# Machine Learning Cell Type Classification for Cancer Diagnosis

*Poplar Yang, Daniel Karkhut, Zach Laswick, Daolong Liu, Muyuan He, Ratul Paul, Shen Wang, Yaling Liu.*

*Department of Bioengineering, Lehigh University, Bethlehem, PA*

## Introduction

- Cell imaging and biophysical analysis are crucial tools in the study of cancer detection and clinical treatment.
- Cell deformability and mechanical properties are important biomarkers for cancer cells detection.
- This study aims to use the deformability index (DI)- the ratio of the major axis to the minor axis- in a narrow constriction microfluidic channel to differentiate white blood cells (WBCs) from cancer cells (HCT-116). An automated imaging processing code analyzes the cell motion and plots the velocity change and DI of each cell which will be used to identify the cell type.

## Cell Culture & Cell Collection

- HCT-116 cells were formed using standard cell culturing method and diluted with Phosphate Buffered Saline in a 1:5 ratio prior to the experiment.
- WBCs were extracted from bovine whole blood sample. Red blood cell lysis was used to isolate the WBCs in the sample.

## Microfluidic Device Setup

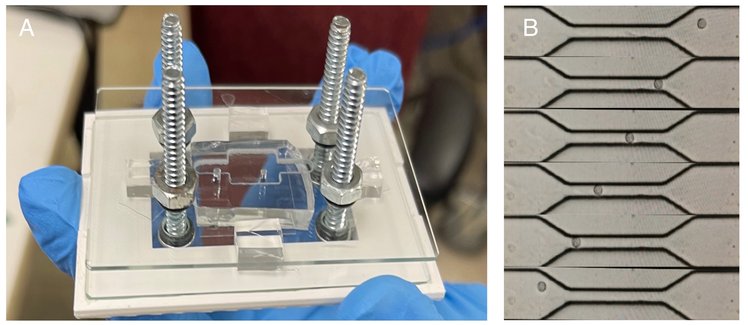


**Figure 1.** (A) Reusable microfluidic device setup. (B) An image of a cell passing through the microfluidic channel from the inlet (the right side) to the outlet (the left side).

- A polydimethylsiloxane (PDMS) microfluidic device was constructed with a height of 40µm, containing 10 narrow constriction channels each having a width of 7.5µm.
- Two glass slides containing inlet/outlet holes on the top and bottom of the device were clamped using multiple 3D-printed frames to make the device reusable, shown in Figure 1A.
- The imaging was done at 5000 fps with a 10µs exposure time, example image shown in Figure 1B.

## Image Processing Code

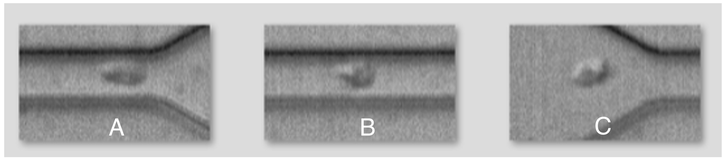


**Figure 2.** Image processing result of a single WBC. (A) WBC in the microfluidic channel upon entry; (B) WBC in the middle of the channel; and (C) WBC at the exit of channel.

After testing the two types of cells in the microfluidic device, the machine learning Python code generated three cropped images for each cell being analyzed: before the entry of channel, during/ in the middle of the channel, and upon the exit of the channel, shown in Figure 2.

## Results

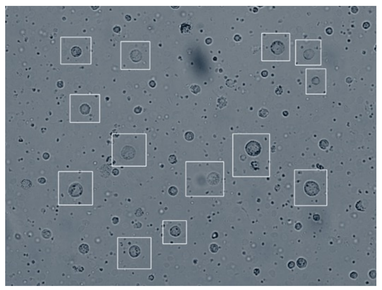

**Figure 3.** Machine learning example output. The squared cells are identified as HCT116 cancer cells, and the unsquared cells are WBCs.

- An automated imaging processing Python code marked the DI of each cell being analyzed before the entry of the channels, within the channels, and after exiting the channels. The DI value of each cell was compared and used to classify the cell type.
- The accuracy of differentiating HCT-116 and WBC is about 95%. An example output is shown in Figure 3.

## Conclusion & Future Works

- It was proven that there is a noticeable difference between the DI of HCT-116 cancer cells and that of WBCs. As a result, this techniques could be used in making a cancer diagnostic device in detecting cancer cells for patients to potentially start treatment at an earlier phase.
- Future works can be done to improve the microfluidic device, in replacing the PDMS with glass, creating more stable and rigid channels that would constantly produce accurate data for DI analysis.

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