classification, identifying hidden patterns, grouping, and predicting the future.

4. Results and Discussion

The compact spectral density concentration at the edges, more significant samples owing to contact with the multiple loading plates, and poor binding characteristics of glass with other components are all likely factors in the early breakage of glass edges. Breaking points in the dataset's converging zone is found by verifying glass's spectral density and clustering features. Spectral clustering samples must be used to assess the input picture for early detection of the damaged state of glass [28, 29]. Input photos of glass particles show poor bonding with their properties, as reflected in the photographs.

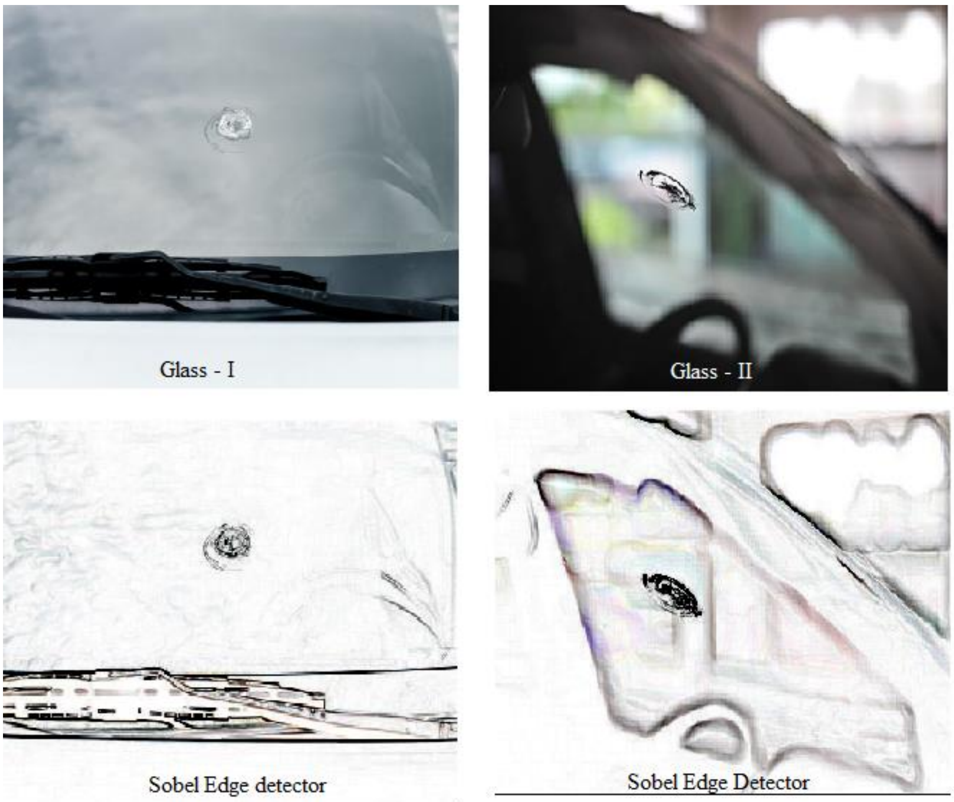

Figure 3. Results obtained at various stage

At the beginning of the breakage process, the tiny glass particles showed excellent binding characteristics. Operator using edge detection, such as Sobel, is more successful in locating such tiny particles on a glass's surface. The database has been created for the CNN classification with a few (around 500) cracked glass images inclusive of good uncracked glass images. Calculating the signal-to-noise ratio is done using the standard sigma value of 3, the low threshold value of 18 percent, and the high threshold value of 50 percent. The hysteresis threshold provides absence of crack detection with standard experimental setup. The signal-to-noise ratio can be calculated using the standard sigma value of 3. After CNN feature extraction, the identification is performed using the values put up in real-time.

Figure 4. Two different extracted features that indicate crack in the glass

The hybrid CNN transformation approach is a mix of CNN feature extraction and edge detection technique used in conjunction with one another. The output of the preprocessing of input image is processed by this hybrid CNN transformation approach. Figure 3 shows the result of the edge detection algorithm on broken glass.

Some of the problems or damages have been discovered quite quickly; however, at this time, the early sector stage may not be detected by a standard edge detection operator. As a result, further feature engineering is required for CNN to extract it, and then the network discovered the fracture at an early stage. Early detection is done by this proposed model and is shown in figure 4. Optimal performance is achieved by changing the settings dynamically and flexibly.

Table 1. Computed values of overall performance metrics

Deep Learning Model	Identification Accuracy	Recognition Error (%)	Early Stage Detection	Accuracy	Precision
Pre-trained CNN	84%	0.091	Partial	88.54%	81.67%
Image Segmentation	82%	0.195	No	89.76%	84.19%
Proposed Hybrid CNN Transformation Approach	94.58%	0.006	Yes	95.12%	90.48%

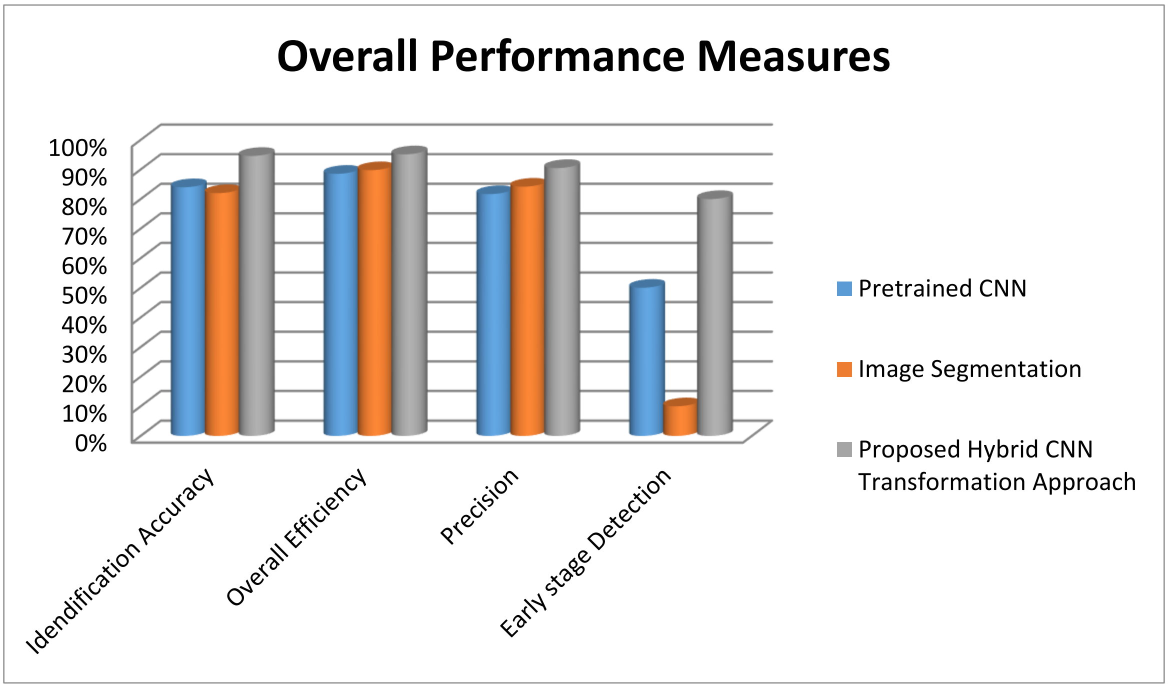

Figure 5. Performance chart between various algorithms

In addition, the CNN network, often known as the "Adam" optimizer, was utilized to identify the bias weights that were optimal for each neuron. The performance chart shown in figure 5 and table 1 that contains the results of the computations, demonstrate that this research methodology outperformed other methodologies in terms of accuracy and precision.

5. Conclusion

In this proposed research work, the upgraded convolutional neural network with image processing steps are used to identify fractures and effectively had a very high accuracy rate which is shown in table 1. The use of optimum convolution and pooling filters approach with fewer network layers is recommended to investigate relatively essential crack identification. The average error lowers as the number of training epochs increases, as seen by the results obtained. On contrary, it took a long time to finish the training session for this suggested framework. Moreover, as a result of overtraining, mistakes may arise. The findings indicated that the radial fractures were prevalent in flat glass with four frames and the resultant fragments mainly were sharp dagger-shaped shards. In the future, fragment analysis may be performed on all kinds of glass specimens. The Color-Crack algorithm might be used to crack different kinds of glass for applications in sectors such as material and forensic science.

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