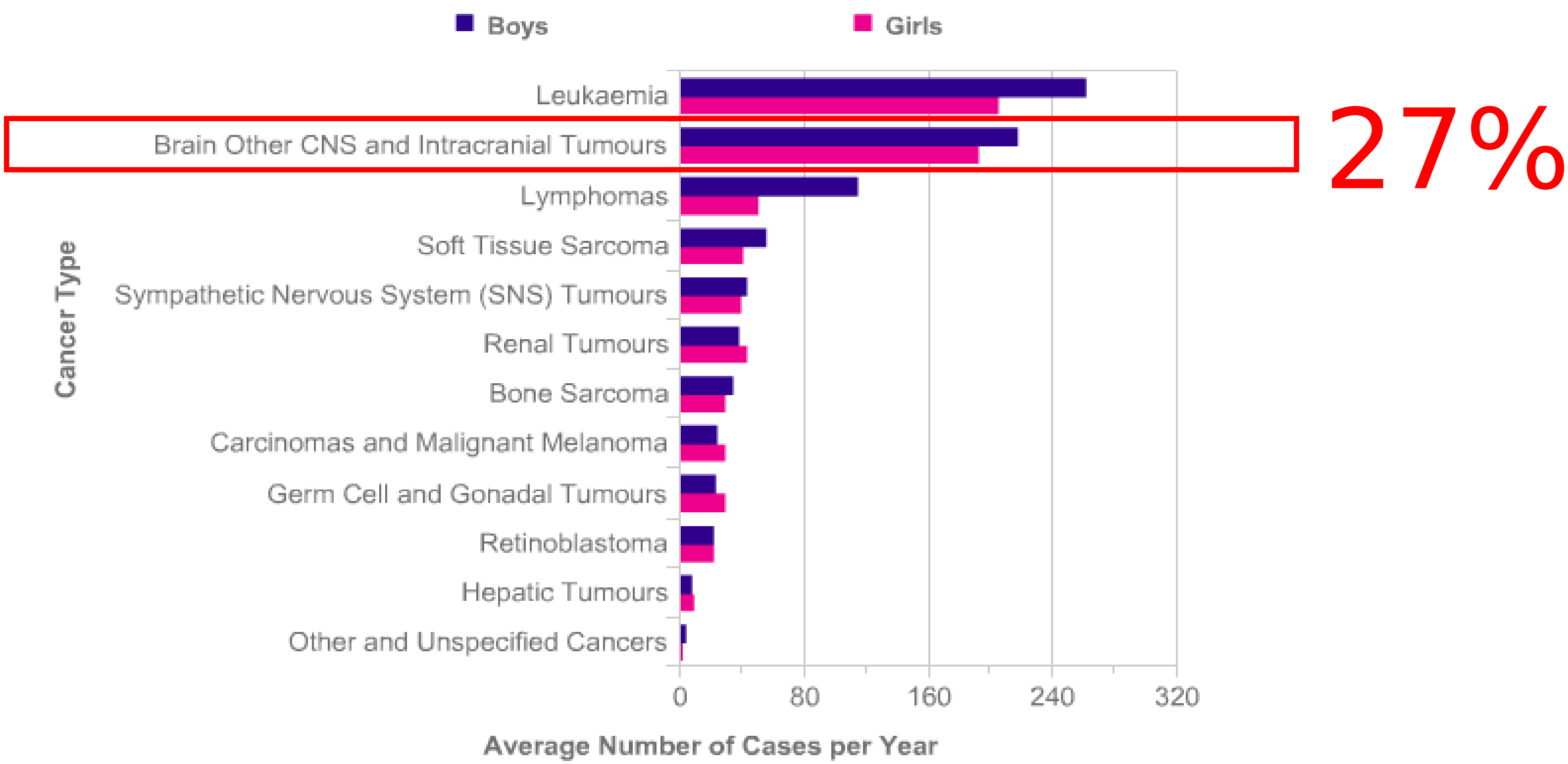
MRI Texture Analysis for the Characterisation of Childhood Brain Tumours

Ahmed E. Fetit
Supervisors: Prof Theo Arvanitis, Prof Andrew Peet and Dr Jan Novak

Problem

Problem

UK Childhood Cancer Statistics:



Obtained from: Cancerresearchuk.org

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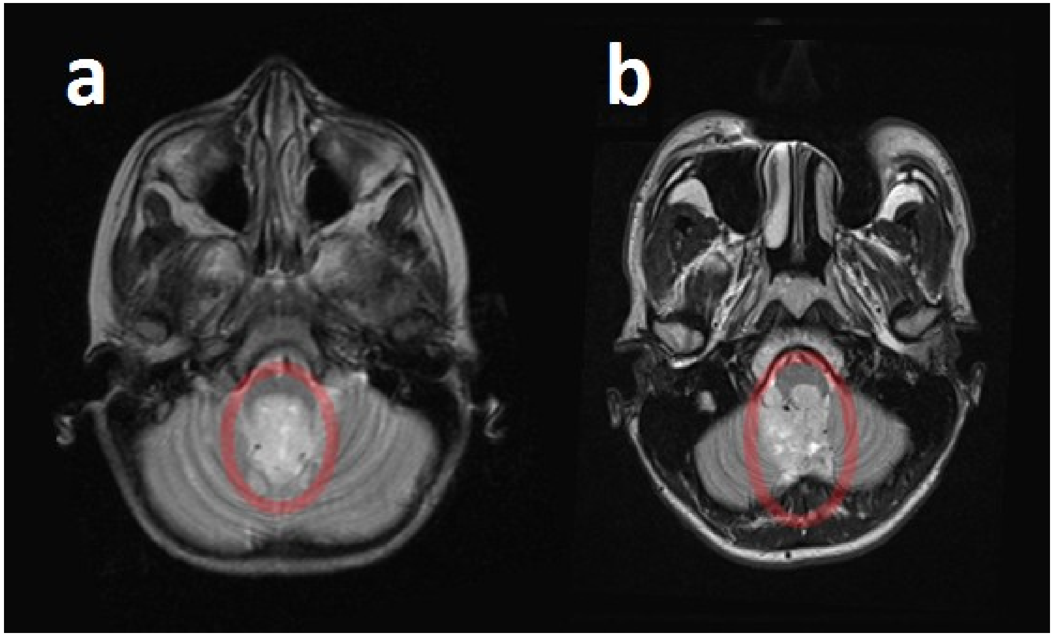
Problem

T2-Weighted MRI scans of two cases of paediatric brain tumours:



Medulloblastoma Ependymoma

Obtained from: CCLG e-Repository

Problem

Initial characterisation of tumours from MRI scans is usually performed via radiologists' visual assessment.

Different brain tumour types do not always demonstrate clear differences in physical appearance. Using conventional MRI to provide a definite diagnosis would lead to inaccurate results.

Current diagnosis gold standard: invasive histopathological examination.

Need for quantitative, accurate and non-invasive diagnostic aid → *Texture ?*

Texture

What is Texture?

What is 'Texture'?

https://www.flickr.com/photos/sergiotumm/15725948227/in/explore-2014-11-30/lightbox/

No universal definition.

In medical image processing: *The spatial variation of pixel intensities*

Based on pixel intensities -> Quantitative -> Captures patterns beyond human vision

Texture Analysis Methods

Textural Feature Extraction:

Statistical:
•First Order (Histogram) Features
•Second Order (Grey-Level Co-Occurence Matrix) Features
•Higher Order (Grey-Level Run-Length Matrix) Features

Transformation:
•Wavelet

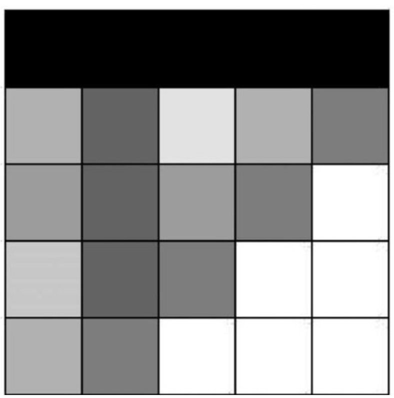
Model-based:
•Autoregressive Model

Texture Analysis Methods

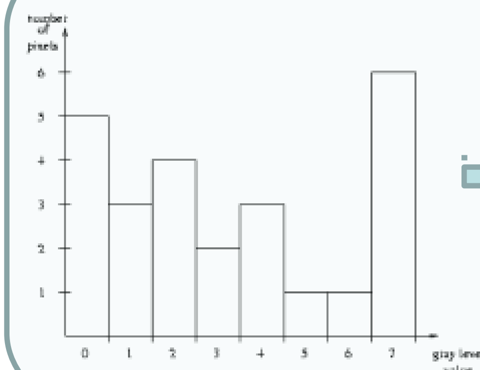
First Order (Histogram):

The lower the pixel intensity value, the darker the value

The histogram represents a count of the number of pixels in the image that have a certain grey value



0	0	0	0	0
4	1	6	4	2
3	1	3	2	7
5	1	2	7	7
4	2	7	7	7



- Mean
- Variance
- Percentiles
- Skewness
- Kurtosis

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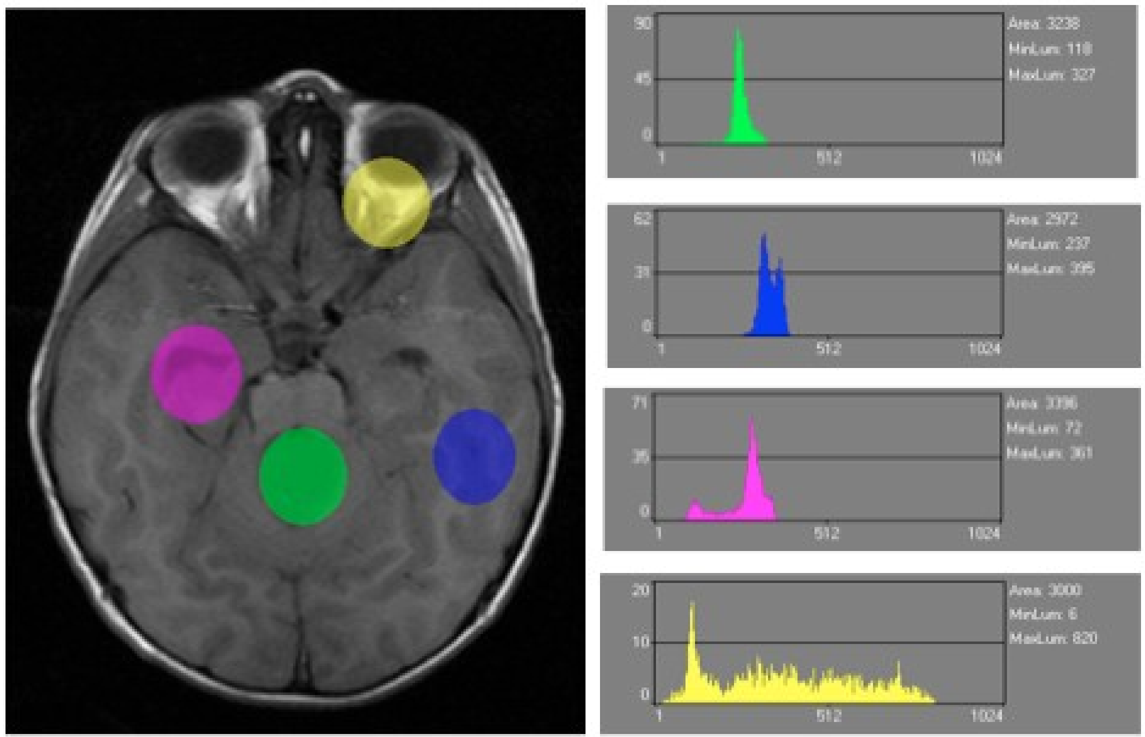
Texture Analysis Methods



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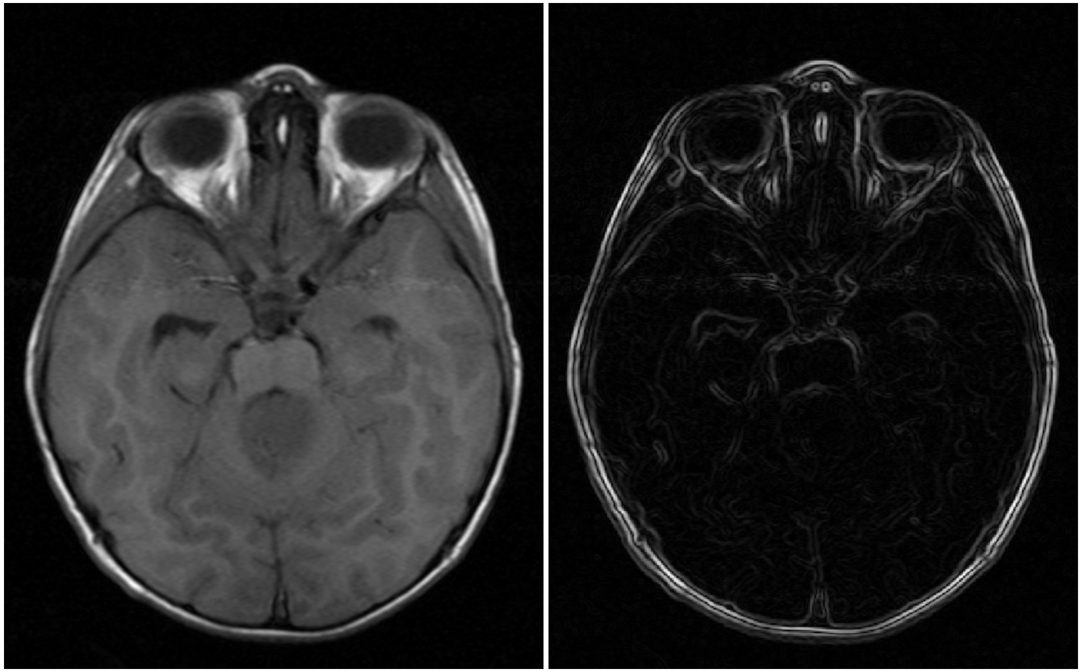
Texture Analysis Methods

Absolute Gradient:

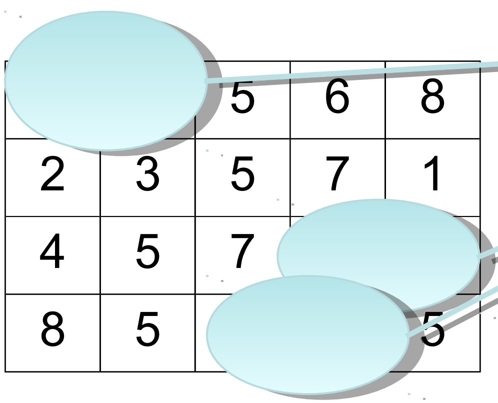


Extract mean, variance, skewness, kurtosis

Texture Analysis Methods

Second Order (Grey-Level Co-Occurence Matrix):

- Define a **direction** and a **distance**
- Count number of pixel pairs that have a certain sequence



Example image

	1	2	3	4	5	6	7	8
1	1	2	0	0	1	0	0	0
2	0	0	1	0	1	0	0	0
3	0	0	0	0	1	0	0	0
4	0	0	0	0	1	0	0	0
5	1	0	0	0	0	1	2	0
6	0	0	0	0	0	0	0	1
7	2	0	0	0	0	0	0	0
8	0	0	0	0	1	0	0	0

GLCM for P0

Texture Analysis Methods

Some GLCM features include:

Angular Second Moment (ASM): Measure of local homogeneity; high ASM values indicate good homogeneity.

Contrast (CON): Estimates local variation; high CON values indicate low homogeneity.

Entropy (ENT): Measure of randomness within the image; high ENT indicates low homogeneity.

14 features. Formulae and explanation available at paper by Haralick et al 1973

Textural Features for Image Classification

ROBERT M. HARALICK, K. SHANMUGAM, AND ITS'HAK DINSTEIN

Texture Analysis Methods

Higher order (Grey-Level Run-Length Matrix):

Example image

0	0	2	2
1	1	0	0
3	2	3	3
3	2	2	2

Grey-level 0 never appears alone

0^0		Run Length			
		1	2	3	4
Grey Level	0	0	2	0	0
	1	0	1	0	0
	2	1	1	1	0
	3	2	1	0	0

Grey-level 0 appears in a pair twice

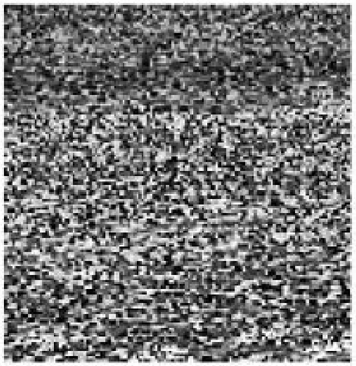
*Run length matrices are computed for 0, 45, 90 and 135 degree directions

Texture Analysis Methods

Some GLRLM features include:

Short Run Emphasis: *Measure of the proportion of runs in the image that have short lengths. Coarse textures tend to assume a high value.*

Long Run Emphasis: *Measure of the proportion of runs in the image that have long lengths. Smooth textures tend to assume a high value.*



SRE	0.932	0.563
LRE	1.349	16.929

11 features; formulae and explanation available at

RUN-LENGTH ENCODING FOR VOLUMETRIC TEXTURE

Dong-Hui Xu, Arati S. Kurani, Jacob D. Furst, Daniela S. Raicu
Intelligent Multimedia Processing Laboratory,
School of Computer Science, Telecommunications, and Information Systems, DePaul University,
Chicago, Illinois, 60604
USA
{dxu, akurani}@students.depaul.edu, {jfurst, draicu}@cs.depaul.edu

Texture Analysis Methods

Detailed Explanation of Techniques:

Clinical Radiology (2004) 59, 1061-1069

REVIEW

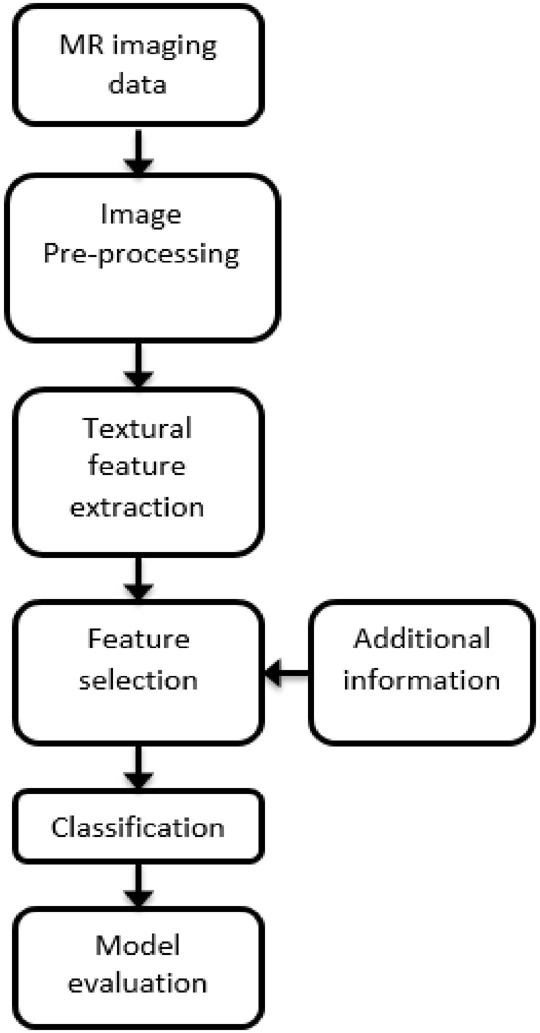
Texture analysis of medical images

G. Castellano*, L. Bonilha, L.M. Li, F. Cendes

Neuroimage Laboratory, Faculty of Medical Sciences, State University of Campinas, Brazil

Some Work in the Literature

Analysis Pipeline



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THE UNIVERSITY OF WARWICK
Institute of Digital Healthcare
design : develop : deploy : evaluate
Birmingham Children's Hospital

Data 1

-40 children with brain tumours
-Medulloblastoma, pilocytic astrocytoma and ependymoma
- T1, T2 and diffusion-weighted MRI

Preprocessing 2

-Normalisation to the mean value of white-matter
-Manual ROI segmentation

TA 3

-Histogram statistics
-GLCM
- In-house MATLAB software was used

Supervised learning 4

- SVM classifier
- Classify tumour types
- Classify MB subtypes
- Randomly split data to training and testing sets
- Repeated 500 times

Results 5

- Up to 79% classification accuracy for tumour type classification, using T1 and T2-weighted images

- Up to 91% using diffusion weighted images

Data 1
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Preprocessing 2
-Manual ROI segmentation
-ImageJ software

TA 3
-Histogram statistics - Autoregressive model
-GLCM -Wavelets
-GLRLM

Supervised learning 4
-PCA for dimensionality reduction
-Neural Network and LDA classifiers
-Leave-One-Out and 10-fold cross validation

5
Results
-PNN yielded 90% accuracy on T1 and 93% accuracy on T2 (Leave-One-Out)
- LDA's results were noticeably poorer (around 57%).

Fetit et al 2014, ICIMTH

Anonymised T1 and T2-weighted MR Images (Secure database)

21 Children diagnosed with brain tumours

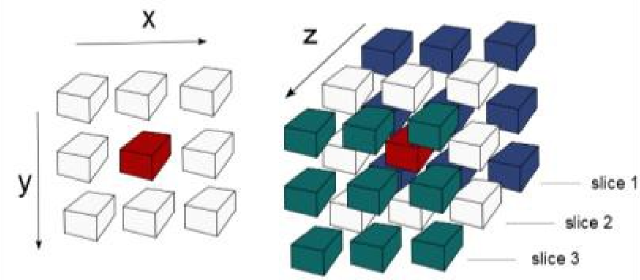
Tumours fall into:
•medulloblastoma (7),
•pilocytic astrocytoma(7)
•ependymoma(7)

(1) Want to see if we could used classifiers trained with textural features to discriminate between the tumour types
(2) Want to see if 3D TA leads to better classification performance

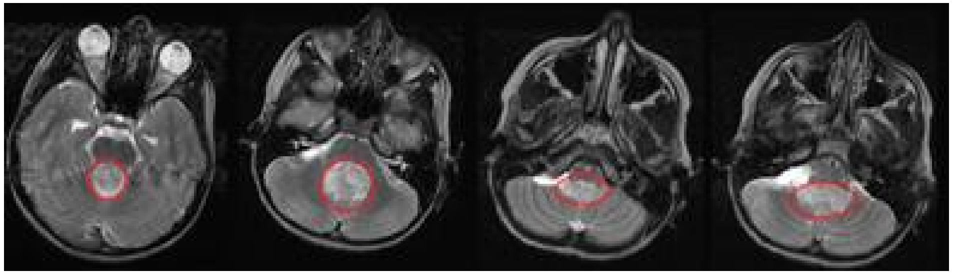
2D vs. 3D

2D: Each voxel has 8 immediate neighbours in 4 directions

3D: Each voxel has 26 immediate neighbours in 13 directions



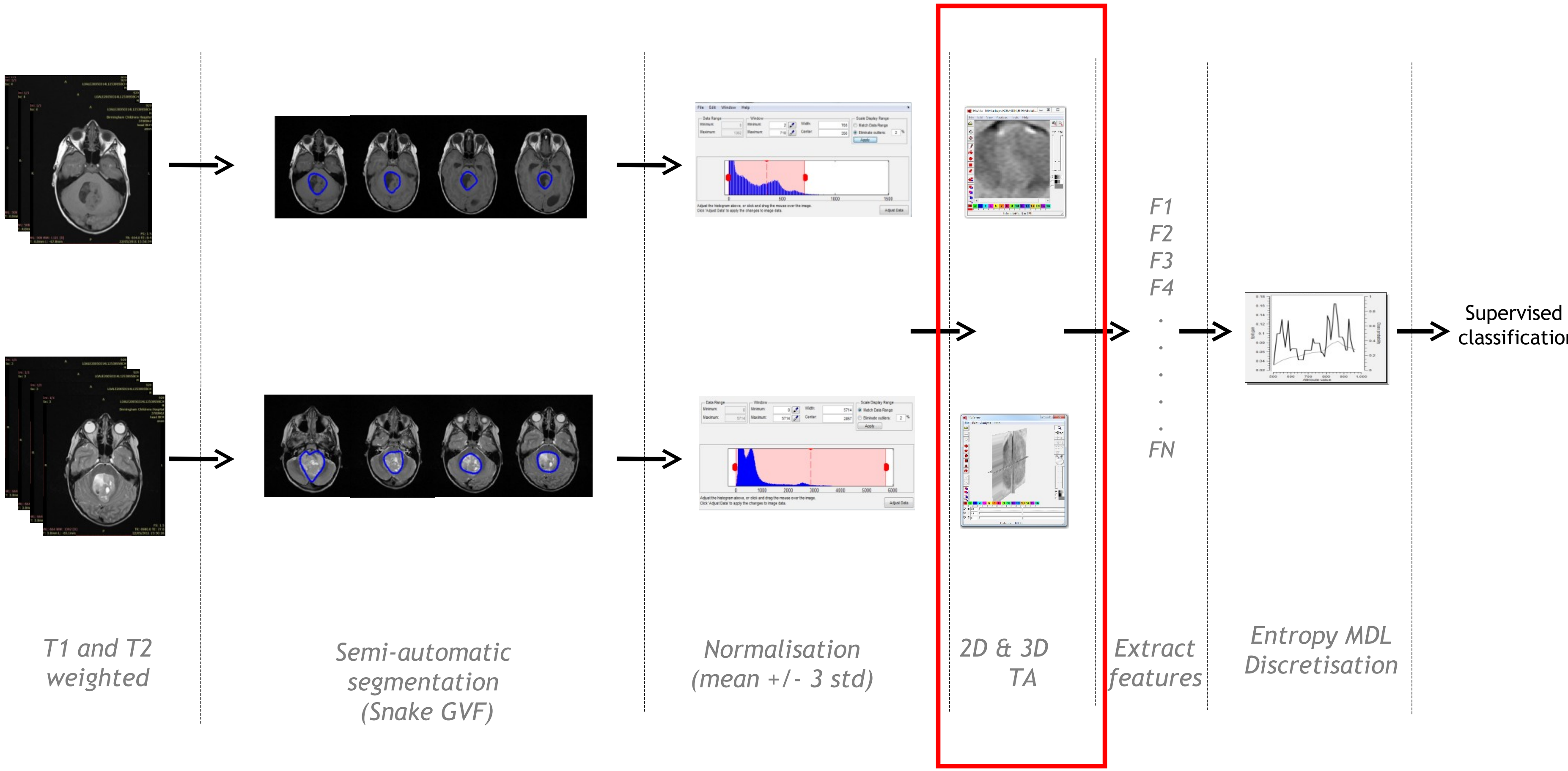
Voxel spatial separation



T2-Weighted slice for one medulloblastoma case.
Obtained from: CCLG e-Repository

Can 3D capture more information?

Analysis Pipeline



Does 3D TA improve classification?

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Results

Model validation used: Leave-One-Out

Feature Set	Classifier	Accuracy %	Medulloblastoma (MB)		Pilocytic Astrocytoma (PA)		Ependymoma (EP)	
			Sens %	Spec %	Sens %	Spec %	Sens %	Spec %
2D	Bayes	62	43	93	71	71	71	79
	kNN	86	86	93	86	100	86	86
	C. Tree	48	43	71	43	64	57	86
	SVM	86	86	93	86	100	86	86
3D	Bayes	71	71	86	71	93	71	79
	kNN	100	100	100	100	100	100	100
	C. Tree	86	86	93	71	93	100	93
	SVM	96	86	100	100	93	100	100

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	SVM	96	86	100	100	93	100	100

(Preliminary) Conclusions

The use of 3D textural information extracted from MR images, instead of 2D features, has the potential to increase computerised classification of childhood brain tumours.

Future Work

Expand the study to include larger datasets in order to confirm the robustness of 3D TA under different protocols.

Investigate possible over-optimistic bias in the results:

3D-trained kNN yielded 100% with all metrics. (Might be because feature selection was carried out outside the leave-one-out loop)

Thank you!

Questions?