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Crack Detection of Pharmaceutical Vials Using Agglomerative Clustering Technique

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Abstract. Pharmaceutical industries remain very profitable but defects in medicine vials are causing losses and adding extra overhead in quality management. In order to minimize these losses and overheads, companies need to find new ways of doing quality management for every vial produced. This paper presents a method for finding cracks on the vials using Agglomerative Clustering Technique. The technique successfully detects all types of cracks on the vials. The algorithm has achieved 100% accuracy in detection of cracks on the Pharmaceutical Vials and can have potential application in pharmaceutical industries in quality control.

Introduction

Defect detection is a part of quality control in various industries [1-9]. It is difficult to control and track the quality of Pharmaceutical Vials during the production process and that is why there has been an increase in cases of contamination of the medicine fluids [1]. This contamination of the medicine fluid brings about many difficulties to the people who consume them. The cracks on the medicine vials are a serious and difficult problem. This directly affects people health and reputation of the company which produces it. This issue has led to a significant loss of revenue for many companies involved in this industry. Hence, the quality monitoring and control procedure needs to be developed in order to prevent any potential problems caused by the cracks on the vials. Fortunately, researchers have found many ways to prevent this problem from happening. They have done extensive research and have come out with various methods and technique.

The method proposed by Li Fu et al. [10] includes techniques such as Median Filtering, Threshold and Canny Edge Detection. It has various steps like image acquisition, preprocessing, flaw detection and locating. In this technique, the rate of defect detection is 100%, 91.6%, and 94.4% respectively for the types of samples selected which includes vials with crack, missing edges in vials and dirty vials. In the technique proposed by Jaina George et al. [11] has the idea of using Fuzzy C Means Clustering for detecting glass bottle flaws. It has unsupervised model building and data analysis. Various filters have been used here for noise removal. K. P. Sinaga et al. [12] has proposed a new approach. In this framework, k-means clustering technique is adopted. Extra clusters will be discarded by the algorithm. Then according to the structure of data, automatically optimal number of clusters are found. It is an unsupervised technique. Huanjun Liu et al. [13] has come up with an intelligent inspection system for the glass bottles. The technique uses machine vision. Watershed transform method is used along with feature extraction. A classifier, fuzzy SVM ensemble is also used. The conducted tests show that the proposed method can reach rate of accuracy above 97.5%. Amin Noroozi et al. [14] has proposed a method where for any given arbitrary crack depth profile will be estimated using ACFM signals. For this an inversion approach is employed. Affine transformation is used by them to map the ACFM signals with respective crack depth. The underlying mapping is found efficiently a general fuzzy alignment algorithm is used. Then for various profiles of crack depth they used two algorithms GFAA and EFAA with simulated signals of ACFM. The experimental data is evaluated for examining the performance of the

algorithm in practical scenario. The results show that in the training stage itself the proposed methods efficiently eliminates irrelevant data effect. In presence of noise the technique exhibits more stability compared to neural networks. Best results are obtained when EFAA is used [15]. Z. Yang and J. Bai [16] has proposed flaw detection technique for vial mouth. It uses HALCON software based on machine vision. In this technique, the vial mouth noise is taken out using a filtering mechanism. In the next stage, threshold segmentation separated the target and background. Then edge detection method extracts the edges and finally detection of flaws on the vial mouth is carried out. Experimental results conducted show that the technique is efficient and rapid in identifying flaws on the vial mouth. The technique also has the advantages of stability along with high precision. The technique proposed by Xianen Zhou et al. [20] uses Saliency Detection and Template Matching for the flaws present at the bottom of the glass bottle. The method also employs multiscale mean filtering to initially filter the image acquired. But the method is having a lower precision level. Xiaoyu Liang et al. [21] has proposed a method for the flaw detection on the surface of the tube-type bottle. The technique uses machine learning to detect the flaws. Location Segmentation followed by Contour Extraction is done to detect flaws on the preprocessed image. Wittaya Koodtalang et al. [22] has proposed that Hough Circle Transform can be used along with Deep Convolution Neural Network (CNN) in order to detect bottom region flaws of the bottle. The methodology is based on Deep Learning. The method uses median and high pass filtering for image processing. In the method, the computation time is on little higher side due to the absence of GPU.

Current technologies used for detecting these cracks have their own limitations. For example, they are slow, expensive and require too much maintenance as well as calibration. The problem with defective or flawed medicine vials has been prevalent for a long time. The reasons could be attributed to the strict regulation of the government, unprofessional manufacturers or just plain human error. Either way, the problems caused by these is a serious matter of concern, even though deployment of good supervision is in place by pharma industries. Since the supervision is done on a collective number of vials or selective units but not on every production unit, the flaws on the vials are retained. So, the companies require a better solution to supervise every production unit. This paper deals with the detection of all sorts of cracks on pharmaceutical vials using image clustering techniques for quality management and analysis in pharmaceutical industries using the power of machine learning. This method can be successfully employed for defect inspection of vials using the model proposed [19].

Problem Definition

There are different types of cracks. These cracks may arise on the various areas of vials like surface, top, base or bottom and neck region. The best way to stop the problem of cracking vials is to identify the flaws in them and take necessary measures before they start affecting the quality, this can be done using an AI machine learning algorithm that identifies any cracks within the vial and alerts production managers. The objective of this paper is to detect cracks on all the regions of the vials which can be caused due to various factors like assembly related, environment, manufacturing procedure, components packaging, etc. This paper deals with a machine learning technique to determine the cracks using clustering techniques. We will also cover how machine learning in conjunction with k-means clustering can be used to find cracks within these containers as well as cracks on other objects manufactured from glass or any transparent material.

Methodology

To detect cracks in vials, the agglomerative clustering is used. This approach can be applied to other problems related to quality management and analysis. The system has been trained using the K-means clustering algorithm with data from 115 number of images and the model is trained using 16 images with different types of flaws.

The process is done using two steps: in the first step, for each image the four corners are detected and in the second step, the similarity between all images is calculated by comparing their corners. Finally, a decision tree model is used to create a classification model based on these calculations.

The cracks in the images were classified into two categories: cracks defects with distinct borders and airline gap defects without sharp borders, based on these categorizations the system had an accuracy rating of 100 percent for detecting cracks on the vials with large visible borders and 100 percent accuracy for air gaps in the vials.

The main objective of this paper is to suggest a viable solution for identification of cracks on the vials for pharmaceutical industry for applications in quality supervision and analysis, we propose a machine learning agglomerative clustering approach for identification of cracks in medicine vial's glass which can provide alerts about cracks before any serious damage occurs, with great precision.

Algorithm Description

The agglomerative clustering algorithm is often used for image classification, such as detecting and classifying objects in images. The main parameter of the algorithm that control the number of clusters can be adjusted by taking into consideration the number of features used in the dataset and other parameters that control the behaviour of a given clustering method.

The agglomerative clustering technique is a hierarchy based on multiple levels (clusters) which are created by finding the k-th nearest neighbour to each element in descending order. This method generates a set of (k-1) trees starting with a single leaf node, where each tree has as many levels as there are clusters found at its root. Each level is represented by an individual cluster which contains all elements within its radius.

Agglomerative clustering is a process that is used to group similar pieces of data or items together. This can be used when we want to group the different types of groups of cracks found in our supply chain in order to see how many are related, or how many are independent.

When we want to use this model, there are four steps that need to be accomplished:

Step 1: Choose a similarity measure.

Step 2: Create clusters by grouping pieces of data with the same similarity measure.

Step 3: Make sure the clusters have been created with no overlaps between them.

Step 4: Name and save clusters based on their content and purpose.

Proposed System

Clusters are formed by combining similar objects, and they can be classified as either static or dynamic. Static clusters are groups of vials that have the same defect categories and dynamic clusters are groups of vials that have the same defect types but different defect categories.

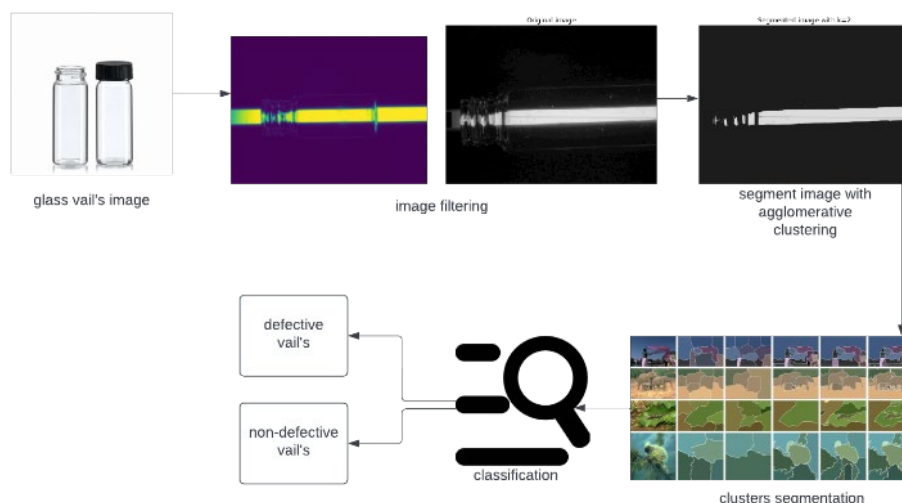


Fig. 1 System Architecture

The mathematical model for agglomerative clustering is used to detect defective parts in vials with cracks caused by quality management and analysis. Machines use this algorithm to categorize the cracks in each vial which increases the efficiency of sorting defective from non-defective parts.

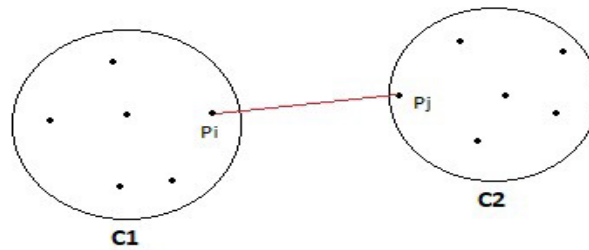
Clusters are the group of similar looking elements. There exist certain methodologies that can be used to find similarity between such clusters. The following way we can find similarity between clusters:

- Min
- Max
- Group Average

Consider the two clusters C1 and C2 and P_i and P_j are points such that P_i is point in C1 and P_j is point on C2

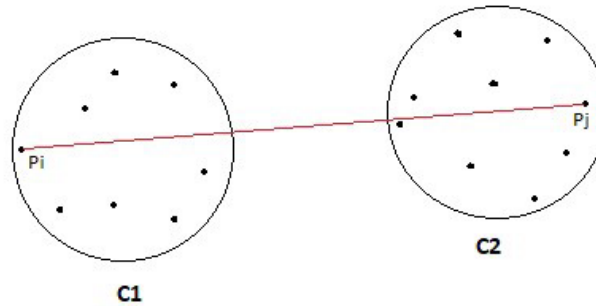
Then the elements required to calculate the similarity can be represented as shown below [17]:

$$\text{MIN} = \text{Sim}(C1, C2) = \text{Min Sim}(P_i, P_j) \text{ such that } P_i \in C1 \text{ \& } P_j \in C2$$



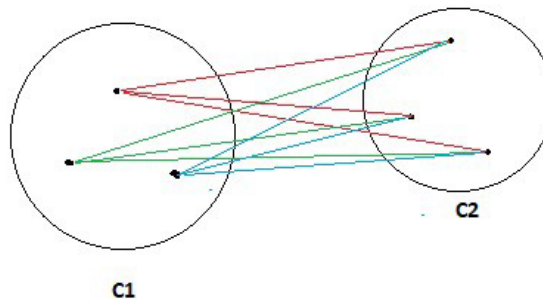
Min of C1 C2 [17]

$$\text{MAX} = \text{Sim}(C1, C2) = \text{Max Sim}(P_i, P_j) \text{ such that } P_i \in C1 \text{ \& } P_j \in C2$$



Max of C1 C2 [17]

$$\text{Group Average} = \text{Sim}(C1, C2) = \sum \text{Sim}(P_i, P_j) / |C1| * |C2|, \text{ where, } P_i \in C1 \text{ \& } P_j \in C2$$



Group Average of C1 and C2 [17]

The agglomerative clustering machine learning k clustering mathematical representation provides perfect results for this type of data. It helps to utilize machine learning and its math-based representation which provides more accurate results instead of using traditional filters like median or mean which may not be as accurate [18].

We can use clustering algorithms to create the image data of the vial, the image data of the vial is taken and then converted RGB to GRAY SCALE based on the filters that are inserted into the machine learning algorithm, then the final image clustered with the edges highlighted can be used to identify the cracks on the vial.

Results and Discussion

The study uses the noisy image mostly caused by the dust particles in the vial, an image which has a lot of unwanted noises and contains some missing information. It was difficult to see the image due to the noise and missing information. The difference between the noised image and the denoised image is compared in the below figure.

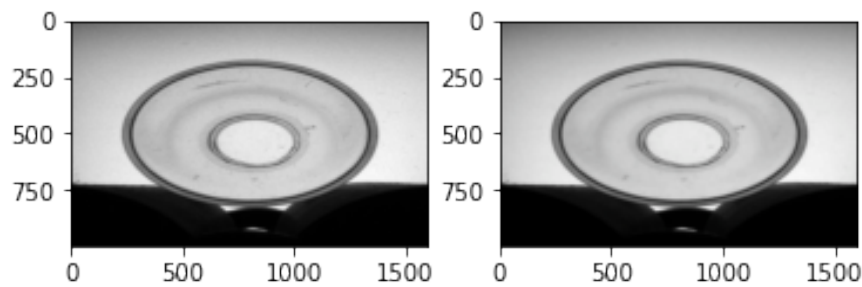


Fig. 2.1 Noise image and denoised image

We have used a real image dataset of vial with defective properties to make the highlights of the clusters in the image using clustering for $k=4$ to achieve optimum results, the main idea is to take a random sample from the whole dataset, apply agglomerative clustering and then perform k-means clustering with the same set of data. Finally, to compare each result by measuring how similar each cluster is with respect to the ground truth cluster labels as shown in the below image.

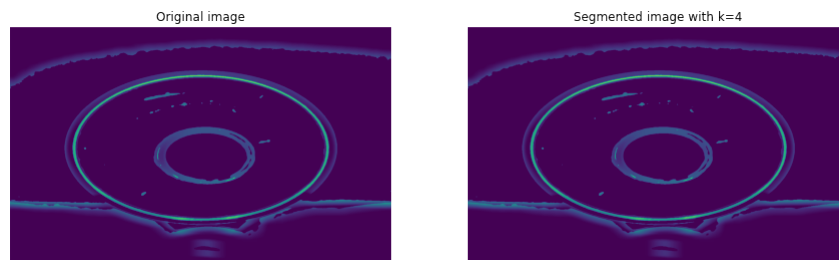


Fig. 2.2 Original dataset filtered and segmented with $k=4$

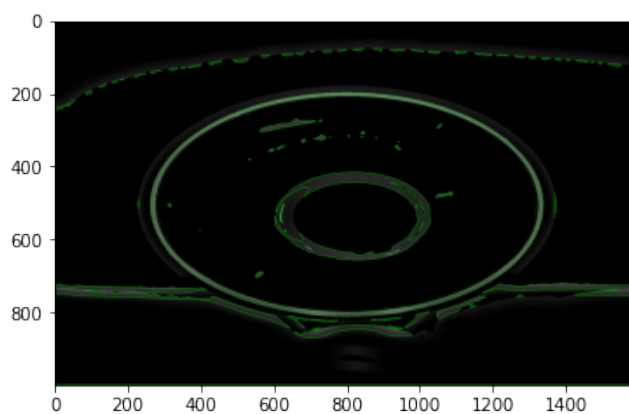


Fig. 2.3 Clusters edges detected and identified

The image processing machine learning tool is used to identify cracks in industrial parts. This can be done by plotting all the points from the part around clusters of similar points.

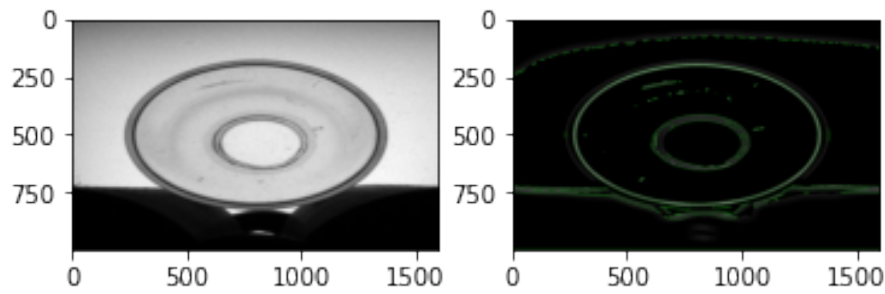


Fig. 2.4 Original image compared to the final result

Machine learning algorithms like agglomerative clustering has power to identify levels of cracks in images that humans couldn't notice otherwise. It enhances the image by visually highlighting damage to make it more visible for people to make better decisions about it, the power of such algorithm was effectively used in our system for quality analysis and identification of minute damage which can be left unnoticed with the human vision. The below figure shows a vial image with a mouth crack. The methodology detects this defect also. The outputs of the defect detection is as shown below.

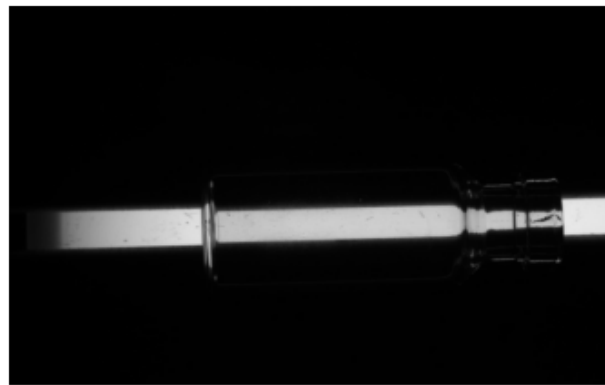


Fig. 3.1 Original vial image with a mouth crack

For the above image also we have used $k=4$ as the segmentation value to achieve optimum results. Then we have applied agglomerative clustering along with k-means clustering. The final result where mouth crack is detected is as shown below.



Fig. 3.2 Image filtered and segmented with $k=4$

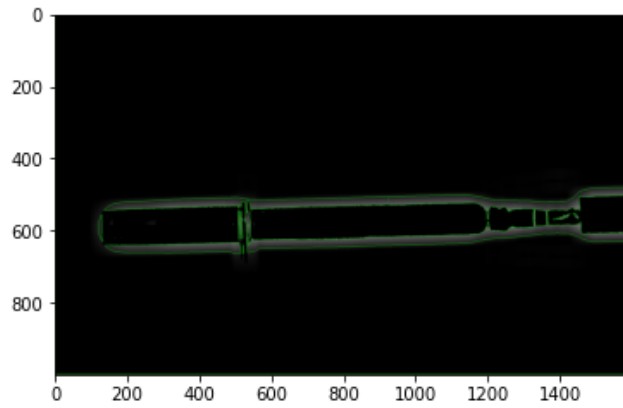


Fig. 3.3 Final result where mouth crack is detected

The same methodology can also detect a hairline crack on the vial. Even though hairline cracks rarely happen during manufacturing, the algorithm can detect it successfully. The initial image along with its final result is as shown below.

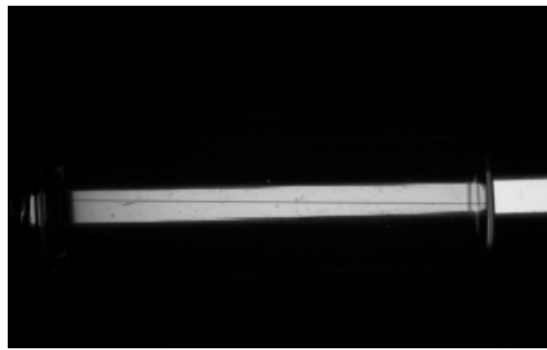


Fig. 4.1 Original vial image with a hairline crack

Segment the image with $k=4$ and then compare the obtained result to measure how similar each cluster is with respect to the other cluster as shown in the below image.

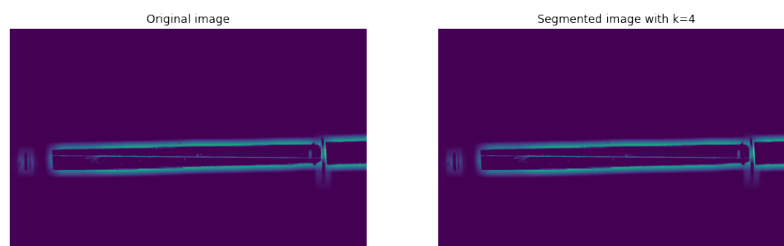


Fig. 4.2 Image filtered and segmented with $k=4$

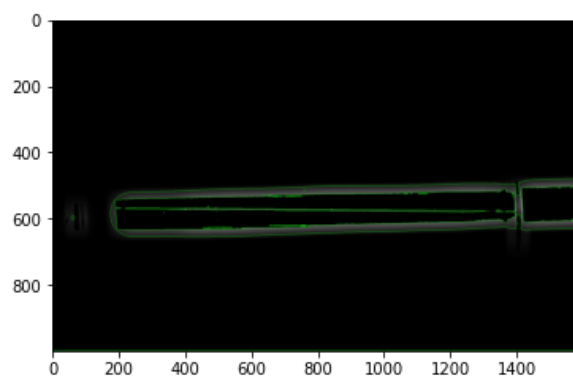


Fig. 4.3 Final result where hairline crack is detected

The below image is having a crack at the neck region. The initial image along with its output is as shown below. The methodology is successfully detecting the neck region defect.



Fig 5.1 Original vial image with a neck crack



Fig. 5.2 Image filtered and segmented with $k=4$

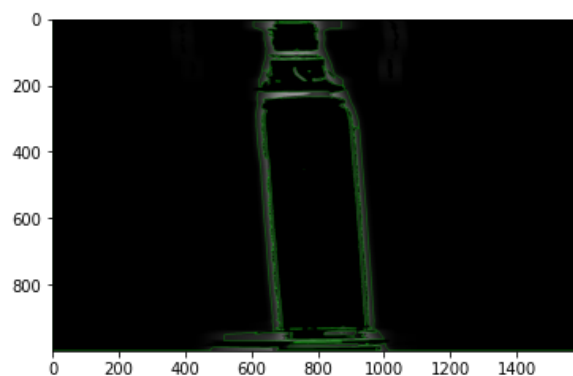


Fig. 5.3 Final result where neck crack is detected

The following figures contains an image with a crack on the surface of the vial. This type of defect is most common during production. The agglomerative clustering algorithm could able to detect it. The results are as shown below.



Fig 6.1 Original vial image with a surface crack

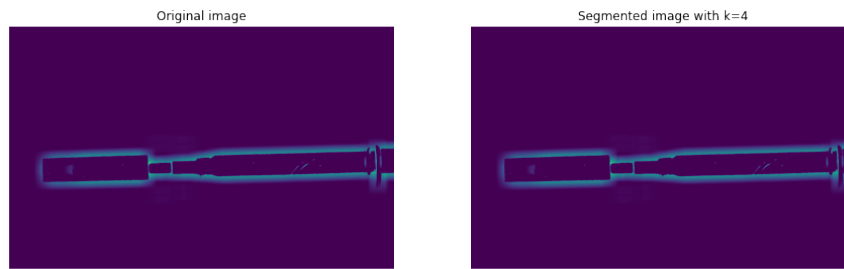


Fig. 6.2 Image filtered and segmented with $k=4$

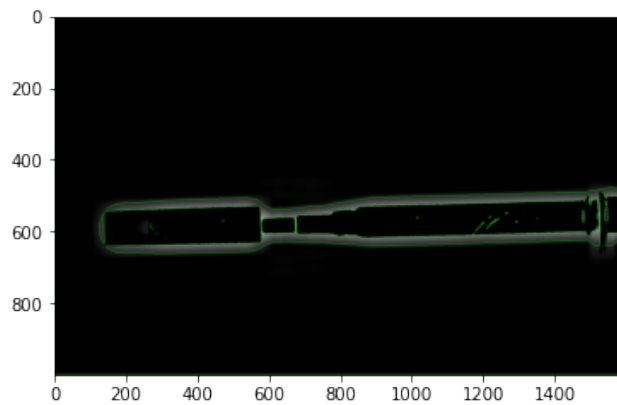


Fig. 6.3 Final result where surface crack is detected

The defect identification problem itself is a challenging one with fusions and breakages, especially when the weldments are heavily deformed. Machine learning algorithms can help identify where these cracks are at a higher rate of accuracy than human observation, which helps in reducing human error and improving quality control.



Fig 7.1 Original vial image with a surface crack



Fig. 7.2 Image filtered and segmented with $k=4$

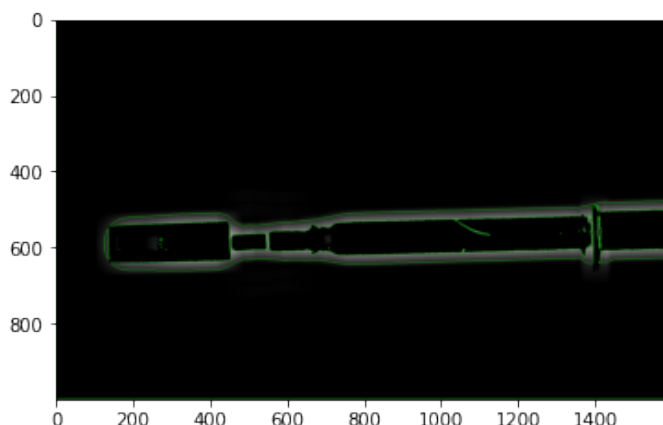


Fig. 7.3 Final result where surface crack is detected

The above image highlights the cracks by drawing an outline around the different clusters. The lines drawn around each individual cluster represent a density of points. The more density, the more cracks are present in that cluster.

Conclusions

The approach was successful in designing a machine-learning technique that is capable of detecting the edges of the cracks in the vial by utilizing agglomerative clustering. This paper presents a technique for the automated detection of cracks on the vial using agglomerative clustering. Agglomerative clustering is a machine learning algorithm. It is used to generate groups of similar values that can be used to identify edges in a clustered data set.

Since the inception of data science and machine learning, there have been many advancements in clustering algorithms which are used in many fields. One of the most popular clustering algorithms is the agglomerative clustering algorithm, which has been widely implemented in various fields. Our paper concludes that it performs well with the given datasets and so it can be used for real time implementation of defect inspection in pharmaceutical industries.

The research concluded with success, the report is completed by concluding that this approach of clustering can be used as a reliable and effective means for identifying the edges of cracks on the vials. The method used 115 number of images and the model is trained using 16 images with different types of flaws. The method has achieved 100 percent accuracy in detecting all types of cracks on the vial. It could be used for both detection and rejection purposes in order to achieve quality control in the pharmaceutical industries, but future work will have to be done on the performance limitations of this approach and on how agglomerative clustering can be used for identifying other types of defects on the vials, such as wrinkles, bubbles, black spots, scratches and so on.

References

- [1] James A. Melchore, 'Sound Practices for Consistent Human Visual Inspection' AAPS PharmSciTech. Mar; 12(1) (2011), 215–221.
- [2] Asha, V., Nagabhushan, P., and Bhajantri, N.U., Unsupervised Detection of Texture Defects using Texture-Periodicity and Universal Quality Index. In: Proceedings of the 5th Indian International conference on Artificial Intelligence (IICAI-2011), Tumkur, India, 14-16 December 2011, pp. 206-217.
- [3] Asha, V., Bhajantri, N.U., and Nagabhushan, P., Automatic Detection of Texture Defects using Texture-Periodicity and Chi-square Histogram Distance. In: Proceedings of the 5th Indian International conference on Artificial Intelligence (IICAI-2011), Tumkur, India, 14-16 December 2011, pp. 91-104.

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- [4] V. Asha, N.U. Bhajantri and P. Nagabhushan. Automatic Detection of Defects on Periodically Patterned Textures, *Journal of Intelligent Systems*, vol. 20 (3), (2011), pp. 279-303.
- [5] V. Asha, N.U. Bhajantri and P. Nagabhushan. GLCM-based chi-square histogram distance for automatic detection of defects on patterned textures. *International Journal of Computational Vision and Robotics (IJCVR)*, vol. 2 (4), (2011), pp. 302-313.
- [6] Asha, V., Bhajantri, N.U., and Nagabhushan, P., Automatic Detection of Texture Defects using Texture-Periodicity and Gabor Wavelets, in: K. R. Venugopal and L. M. Patnaik (Eds.): *International Conference on Information Processing 2011, Communication in Computer and Information Science (CCIS) 157*, pp. 548–553, Springer–Verlag, Berlin Heidelberg, 2011.
- [7] V. Asha, N.U. Bhajantri and P. Nagabhushan. Similarity measures for automatic defect detection on patterned textures. *International Journal of Information and Communication Technology*, vol. 4 (2/3/4), (2012), pp. 118-131.
- [8] V. Asha, N.U. Bhajantri and P. Nagabhushan. Automatic Detection of Texture-defects using Texture-periodicity and Jensen-Shannon Divergence. *Journal of Information Processing Systems*, vol. 8 (2), (2012) pp. 359-374.
- [9] V. Asha. Texture Defect Detection using Human Vision Perception based Contrast. *International Journal of Tomography and Simulation (IJTS)*, vol 32, Issue 3, (2019), pp 86-97.
- [10] Li Fu, Shuai Zhang, Yu Gong, Qunjun Huang, “Medicine Glass Bottle Defect Detection Based on Machine Vision”, *IEEE*, pp. 5681-5685 (2019).
- [11] Jaina George, S.Janardhana, Dr.J.Jaya, K.J.Sabareesan, “Automatic Defect Detection Inspectacles And Glass Bottles Based On Fuzzy C Means Clustering”, *International Conference on Current Trends in Engineering and Technology, ICCTET’13*, pp.8-12 (2013).
- [12] K. P. Sinaga and M. Yang, "Unsupervised K-Means Clustering Algorithm," *IEEE Access*, vol. 8, pp. 80716-80727, (2020).
- [13] Huanjun Liu, Yaonan Wang, Feng Duan, “Glass Bottle Inspector Based on Machine Vision”, *International Journal of Computer, Electrical, Automation, Control and Information Engineering* Vol: 2, No: 8, pp. 2682-2687, (2008).
- [14] Noroozi, R. P. R. Hasanzadeh and M. Ravan, "A Fuzzy Learning Approach for Identification of Arbitrary Crack Profiles Using ACFM Technique," in *IEEE Transactions on Magnetics*, vol. 49, no. 9, pp. 5016-5027, Sept. (2013).
- [15] Heena Gupta, B., Asha V, Impact of Encoding of High Cardinality Categorical Data to Solve Prediction problems, *Journal of Computational and Theoretical Nanoscience*, vol. 17, No. 9-10, pp. 4197-4201 Sep/Oct (2020), (5) ISSN: 1546-1955 (Print): EISSN: 1546-1963 (Online), Published on Sep/Oct 2020.
- [16] Z. Yang and J. Bai, "Vial mouth defect detection based on machine vision," 2015 *IEEE International Conference on Information and Automation*, 2015, pp. 2638-2642, doi: 10.1109/ICInfA.2015.7279730.
- [17] Chaitanya Reddy Patlolla. “Understanding the concept of Hierarchical clustering Technique” Medium. Published December 10, 2018. Accessed April 26, 2022.
- [18] Asha, V., Undithering using Linear Filtering and Non-linear Diffusion Techniques, *International Journal of Artificial Intelligence (IJAI)*, vol. 2 (S09), 66-76, 2009. ISSN: 0974-0635.
- [19] C.R. Vishwanatha and V. Asha, “Prototype Model for Defect Inspection of Vials”, *International Journal of Psychosocial Rehabilitation*, Vol. 24, Issue 05, pp. 6981-6986, 2020.

-
- [20] Xianen Zhou, Yaonan Wang, Changyan Xiao, Qing Zhu, Xiao Lu, Hui Zhang, Ji Ge and Huihuang Zhao, “Automated Visual Inspection of Glass Bottle Bottom With Saliency Detection and Template Matching”, IEEE, pp. 1-15 (2019).
- [21] Xiaoyu Liang, Liangyan Dong, Youyu Wu, “Research on Surface Defect Detection Algorithm of Tube-type Bottle Based on Machine Vision Xiaoyu”, 10th International Conference on Intelligent Computation Technology and Automation, pp. 114-117, (2017).
- [22] Wittaya Koodtalang, Thaksin Sangsuwan and Surat Sukanna, “Glass Bottle Bottom Inspection Based on Image Processing and Deep Learning”, Research, Invention, and Innovation Congress (RI2C 2019) (2019).