

Stanford Papers

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1. DualCheXNet

- Chest radiograph interpretation
- Stanford CheXpert Dataset of frontal & lateral
- 14 classes, 65K patients \rightarrow 223K radiographs
- 15% are lateral, 85% are frontal
- Trained separate DenseNets for frontal & lateral
- Averaged the output probabilities for both models
- AUROC of 0.823 (There is scope)

X 2. Diagnosis of AD using MR

- 3D CNN
- ADNI-1 dataset & ADNI-2 dataset
- Both are T1-weighted structural MR
- 3 classes: NC, MCI, AD; Imbalanced
- Spool stripping algo using SPM, using BET
- Poor validation accuracy; few datapoints

X 3. DL for Congenital Lung using MRI

- 2D and 3D CNN
- binary class prediction - normal vs abnormal
- Fetal MRI scans. SSFSE dataset (T2 weighted)
- class imbalanced. 2D densenet & 3D resnet
- Accuracy ~100

4. Brain Tumor Segmentation UWMRCNN

- 1st method: Cascade of WNet and a UNet
- 2nd method: Mask R-CNN
- BraTS 2018 dataset
- Cascaded performed better
- 1st method: MRI scan WNet bounding box $\xrightarrow{\text{UNet}}$ segment
- 2nd ": ilp: slices & thin masks
o/p: segmented image
- Huge dataset 330K train images
- They trained locally using only 10.5K images

5. Semantic Segmentation Aortic Dissection U-Net

- CT scans
- segment into 3 regions: true lumen & background, false lumen
- 2D U-Net and LinkNet comparison
- Dice-coefficient metric in loss function
- 24 CT aortograms from Stanford Medical
- Each CT made of 800 256×256 grayscale slices
- Less Data (very). UNet & LinkNet easily trainable
- CCE loss + Dice loss
- 3D UNet. Dice scores of 0.05 +

X 6. Knee Osteo using radiographs

- Osteoarthritis (OA) is leading cause of disability in US.
- VGG-16; DAI dataset of X-ray of left & right knee
- Binary classification

X 7. ~~Brain~~ seizures from EEG recordings

- Detect Brain activity by electrodes in dogs (30 seconds)
- CNN and RNN, binary classification
- = Presence of seizure in next 10 mins or absence
- Kaggle competition dataset. Leaderboard to beat 0.84
- 4 American Epilepsy seizure prediction
- Poor results; couldn't beat leaderboard at all

8. Instance UNet and watershed breast cancer

- Performs highly accurate cell segmentation & ^{cell} count
- Dataset - Region Proposal Networks to detect cells with bounding box
- they - Instance U-Net for segmentation
- collected - Watershed algorithm to improve on net's output
- under - Beat SOTA. Very cool pipeline RPN + UNet + Watershed
- microscope - Identifies cells in images (issues: high density & bad illumination)



- Input: 40x fluorescent nucleus image 448×448
- RPN + bounding box; UNet + segmentation

↓ watershed

↓
separates touching cells & gives
(like instance segmentation) map + count



X 9. Automatic Brain Aneurysm segment CT

- Segments CT angiographs.
- Tries different ~~brain~~ architectures.
- Encoder: ResNet50; Decoder: PPM & UPerNet
- Class imbalance (99.998%, 0.002%)
- Solved by randomly resampling scans of this class.
- Stanford medical school dataset from Prof ☹️

X 10. SomaNet & Segment neurons for brain

- segments neuron some in 2D microscopy images
- Got dataset from Prof. UNet
- Pre-trained on non-neuron cell nucleus segmentation data from Kaggle Data Science Bowl
- Then employed TL, retrained last layers on few images.

X 11. Diabetic Retinopathy

- 5 class ; DenseNet CNN.
- Input retine image from microscope.
- Class imbalance : 73-7-15-3-2
- Modified loss function ; gave different weights to misclassification of each class.
- Kaggle dataset ; 87.6% accuracy
- Class activation map ~~to~~ for model interpretability

X 12. Melanetic cancer

- 2019 Kaggle competition ; Playground ☹️
- Binary classification
- 4 layer CNN
- Looked at FP, FN ; TP, TN (Error analysis)

X 13. Melanoma segmentation

- = Two novel U-Net based models
- ISIC 2018 melanoma dataset
- Attention U-Net built on top of Biggus Leaky U-Net
- Top 10 ; Methodical testing of loss/hyperparameters (good)

X14. Image Restoration low quality med images

- Denoising low resolution retinal images while retaining small features (like ^{thin} blood vessels) _{in retina}
- Try autoencoder vs DeepCNN vs GAN
(9-days) (17-days)
- Metric for noisiness is PSNR & SSIM (higher → better)
- GAN was a pre-trained network for superresolution
- Dataset had high res images
- PSNR → realism; SSIM → reconstruction
- Final results are based on these two metrics
- CNN did the best $\ddot{\smile}$. So ~~cool~~ cool things did not work well
- Good idea; but different technique should be tried

'15 Boost MRI quality

- DL model to learn mapping from raw sensor data to image domain of MRI knee scans
- Signal-to-noise of 20.2; beats standard reconstruction methods. Input: k-space image in sensor domain
Output: Reconstructed MRI image
- AUTOMAP SOTA image reconstruction model uses CNN
- Uses the primary architecture of AUTOMAP builds on top of it, for knee MRI.
- Risk of using GANs for medical images: realism. They use CNN & not GAN for that reason.
- DCGAN used for MRI reconstruction.
- fastMRI dataset by Facebook AI research
- Novel problem; easy to code; not sure of scope for improvement
- The reconstruction from k-space input looks really good, compared to ground truth
- Pros: Good problem statement; nice outputs
Con: Simple DL code; future scope

X

16.

ElderNet: electroencephalography sleep stage scoring for elderly.

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- Dataset from Prof
- Too specific
 - Time series; spectrograms; wavelet coeffs
- Baseline + FC; Wavelets + RNN; Spectrogram + CNN + RNN; spectrogram + CNN + Attention
- A lot of different architectures - tried
- Too much domain knowledge required

17. GAN translation between image modalities

- Translate between T1 & T2 modalities on Brain MRI dataset from Human Connectome Project.
- UNIT network (Image to Image translation)
- Improved by trying self-attention layers, spectral normalization, charbonnier penalty
- They have replicated the paper with same dataset and used as their baseline.
- MedGAN paper: PET \leftrightarrow CT
 - ↳ based on U-Net
- The ~~same~~ ¹¹¹³ patients, small dataset
- Pros: Cool network; baseline paper; simple PS
- Cons: Requires higher DL knowledge than segmentation. Purely DL based.
 - Aim, to improve on baseline paper
- SSIM metric; Couldn't beat baseline

18.

X

18.

Latent model for critical care using VAE

- Uses VAE to get latent representation of large patient data from EHR.
- Deep Patient, uses stacked denoising autoencoder to extract clinically relevant features from EHR
- Introduced a novel GMVAE (Gaussian mixture VAE) which incorporates cluster discovery into feature learning process

X 19. Semantic segment of 3D protein

- Dataset not available
- High bio protein knowledge; author is protein ^{researcher}
- simple Network; complex preprocessor & later analysis. Work does not look parallelizable.

Final papers

Classification → (1.) DualChexNet

- ↳ Good dataset; easy to gauge progress
- ↳ Highly parallelizable work
- ↳ Simpler DL than other tasks
- ↳ Ongoing leaderboard by Stanford KG.
- ↳ Cons: Classification; Iterative

Segmentation → (4.) Brain Tumour Segmentation U-Net

- ↳ Good Brats dataset; easy to gauge progress
- ↳ Highly parallelizable work; Ongoing leaderboard
- ↳ Cons: Tougher DL; Just U-Net won't cut it.
Longer training time; Can't iteratively improve because of long training; generic PS

(8.) Instance U-Net & watershed forest cancer

- ↳ Beautiful use of algorithms in sequential manner
- ↳ Best SOTA; easy to gauge progress; Novel PS
- ↳ Cons: Dataset not available; PS not related to MR/CT/Xray. ~~At~~ Tougher DL (but slightly).
Biggest issue is dataset & fluorescence microscopy PS.

Image Translation: ~~later~~ (17.) GAN between T₁ & T₂

- ↳ PS is cool; Baseline paper exists with code
- ↳ Easy to gauge progress; Dataset is available
- ↳ Cons: DL knowledge; Beating paper baseline might not be possible; Purely DL based; high current advancement knowledge needed for testing & improving. Not parallelizable