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

Katie Lee

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 construct 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 instrument using microscope cameras. Through a neural networks and encoders, my code will be able to distinguish cellular debris from physical damage and highlight areas needed to clean 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 that a tool has been successfully sterilized. Ultimately reducing the cost of re-sterilization, prolonging the device's longevity and most importantly, reducing the amount of patients dying from bacterial infections.

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 had debris and loose fiber strands that could cause intraocular inflammation and disease transmission (Dinakaran, 2002). To further emphasize this issue, 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). It is easy to find a common theme when examining these tragic case studies. In all of these medical procedures, doctors used complex medical instruments such as an endoscope, which has high risks of HAI due to their intricate parts being susceptible to damage and cell debris (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 not gentle with an instrument. Many medical tools use semiconductor technologies that cannot withstand the current sterilization methods due to high temperatures, radiation, plasma discharge, etc. In addition, since all semiconductors use embedded batteries, when these pieces undergo steam sterilization the steam, and heat erases and erodes the floating-gate memory cells which shortens the lifetime of the medical toolm (Porto, 2001).

In hospitals to test whether an instrument is clean, hospital technicians a process that combines mechanical, chemical, and biological indicators. While these techniques can detect

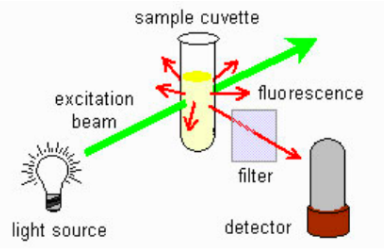
bacteria or debris on medical instruments, they fail to detect damages and precisely locate the debris. Furthermore, all these processes are tested by batch for efficiency. While it shortens the time to detect debris when a batch tests positive for bacterial residue, the entire batch is re-sterilized until all tools test negative. Constant re-sterilization is costly and damaging to the instrument (Porto, 2001).

In the last decade, many studies have investigated and created techniques and prototypes to reduce 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 identity bacteria and, in some cases, viruses. Pathspots 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 researches collected a database of frequencies that bacterias respond to and compared it to the bacteria the frequencies emitted from user's hand.

When trying to automate methods to identify bacteria and damage on metallic surfaces, it is crucial to analyze code structure in these research projects. A standard coding structure used to detect defects are neural networks. In a recent study, the researcher used a Cascaded Autoencoder (CASAE) architecture and Convolutional Neural Network (CNN) to identify and localize defects and damages such as scratches on 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 segue to the CNN will can specifically sort what type of abnormality is found in the image. My code structure will follow this structure because my device also has to identify and localize debris and defects on metallic surfaces (fig 4). Furthermore, to validate the success of the CNN, Salama conducted a study that incorporated a CNN to determine facial recognition through taking key features such as the eyes, mouth, and nose on faces to match people's features to their face. (Salama, 2020) Lastly, I will derive my research regarding 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 technique, specifically nonlinear filter methods such as fuzzy or classical techniques, best reduces noises. (Mohamed, 2017).

Figure 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 fluorophor pass to the detector.

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



1b:

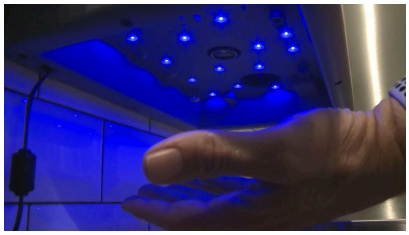
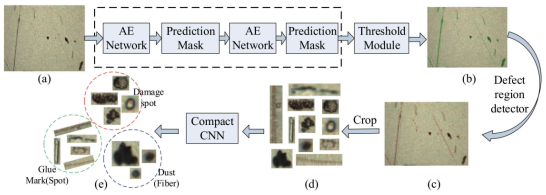


Figure 3
Pipeline of the metal surface defect inspection architecture. a) original image, b) detect segment, c) defect location d) cropped results e) classification



Research Question

In recent years, new technology in the biomedical field integrated semiconductors which are highly sensitive to high temperatures, scratches, etc. Semiconductors require manual cleaning because they are sensitive to sterilization techniques. So, I will create a device that removes the mental and intensive labor of people in the medical field. To solve this problem, my device will automatically identify and localize different types of damage and reduce the chances of cross-infection. In my research from last year, I developed a device that can spot debris on medical instruments, but it was slow and inefficient. This year, I will continue my project and it will be based on a CAEAE architecture and a convoluted neural networks (CNN) to identify and locate debris on medical devices that are difficult to clean. My device improves current technologies because it will be able to locate contaminated areas on a medical instrument and accurately determine whether a tool has been successfully sterilized. This device reduces the amount of patients dying from HAI, the cost of re-sterilization and prolongs the device's longevity. I hope to measure my devices success by having an 90% accuracy rate in finding debris or defects and identifying the type of damage or cellular debris. I based my accuracy percentage to Tao's neural network accuracy percentage (90.2%) which calculated the rate accuracy of identification and classification.

Methods

Procedures:

1) My experiment will be 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 experieriment, I will be using the same technique and I will create the dataset by using a 100x microscope in order to identify bacterial debris.

2) Using this dataset, I will separate the images into a training set and a experimental set. The training set will teach the neural network what is a abnormally, and different types of debris. The experiment set is the used when testing the accuracy of the program.
3) When examining the process my code will be able to identity and sort images inside of the dataset by type of debris into different categories.
    a) The detection module will use a CASAE architecture which includes two autoencoders levels that have prediction and filter masks to identify defects. These prediction masks augment the image's colors, detect features, and etc. to detect whether an image has an anomaly. The images that have anomalies will be sent to the classification module which will be inspected and identified.
    b) The classification module is built from a convolution neural network (CNN) that contains convolutional layers - a filter that moves right to left aiming to collect high-level features such as edges - and three max-pooling layers. These features will 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 will determine the shape of the defect - pivotal for classification.

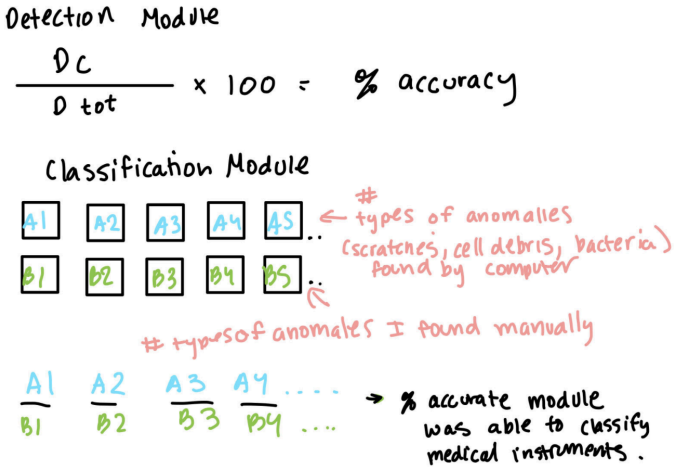


Figure 4: Equations to calculate accuracy of detection and classification module

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 test the detection code by dividing the number of correct identified defect images found from the computer (dC) by total number of defect images that I manually inputted (Dtot) (fig. 4). 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. 4)

Due to the scale of the project, I will use smaller datasets. So instead of creating 3000 training sets, I will make 200 training data sets. Additionally, since we cannot examine complex medical tools when checking for damage and debris, I will use items are similar to these tools that have metallic surfaces and intricate designs.

Method	Tools	Hazards/Safety Precations
Neural Network	Computer; Visual Studio Code; Python	N/A
Autoencoder; pixel max pooling; convolution networks	Computer; Visual Studio Code; Python	N/A
Image Comparison: SIFT, ORB, SURF	Computer; Visual Studio Code; Python	N/A
Placing cell debris and Bacteria on medical instrument	Gloves, Swab	Wear gloves when handling debris.

Materials and Equipment

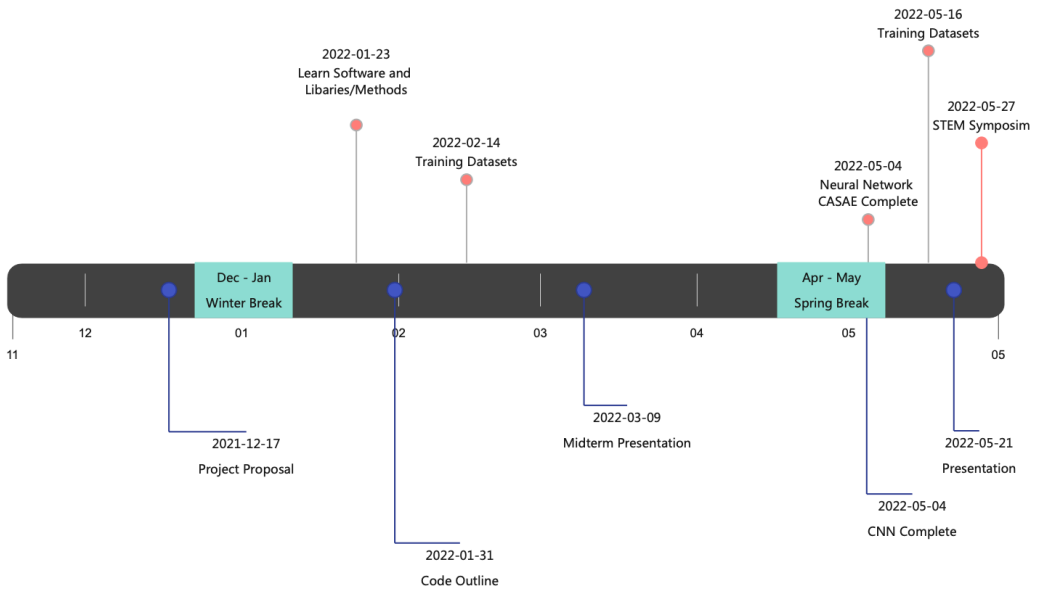
Product	Vendor/ Part #	Quantity	Cost	Hazards/Safety Precautions
*Computer	N/A	1	N/A	N/A
*Microscope 1000x magnification	N/A	1	N/A	Handle glass slides carefully. When carrying the microscope, always use two hands
5MP USB 2.0 High-speed Color CMOS C-Mount Microscope Camera with Reduction Lens and Calibration Slide	Am Scope	1	$239.99	N/A
*Microsoft Windows	N/A	1	N/A	N/A

FML27 27-Watt 6500 K Compact Fluorescent Light Bulb	Amazon	1	$13.99	fluorescent lights must be disposed of as hazardous waste
*Forceps/Metallic Surface	N/A	1	N/A	Clean and wash before and after washing

*Asterisk: Do not need to purchase

Timeline and Major Milestones

Major Milestones and Important Tasks	Estimate Time Spent	Date Completed
Learning Python: libraries, datasets, neural networks, autoencoders, image comparison libraries	2 Months	Mid January
Outline of Code's structure (process)	7 days	Late January
Creating Datasets (Experimental and Training Sets): Taking pictures of medical device under microscope and labeling/identify damage/debris on each image	2 weeks	Early February
Midterm Presentation	5 days	March
Complete Neural Network autoencoder	3 months	Early May
Complete CNN	3 months	Early May
Attaching the image comparison code to neural network autoencoder and CNN	5 months (accumulation)	Early May
Test training datasets on entire structure	5 days	Early May
Final Presentation	5 days	Late May
STEM symposium	5 days	Late May



Timeline

Citations

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