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## **2. Detecting and Identifying Cell Debris and Foreign Material on Complex Medical Instruments through Neural Networks and Image Comparison**

### **3. Abstract**

Antibiotic-resistant bacteria cause 25% of Healthcare-Associated Infections (HAI) with mortality rates as high as 50%. (CDC, 2020). To remedy this widespread problem, building on my previous work, I propose to develop a program that will detect and identify cellular/material debris and physical damage on medical instruments after sterilization. The device will collect precise images of medical instruments using microscope cameras. Through neural networks and encoders, my code will be able to distinguish cellular debris from physical damage and highlight areas needed to be cleaned and damage such as scratches on any medical instrument. My device improves current technologies by locating contaminated areas on a medical instrument and accurately verifying if a tool has been successfully sterilized using computer vision and neural networks. This will ultimately reduce the cost of re-sterilization, prolonging the device's longevity and most importantly, reducing the amount of patients dying from bacterial infections. My training program has yet to be tested on the final test set and so far the training program has an accuracy of 94%.

### **4. Introduction and Background**

On any given day, at least 3% of hospital patients suffer from one or more Healthcare-Associated Infections (HAI) (CDC, 2020). A significant factor that causes these infections is medical tools that are not adequately sterilized. For example, researchers found that 62% of sterilized ophthalmic instruments used for cataract surgery contained debris and loose fiber strands that could cause intraocular inflammation and disease transmission (Dinakaran, 2002). To further emphasize this issue, a similar case occurred at Cedar-Sinai and the UCLA medical center. More than 200 patients were exposed, and 6 patients died to a deadly bacteria carbapenem-resistant Enterobacteriaceae (CRE) through improperly sterilized endoscopic instruments. This is not just a one-time event; infections also occurred in Washington, Illinois, and Pennsylvania (Cedar-Sinai, 2015; Suter, 2018). In examining several case studies involving medical procedures resulting in healthcare-associated infections (HAIs), a common theme emerges: the use of complex medical instruments, such as endoscopes, played a role in the development of HAIs. These instruments often have many intricate parts that are susceptible to damage and the accumulation of cell debris, which can increase the risk of HAIs. (CDC, 2018).

Current sterilization procedures can compromise the instrument's durability and effectiveness through heat and UV damage. Autoclaves, dry heat, radiation, ethylene oxide gas, vaporized hydrogen peroxide, and other techniques are harsh on the instrument due to the high temperatures or chemical exposure involved in the sterilization process. Many medical tools use semiconductor technologies that cannot withstand the current sterilization methods due to high temperatures, radiation, plasma discharge, etc. In addition, all semiconductors use embedded batteries, so when these tools undergo steam sterilization the steam, and heat erases and erodes the floating-gate memory cells which shortens the lifetime of the medical tool (Porto, 2001).

In hospitals to test whether an instrument is clean, hospital technicians use a process that combines mechanical, chemical, and biological indicators. While these techniques can detect bacteria or debris on medical instruments, they fail to detect physical damages and are precisely able to locate the debris on a specific instrument. All the instruments are tested by batch for efficiency. When a batch tests positive for bacterial residue, the entire group is re-sterilized until all tools test negative. Frequent sterilization of medical instruments can be costly and can also cause damage to the instruments. A major disadvantage of constantly re-sterilizing instruments is that it can reduce their lifespan and durability. This can lead to the need for more frequent replacement of instruments, which can be a financial burden for healthcare facilities. (Porto, 2001).

In the medical field, there is a lack of prior art regarding the automation of sterilizing complex medical instruments. In the last decade, studies have investigated and created programs and prototypes to reduce infection using fluorescent light on bacterial-prone objects. These techniques can be applied on medical instruments to further reduce risk of infection. Researchers and scientists often use fluorescent spectrography and high-resolution image capturing methods to identify bacteria on metal surfaces in mechanical workspaces and the medical field (Bumstead, 2019). Visible light fluorescent spectroscopy uses non-ultraviolet to excite the electrons in a compound, which causes the compound to emit light (fig 2), allowing researchers to identify bacteria, and in some cases, viruses. Pathspot uses this knowledge by creating a device that can scan people's hands for bacteria and microscopic debris such as e-coli and Hepatitis A (fig 1a) (Pathspot, 2020). These researchers collected a database of frequencies that bacteria respond to and compared it to the bacteria the frequencies emitted from the user's hand.

When automating methods to identify bacteria and damage on metallic surfaces, it is crucial to analyze the research projects' code structure, specifically programs using neural networks. In a recent study, the researcher programmed a cascaded Autoencoder (CASAE) architecture and Convolutional Neural Network (CNN) to identify and localize defects and damages such as scratches on industrial metallic material. (Tao, 2018) An encoder-decoder + CNN architecture is incredibly useful since the process can quickly identify abnormalities on images. The CASAE architecture is a perfect transition to the CNN which specifically sorts what type of abnormality is found in the image. My code structure will follow this structure because my program has to identify and localize debris and defects on metallic surfaces (fig 4). In another research project, programmers built a code to identify objects under noise and distortion by

using image noise reduction and filtering techniques. Noise removal is an essential task in image processing since it strongly influences the quality of the image processing technique. The researcher studied different techniques, specifically nonlinear filter methods such as fuzzy or classical techniques, best reduced noises. (Mohamed, 2017).

fig 2

A fluorescent microscope detects bacteria by exciting the protons in the sample. Then it uses an emission filter to only let the emission range of fluorophore pass to the detector.

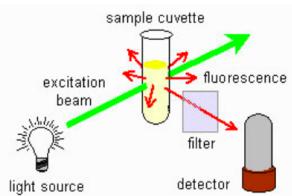
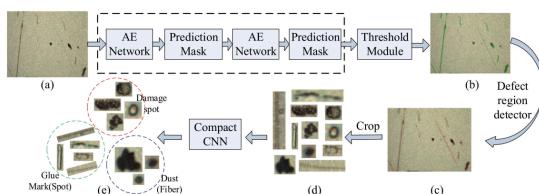


fig 3

Pipeline of the metal surface defect inspection architecture. a) original image, b) detect segment, c) defect location d) cropped results e) classification



## Prior Work

In prior work done by myself in 2020, I created a detection and sorting module using fluorescent microscope and computer vision techniques to identify cell debris and damage on medical instruments. Under fluorescent lighting, the camera would scan an unused medical instrument to collect images of the instrument. After the instrument is used and sterilized, the camera would repeat the procedure. After collecting two images sets of the same instrument before and after sterilization, these sets were compared to each other through computer vision libraries in OpenCV, specifically oriented FAST and rotated BRIEF (ORB), speeded up robust features (SURF) and Scale-invariant feature transform (SIFT). (fig 4) The images that have anomalies are sent to the classification module which will be inspected and identified.

These libraries blurs images to identify "key points" through Difference of Gaussians of each photo to do a scale-space extrema detection and identifies key points if the extrema is greater than threshold value. The next phase involves finding key point descriptor and key point

fig 1 PathSpot hand scanner uses fluorescent light to scan bacteria and cell debris on hands through detecting fluorophore in bacteria  
1a:



1b:



matching. These descriptors are vectors of size achieved from orient histogram and key point matching between two images is done by identifying nearest neighbors (Lowe's ratio). While this method was slow, the program was able identify differences of medical instruments before and after used.

Figure 1a. OpenCV's (SIFT) image matching algorithm

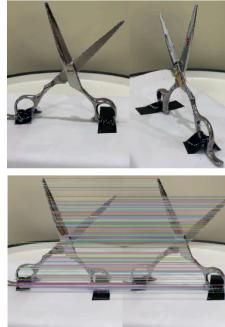


Figure 1b. Aligning Images and



Figure 2. SIFT and ORB  
Identifying key points and  
comparison

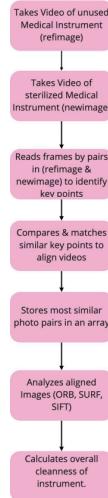


Figure 3.  
Data Flow  
Chart

Fig 4 Depicts code outline, SIFT program, and results regarding image alignment and % accuracy via chart and data.

## **Research Objective**

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## 5. Methods

- 1) My experiment was conducted in a similar procedure to Tao's research. This involves creating a dataset of metallic defect images in order to detect damage. These images were inspected by an examiner (which would be me) in advance and labeled by its defective region and category (type of debris it has). In my experierment, I combined two datasets which included physical damages and cellular debris (fig 5). The classes of physical damages include scratches, patches, pitted, crazing, and inclusions.

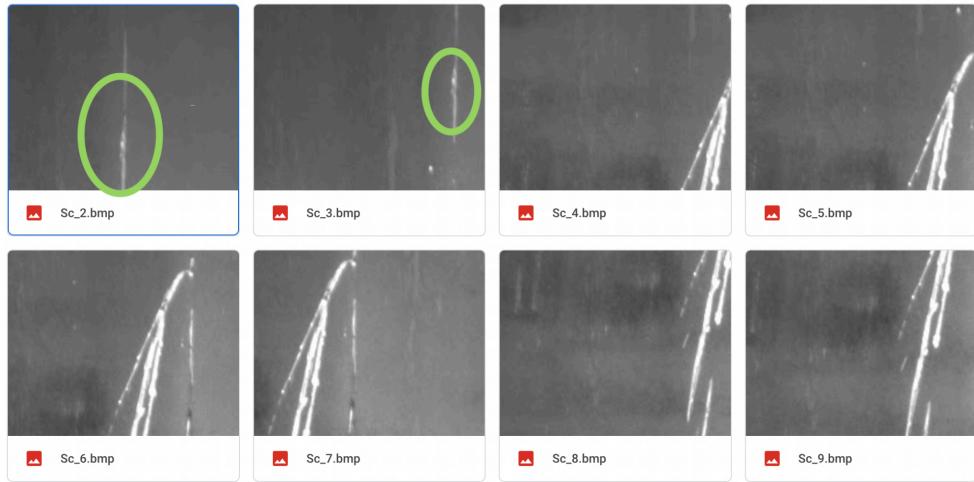


Fig 5 Test dataset of the scratches class. Green outline indicates the location of scratches.

- 2) Using this dataset, I separated the images into a training set and an experimental set. The training set teaches the neural network to determine abnormalities, and different types of debris. The experiment set is used when testing the accuracy of the program.
- 3) I imported a Kaggle API and all my code is in google Colab (a coding environment for ML providing free GPUs and TPUs) based in Python. The program identifies and sort images inside of the dataset by type of debris into different categories.
  - a) The classification module is built from a convolution neural network (CNN) that is based on sequential (fig 6a) and model (fig 6b) architecture. These CNNs include prediction masks and convolutional layers - a filter that moves right to left aiming to collect high-level features such as edges - and three max-pooling layers. The features both reduce noise and extract dominant features by finding the highest areas of contrast in pixels to detect edges/dominant features. Through finding the dominant features of an image, my code can determine the shape of the defect - pivotal for classification.
  - b) In addition to testing the model's accuracy, I used fifty one (API) to manually check whether the program can correctly determine the type of damage/debris.

Model: "sequential"			Model: "model_1"			
Layer (type)	Output Shape	Param #	Layer (type)	Output Shape	Param #	Connected to
input_tensor (Conv2D)	(None, 28, 28, 20)	520	input_1 (InputLayer)	(None, 224, 224, 3 0 )	0	[]
activation (Activation)	(None, 28, 28, 20)	0	conv2d (Conv2D)	(None, 111, 111, 32 864 )	864	['input_1[0][0]']
max_pooling2d (MaxPooling2D)	(None, 14, 14, 20)	0	batch_normalization (BatchNorm alization)	(None, 111, 111, 32 96 )	96	['conv2d[0][0]']
conv2d (Conv2D)	(None, 14, 14, 20)	10020	activation (Activation)	(None, 111, 111, 32 0 )	0	['batch_normalization[0][0]']
activation_1 (Activation)	(None, 14, 14, 20)	0	conv2d_1 (Conv2D)	(None, 109, 109, 32 9216 )	9216	['activation[0][0]']
max_pooling2d_1 (MaxPooling 2D)	(None, 7, 7, 20)	0	batch_normalization_1 (BatchNo rmalization)	(None, 109, 109, 32 96 )	96	['conv2d_1[0][0]']
conv2d_1 (Conv2D)	(None, 7, 7, 20)	10020	activation_1 (Activation)	(None, 109, 109, 32 0 )	0	['batch_normalization_1[0][0]']
activation_2 (Activation)	(None, 7, 7, 20)	0	conv2d_2 (Conv2D)	(None, 109, 109, 64 18432 )	18432	['activation_1[0][0]']
flatten (Flatten)	(None, 980)	0	batch_normalization_2 (BatchNo rmalization)	(None, 109, 109, 64 192 )	192	['conv2d_2[0][0]']
dense (Dense)	(None, 10)	9810	activation_2 (Activation)	(None, 109, 109, 64 0 )	0	['batch_normalization_2[0][0]']
output_tensor (Dense)	(None, 6)	66	max_pooling2d (MaxPooling2D)	(None, 54, 54, 64) 0	0	['activation_2[0][0]']

Fig 6a (sequential CNN)

Fig 6b (model CNN)

**Detection Module**

$$\frac{dC}{D_{tot}} \times 100 = \% \text{ accuracy}$$

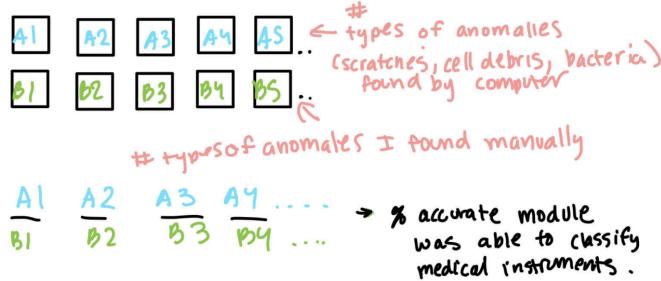
**Classification Module**

Figure 7: Equations to calculate accuracy of detection and classification module

To test the success of my detection and classification module, I plan to calculate the percent accuracy, which will quantify how well my code identifies debris and damage on the experimental datasets. I will test the detection code by dividing the number of correctly identified defect images found from the computer ( $dC$ ) by the total number of defect images that I manually inputted ( $D_{tot}$ ) ( fig. 7). To determine the success of the classification module, I will calculate the accuracy by dividing the type of damage found from the code to the labeled dataset found manually, (fig. 7).

## 6. Results

After passing the training dataset through the neural network more than 38 times (38 epoch), the training accuracy reaches a high 94% (fig 8 & 9) with less than .001% error. When running Fifty-One and manually checking for errored identification there is a .004% error rate that it fails to correctly identify and sort the type of damage. The neural network has yet to be passed through the test dataset, so currently there are no final results. When testing the CNN

through the test dataset, I hope to retain the same high accuracy as I reached when passing the training sets through the network.

```
Epoch 32/90
331/331 [=====] - 6s 18ms/step - loss: 0.2384 - accuracy: 0.9140 - val_loss: 0.1455 - val_accuracy: 0.9486
Epoch 33/90
331/331 [=====] - 6s 19ms/step - loss: 0.1637 - accuracy: 0.9479 - val_loss: 0.1399 - val_accuracy: 0.9426
Epoch 34/90
331/331 [=====] - 6s 19ms/step - loss: 0.1873 - accuracy: 0.9249 - val_loss: 0.1758 - val_accuracy: 0.9317
Epoch 35/90
331/331 [=====] - 6s 19ms/step - loss: 0.4249 - accuracy: 0.8728 - val_loss: 0.4774 - val_accuracy: 0.8302
Epoch 36/90
331/331 [=====] - 7s 20ms/step - loss: 0.2308 - accuracy: 0.9091 - val_loss: 0.1469 - val_accuracy: 0.9462
Epoch 37/90
331/331 [=====] - 9s 26ms/step - loss: 0.1595 - accuracy: 0.9376 - val_loss: 0.1452 - val_accuracy: 0.9492
Epoch 38/90
331/331 [=====] - 6s 19ms/step - loss: 0.1534 - accuracy: 0.9400 - val_loss: 0.1119 - val_accuracy: 0.9637
```

Fig 8 After 38 Epoch, the CNN reaches a 94% accuracy rate

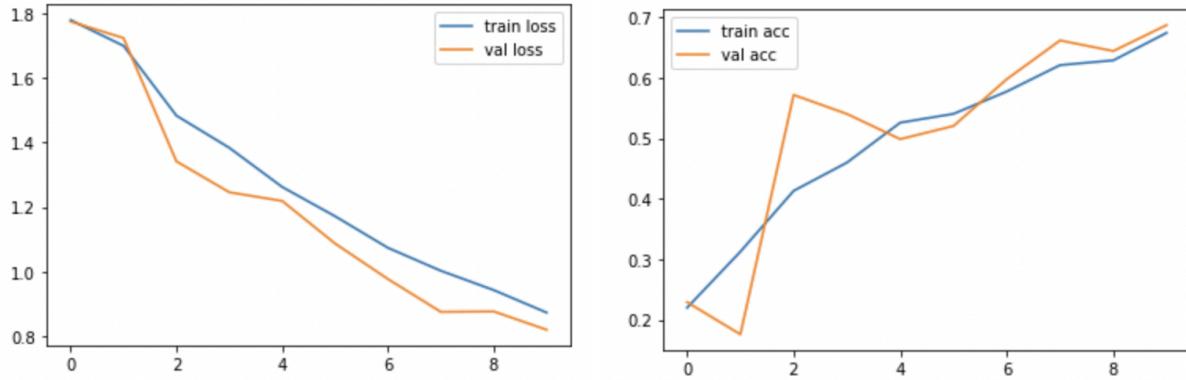


Fig 9 Steady increase of training accuracy with a decreasing amount of inaccuracy.

## 7. Discussion & Conclusion

In this research, I developed a program that can accurately localize and determine the type of damage or cell debris on a medical instrument. Although my results are not fully conclusive, this data could reduce the amount of patients being infected or dying due to improperly cleaned or damaged medical instruments. Unless an instrument is manually inspected, current sterilization methods fail to efficiently inspect physical damages on medical devices unless used or tested, thus this program will automate this step and decipher the type of damage on the instrument. My research has the potential to improve patient safety by enabling researchers to make informed decisions about whether an instrument is suitable for use in surgery or needs to be discarded.

## 8. Works Cited, References & Acknowledgements

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