Ultrasound Image Auto-Segmentation: Trainable Weka Segmentation

CHE4180 S1 2020 - Chemical Engineering Project

Supervised by Dr. Simon Corrie

IMAGEJ

An open platform for scientific image analysis

Presented by:

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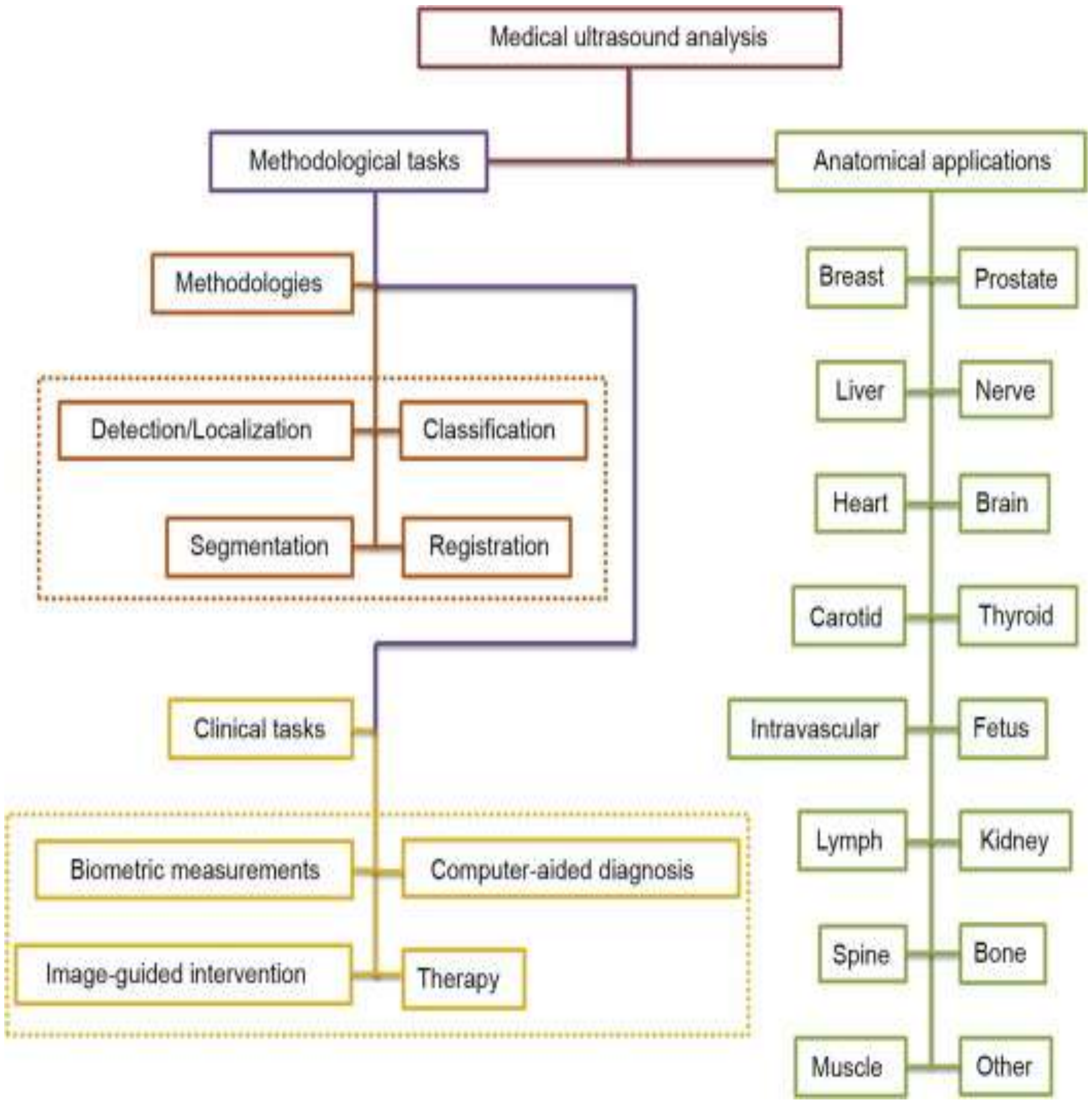
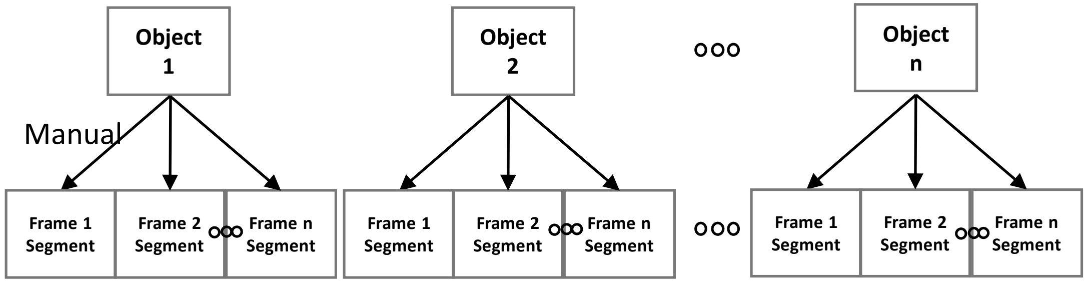
BACKGROUND:
US imaging and TWS



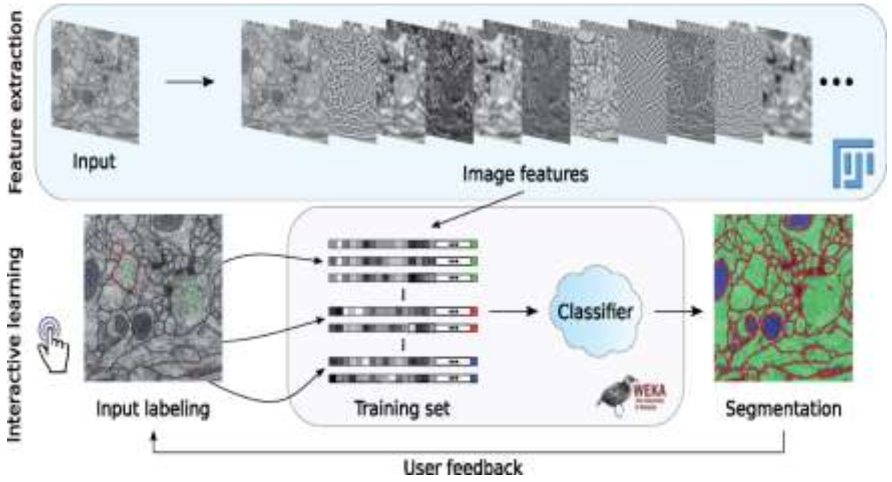
(Liu et al., 2019)

BACKGROUND:
US imaging and TWS

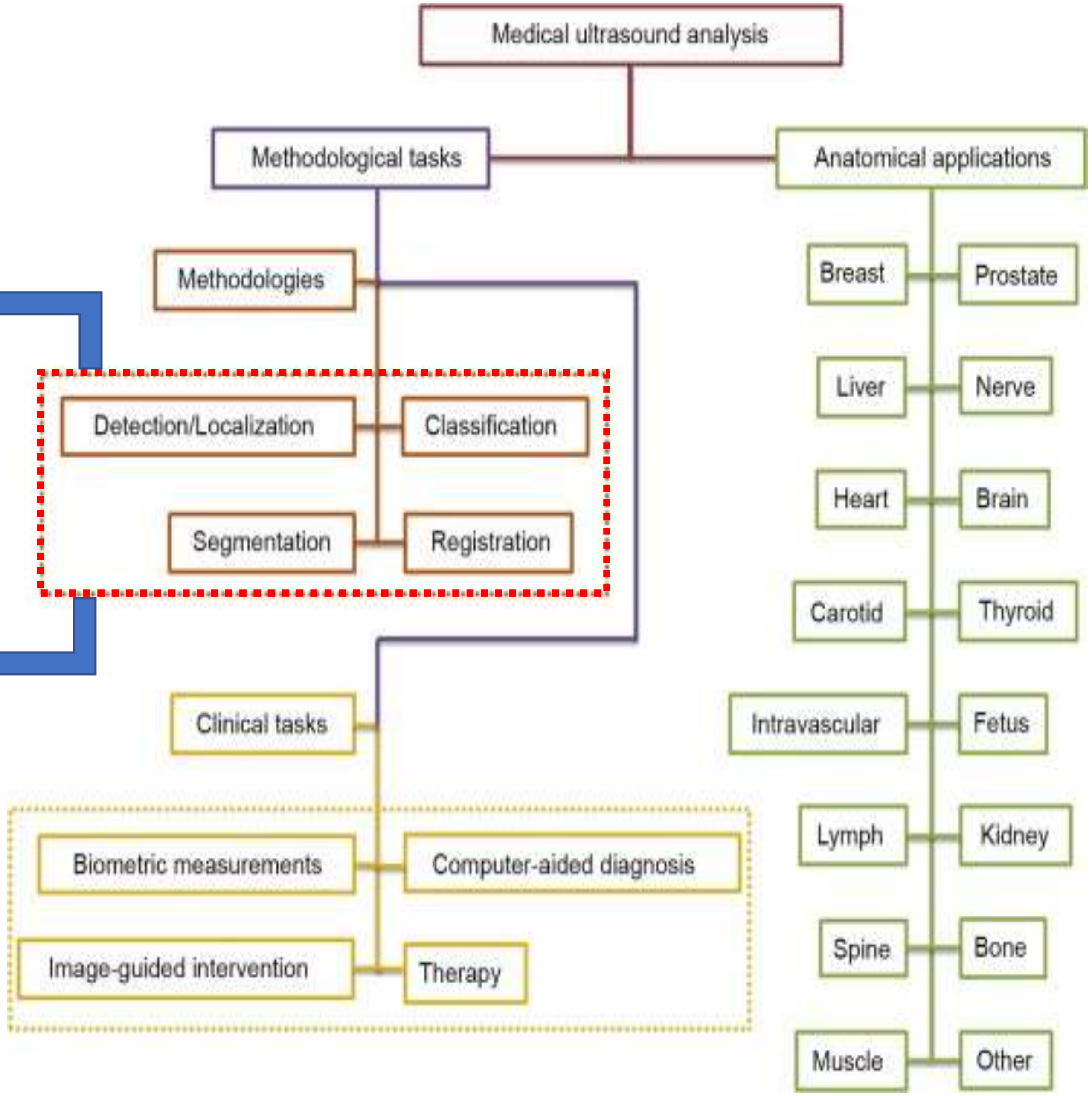
Manual Operation



Automatic Operation (Trainable Weka Segmentation)

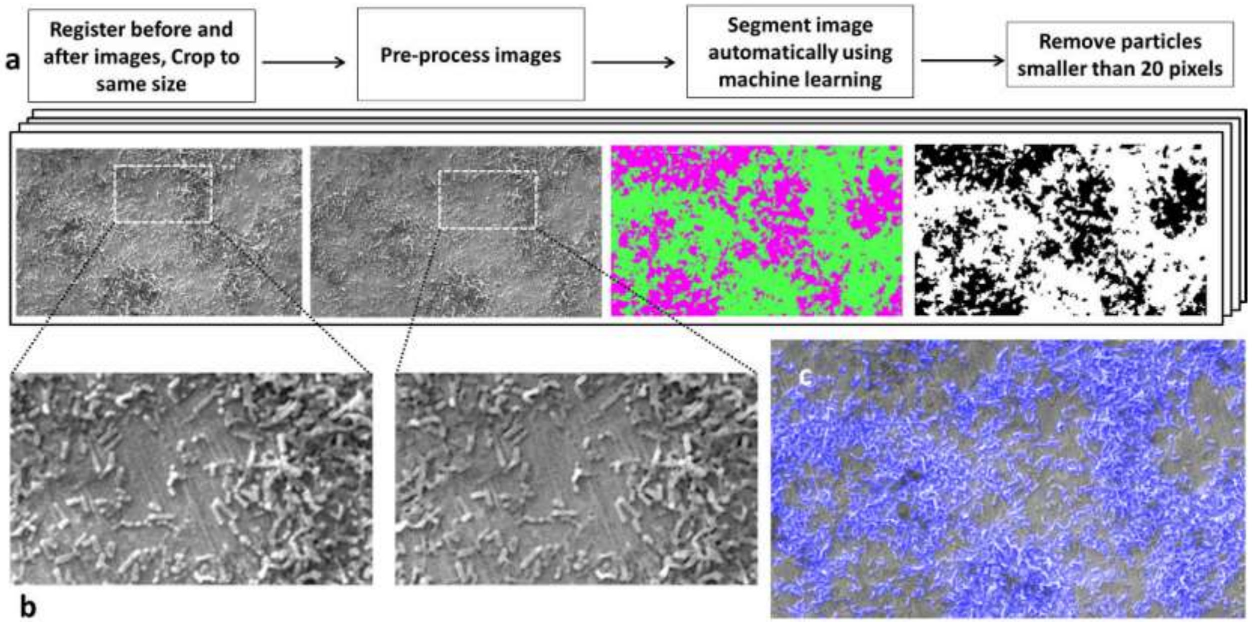


(Carreras et al., 2016)

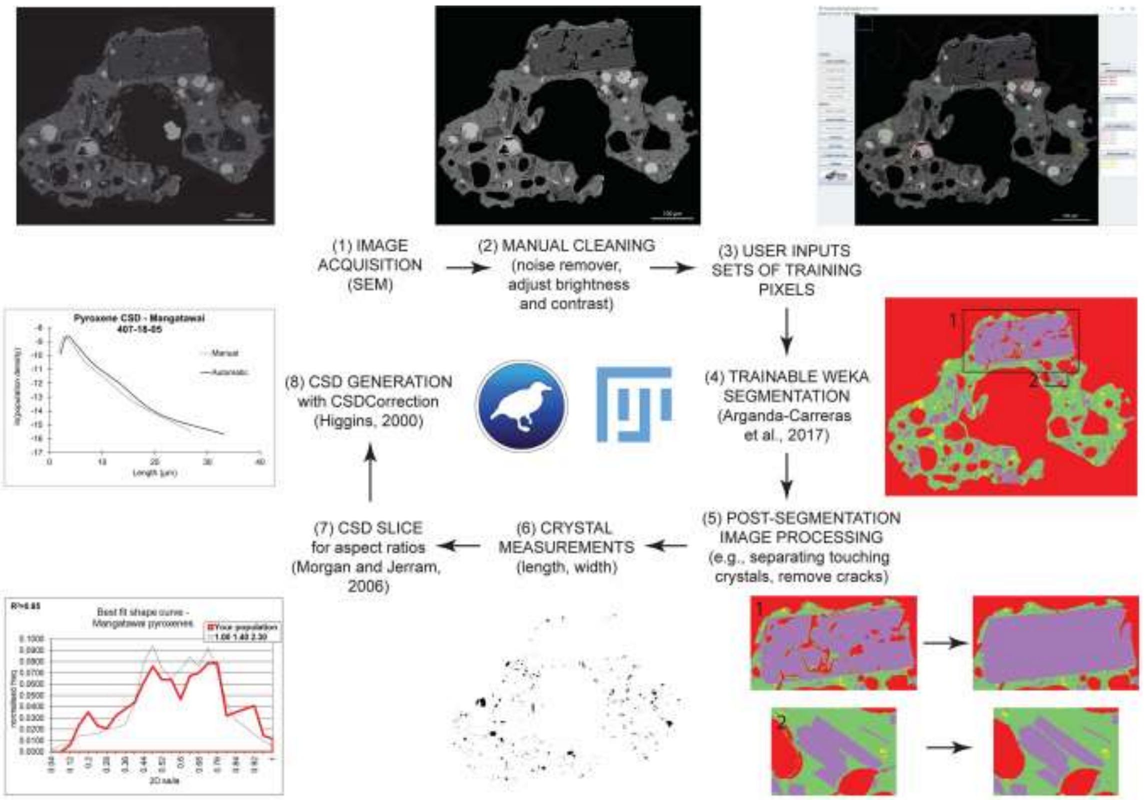


(Liu et al., 2019)

LITERATURE REVIEW: Application of TWS



TWS on SEM image of biomaterial surfaces
(Vyas et.al., 2016)



TWS on SEM image of volcanic rocks
(Lormand et.al., 2018)

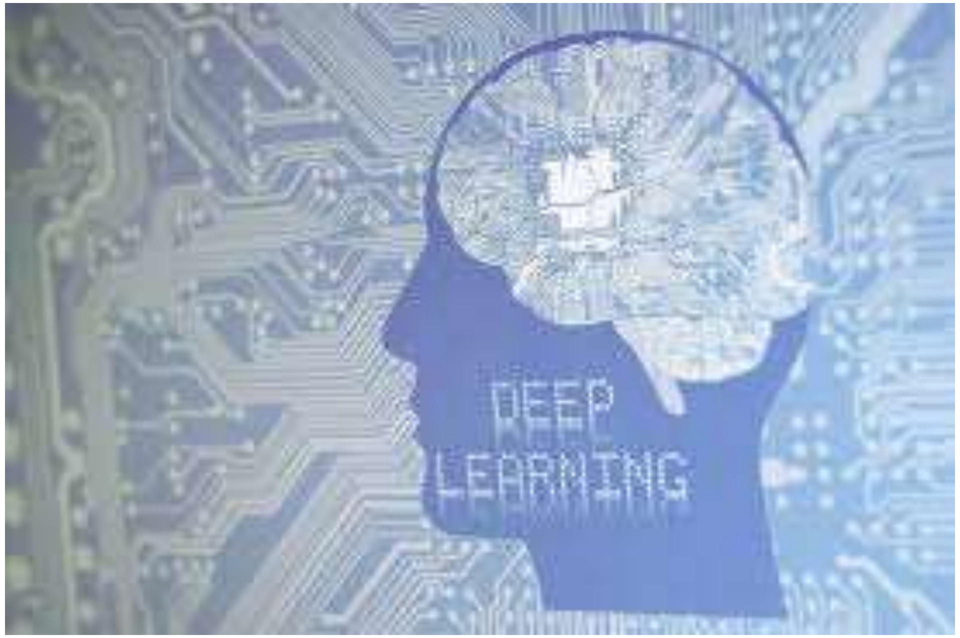
Problem Statement:
What is the performance of TWS on Ultrasound Image Auto-Segmentation

OBJECTIVES

1 Will **auto-segmentation** by TWS on ultrasound images give comparable results to **manual** segmentation?

2 Will different Machine Learning models **(Random Forest vs Naïve Bayesian)** affect segmentation results?

3 Will the application of **generalised model** give comparable results to the ordinary approach of training models on each dataset **individually**?



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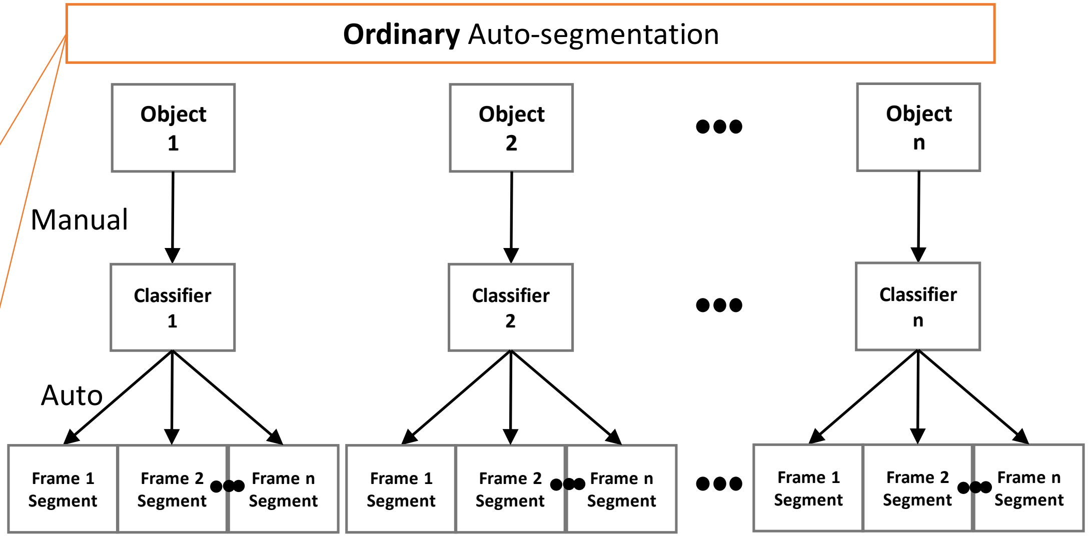
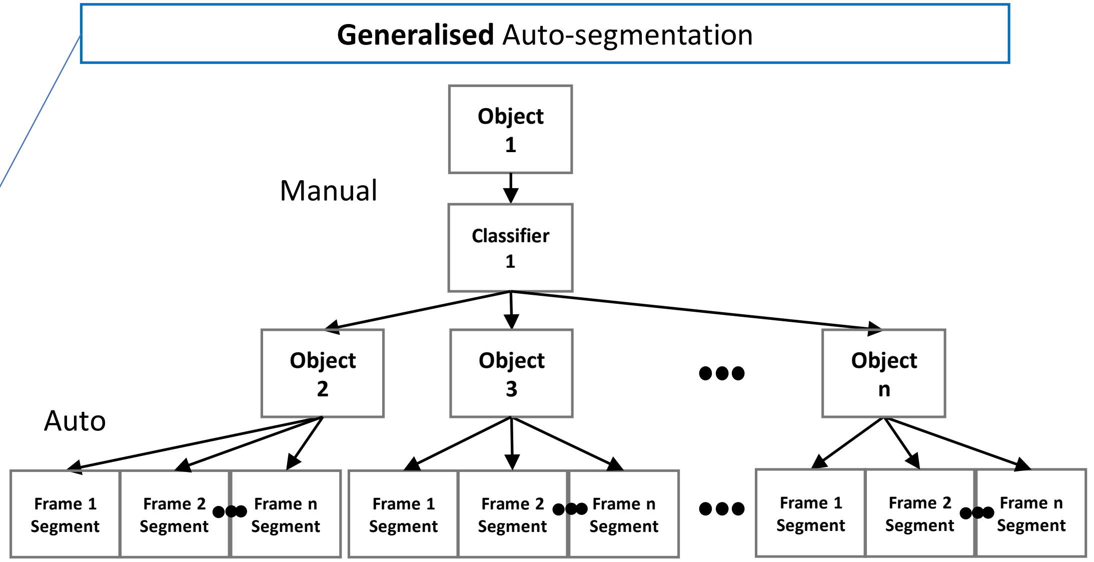


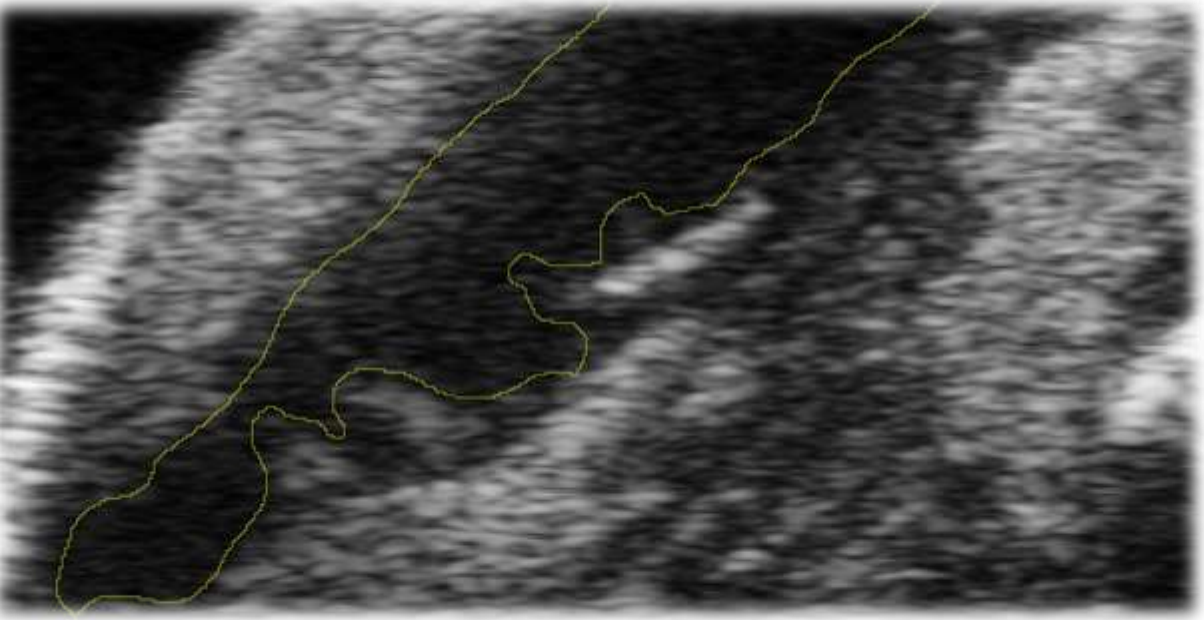


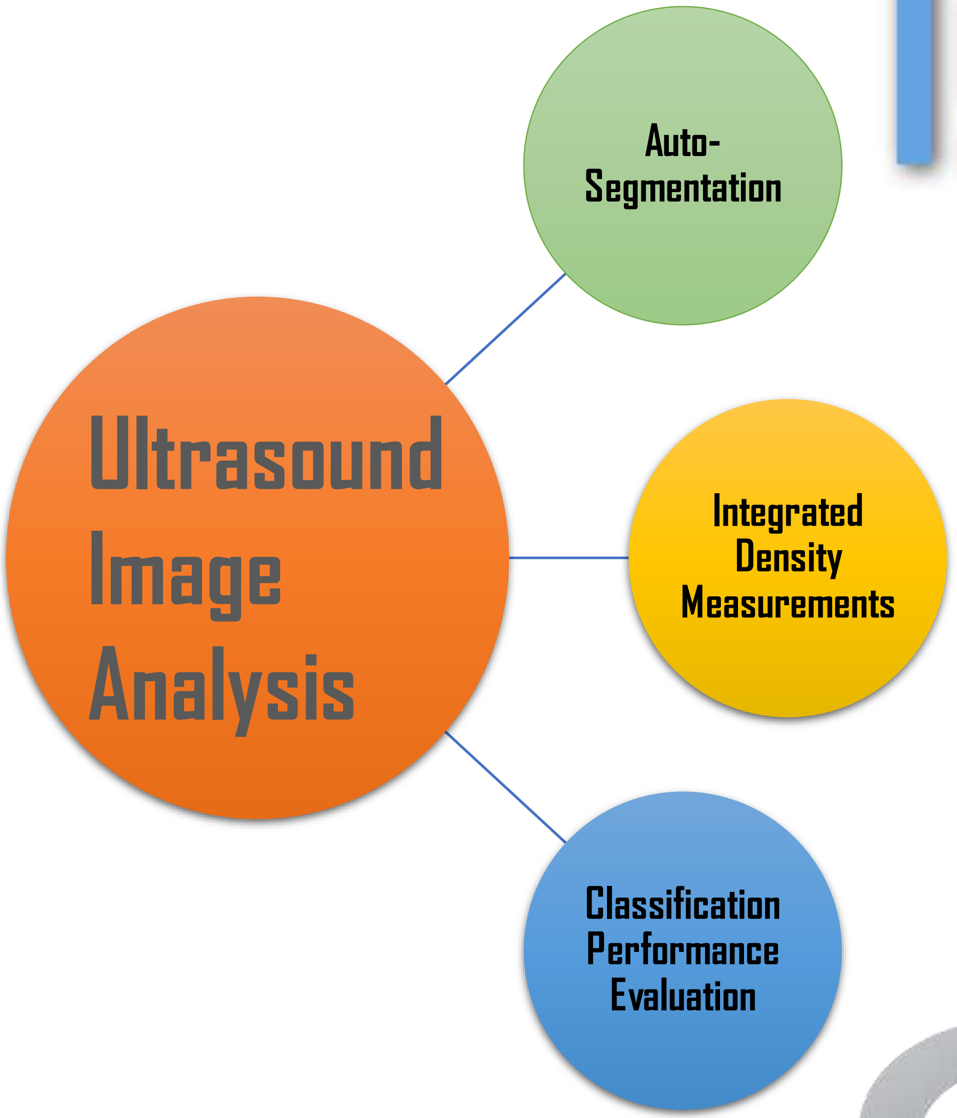
RESEARCH SCOPE

Raw Ultrasound Image Datasets: **Walker et.al. (2020)**

- Nanosensor Engineering Lab (NEL)
- Department of Chem.Eng., Monash Uni

- pH-responsive nanoparticle-injected lab mouse
- 4 image stacks taken at 0, 5, 10 and 15 mins
- 100 frames per image stack





METHODLOGY: Experimental Design

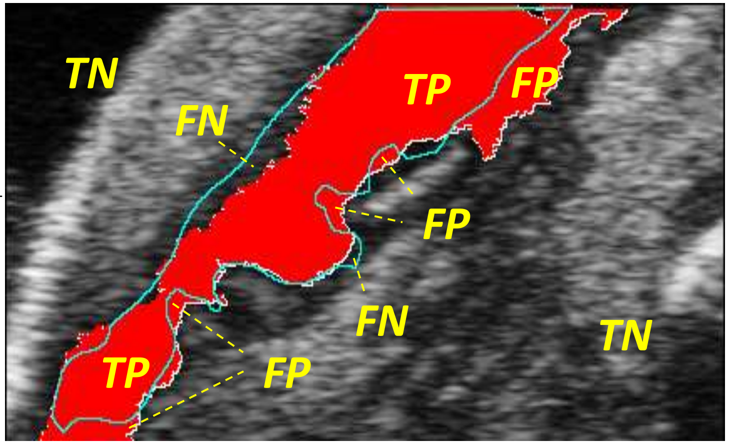
***Control Set**: Manual Segmentation Results*

Experimental Design

Objectives	Methodology
Manual *vs* **Auto-segmentation**	Comparison of Integrated Density (APE)
Random Forest *vs* **Naïve Bayesian**	➢ Binary Classification Features ➢ Receiver Operating Characteristics (ROC) Analysis
Generalised *vs* **Ordinary Approach**	

Absolute Percentage Error (APE%)

$$= \left| \frac{AI\ IntDen\ -\ Manual\ IntDen}{Manual\ IntDen} \right| \times 100\%$$



Binary Features:
- *True Positive (TP)*
- *True Negative (TN)*
- *False Positive (FP)*
- *False Negative (FN)*

TWS Segmentation

Manual Segmentation

METHODLOGY: Statistical Analysis

Receiver Operating Characteristic (ROC) Analysis

Binary Performance Metrics

Sensitivity $\frac{TP}{TP+FN}$

level of under-prediction of desired pixels

Specificity $\frac{TN}{TN+FP}$

Level of under-prediction of undesired pixels

Precision $\frac{TP}{TP+FP}$

level of over-prediction of desired pixels

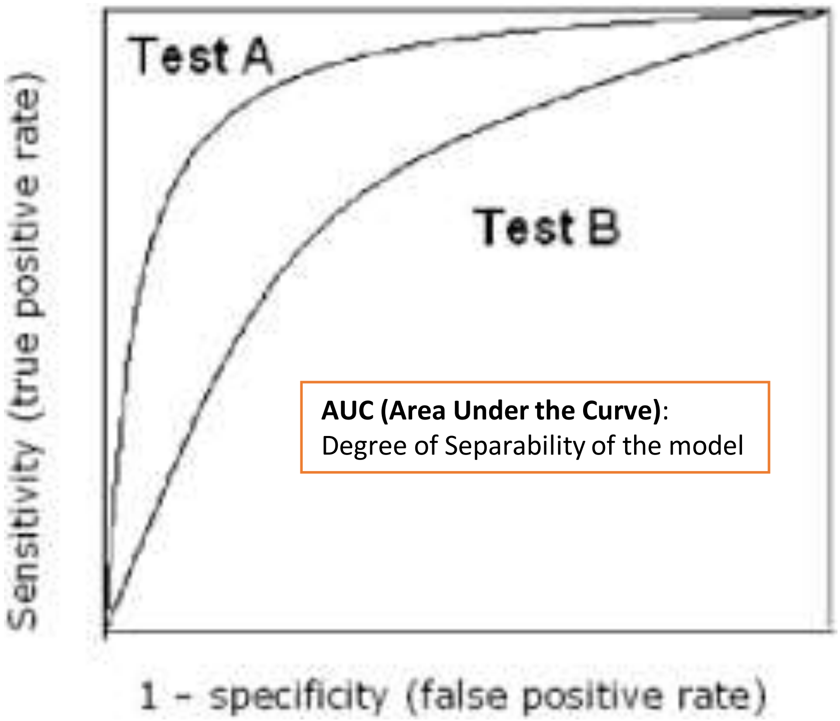
F-score $\frac{1}{\frac{0.5}{Prec}+\frac{0.5}{Sens}}$

Harmonic mean of sens. and prec.
Overall Performance

$'ROCR'$ *Package in R* (Sing, 2005)

ROCR v1.0-7

ROC Curve



AUC (Area Under the Curve):
Degree of Separability of the model

$'ggplot2'$ *Package in R* (Wickham, 2016)

ggplot2

Note: The R script code can be found at https://github.com/georgewang229/CHE4180-Project/blob/master/CHE4180_Project_DataAnalysis.R

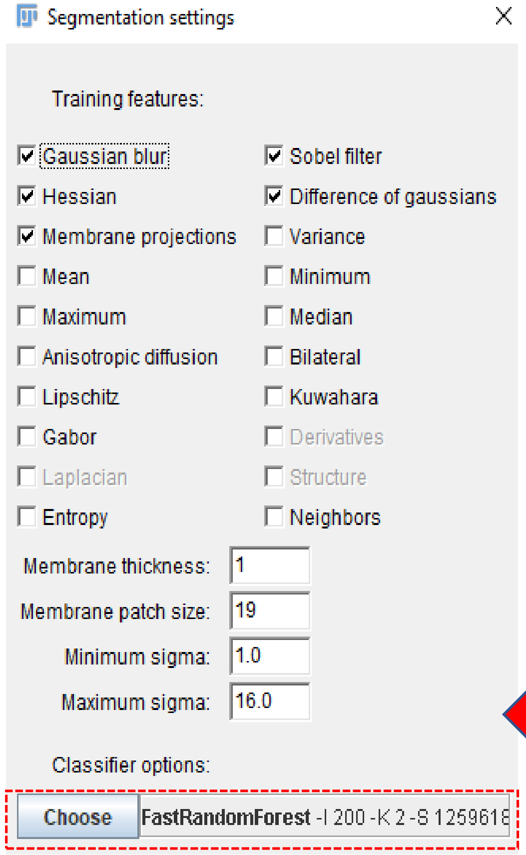
METHODLOGY: Image Segmentation

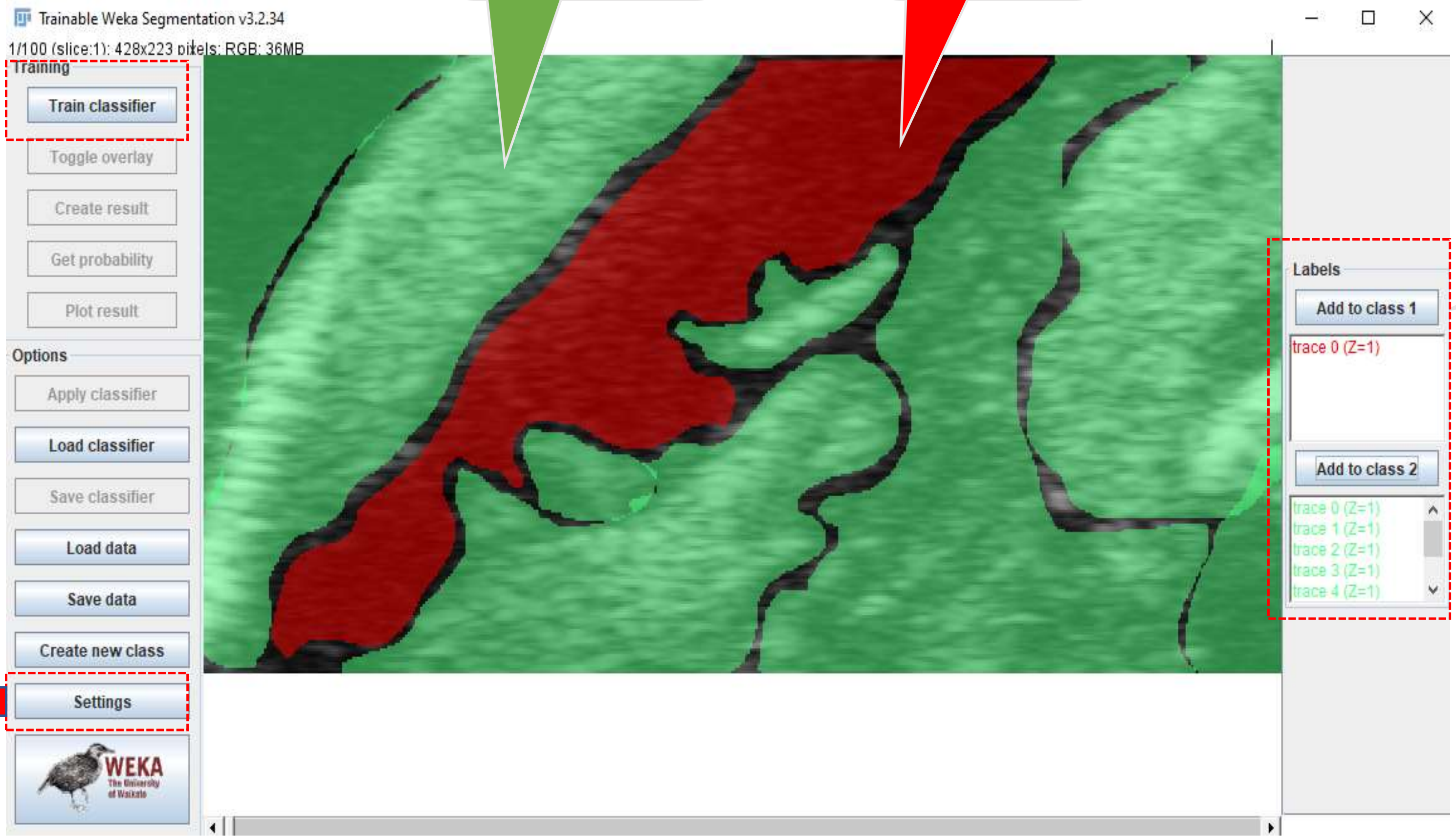
Auto-Segmentation

Undesired Region

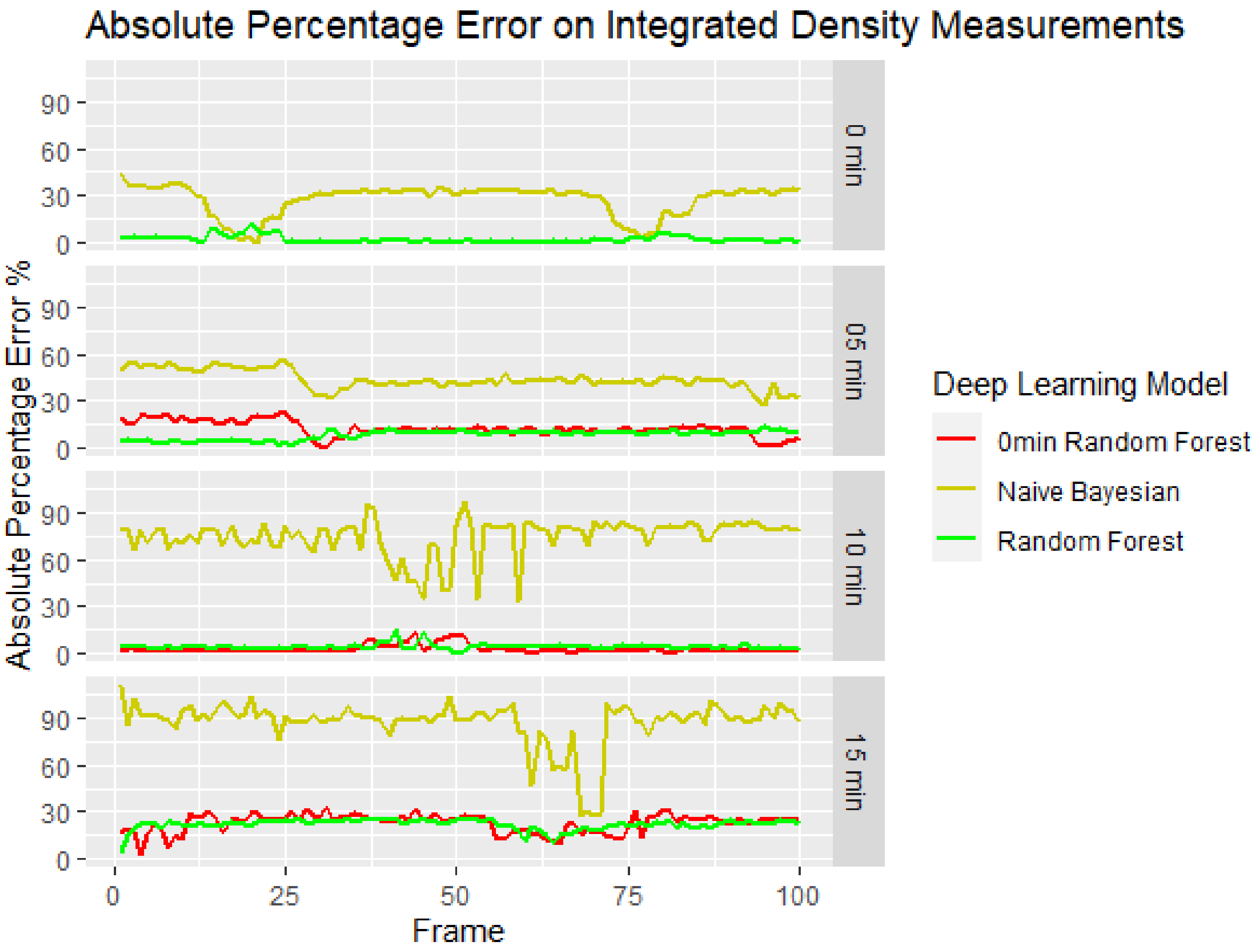
Desired Region

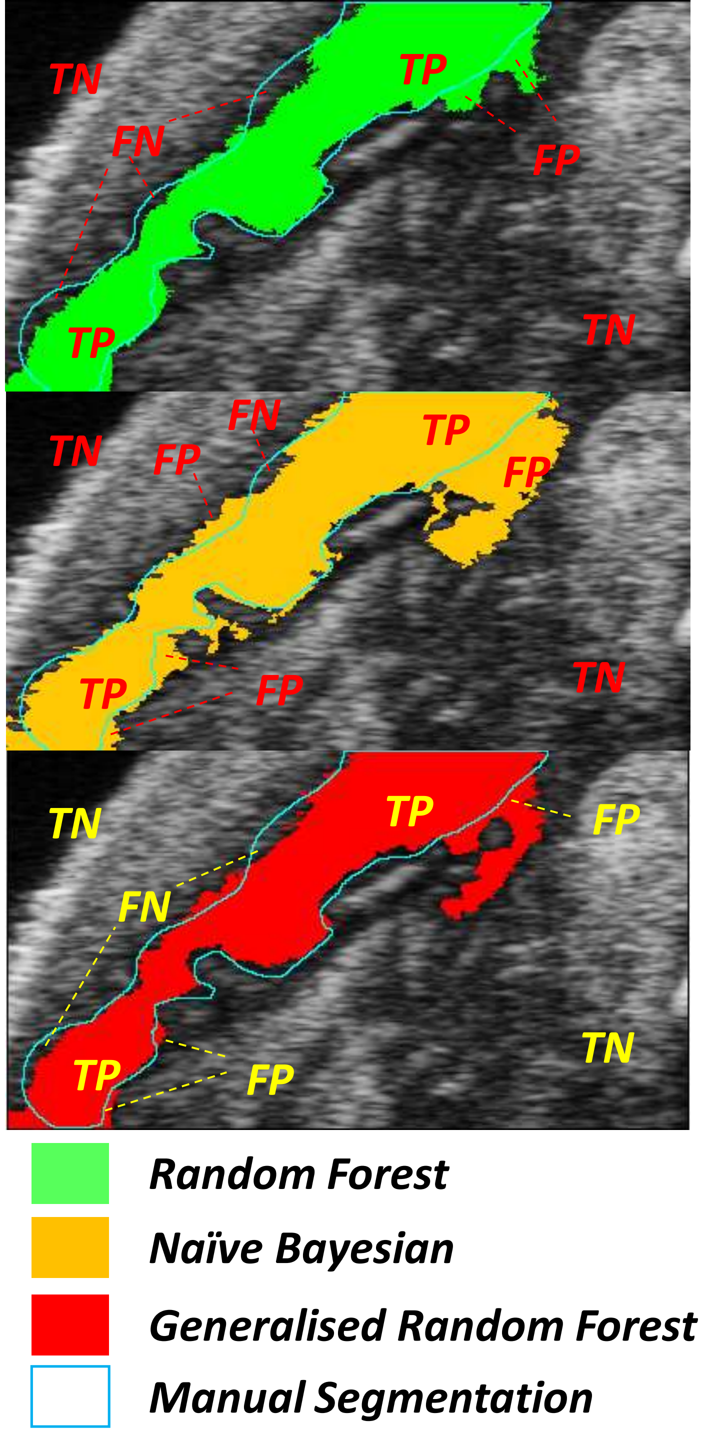
Binary Classification





Results & Discussion: Integrated Density





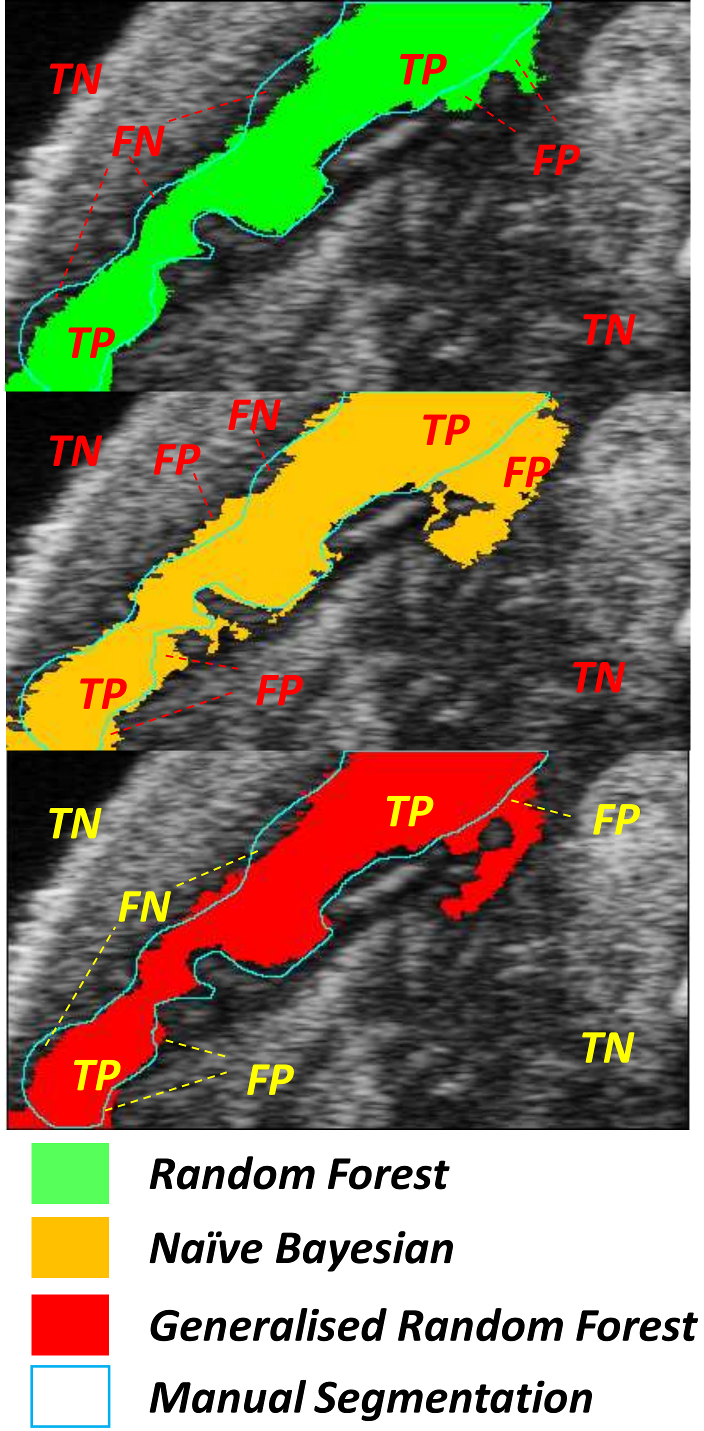
- Random Forest: Better flexibility and Good generalisation ability

Results & Discussion: Performance Metrics

Model	Average Sensitivity*	Average Specificity*	Average Precision*	Average F-score*
Random Forest	0.854 ± 0.045	0.972 ± 0.010	0.878 ± 0.036	0.865 ± 0.022
Naïve Bayesian	0.948 ± 0.016	0.988 ± 0.042	0.661 ± 0.079	0.776 ± 0.052
Generalised RF	0.886 ± 0.011	0.944 ± 0.016	0.791 ± 0.054	0.834 ± 0.031

Sensitivity: Level of under-prediction of desired region
Specificity: Level of under-prediction of un-desired region
Precision: Level of over-prediction of desired region
F-score: Overall Performance

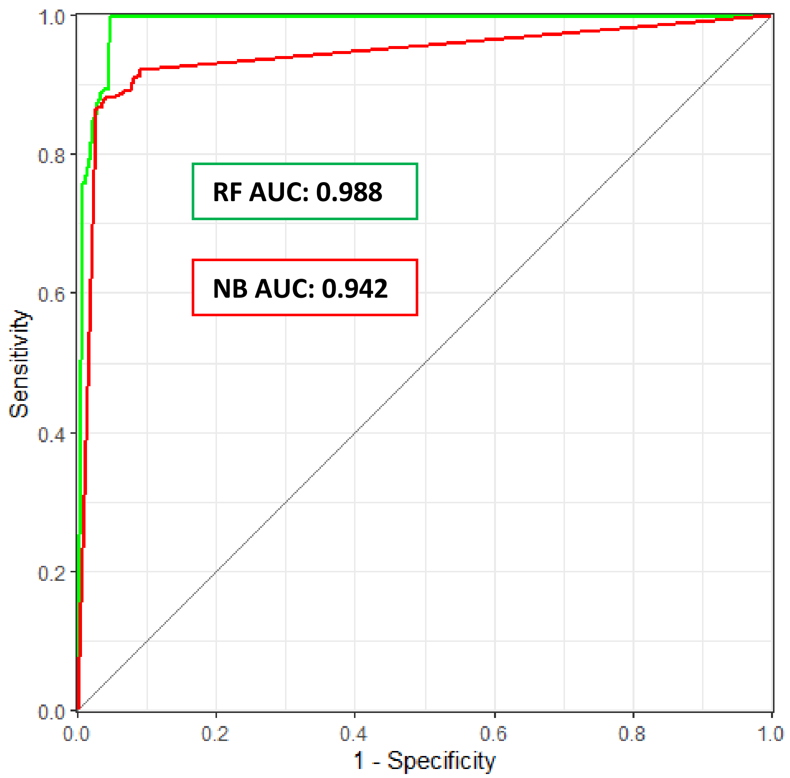
Random Forest: In general, Best **F-score**: 0.865 (Overall Performance)
→ Best Model in terms of Performance Metrics
Generalised RF: Good **F-score**: 0.834 (Overall Performance)
→ Satisfactory Performance

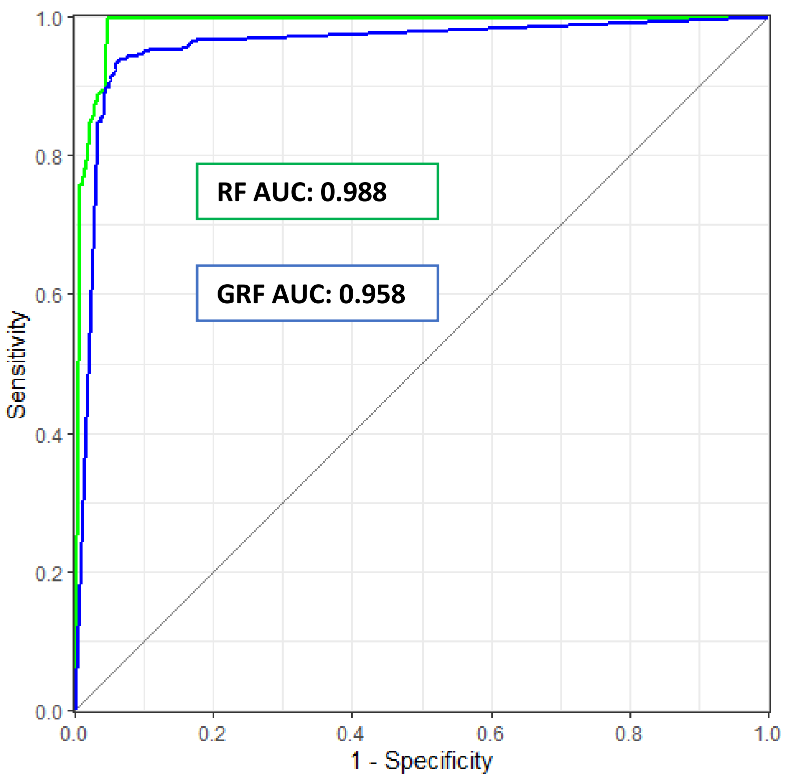


Results & Discussion: ROC curves & AUC

Model / Time	Random Forest	Naïve Bayesian	Generalised RF
AUC*	0.988	0.942	0.958

AUC (Area Under the Curve): Degree of Separability of the model





Random Forest
Naïve Bayesian
Generalised RF

- Random Forest: higher **Area Under Curve** (0.988) than NB (0.942) → Better Model in terms of AUC
- Generalised RF: Slightly lower **Area Under Curve** (0.958) than RF (0.988) → Satisfactory Performance

LIMITATION & FUTURE PRESPECTIVE

Technological Limitation

Reproducibility

Poor Interpretability

3D Ultrasound Image

Limited Sample Images

Better algorithms to be developed

CONCLUSION

- TWS gives satisfactory auto-segmentation results
- Random Forest >>> Naïve Bayesian
- Generalised Model is viable, but less reliable

ACKOWNLEDGEMENT

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THANK YOU!

George and Mark

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