# Machine learning supported image analysis of microfluidic droplets

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### Microfluidic droplets

- Collaboration with Bio-Pilot Plant at Leibniz-HIK and Fraunhofer IOF •
- Encapsulation of single cells in droplets

- by Microtiterplate (MTP) experiments
- •

### **Droplet encoding**



### **Droplet content determination**

#### **Bead classification Droplet decoding** $C_T$ : True bead color Each droplet has a true code $(K_T)$ and the RF gives a detected code $(K_D)$ $C_D$ : Bead color detected by RF $K_D = \{C_{D,1}, \dots, C_{D,N_D}\}$ RF are resistant to faulty labels in training data [2] • We are looking for the most likely code given: • Bayes theorem 0.0028 1e-06 0.00034 0.023 0.015 0.00014 0.00011 black $K_D = \{g, o\}$ $p(K_T|K_D) \sim p(K_D|K_T)p(K_T)$ $\boldsymbol{v}_{K_D} = [k_1, k_2] = [22, 1]$ blue 0.00029 1.9e-05 2.8e-05 0.0047 5.4e-05 1e-06 6.7e-05 • The misclassification rate of the RF $K_T = \{g, o\}, \{g\} \text{ or } \{o\}$ red 1e-06 5.4e-05 0.96 0.00012 0.00028 1e-06 0.012 0.0022 $N_D$ : Number of detected colors $p(K_D|K_T) = \prod_{j=1}^{k} p(C_{D,j}|C_{T,j})^{k_j}$ in a droplet orange 0.00026 5.4e-05 0.0013 0.99 0.00036 0.011 0.0039 0.0014 Number of beads of color j $C_D$ 0.019 0.016 1.9e-05 0.0016 0.97 0.0015 2.8e-05 0.00011 8 bead colors green • A multinomial distribution with equal probability for each color 11x11 pixels $p(K_T) = p_{MN}(\boldsymbol{v}_{K_T}) = \frac{\sum_{j=1}^{N_T} k_j}{\prod_{j=1}^{N_T} (k_j!)} \left(\frac{1}{N_T}\right)^{\sum_{j=1}^{N_T} k_j}$ 0.034 0.00011 0.00015 0.0077 0.0012 0.97 0.00041 0.00021 yellow Lab colour space Random forest (RF) with 5000 trees dark purple 3.4e-05 0.00011 0.035 0.00094 7e-05 0.00011 0.98

Implemented in Python using *scikit-learn* 

## GitHub



github.com/applied-systems-biology/Droplet\_segmentation

### **Growth detection**



3000 droplets: Acc = 0.925, Rec = 0.788 and Pre = 0.992

### Future developments

### **Deep learning**

- Use Convolutional Neural Networks to learn growth at different time points
- Tuned version of the EfficientNet-B4 was used [3]
- Trained and evaluated on *E. coli* calibration curves





![](_page_0_Figure_30.jpeg)

### Angle resolved spectra

- Droplets in flow imaged using angle resolved scattering techniques [4]
- Will use traditional image analysis and Deep Learning technique to quantify small changes in spectra
- Goal is to detect single cell division events for rapid antibiotic susceptibility testing (<1 h after lag phase)

![](_page_0_Picture_35.jpeg)

![](_page_0_Picture_36.jpeg)

![](_page_0_Picture_37.jpeg)

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#### References

[1] Svensson *et al.* 2019. *Small.* 15(4):e1802384 [2] Svensson et al. 2015. / Immunol Res. 2015:573165 [3] Tan and Le. 2020. *ArXiv*. 1905.11946v5 [4] Schröder *et al.* 2011. *Appl Opt*. 50(9):C164-C171

Funded by Thüringer Aufbaubank through the projects Dropcode (2014FE9037) and Autoscreen (2017FE9071). Angle resolved scattering work is funded by BMBF through InfectoGnostics 2 (ADA Nr. 13GW0456B)

![](_page_0_Picture_43.jpeg)

![](_page_0_Picture_44.jpeg)

Bundesministerium für Bildung und Forschung