# Identifying Cell Debris and Foreign Material on Complex Medical Instruments through Machine Learning Neural Networks and Computer Vision

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Current sterilization procedures reduce the longevity of medical instruments due to heat and chemical damage. Additionally, medical practices also fail to identify faulty instruments which could impact a doctor's ability to perform surgeries. Therefore:

**I developed neural network model using AI Algorithms to identify and locate physical damage and cell debris on medical devices, preventing unsterilized and defective medical instruments from being used which will reduce cross infection and surgical injuries in hospitals.**

## Background

- Antibiotic-resistant bacteria cause 25% of Healthcare-Associated Infections (HAI) and increase human mortality rates to as high as 50% (CDC, 2020).
- In a study, 62% of sterilized ophthalmic instruments used for cataract surgery had debris and loose fiber strands that could cause intraocular inflammation and transmission from prior disease (Dinakaran, 2002).
- On any given day about one in 31 hospital patients has at least one HAI (CDC, 2018).

## Prior Art

- Researchers trained a deep learning convolutional neural networks (CNN) and auto-encoder model to identify scratches and damage on industrial material (Tao, 2018).
- PathSpot's hand scanner uses fluorescent light to scan bacteria through fluorophore detection (Pathspots, 2020).
- Researchers developed a classification-type CNN model that automates the classification of bacterial cell sub-populations (Tamiev, 2020).

## Future Development

- An interactive user-friendly interface/app that interprets the data in a simple and easy.
- Connecting HREI's computer vision image alignment model w/ HREII's CNN classification model.
- The model needs more training datasets in order to improve its classification accuracy and speed.

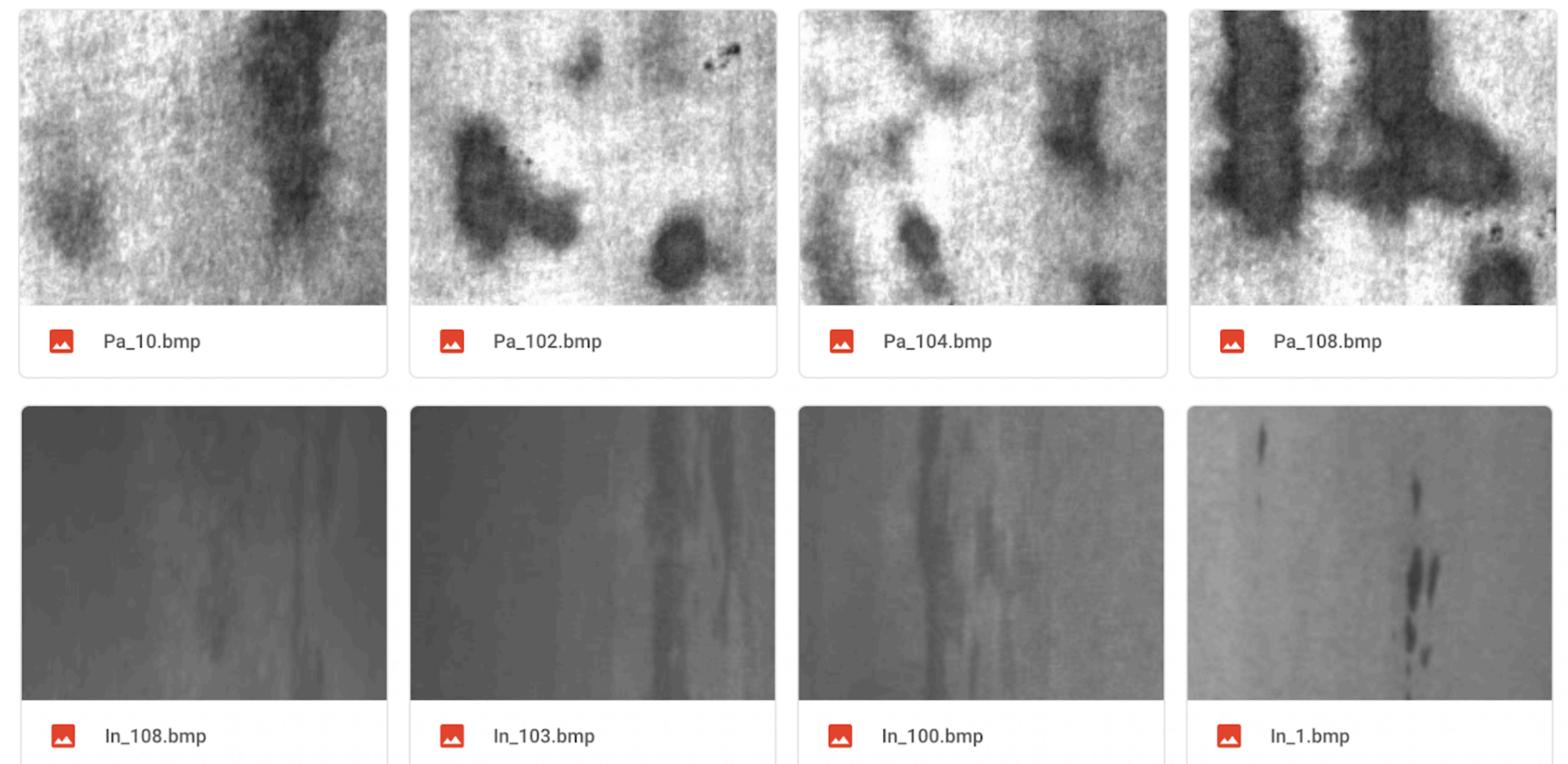


Fig 1: Test dataset: images of patches and incisors

## Metal Surface Defects + Cell Debris Datasets

- Dataset includes images taken at a microscopic level.
- Dataset includes images of both physical damage (scratches, pits, patches, etc) and cell debris (bacteria, etc).
- The model extracts and identifies features (bio-matter/damages) on each image through AI algorithms (CNN).

Model: "sequential"

| Layer (type) | Output Shape | Param # |
|---|---|---|
| input_tensor (Conv2D) | (None, 28, 28, 20) | 520 |
| activation (Activation) | (None, 28, 28, 20) | 0 |
| max_pooling2d (MaxPooling2D) | (None, 14, 14, 20) | 0 |
| conv2d (Conv2D) | (None, 14, 14, 20) | 10020 |
| activation_1 (Activation) | (None, 14, 14, 20) | 0 |
| max_pooling2d_1 (MaxPooling2D) | (None, 7, 7, 20) | 0 |
| conv2d_1 (Conv2D) | (None, 7, 7, 20) | 10020 |
| activation_2 (Activation) | (None, 7, 7, 20) | 0 |
| flatten (Flatten) | (None, 980) | 0 |
| dense (Dense) | (None, 10) | 9810 |
| output_tensor (Dense) | (None, 6) | 66 |

Fig 2: CNN model

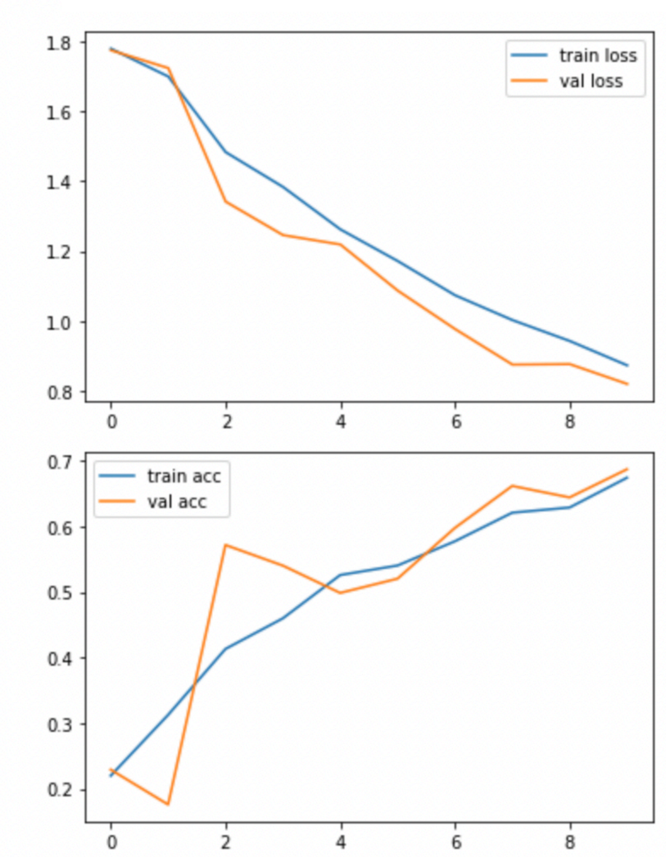


Fig 3: accuracy increases as CNN is being trained

## Layers of Sequential Model Neural Network

- Layers are filters and applied to the original image. Filters process data and augment images to collect & read the image's data.
- The model reads the image as multiple 2D array (matrices), examining the image's features, different shades of tone, and etc.
- After reading and "learning" from thousands of images, the model uses that data to recognize images with the similar/same features.

## Data flow chart

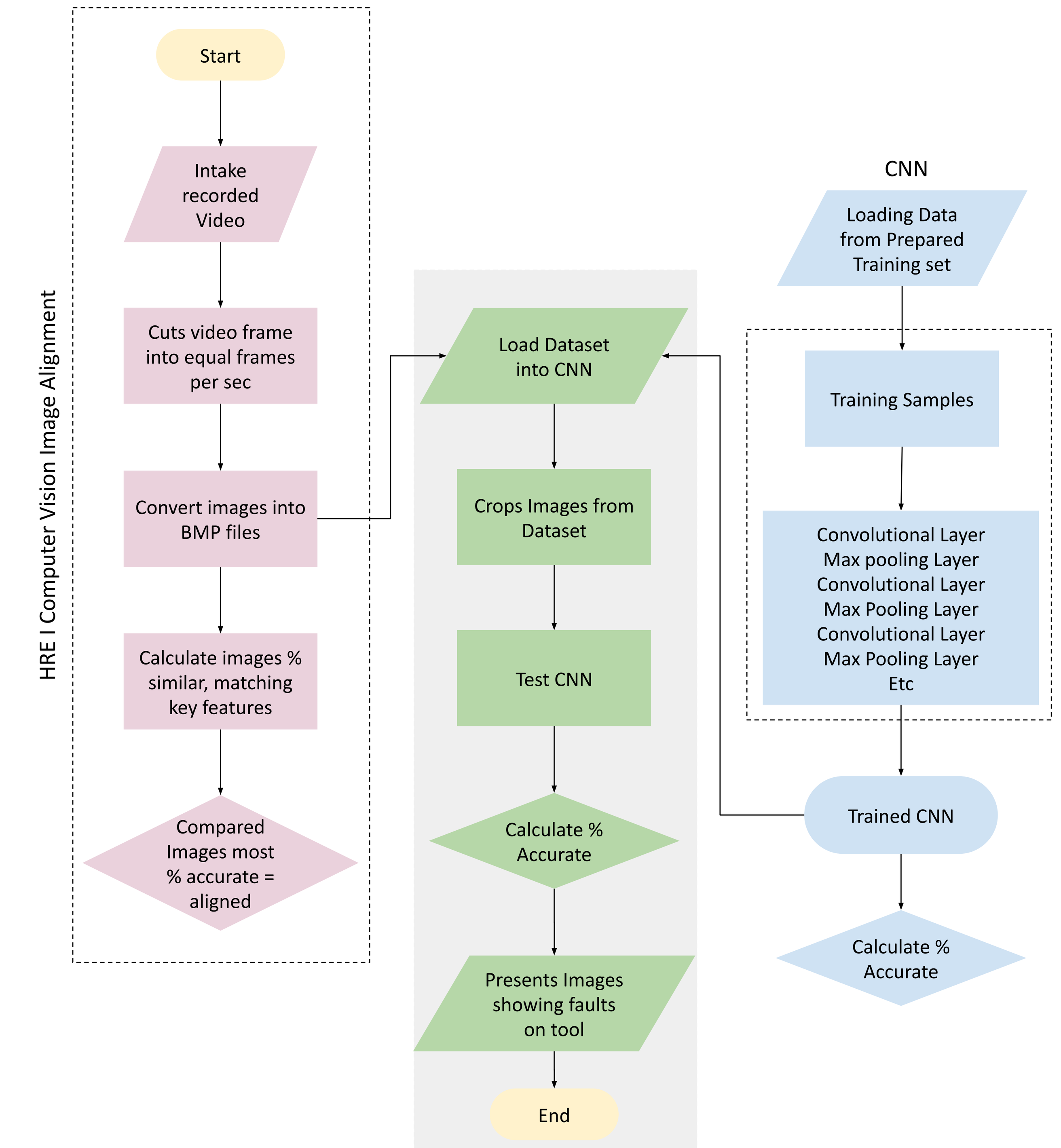


Fig 4: Code outline describing code sequence of computer alignment software (left) and CNN model (right).
Purple = Image Alignment Software; Green = Applied in practice; Blue = Trained model

## HRE I Background

A detection and sorting module that uses a fluorescent microscope and computer vision techniques to identify cell debris and damage on medical instruments. Under fluorescent lighting, the camera scans a medical instrument twice: before use and after sterilization to collect images of the instrument. The libraries will detect differences and abnormalities using computer vision libraries ORB, SIFT, and SURF. I only used a segment of the code for HREII to take pictures of the medical instrument.

## References


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