



Master Thesis Presentation

Classification of cells using Real-Time Deformability Cytometry data

Ru Hui Tay 14th Oct 2022, 11:00

Agenda







01 Background

02 Problem Statement

03 Methods

04 Results

05 Conclusion

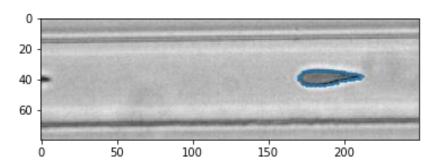


Image of a deformed singlet RBC taken by RTDC device. RBC is 14.62μm in length and 3.74μm in height.

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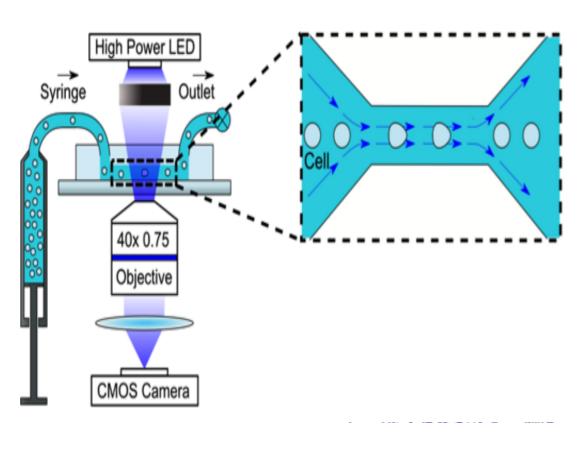
Background

Background









Diagnosis

sick

not sick

https://www.google.com/uri?sa=i&url=https%3A%2F%2Fcoronadashboard.government.nl%2Flandelijk%2Fziekenhuis-opnames&psig=AOWaw2fBbFe1HscONzMyiuk_Oh5&ust=1665768950763000&source=images&cd=vfe&ved=0CAwQjRxqFwoTCMj5pIXf3foCFQAAAAAdAAAAABAE
https://www.google.com/uri?sa=i&url=https%3A%2F%2Fwww.legaltoday.com%2Fpractica-juridica%2Fderecho-penal%2Fpractica-juri

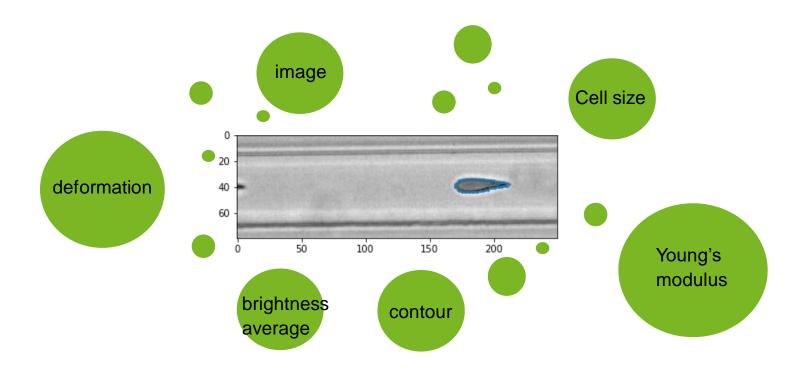
Common features the RTDC provides.







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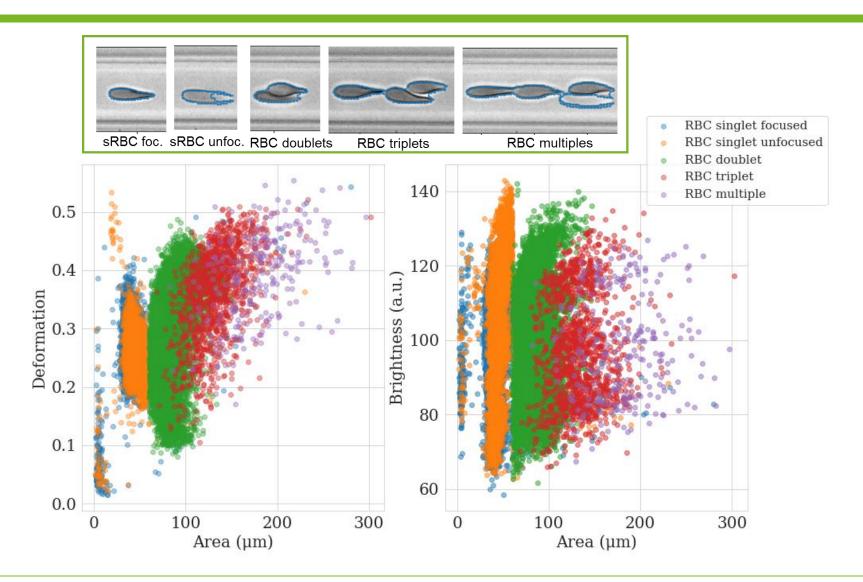


RBC multiplets cannot be well-differentiated by scalar features.





Background



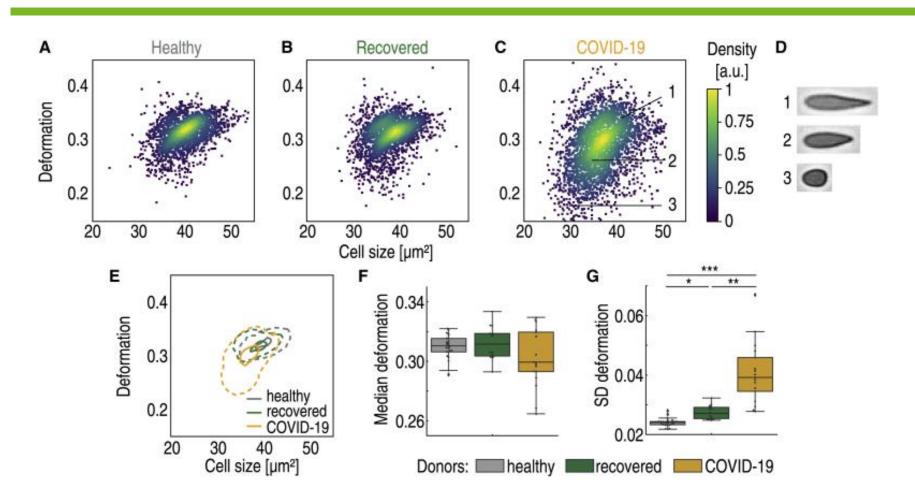
Covid - singlet RBC differentiated by scalar features.





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Background



Kubánková, M., Hohberger, B., Hoffmanns, J., Fürst, J., Herrmann, M., Guck, J., & Kräter, M. (2021). Physical phenotype of blood cells is altered in COVID-19. *Biophysical journal*, *120*(14), 2838-2847.





Problem Statement

Problem Statement

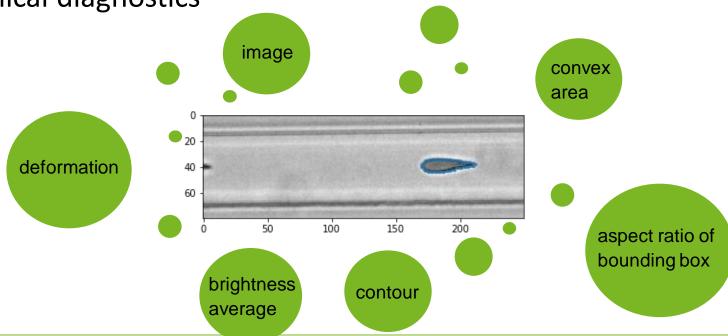




Scalar quantities are insufficient when cell types need to be distinguished

Need a method to distinguish cell types → application in

clinical diagnostics



Defining the boundaries of the thesis.

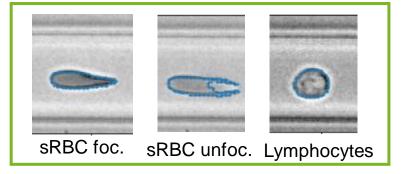




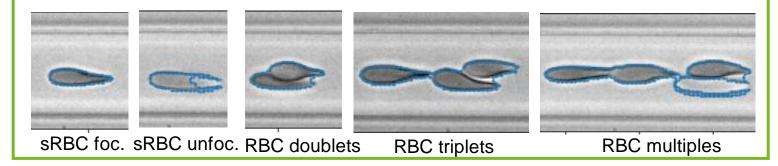


experiments

1



2



3

Classify between control versus long covid. Tested 15 blood cell types.

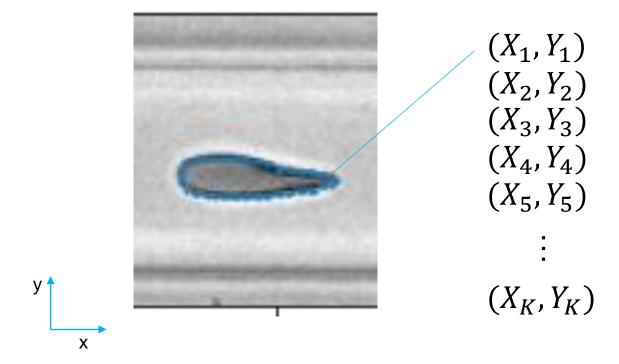
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How to classify contours?

Problem Statement











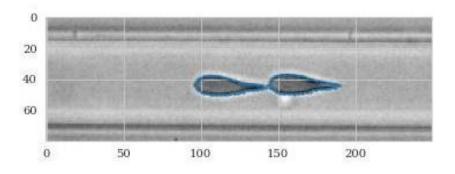
Methods

Fourier Descriptors

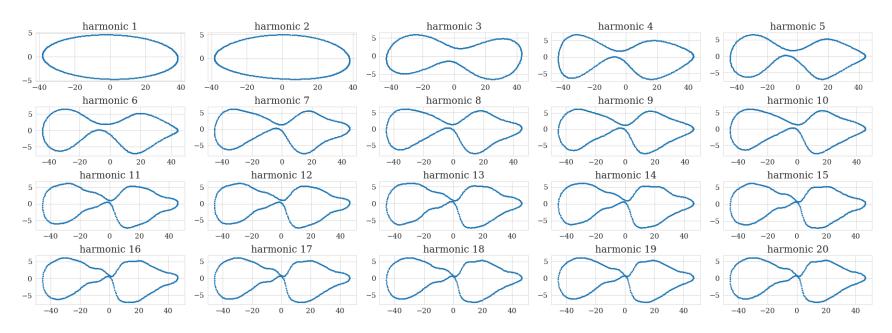
Methods







RBC doublet



Fourier Descriptors

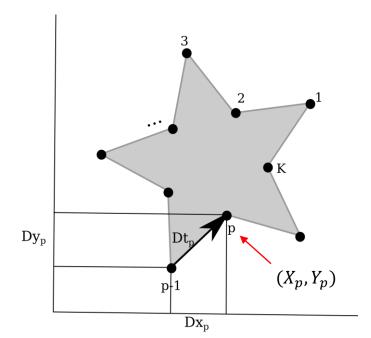
Methods





$$X_p = X_{cen} + \sum_{n=1}^{N} \frac{a_n}{T} \cos \frac{2n\pi t_p}{T} + \frac{b_n}{T} \sin \frac{2n\pi t_p}{T}$$

$$Y_p = Y_{cen} + \sum_{n=1}^{N} \frac{c_n}{T} \cos \frac{2n\pi t_p}{T} + \frac{d_n}{T} \sin \frac{2n\pi t_p}{T}$$



- (X_p, Y_p) an arbitrary set of cartesian coordinates
- N chosen harmonic number
- a_n, b_n, c_n, d_n Fourier Descriptors coefficients

•
$$t_p = \sum_{j=1}^p Dt_j$$

•
$$T = t_K$$

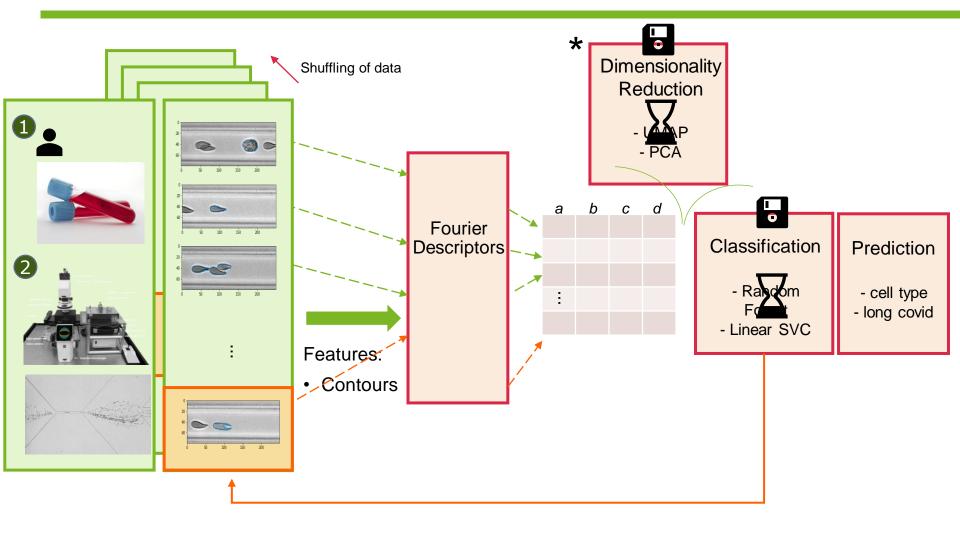
Diaz, G., Zuccarelli, A., Pelligra, I., & Ghiani, A. (1989). Elliptic Fourier analysis of cell and nuclear shapes. *Computers and biomedical research*, 22(5), 405-414

Analysis Pipeline

Methods











Results

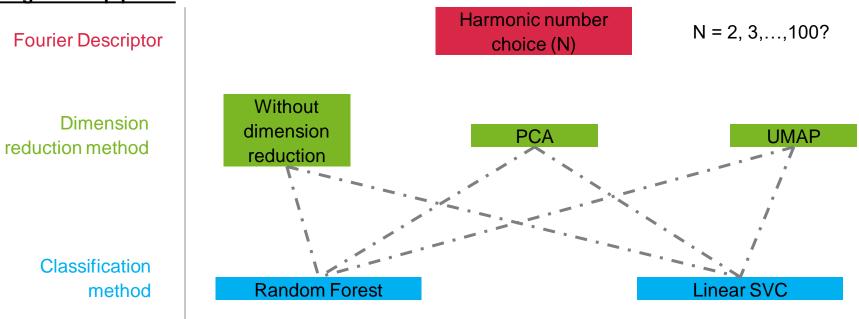
Results





- Problem Statement: Can we classify cells using contours?
- Which combination of methods are best for classification?

Stage of the pipeline



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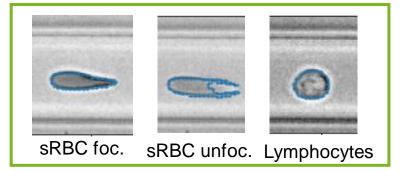
Recap

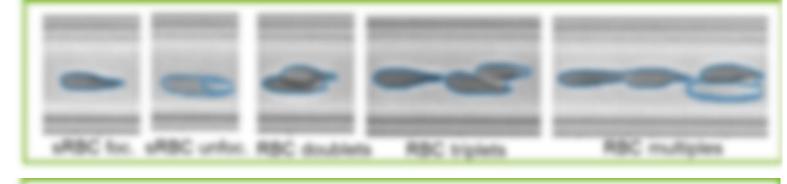
Defining the boundaries of the thesis.





experiments







PCA (8→2 dimensions)

Experiment 1

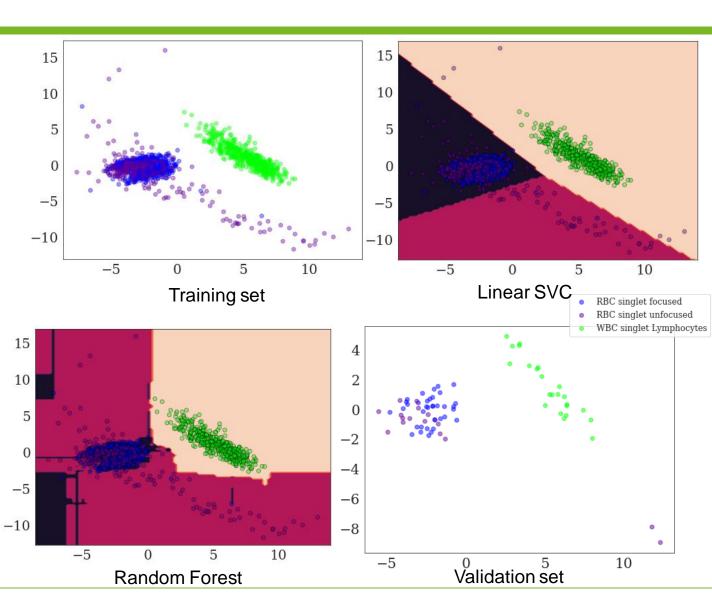




 Reduced from harmonic number 2

PCA

 Random Forest - more sophisticated decision boundaries.

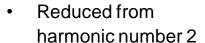


UMAP (8→2 dimensions)

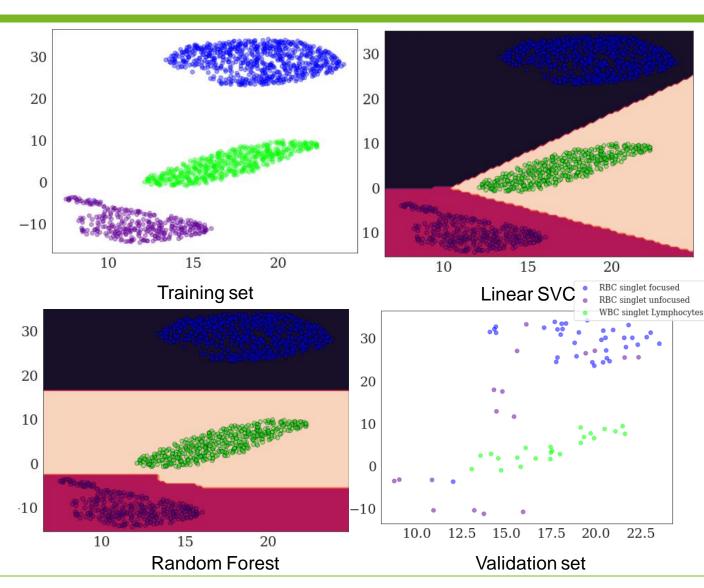
Experiment 1







Supervised UMAP



Comparing classification algorithms







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	Accuracy
Random Forest	0.9
Linear SVC	0.87

- Result for without dimension reduction.
- Random forest method gives slightly better accuracy than Linear SVC.

Comparing dimension reduction methods and how harmonic number affects classifier.





Experiment 1

Using Random Forest classifier:

	Mean of accuracies	Standard deviation
W/o dimensionality reduction	0.915	0.00568
PCA	0.818	0.000620
UMAP	0.867	0.000420

Mean and standard deviation of accuracy values over 2 to 15 harmonic number.

- Small std dev → large harmonic numbers ≠ better classification
- No dimension reduction yields best classification outcome followed by UMAP then PCA

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Experiment 1 Summary







- FDs is a good feature to differentiate sRBCs from Lymphocytes.
- Classification of singlet RBC focused and unfocused not perfect.
- Chosen harmonic number N=2 is more than sufficient for classification.
- No dimension reduction gives best classification accuracy.
- Random Forest offers only slightly better accuracy than Linear SVC.

Recap

Defining the boundaries of the thesis.



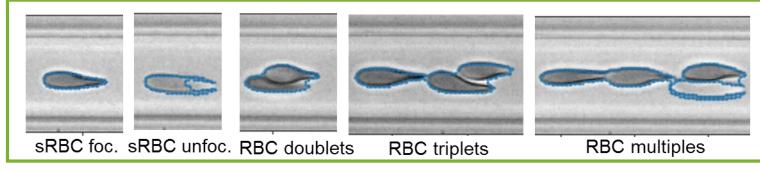


experiments

1



2



3

Classify between control versus long covid.
Tested 15 blood cell types.

PCA (8→2 dimensions)

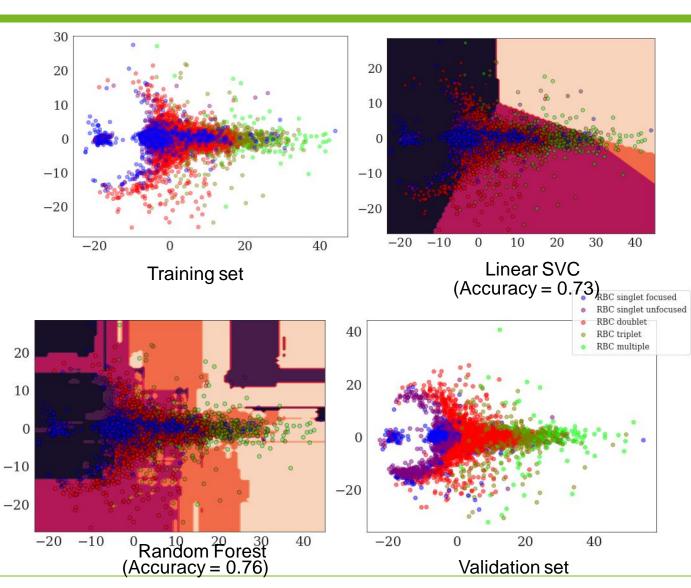
Experiment 2





 Reduced from harmonic number 2

• PCA



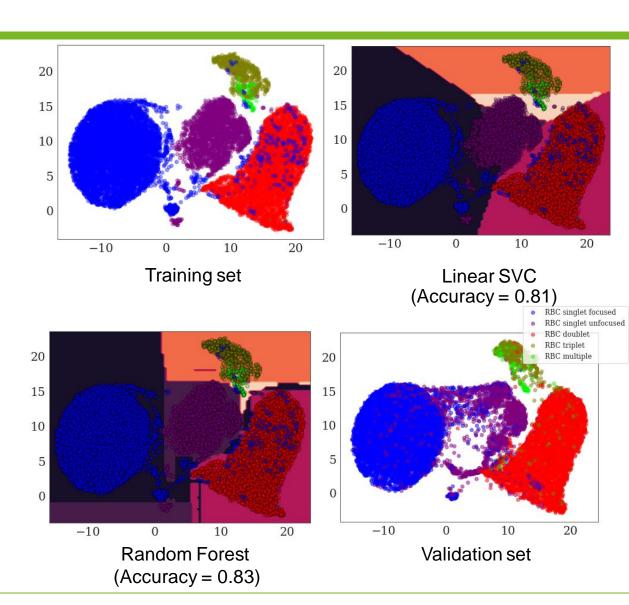
UMAP (8→2 dimensions)

Experiment 2





- Reduced from harmonic number 2
- Supervised UMAP

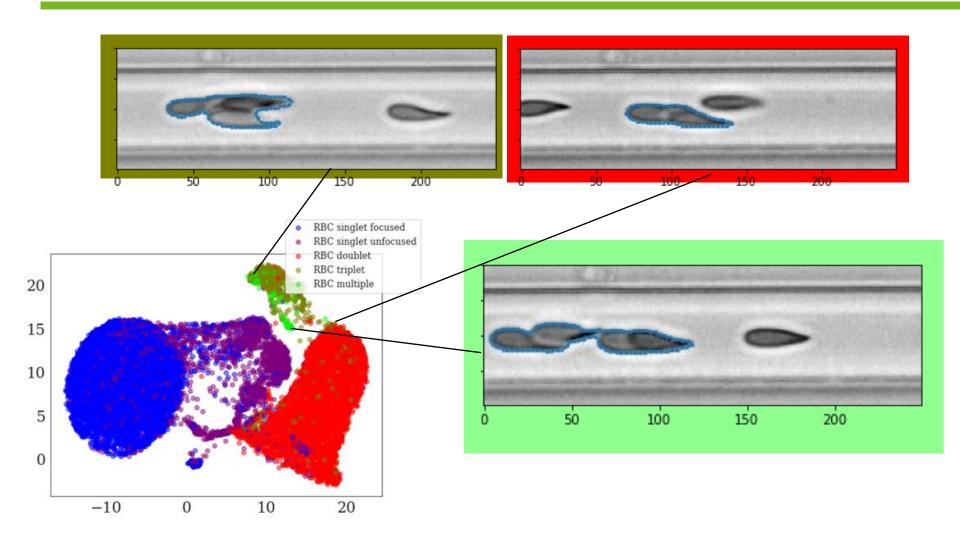


RBC multiples can sometimes have contours that resemble triplets.





Experiment 2



Comparing dimension reduction methods and how harmonic number affects classifier.





Experiment 2

Using Random Forest classifier:

	Mean of accuracies	Standard deviation
W/o dimensionality reduction	0.843	0.00407
PCA	0.764	0.000268
UMAP	0.835	0.000768

Mean and standard deviation of accuracy values from harmonic 2 to 27.

- Small std → large harmonic numbers ≠ better classification
- w/o dimension >UMAP > PCA
- UMAP has similar accuracy to w/o dimension reduction

How classifier method affects classification and reduced space affects performance.





Experiment 2

Random Forest

Accuracy	Embedded space				
Dimension reduction method	2 d	3d	4d	5d	8d
PCA	0.76	0.79	0.82	0.83	-
UMAP	0.83	0.83	0.83	0.83	-
w/o	-	-	-	-	0.84

Linear SVC

Accuracy	Embedded space				
Dimension reduction method	2d	3d	4d	5d	8d
PCA	0.73	0.73	0.78	0.78	-
UMAP	0.83	0.81	0.82	0.82	-
w/o	-	-	-	-	0.79

Experiment 2 Summary

Results





- FDs are good features for RBC multiplets classification.
- No dimension reduction with Random Forest again yields the best classification.
- UMAP yields similar classification outcome to no dimension reduction already in 2d, and is good for visualization.
- RBC multiples are often confused with triplets regardless of method.

Recap

Defining the boundaries of the thesis.



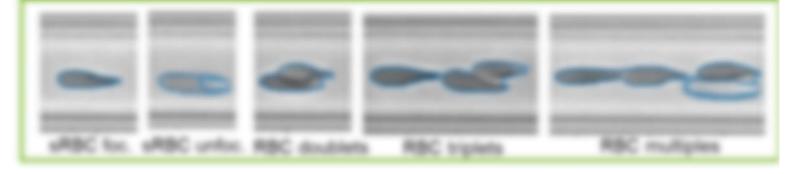


experiments

1



2



3

Classify between control versus long covid. Tested 15 blood cell types.

No learning was observed in Random Forest

Experiment 3





	Random Forest		
	no dim	PCA	UMAP
RBC singlet focused			
RBC singlet unfocused			
RBC doublet			
RBC triplet			
RBC multiple	Balanced Accuracy mean<0.5		
WBC singlet Lymphocytes			
Thrombocyte singlet focused			
Thrombocyte singlet unfocused			
WBC singlet Neutrophil			
WBC singlet Eosinophil			
WBC singlet Basophil			
WBC singlet Monocytes			
Thrombocyte multiple			
Mixed cell doublet			
Mixed cell triplet			

- Mean of balanced accuracy and standard deviation from harmonic number 2 to 29.
- Balanced Accuracy
 Mean < 0.5
- Randomly assigning long –covid and control groups can yield better results.

No learning was observed in Linear SVC

Experiment 3





	Linear SVC		
	no dim	PCA	UMAP
RBC singlet focused			
RBC singlet unfocused			
RBC doublet			
RBC triplet	Balanced Accuracy mean<0.5		
RBC multiple			
WBC singlet Lymphocytes			
Thrombocyte singlet focused			
Thrombocyte singlet unfocused	0.55 <balanced ac<="" td=""><td>curacy mean<0.6</td><td></td></balanced>	curacy mean<0.6	
WBC singlet Neutrophil			
WBC singlet Eosinophil			
WBC singlet Basophil			
WBC singlet Monocytes			
Thrombocyte multiple			
Mixed cell doublet			
Mixed cell triplet			

- Mean of balanced accuracy and standard deviation from harmonic number 2 to 29.
- Balanced Accuracy
 Mean < 0.5
- Randomly assigning long –covid and control groups can yield better results.
- Outliers? (in red)

Experiment 3 Summary

Results





- Fourier Descriptors are not good features to classify control versus long covid groups.
- No learning took place.
- Control cells and long covid cells look alike.





Conclusion

Conclusion





- FDs are only suitable if shapes of cell are highly different from each other.
- Worked rather well for RBC multiplets, promising extension to another classification pipeline.
- Overall no dimension reduction gave the best classification outcome, although
 UMAP also performs sufficiently well and can allow us to visualise the plots.
- Random Forest method is robust as a classification algorithm choice.
- Large number of harmonics does not improve classification.





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