# *Enhancing Pharmaceutical Inspection through Poisson Image Editing Techniques*

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***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, the researcher aim to improve the accuracy and efficiency of machine learning models used in pharmaceutical quality control. The outcomes indicated 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 realm of global healthcare, the pharmaceutical and medical device industries are foundational pillars, tasked with the critical mission of delivering safe and effective treatments to patients worldwide. Central to this mission are glass contains like vials and syringes, the primary vessels through which medical interventions—ranging from routine vaccinations to complex treatments—are administered. The integrity, quality, and reliability of these containers are not merely operational concerns, but are of paramount importance for ensuring patient safety, preventing medication errors, and avoiding contamination that could lead to adverse health outcomes. Studies have highlighted the crucial role of packaging integrity in pharmaceuticals, emphasizing the need for stringent quality control measures to prevent contamination and ensure patient safety [1].

The recent years have witnessed a transformative shift in these industries, driven by the convergence of technology and healthcare. This evolution has seen the emergence of image processing models and deep learning algorithms as potent tools for automating a variety of tasks that glass was traditionally performed manually [2]. Specifically, in the context of glass containers, these technological advancements have been leveraged to develop classification models capable of analyzing visual data to determine the usability of these containers. By identifying defects that render glass containers unfit for use, these models play a crucial role in upholding the standards of patient care and safety. Deep learning applications for pharmaceutical packaging inspection have underscored the potential of these technologies to enhance quality assurance processes significantly [3] [4] [18].

Despite the promise and potential of these technologies, the journey towards developing accurate and reliable classification models is fraught with challenges. Central among these is the reliance on extensive datasets comprising both defect-free (good-quality) and defective samples—a requirement that is both resource-intensive and costly [5]. Traditionally, these datasets are created in laboratory settings, where defects are artificially induced under controlled conditions. This process, while necessary, is time-consuming and financially burdensome, posing significant logistical challenges that can impede the pace of model development and innovation.

Considering the challenges mentioned above, there is a need to explore alternative methodologies that can circumvent the limitations posed by the traditional approach to dataset creation. Among the most promising of these alternatives is the exploration of data augmentation techniques, particularly those that can synthetically enhance the size and variability of datasets [6]. Such techniques hold the potential to not only mitigate the reliance on costly physical samples but also to accelerate the development of robust classification models capable of meeting the stringent demands of the pharmaceutical and medical device industries.

This research project seeks to contribute to this evolving landscape by exploring the application of Poisson image editing—a technique that operates by seamlessly integrating image gradients—to enhance the identification and classification of defective and non-defective glass containers [7]. By delving into the mathematical foundations of Poisson image editing, its practical implementation, and the subsequent evaluation of its efficacy, this project aims to illuminate a path forward for leveraging image augmentation techniques in the pursuit of ensuring the highest standards of safety and reliability in healthcare delivery.

## LITERATURE REVIEW

The exploration of image augmentation techniques, particularly Poisson image editing, offers a promising avenue for addressing the challenges inherent in the classification of defective and non-defective pharmaceutical glass containers. This section delves into the key areas of challenge and opportunity within this domain, supported by a review of existing methodologies and the introduction of Poisson image editing as a solution.

### Image Variability and Data Imbalance

A significant challenge in automating the inspection of glass containers arises from the inherent variability in their shape, size, and appearance [8]. This variability, compounded by diverse image conditions such as lighting variations and occlusions, often stymies existing classification methods. Moreover, the imbalance between defect-free (good-quality) and defective images during model training exacerbates the difficulty, as collecting a well-balanced dataset is a critical yet challenging task [9]. These issues underscore the necessity for robust image classification models that can effectively handle such variability and imbalance.

### Robustness and Generalization

Is crucial to achieving robust performance across different types of glass containers and ensuring that these methods generalize well to unseen data. The real-world application of these models demands a high degree of accuracy and reliability, especially when dealing with a variety of defects that can compromise the safety and efficacy of pharmaceutical products. For this reason, the USP Chapter <1790>, requires a 100% inspection of all injectables [1] [10].

### Deep Learning Approaches and Ensemble Methods

The advent of Convolutional Neural Networks (CNNs) has revolutionized the field of image classification, offering profound improvements over traditional methods [11]. Techniques such as transfer learning, where pre-trained models on large datasets are fine-tuned for specific tasks and using attention mechanisms to improve focus on relevant image features, represent promising avenues for enhancing classification performance [12]. Similarly, ensemble methods that combine predictions from multiple models can offer increased robustness and accuracy, presenting another viable strategy for tackling the challenges in this domain [13].

### Domain Adaptation

The concept of domain adaptation is particularly relevant when considering the application of models trained on synthetic or augmented data to real-world scenarios. Techniques that enable models to adapt from synthetic to real-world data are crucial in ensuring that the improvements seen during training translate into effective performance in practical applications [6] [14].

### Poisson Image Editing: Bridging the Gap

One of the most promising techniques emerging in this context is Poisson image editing [7] [15].

Originally proposed by Pérez et al. [3], this technique operates by seamlessly blending images through the integration of gradient information rather than direct pixel values. This approach offers several advantages for image augmentation:

- Mathematical Foundations: At its core, Poisson image editing leverages the Laplacian operator to capture the essence of how a scalar field, such as pixel intensity, varies across an image. The subsequent formulation of the Poisson equation facilitates the construction of new images that approximate a desired gradient field, enabling the seamless integration of synthetic defects into defect-free images.
- Applications and Benefits: This technique finds utility in a range of applications, from seamless cloning, which allows for the clean integration of new elements into an image, to texture flattening and high-dynamic-range imaging. Its ability to generate realistic, seamlessly blended images makes it particularly valuable for augmenting datasets with synthetic defects, thereby addressing the challenges of data imbalance and the need for robust, generalized models.

The exploration of Poisson image editing in the context of pharmaceutical glass containers classification represents a great approach to overcoming the limitations of current methodologies. By enhancing the quality and diversity of training datasets through synthetic augmentation, this technique holds the promise of accelerating the development of highly accurate and reliable classification models, marking a significant step forward in the pursuit of ensuring the safety and efficacy of pharmaceutical products.

## METHODOLOGY

This section delves into the methodological framework utilized to exploit Poisson image editing techniques, aimed at augmenting the accuracy of defect classification in pharmaceutical glass containers, with a particular focus on the neck area of vials. The integrity and cleanliness of this area are paramount for ensuring the overall quality and safety of pharmaceutical products.

This investigation zeroes in on cosmetic defects located specifically in the neck region of these vials, recognizing this zone as crucial for maintaining the sterility and efficacy of the pharmaceutical contents. The defect types scrutinized in this study include Twist, Lap, Check, Crack, Spitticule, and Ondulation. These defects, ranging from minor visual flaws to more significant structural weaknesses, can compromise the vial's integrity and, by extension, patient safety.

Additionally, to complement investigation rigorous quantitative analysis, the researcher integrated a qualitative testing phase into the methodology. It evaluates the performance of the Poisson method in different backgrounds.

### Poisson Equation for Image Editing

At the core of Poisson image editing lies the Poisson equation, which is utilized to blend images seamlessly. Mathematically, the problem is set up as follows:

- Guided Interpolation: This method involves solving a Poisson equation for each color component of the image, treating the image as a scalar function. The aim is to find an unknown function $f$ that, within a domain $\Omega$, best matches the gradient of a guidance vector field $v$, under certain boundary conditions defined by the target image.
- Mathematical Formulation: Given a guidance field $v$, the goal is to minimize the difference between the gradient of the unknown function $f$ and $v$, formulated as a variational problem:

  $$min_f \int_{\Omega} \|\nabla f - v\|^2 dx, \quad (1)$$

  subject to boundary conditions on $f$ that ensure it matches the target image at the domain's boundary.
- Poisson Equation with Dirichlet Boundary Conditions: The solution to the minimization problem leads to the Poisson equation:

  $$\Delta f = div(v) \ in \ \Omega \quad (2)$$

with $f = f^*$ on $\partial\Omega$, where $f^*$ represents the known values on the boundary of $\Omega$, $\Delta$ denotes the Laplacian operator, and $div$ denotes the divergence operator.

- Numerical Solution: In practice, the Poisson equation is solved numerically since digital images are discrete. This involves discretizing the continuous domain into pixels and solving a sparse linear system that approximates the Poisson equation [7].
- Applications in Image Editing: This mathematical framework enables a range of image editing tasks, such as seamless cloning, object removal, and texture blending. By choosing appropriate guidance fields, one can manipulate images in ways that preserve natural gradients and textures, achieving effects that are difficult or impossible with traditional image editing tools [7].

### Enhanced Clarity on Discrete Poisson Solver

The discrete version of this problem considers the pixelated nature of digital images. Here, the image domain is represented as a grid of pixels, and the Poisson equation is solved for each pixel. The process involves setting up and solving a system of linear equations that represent the discretized version of the Poisson equation, with the solution providing the new pixel values for the edited image.

This approach offers unprecedented control over how image features are blended, allowing for edits that maintain the coherence of lighting, texture, and color, even when introducing elements from another image or altering existing components of the picture.

By grounding the editing process in the mathematical principles of the Poisson equation, Poisson image editing leverages the natural properties of images (such as gradients and boundary conditions) to produce results that are visually harmonious and free of artifacts commonly associated with image manipulation, such as abrupt transitions or halo effects.

This in-depth understanding of the mathematical foundations not only enriches the technical description of Poisson Image Editing but also underscores its versatility and power as a tool for creative and corrective image manipulation.

### Practical Implementation

The practical implementation of Poisson image editing was achieved using Python and the OpenCV library, known for its comprehensive set of functions catering to computer vision tasks, including image blending [16].

- Python and OpenCV: The implementation involved leveraging OpenCV's “seamlessClone” function, which is designed for tasks like object insertion and image blending, based on the Poisson equation. This function simplifies the blending process, allowing for the automatic adjustment of colors and illumination to match the source image with the target background.
- Custom User Interface (UI): A custom UI was developed to facilitate interaction with the Poisson blending process. This UI allows users to:
    - Interactively extract defects and create masks (source of the defect image), providing precise control over areas for blending.

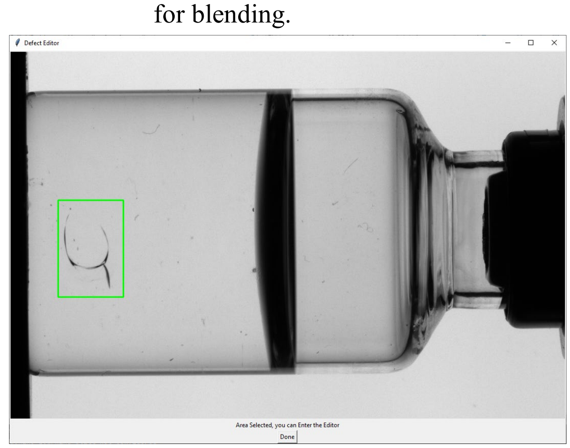


**Figure 1**
**UI for Area Selection of the Area with a Defect to be Extracted**

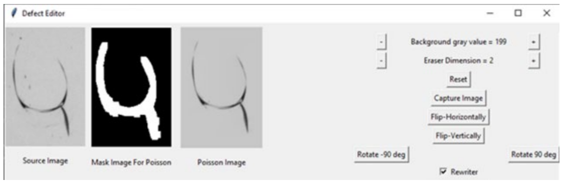


**Figure 2**
**UI for Mask Creation and Poisson Image Editing Progress**

- Visualize the blending process, including the selection of defect, mask application, and the final Poisson-blended image, providing immediate feedback on the blending outcome in the destination image D.

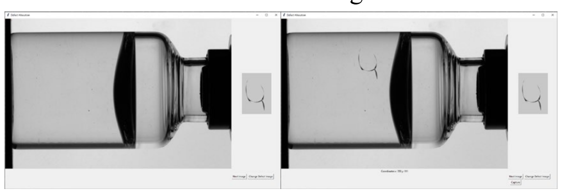

**Figure 3**
**UI for Image Blending Using the Poisson. To the Left, the Destination Image is Without Defect. To the Right, the Destination Image After the Blending**

## Evaluation

The evaluation of the enhanced classification models, incorporating images augmented through Poisson blending, involved several key steps:

- **Neural Network Training:** A Convolutional Neural Network (CNN) was trained to distinguish between good (defect-free) and bad (defective) images. The training set was augmented using Poisson blending to artificially introduce defects into good images, creating a complete set of images with artificially blended defects.
- **Testing:** The trained model was then evaluated on unseen data, including both real-world defective images and additional good images not used during training. This step aimed to assess the model's ability to generalize and perform accurately on new, unencountered samples.
- **Performance Metrics:** The evaluation focused on standard performance metrics such as accuracy, precision, recall, and F1 score, providing a comprehensive assessment of the model's classification capabilities post-augmentation [17]. These metrics are fundamental in assessing the effectiveness of classification models. Below are the definitions and formulas for each metric:

- TP (True Positives): The number of correct positive predictions.
- TN (True Negatives): The number of correct negative predictions.
- FP (False Positives): The number of negative cases incorrectly categorized as positive.
- Accuracy: This measures the proportion of true results among the total number of cases examined. It is calculated as the sum of true positives and true negatives divided by the total number of cases.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

- Precision: This measures the proportion of true positive predictions in the total positive predictions. It is also known as the positive predictive value.

$$Precision = \frac{TP}{TP+FP} \quad (4)$$

- Recall (or Sensitivity): This measures the proportion of actual positives that were identified correctly. It is calculated as the number of true positives divided by the sum of true positives and false negatives.

$$Recall = \frac{TP}{TP+FN} \quad (5)$$

- F1 Score: This is the harmonic mean of precision and recall and is a measure of the model's accuracy. An F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0.
- $F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$ (6)

Through this methodology, the project aims to demonstrate the effectiveness of Poisson image editing in enhancing the performance of classification models for defective and non-defective pharmaceutical glass containers, addressing key challenges such as data imbalance and the need for robust generalization. It’s important to note that while the testing was performed using only vials, the same principles will apply to all types of glass containers.

## DISCUSSION

### Quantitative Evaluation of Model Performance

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 |

Based on these outcomes, the performance metrics were calculated as follows:

**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 reveals exemplary model performance in the training phase, with nearly all metrics approaching the upper theoretical limits. Such findings suggest that the Poisson image editing technique, employed in the augmentation of the training set, has substantially contributed to the model's discriminative capabilities.

Conversely, the testing phase metrics, while exhibiting a marginal decrement, maintain a high level of accuracy and an unblemished recall rate. The preservation of a maximal recall rate in the testing phase is critical, as it ensures that all defective items are invariably identified, thereby affirming the model's operational efficacy. Nevertheless, the observed reduction in precision, albeit slight, warrants a closer examination to mitigate the incidence of false positives in practical deployment scenarios.

### Qualitative Assessment of Augmented Image Fidelity

Complementing the quantitative analysis, a qualitative examination of the augmented images was conducted. This assessment entailed comparative visual scrutiny between images generated via the Poisson blending technique and those produced through conventional copy-paste augmentation methods. Refer to Figures 4 and 5.

**Figure 4**
**Crack Defect Insertion Using Copy and Paste**

**Figure 5**
**Crack Defect Insertion Using the Poisson Image Editing Technique**

The images subjected to Poisson blending exhibited a pronounced enhancement in realism, with artificial defects seamlessly integrated into the vial imagery. This seamless integration is pivotal in ensuring the authenticity of the training data.

However, certain images, particularly those with intricate background gradients, displayed minor shadowing phenomena post-blending. These visual anomalies, although not significantly deterring the quantitative metrics, highlight the necessity for algorithmic refinement to optimize the visual congruity of the training images. (Refer to Figure 6).

**Figure 6:**
**Blending Difficulties When an Uneven Background is Present**

## CONCLUSION

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.

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