Enhancing Pharmaceutical Inspection through Poisson Image Editing Technique

Author: Christian O. Pérez Pérez
Advisor: Viktor Zaharov
Electrical Engineering

Abstract

This research explores the application of Poisson image editing techniques for enhancing the dataset quality in the detection of defects within pharmaceutical products. The focus is on addressing common defect types that compromise product integrity and safety. By employing Poisson image editing, we aim to improve the accuracy and efficiency of machine learning models used in pharmaceutical quality control. The outcomes indicate substantial enhancements in detecting and classifying defects, thereby promising to elevate the standards of pharmaceutical safety. This study not only underscores the value of advanced image editing in quality assurance processes but also encourages further exploration into its potential across various aspects of pharmaceutical manufacturing and inspection.

Key Terms *— Data Augmentation, Image Blending, Pharmaceutical Vials, Quality Assurance.*

Introduction

In the complex landscape of global healthcare, the safety and efficacy of pharmaceutical products are non-negotiable priorities. Central to these priorities is the packaging integrity of glass containers, such as vials and syringes, which play a pivotal role in delivering treatments. The integrity of these containers directly impacts patient safety, making it crucial to identify and address any defects that could compromise their quality.[1] As the pharmaceutical industry strives to meet these high standards, the integration of technological advancements in quality assurance processes becomes increasingly essential. [3][4]

Background

The convergence of technology and healthcare has introduced revolutionary changes in how pharmaceutical companies approach quality control. Image processing and deep learning technologies have emerged as powerful tools, automating the inspection of pharmaceutical containers that was traditionally done manually. [2] These technologies enable the development of sophisticated models capable of detecting a wide range of defects with unprecedented accuracy and efficiency. [5] However, the transition towards fully automated inspection systems brings its own set of challenges, chief among them being the creation and maintenance of extensive, high-quality datasets necessary for training and testing these models. This backdrop sets the stage for our research, which seeks to leverage cutting-edge image editing techniques to overcome the limitations of existing dataset enhancement methods.

Problem

Despite these advancements, the effectiveness of classification models is limited by the availability of high-quality datasets. Traditional dataset creation methods are both costly and time-consuming, challenging the pace of progress in automated defect detection. [6] Our research addresses this bottleneck by employing Poisson image editing techniques to enhance dataset quality and model performance. [7]

Methodology

Our methodology leveraged Poisson image editing techniques within Python and OpenCV to refine defect detection in pharmaceutical vials.[8] Focusing on the critical neck region, we applied the Poisson equation to seamlessly blend synthetic defects such as Twist, Lap, Check, Crack, Spitticule, and Ondulation into images, ensuring authentic augmentation. Numerical solutions helped approximate the equation digitally for precise image edits.

The practical application of Poisson image editing was successfully realized through Python and the OpenCV library, capitalizing on OpenCV's "seamlessClone" function for efficient image blending based on the Poisson equation. A custom User Interface (UI) was developed, enhancing user engagement by enabling interactive defect extraction and mask creation, alongside real-time visualization of the blending process. This UI provided users with tools for the seamless integration of synthetic defects into defect-free images.

Figure 1:
UI for area selection of the area with a defect to be extracted.

Figure 2:
UI for mask creation and Poisson image editing progress.

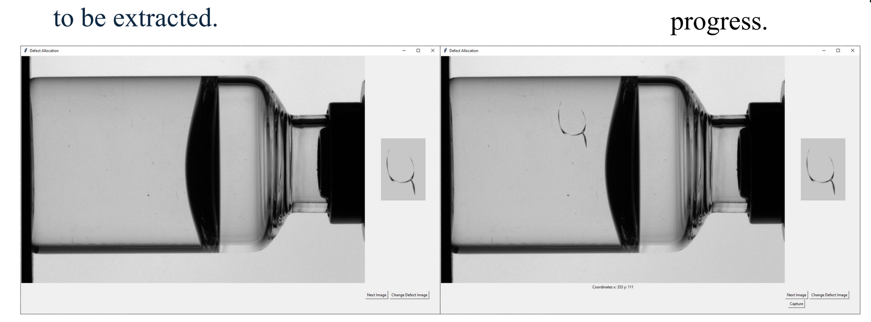

Figure 3:
UI for image blending using the Poisson. To the left, the Destination image is without defect. To the right, The Destination image after the blending.

To evaluate quantitively the efficacy of the Poisson Image editing tool, a Convolutional Neural Network (CNN) was trained to effectively differentiate between good (defect-free) and bad (defective) images. Poisson blending was utilized to create all the synthetic defects. During the testing phase, the trained model was evaluated on unseen data, which included both real-world defective images and additional good images that were not part of the initial training set. This evaluation aimed to assess the model's ability to generalize and accurately classify new, unencountered samples.

Focused on standard metrics such as accuracy, precision, recall, and F1 score for a detailed assessment of model performance post-augmentation.[8]

- Accuracy: Measures the proportion of true results (both positives and negatives) among the total number of cases examined.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN}$$

- Precision: Measures the proportion of true positive predictions in all positive predictions.

$$Precision = \frac{TP}{TP+FP}$$

- Recall: Measures the proportion of actual positives correctly identified.

$$Recall = \frac{TP}{TP + FN}$$

- F1 Score: The harmonic mean of precision and recall, providing a balance between them for model accuracy.

$$F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Results and Discussion

Quantitative Evaluation

The following tables encapsulate the performance metrics derived from the empirical evaluation of the classification model. These metrics furnish a quantitative appraisal of the model's proficiency in discerning between non-defective ('good') and defective ('bad') pharmaceutical vials across the training and independent testing datasets. specifically, the defects are localized to the neck of the vials.

Table 1
Neural Network Results

Outcome	Training Dataset	Testing Dataset
True Positives	1254	**647**
True Negatives	1255	**939**
False Positives	1	**66**
False Negatives	**0**	**0**

Table 2
Neural Network Metric Results

Metric	Training Dataset	Testing Dataset
Accuracy	99.96%	**97.66%**
Precision	99.92%	**94.45%**
Recall	100.00%	**100.00%**
F1 Score	**99.96%**	**97.15%**

The analysis showed that the model performed exceptionally well during training. This indicates that the Poisson image editing used for data augmentation significantly improved the model's ability to distinguish between different classes. In the testing phase, while there was a slight drop in some metrics, the accuracy remained high, and the recall rate was perfect, ensuring all defects were detected. However, a slight decrease in precision suggests a need to reduce false positives before the model is deployed in real-world settings.

Qualitative Evaluation

In addition to quantitative analysis, the augmented images underwent qualitative review, comparing those edited with Poisson blending to traditional copy-paste methods. The Poisson-blended images showed significant improvements in realism, crucial for the authenticity of the training data. Yet, images with complex background gradients experienced slight shadow effects, indicating a need for refining the algorithm to enhance visual consistency.

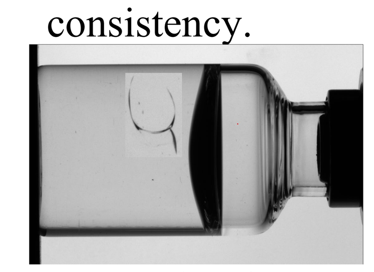

Figure 4:
Crack defect insertion using Copy and Paste

Figure 5:
Crack defect insertion using the Poisson Image editing technique.

Figure 6:
Blending difficulties when an uneven background is present..

Conclusions

The research successfully demonstrated the efficacy of Poisson image editing in creating augmented datasets for the classification of cosmetic defects in pharmaceutical vials. The quantitative evaluation revealed that the CNN model achieved high accuracy and recall rates, with precision indicating a need for further model refinement. Qualitatively, the blended images showed enhanced realism, although some introduced shadows in gradient-varied backgrounds suggest areas for future improvement. This study paves the way for further research into advanced data augmentation techniques and their application in ensuring the safety and integrity of pharmaceutical glass containers.

Future Work

Moving forward, we aim to refine the Poisson image editing algorithms to enhance realism and reduce shadow effects in complex images, and we plan to expand the scope of our research to apply these improved techniques across a more diverse range of pharmaceutical packaging types.

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