healthitnews

Session:
Imaging for Clinical Decision Support

Chair: Ian Poole, PhD
Scientific Fellow

Toshiba Medical Visualisation Systems, Edinburgh
A Canon Group Company

What is Clinical Decision Support?

.... its not a rhetorical question!

What is Clinical Decision Support?

Clinical decision support (CDS) provides clinicians, staff, patients or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health care. CDS encompasses a variety of tools to enhance decision-making in the clinical workflow, addressing information overload.

HealthIT.gov, abbreviated

Session Agenda

1. Session Introduction
2. *Statistical framework for modelling inter-object relationship in multi object image analysis.* Surajit Ray, University of Glasgow
3. *Challenges for Machine Learning in Clinical Decision Support: Focus on Stroke.* Ian Poole, TMVS
4. Discussion

Challenges for Machine Learning in Clinical Decision Support: Focus on Stroke

Ian Poole, PhD., Scientific Fellow

Toshiba Medical Visualisation Systems, Edinburgh
A Canon Group Company

Talk Outline

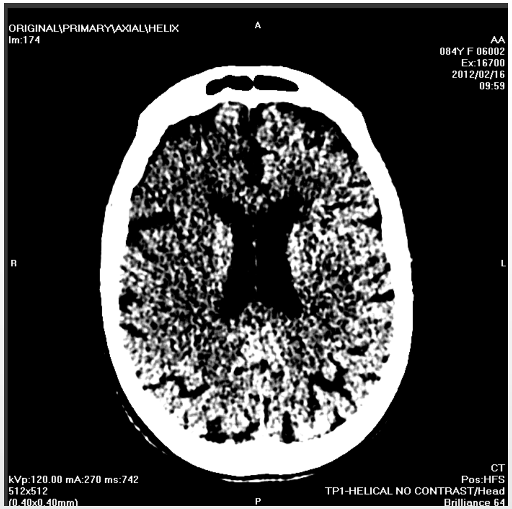
1. Stroke pathology
2. Features of a CDSS for Stroke
3. Stroke Signs Detection Method
4. Results
5. Challenges for Machine Learning in imaging for CDS
6. Conclusions

Overview: Detect Signs of Early Ischemic change in NCCT & calculate ASPECTS score

Hypodensity

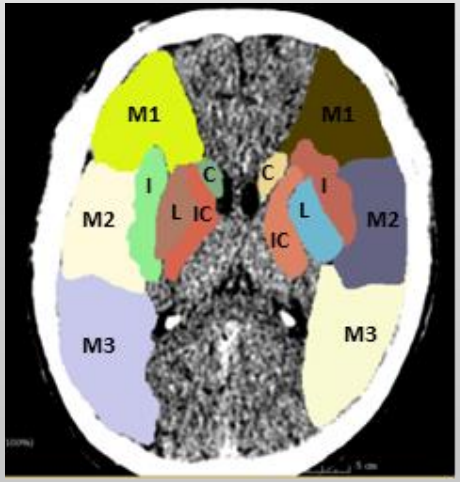
Obscuration of Lentiform Nucleus

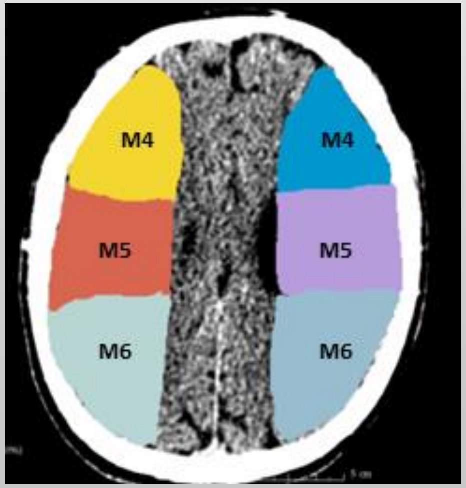
Loss of Insular Ribbon



Loss of Grey matter/white matter differentiation

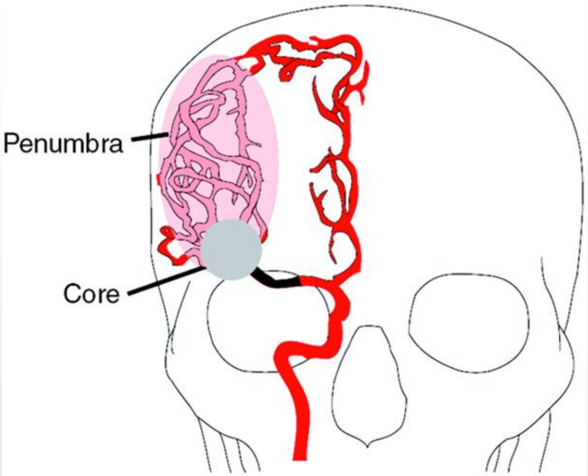
Compute ASPECTS score





Dense Vessels

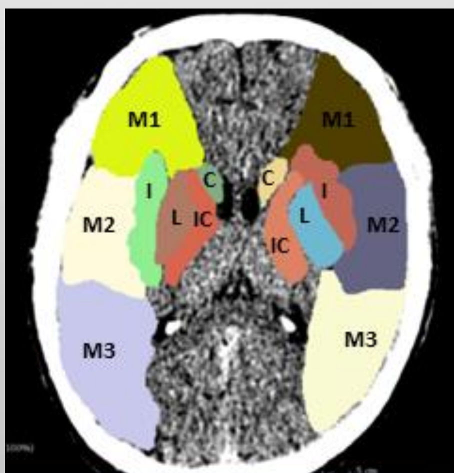
Clinical Context : Acute Ischemic Stroke

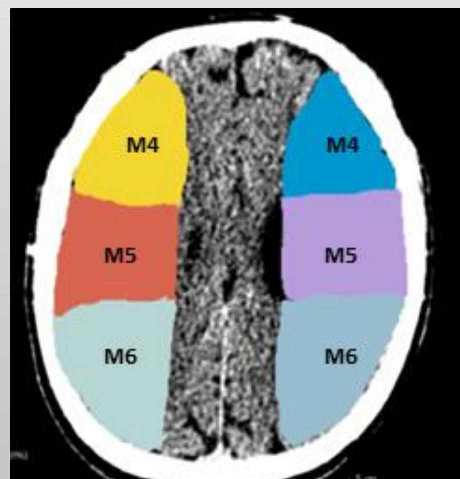


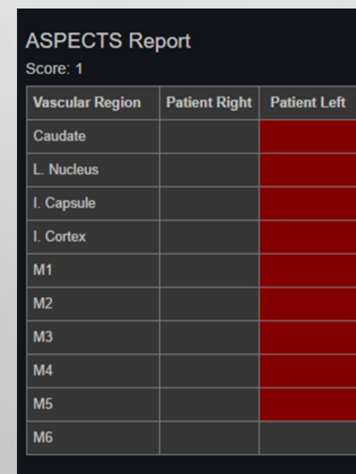
Clinical goal in Acute Ischemic stroke patients:

Re-perfuse any salvageable brain tissue in **all eligible patients**:

Determining eligible patients – Treatment decision: ASPECTS score







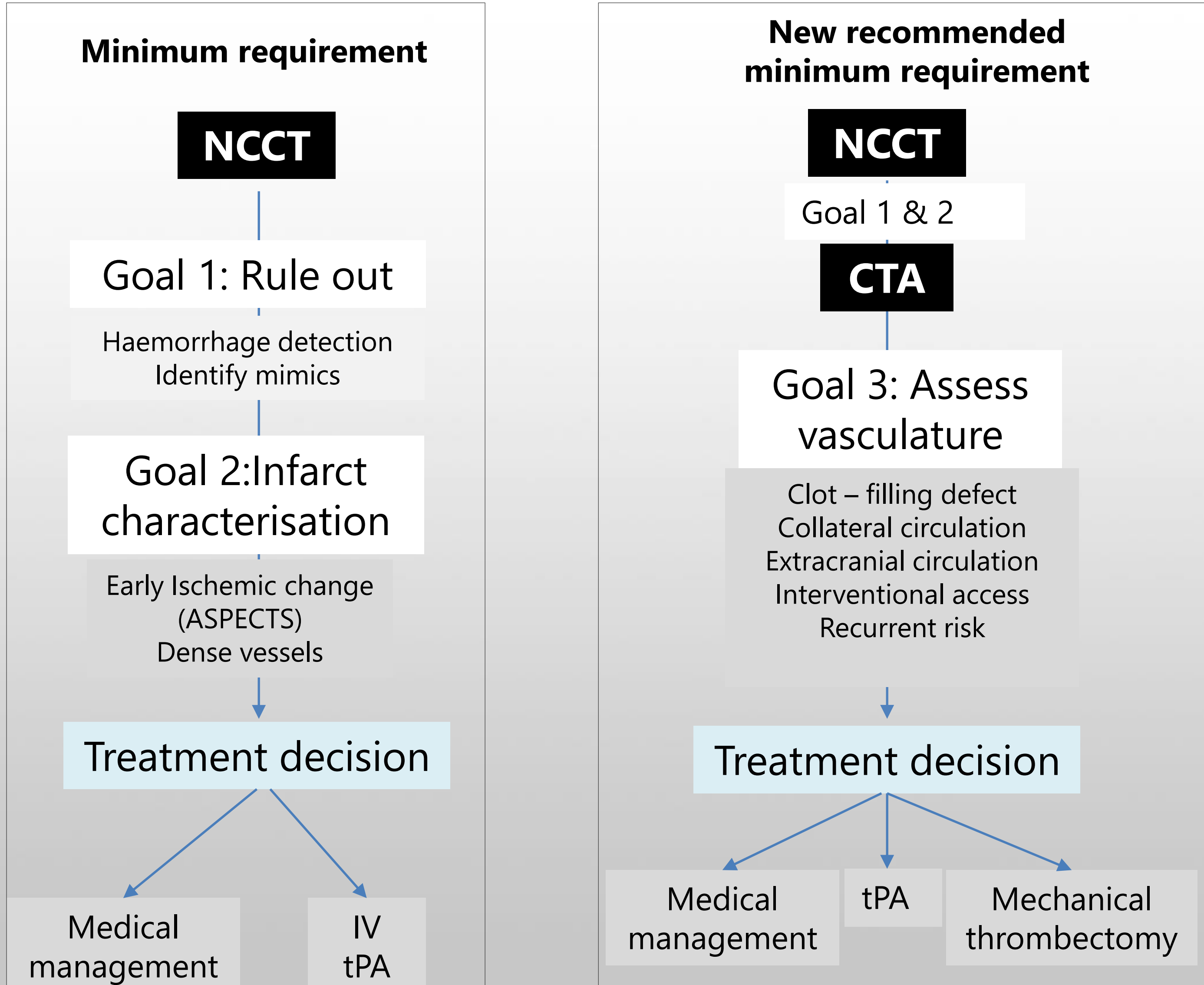
ASPECTS Report

Score: 1

Vascular Region	Patient Right	Patient Left
Caudate		
L. Nucleus		
I. Capsule		
I. Cortex		
M1		
M2		
M3		
M4		
M5		
M6		

Need for and features of a CDSS in Stroke

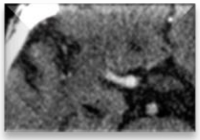
Workflows (CT only)

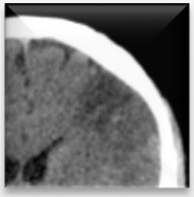


Features of a CDSS for Stroke

IV Thrombolisis – treat or not treat?

- Rule out haemorrhage
- Detection of early ischemic changes in NCCT
  - Presence / absence of dense vessels
  - Presence / absence of core infarct – ischemia





Mechanical Thrombectomy – treat or not treat?

- Accurate characterisation of ischemic change in NCCT
  - Dense vessel segmentation and measurement
  - Core infarct segmentation
  - ASPECTS score global and regional

Decisions may be down to inexperienced clinicians, out of hours under stressful conditions.

Materials and Methods

Stroke Signs Detection by a Symmetry Exploiting CNN

- Dense vessels
- Ischemia
- ASPECTS

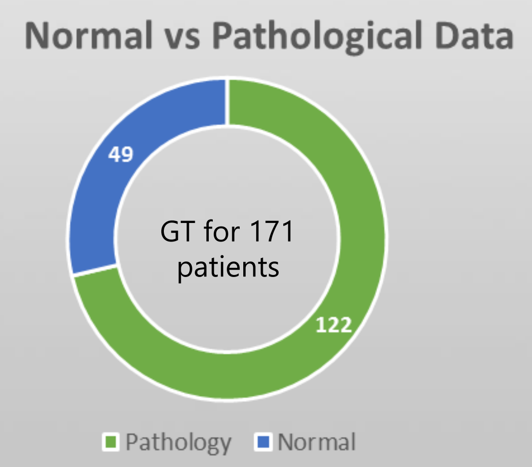
Development Datasets

- Supplied by Dept. Neuroscience and Psychology, QEUH, Glasgow.
- Data from 3 clinical trials, all suspected stroke within 4.5hours of onset.
- Haemorrhagic patients excluded

Imaging:
- Acute NCCT, CTA, CTP
- Follow-up NCCT, CTA
- (some MR)

Other clinical (non-imaging) data including:
- Radiology reports
- Blood test results
- Vital signs
- ASPECTS scores
- Outcome measures.

Ground Truth:
- Segmentations (guided by neuroradiologist & radiology reports)
    - Dense vessels
    - Acute Ischemia
    - Old Ischemic change
    - Incidental findings

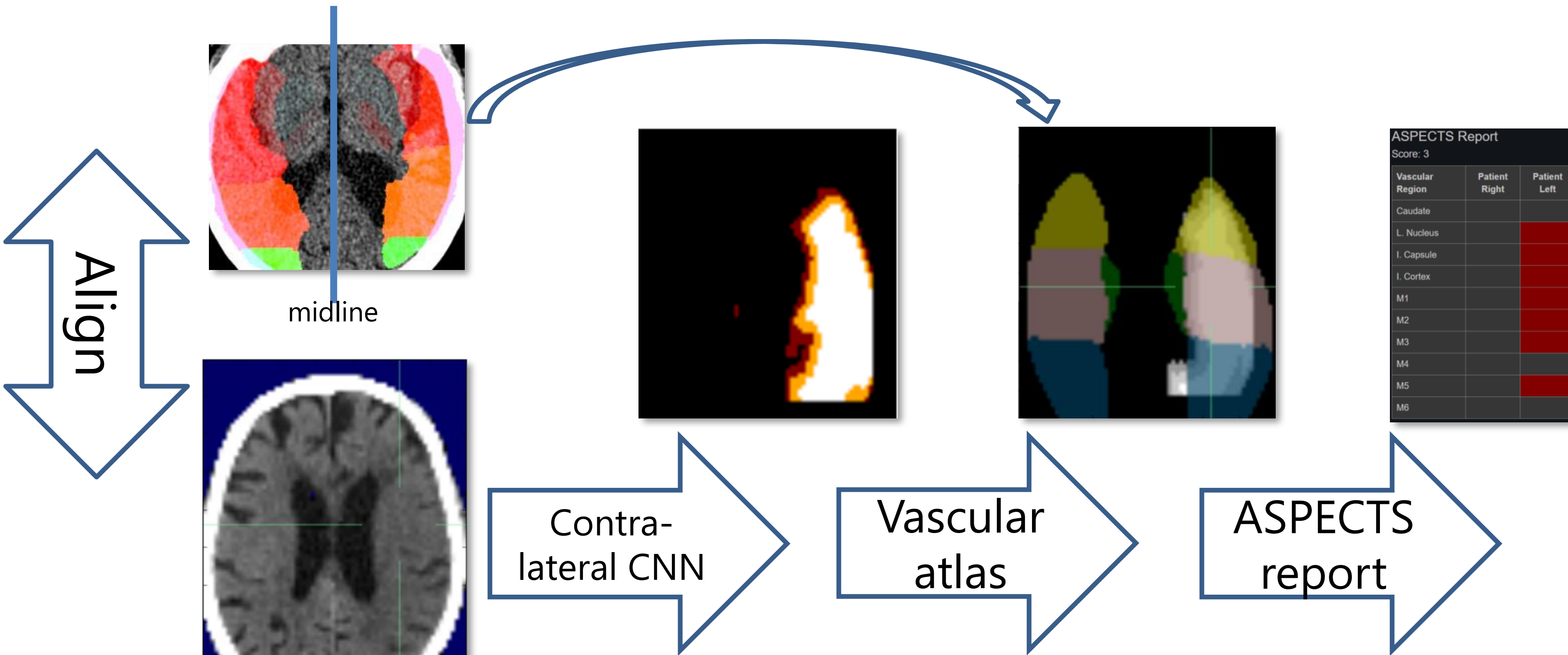


SS&A Algorithms Overview

TMVS have developed algorithms for detection of dense-vessel signs and ischemia from acute stroke NCCT.

A deep learning CNN approach, exploiting contra-lateral comparison is used.

Detection of ischemia in conjunction with alignment of a vascular atlas enables automatic ASPECT score calculation.



TOSHIBA

Stroke Signs Detection

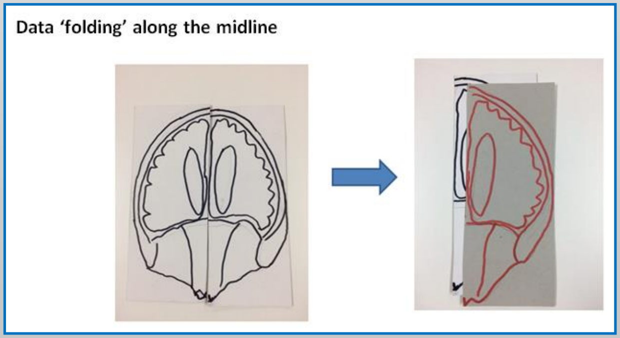
In identifying stroke signs, a human expert will use:

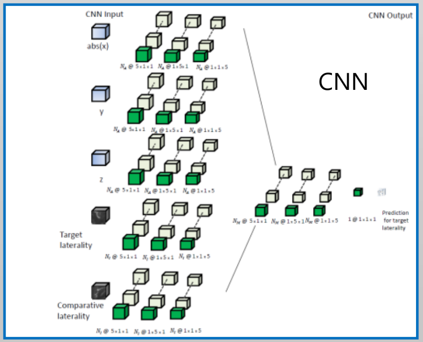
- Learned experience from viewing thousands of examples
- Expected approximate left/right symmetry where relevant
- Anatomical context.

Any successful approach to automatic detection needs to similarly exploit these factors.

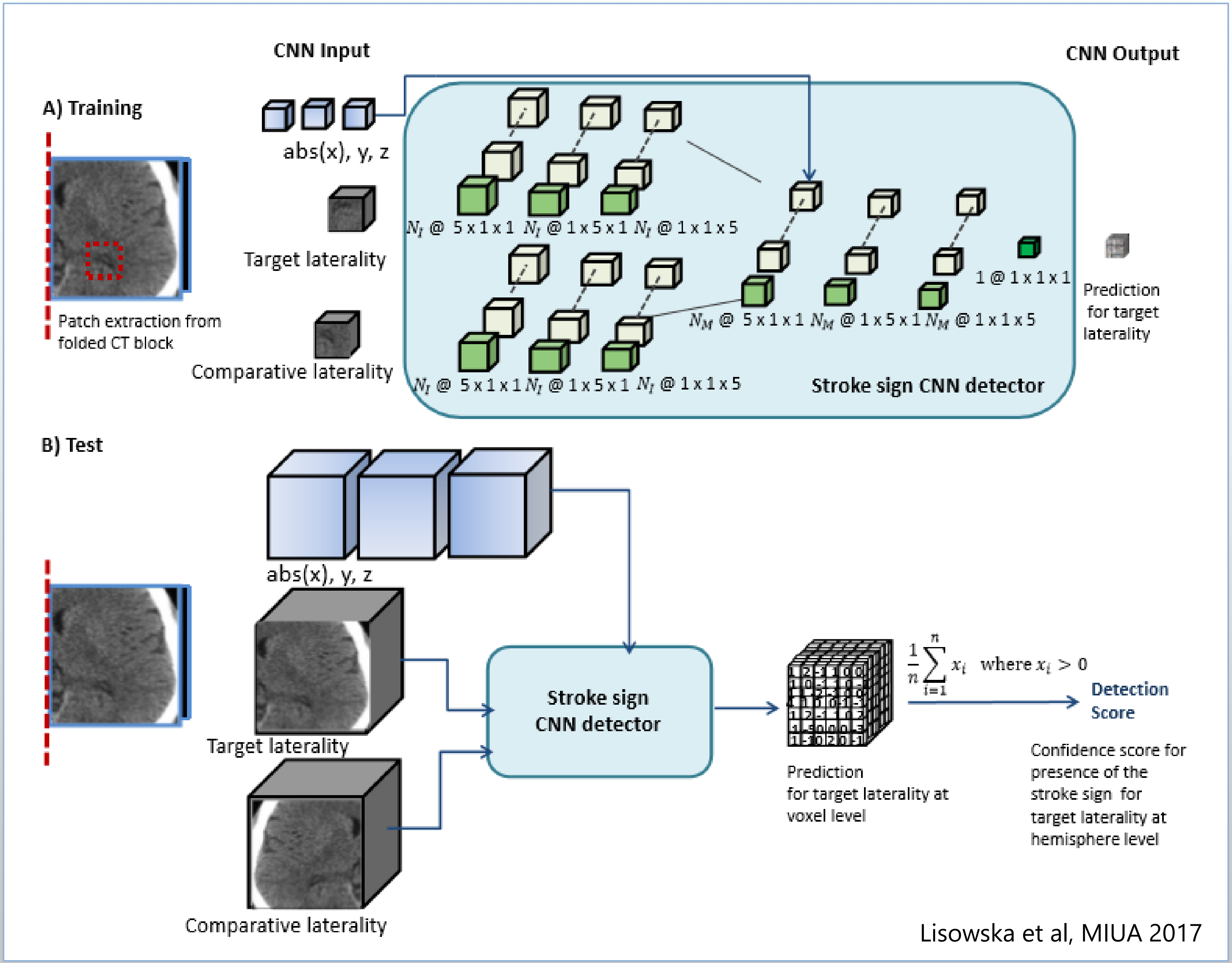
Our method mirrors this by:

✓ A convolutional neural network (CNN) trained images and manual GT
✓ Image 'folding' at the brain midline to bring contra-lateral regions together
✓ Aligned anatomical atlas aligned by landmarks.





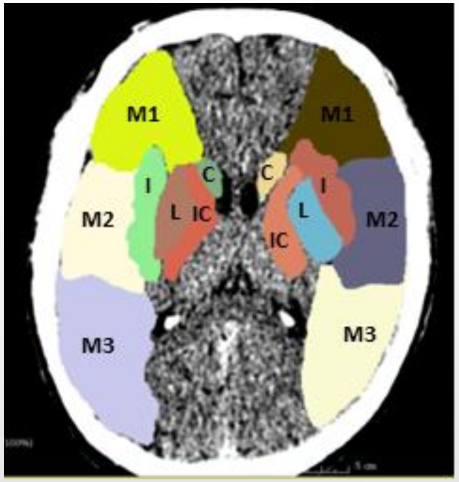
Butterfly CNN architecture



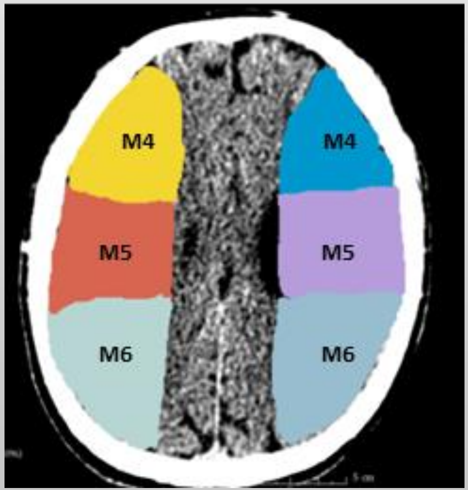
Lisowska et al, MIUA 2017

ASPECTS: Alberta Stroke Program Early CT Score

ASPECTS Atlas + Acute Ischaemia GT = ASPECTS Report



Ganglionic level



Supraganglionic level

ASPECTS is a 10 - 0 scoring of the extent of ischemia across the middle cerebral artery (MCA). 10 is normal.

Dichotomised score of <7 is often used as a treatment threshold.

Patient Name: 06095	**D.O.B:** 01/01/1975
Scan: Head NCCT	**Sex:** M
ASPECTS score: 8	**Total Lesion Volume:** 10 mL

Region	Right	Left
Caudate		
Lentiform Nucleus		
Internal Capsule		
Insular Cortex		
M1		
M2		
M3		
M4		
M5		
M6		

Results

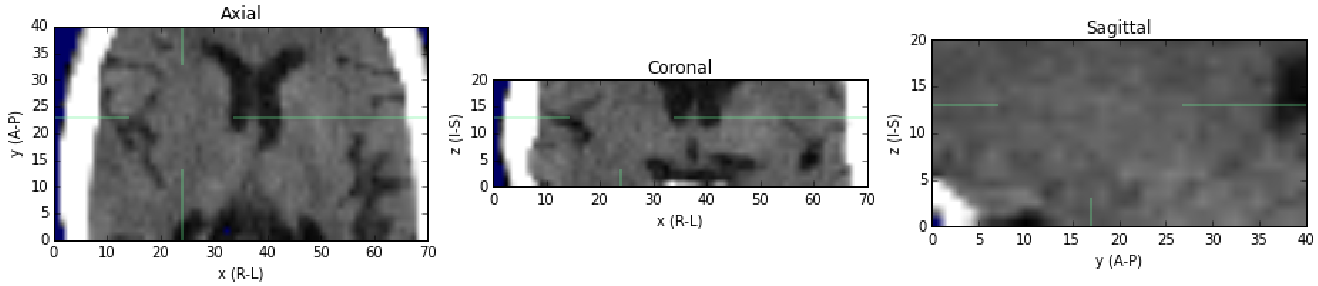
We show example and quantitative results for each of:

- Ischemia Detection
- Dense Vessel (thrombus) detection
- ASPECTS

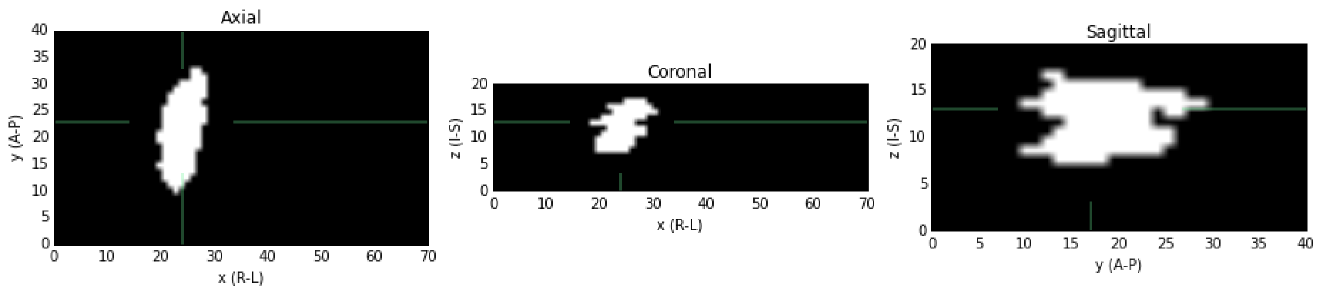
Datasets are from 156 consented trial patients from

Result for Ischemia Detection Example

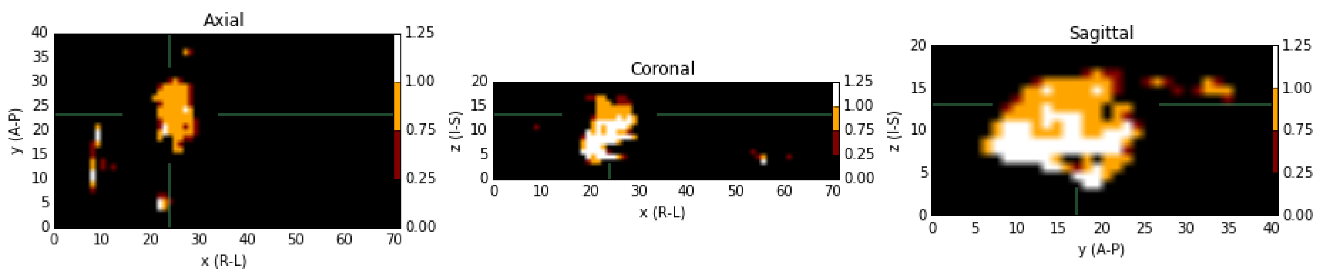
('Volume', '06085_2')



Ground Truth at abnormal slice



GT Patient-level Score (Left, Right): 1, -1
Detections (Probability volumes) at abnormal slice



Detected Patient-level Score (Left, Right): 0.873, 0.384

Ischemia Detection Results

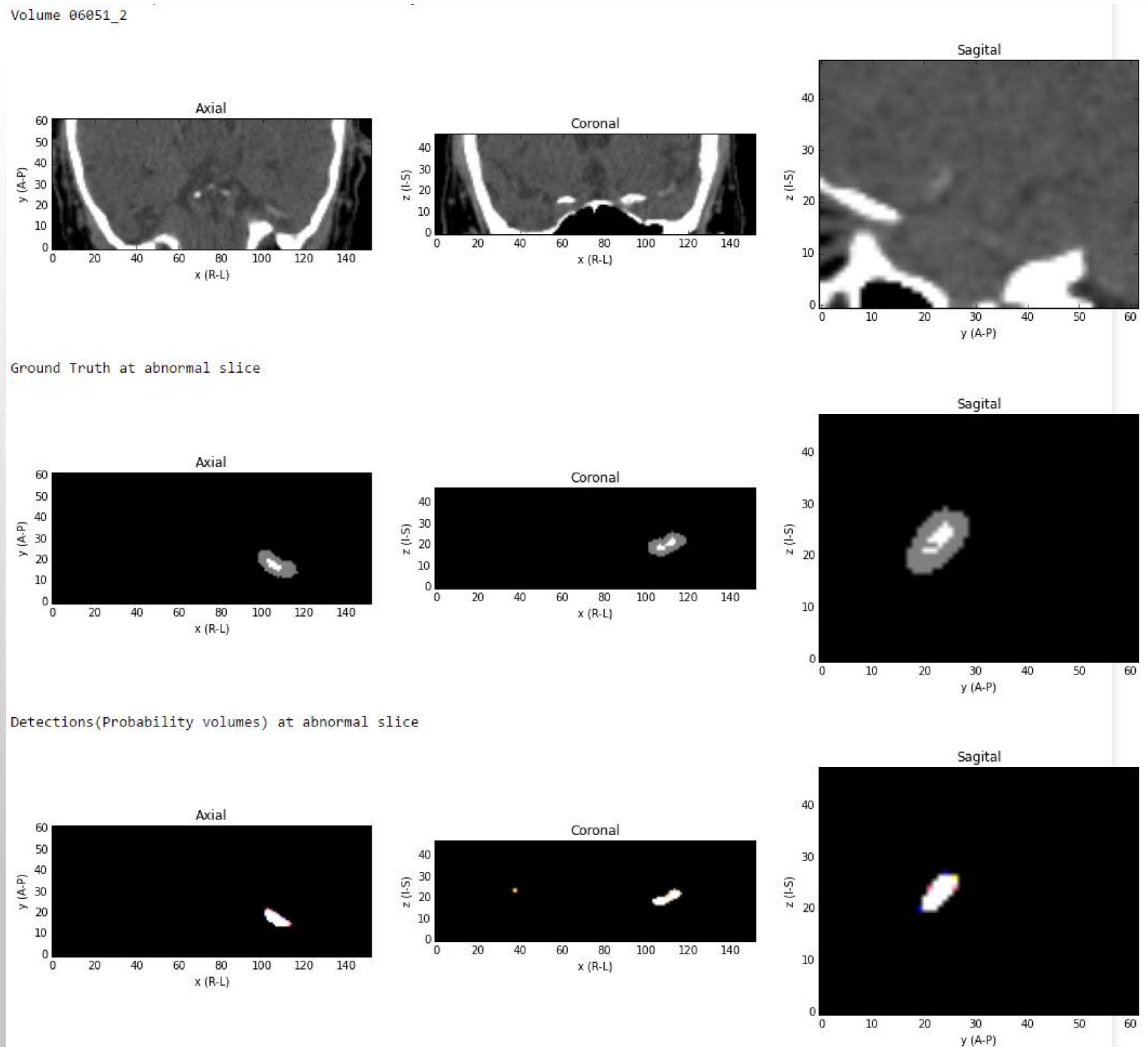
Model	ROC AUC [std]	PR AUC [std]
Bilateral CNN + atlas	0.915 [0.006]	0.783 [0.014]
Bilateral CNN	0.912 [0.007]	0.782 [0.006]
Single intensity channel CNN + atlas	0.738 [0.003]	0.483 [0.021]
Single intensity channel CNN	0.743 [0.012]	0.461 [0.022]

Lisowska et al, MIUA 2017

Ischemia detection at the hemisphere level.

- Bilateral channels yield substantial benefit
- Atlas yields little benefit.

Dense Vessel Detection Example



Dense Vessel Detection Results

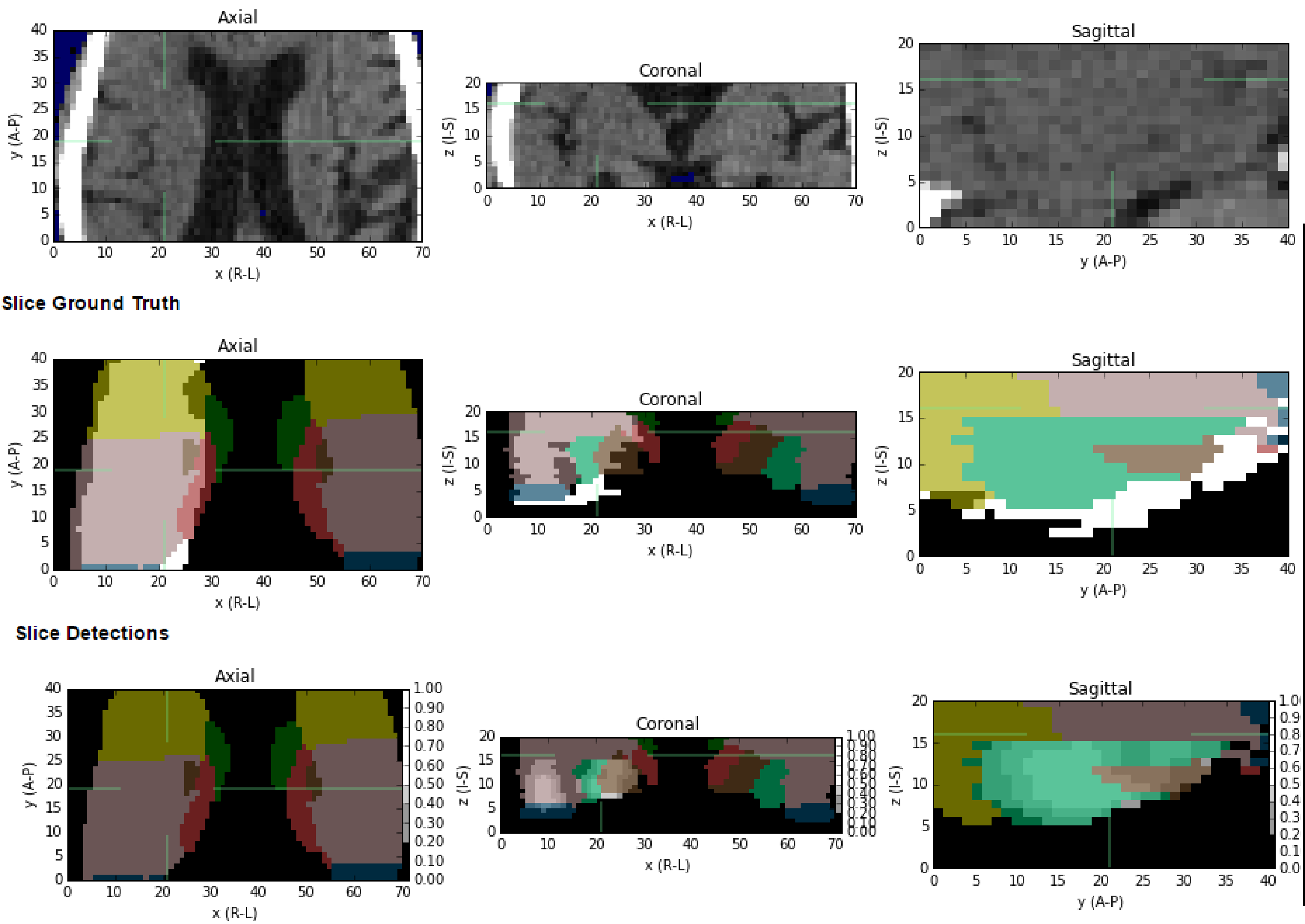
Model	ROC AUC [std]	PR AUC [std]
Bilateral CNN + atlas (A)	0.964 [0.005]	0.898 [0.029]
Bilateral CNN + atlas (B)	0.950 [0.011]	0.817 [0.062]
Single intensity channel CNN + atlas (A)	0.936 [0.026]	0.790 [0.063]
Bilateral CNN + atlas (C)	0.927 [0.019]	0.718 [0.072]
Bilateral CNN	0.891 [0.011]	0.691 [0.036]
Single intensity channel CNN	0.876 [0.013]	0.514 [0.060]

Lisowska et al, MIUA 2017

Dense vessel detection at the hemisphere level.

- Bilateral channels show moderate benefit
- Variant (A) merges atlas channels at lowest level.

Ischemia and ASPECTS Example



ASPECT SCORES:

Clinical: 5 (example)

GT: 4

Detection: 4

	Right		Left	
Region	**GT**	**Detected**	**GT**	**Detected**
Caudate	0	-0.44	0	-0.45
L. Nucleus	1	0.62	0	-0.23
I. Capsule	1	0.45	0	-0.20
I. Cortex	1	0.61	0	-0.27
M1	1	0.15	0	-0.44
M2	1	0.55	0	-0.40
M3	1	0.46	0	-0.45
M4	nan	nan	nan	nan
M5	nan	nan	nan	nan
M6	nan	nan	nan	nan

ASPECTS Results

Evaluation	Clinical	Observed	Ground Truth	CNN
Dichotomised Score Sensitivity	0.87	0.72	0.48	0.50
Dichotomised Score Specificity	0.82	0.98	1.00	0.97
Region Sensitivity	N/A	0.84	0.72	0.49
Region Specificity	N/A	0.98	0.99	0.97

Daykin et al, MIUA 2017

Dichotomised ASPECTS (< 7) typically used as a treatment threshold.

- Evaluation by 5-fold cross-validation against STAPLE consensus.
- Sensitivity of 0.50 needs to improve for clinical use
- But note that 0.48 from ischemia ground truth is no better!

Challenges for Machine Learning

Data and GT

❖ Difficulty obtaining clinical datasets

- Non-consented data subject to strict 'Caldecott' guidelines.
- De-identification is time consuming and costly
- Contractual negations are time consuming (and costly!)
- Take the algorithm to the data? – needs standard Safe Havens protocols

❖ Obtaining gold standard GT

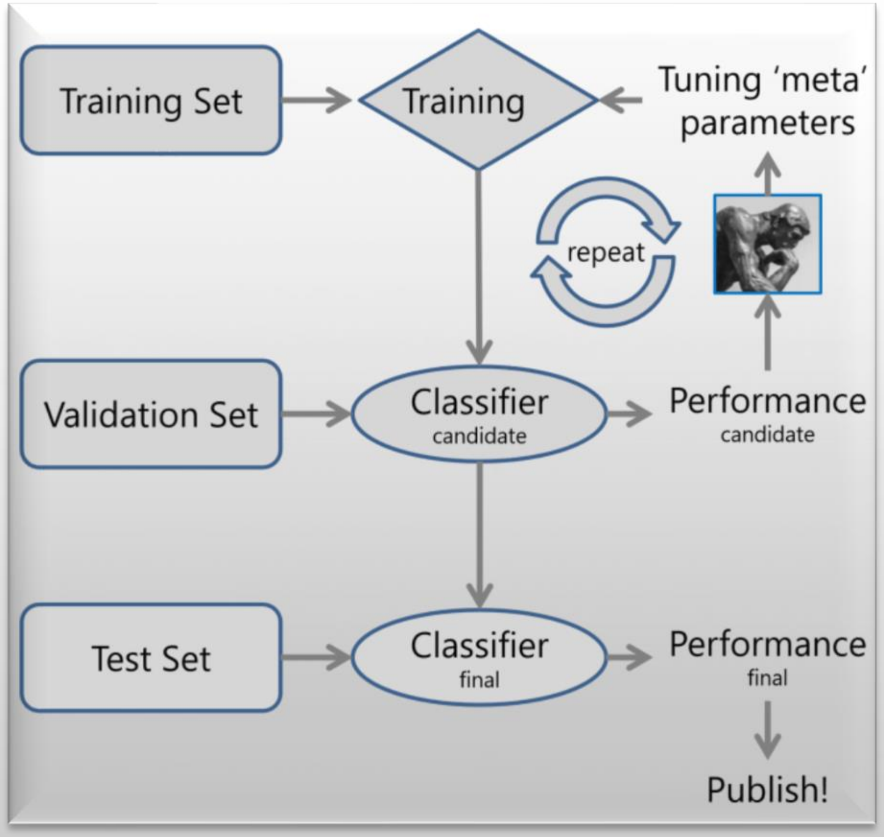
- Voxel level or patient level ('weak') supervision?
- Inter-observer (dis)agreement
- *Mimicking the expert is no longer good enough* – we need deeper Gold Standard GT – e.g. from biopsies or other imaging modalities.

❖ Overfitting….

Overfitting and overfitting!

Even when we have followed best practice….

Over-fitting to our development cohort remains an issue.



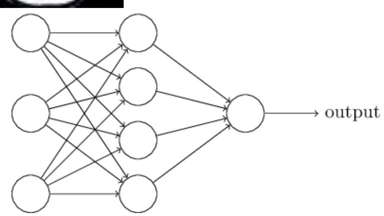
Virtuous ML Methodology

Overfitting to a development cohort

Development

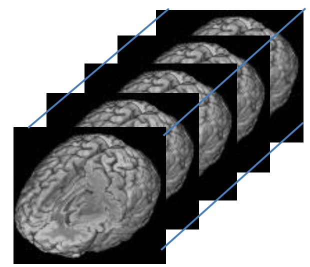

Data: X_S

Labels: Y_S



 $F_S(X_S) \text{ -> } Y$

Deployment

Data: X_T

Labels: none!

 $F_S(X_T) \text{ -> } Y$

How do we adapt our network F_S

to work well in the deployment domain?

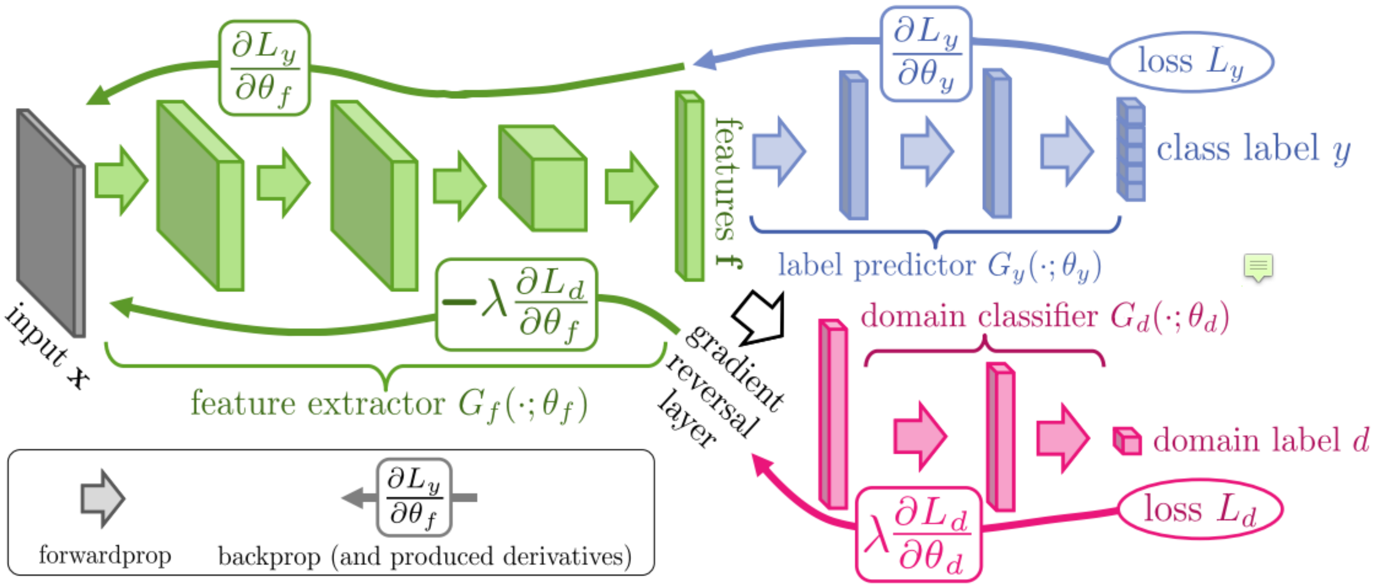
Adversarial Domain Adaptation

Domain-Adversarial Training of Neural Networks

Yaroslav Ganin GANIN@SKOLTECH.RU
Evgeniya Ustinova EVGENIYA.USTINOVA@SKOLTECH.RU
Skolkovo Institute of Science and Technology (Skoltech)
Skolkovo, Moscow Region, Russia
et al

Key insight:

- Find a feature space which is *insensitive* to the domain D, yet still *sensitive* to desired Y.



Conclusions

- Clinicians need CDS to rule our haemorrhage and identify subtle early ischemic changes.
- A symmetry exploiting CNN shows promise in detecting dense vessels and ischemia.
- ASPECTS is a 10 – 0 scale summarising extent of ischemia in the MCA.
- Clinical datasets are difficult to obtain.
- Gold standard GT from other imaging modalities is ideally required.
- Overfitting to a development cohort is an ever present issue.

Acknowledgements

➢ Erin Beveridge	Clinical Analyst
➢ Aneta Lisowska	EngD Research Student
➢ Matthew Daykin	EngD Research Student
➢ Vismantas Dilys	Scientist
➢ Keith Muir	Professor of Neuroradiology, QEUH Glasgow

And…

We're hiring in Edinburgh!

- Head of AI Research
- Several AI/ML Scientists.

See www.tmvse.com – soon!

Thank you!

Made For life

For over 100 years, the Toshiba Medical `Made for Life’ philosophy prevails
as our ongoing commitment to humanity. generations of inherited passion creates
a legacy of medical innovation and service that continues to evolve as we do.
By engaging the brilliant minds of many, we continue to set the benchmark
because we believe quality of life should be a given, not the exception.

TOSHIBA
MEDICAL

Canon
CANON GROUP