EEP 596: AI and Health Care || Lecture ~~7~~ 8

Dr. Karthik Mohan

Univ. of Washington, Seattle

Apr ~~18~~ 21, 2022

Logistics

- Mini Project 1 on Arryhthmia Detection assigned and due ~~Wednesday, May 4.~~

Due Date 1 :- May 1 } Initial Deliverables

Due Date 2 :- May 6 } Final —||—

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Last Lecture

- **Deep Learning Recap and Focus**

Last Lecture

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- **Deep Learning Methods for Anomaly Detection**

Last Lecture

- **Deep Learning Recap and Focus**
- **Deep Learning Methods for Anomaly Detection**
- **Deep Learning for other health care problems**

Today

- **Auto Encoders Recap**

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- **Medical Imaging Use Cases**

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- **Auto Encoders Recap**
- **Medical Imaging Use Cases**
- **Methods for Medical Imaging** & DL!

Today

- **Auto Encoders Recap**
- **Medical Imaging Use Cases**
- **Methods for Medical Imaging**
- **Deep Learning for Medical Imaging**

Mini-Project Overview

Arrhythmia or "irregular heart beats" is a very common heart rate problem and often goes un-diagnosed. This mini-project looks into super fine-grained data on heart beats and characteristics of normal and abnormal heartbeats. Having ML algorithms that can automate detection of possible Arrhythmia is super impactful in helping doctors and hospitals be more efficient and effective in diagnosis and treatment of heart rate issues and also avert medical emergencies, prevent deaths. Since this is a mini-project, it is much more involved than a regular assignment - Plan a good amount of time for going through all the deliverables. To make it easy for you, we give you two deadline dates for the mini-project - An early deadline to help you get your feet wet and submit code on early models. And a final deadline to submit all your work. Mini-project has twice the grade weightage as a regular assignment and so you also get two weeks to do it. Enjoy! (Thanks to Ayush for working with us on majority of the content creation for this mini-project!!)

360 samples/second

Submission Guidelines

- You get to work in teams of 2 for the Kaggle and modeling piece!! Please make sure each person of the team gets to work on all aspects of the mini-project and mention at the top of your report the contributions from each person.
- The submission is in 3 parts
- **Code:** Please submit a Jupyter/IPython notebook file, report and Kaggle predictions as part of your submission. You can start with the template notebook provided and add in your solutions to it.
- **Report:** The report should be in a pdf format and have plots, correlation matrices and tables added in as mentioned in the **Heart Rate Deliverables below**. Feel free to use either latex or word for creating it. Include answers to conceptual questions, and your insights as well. Ideally you should NOT use comments in ipynb to answer any conceptual question.
- **Kaggle Contest:** There is a Kaggle competition as well, where you submit predictions on a "held out" data set.

Dataset Description

We have the following classes of heartbeats present in the dataset :

- N: Normal beat
- L: Left bundle branch block beat
- R: Right bundle branch block beat
- A: Atrial premature beat
- V: Premature ventricular contraction
- U: All other types of beats should be classified as this (this would require relabelling of the data)

Dataset description

The database contains 44 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 43 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The recordings were digitized at 360 samples per second per channel, and were labelled manually by cardiologists. You can only use MLII information to train the model for all the part except the last one, this is because we have maximum availability of this feature. The txt file contains time, sample number and type of the heartbeat.

$1800 \times 44 \approx$ 90K data pts!

Required preprocessing

The first objective is to split MIT-BIH record at the R-peaks into individual heartbeat records. This can be done by creating a file which shall have the required information from the csv and txt files. The txt file contains time, sample number and type of the heartbeat. For each row of txt files, take 180 samples before and 179 samples after this sample number to create a time series from the corresponding csv file with the corresponding type as the label. Hence the final file you shall create shall have 360 features, along with it's label.
Feel free to try out any other method for pre-processing, and clearly explain the steps taken for it in the report. (There are no additional marks for this)

Heartbeat Prediction Deliverables

- Do the preprocessing defined in the previous page. Then plot 3 heartbeats which are classified N and 3 which are classified as another class. How many heartbeats do you have in total? (30 marks)
- Data normalization(can normalize to range [0,1]). Feel free to add any other pre-processing you deem useful. (5 marks) (5 bonus marks for any other pre-processing added)
- Class imbalance handling
    - Show the class imbalance present in the database with the help of plots. Use an autoencoder to augment data for classes with lesser data(especially for the A class). (20 marks)
    - Show some plots of true anomalies and generated anomalies - And compare them side by side visually. (5 marks)
    - Use a Variational autoencoder(VAE) architecture for the same. Discuss it's performance. (10 bonus marks)

Heartbeat Prediction Deliverables

- Data denoising
  - Apply any noise reduction method(like Fourier transform, wavelet transform etc). Then plot the heartbeat with and without this filtering, and discuss the differences. Briefly describe how is your method useful. (HINT: Find a method to make the frequency component of noise zero) (10 marks)
- Run at least one non-deep learning (ML) model on the processed dataset. Do hyperparameter tuning for the same. Show the confusion matrix, f1 score and accuracy score. Specifically mention the metrics for 'A' class as well.(5 marks)
- Apply a feed-forward neural network and discuss it's performance w.r.t. the machine learning model used(on metrics defined in previous question). (10 marks)

Heartbeat Prediction Deliverables

- Implement the neural network architecture from any recent paper on the MIT BIH Arrhythmia Database (check references for some papers). It is expected that the implementation should be your own and briefly describe the approach taken. How was the performance of this model? Were you able to get similar scores to the reference paper? Submit your implementation as well. (30 marks)
- Plot the curves of training, validation and test sets losses and accuracy scores with number of epochs on the x-axis. Show a table with performances of different models. (5 marks)
- Run the last neural network model with usage of one more feature in addition to MLII for which there is enough data. You can choose any one of V1, V2, V3, V4, V5. Compare it's performance with the usage of only MLII feature on the accuracy score. (10 marks)
- Interpretability - Print/plot examples or time-series snippets of mis-classified arrhythmia (False positives) and also false negatives. Why do you think the model might have done a mis-classification

References

- MIT-BIH Arrhythmia Database
- Noise Reduction in ECG Signals Using Fully Convolutional Denoising Autoencoders

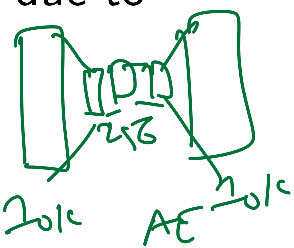
Auto Encoders Recap

- **Types:** Regular, De-noising, Sparse and Vaiational AEs

Auto Encoders Recap

Data Aug.

- **Types:** Regular, De-noising, Sparse and Vaiational AEs
- **Dimensionality Reduction:** Better than PCA/SVD due to non-linearity.



10k

AE

256

Dense low-dim feature

Bag-of-words

Sparse

AutoEncoder (NLP)

Auto Encoders Recap

- **Types:** Regular, De-noising, Sparse and Vaiational AEs
- **Dimensionality Reduction:** Better than PCA/SVD due to non-linearity. } visualization
- **Feature Extraction/Feature Reduction** → Reduces over-fitting

Auto Encoders Recap

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Auto Encoders Recap

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- **Data Augmentation:** Example, through Variational Auto-Encoders. Will get to try this out in Mini-Project 1
- **Data De-noising:** Through de-noising Auto Encoders.

Week by Week Breakdown

Week 1

Health care problems. Personalized health tracking. Patient diagnosis and monitoring. Automating health records. Other problems? How can AI help ? Case studies and examples. Getting started with foundations of AI for health care.

Week 2,3 & 4

Health focus: Disease diagnosis and patient monitoring: Case studies
Data focus: Data from wearables and other sensors - Reliability and Signal/Noise
Data focus: Data sources, data cleaning, pre-processing and post-processing techniques in ML
Imaging
Model focus: Modeling AI for Disease diagnosis Machine learning models - Foundations and libraries Unsupervised, Supervised ML and contexts Specific applications Conceptual assignments and programming portions for case study

Week by Week Breakdown

Week 5 and 6

Health focus: Automating health records - Case study
ML focus: Natural Language Processing - Foundations and applications to health care Classic example of handwriting recognition and document generation Conceptual assignments and programming portions for structured learning from NLP data sets Project: Discussion of final project

Week 7

Health focus: Interpretability in Health care and Machine Learning - Case study
ML focus: Why is interpretability of models important and how to measure it? ML focus: Deep dive into models in ML from standpoint of interpretability Conceptual + programming portion for Interpretability case study in health care

Week by Week

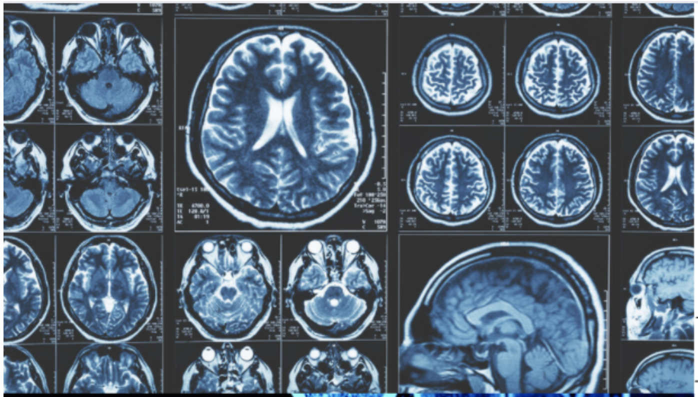
Week 8

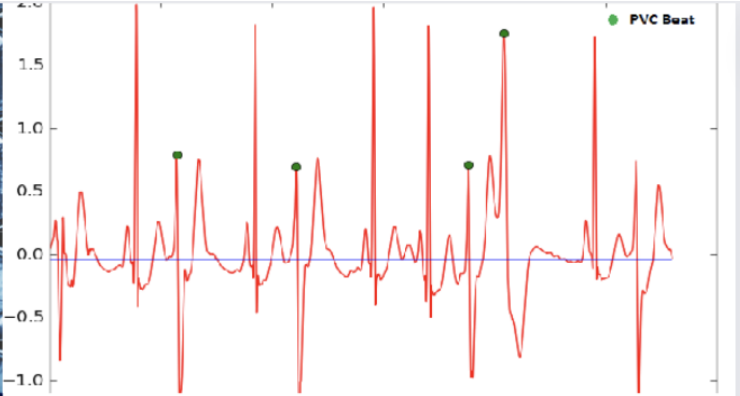
Health focus: Assessing patient risks for treatments **ML focus:** Models for risk assessment Conceptual + programming portion for Interpretability case study in health care

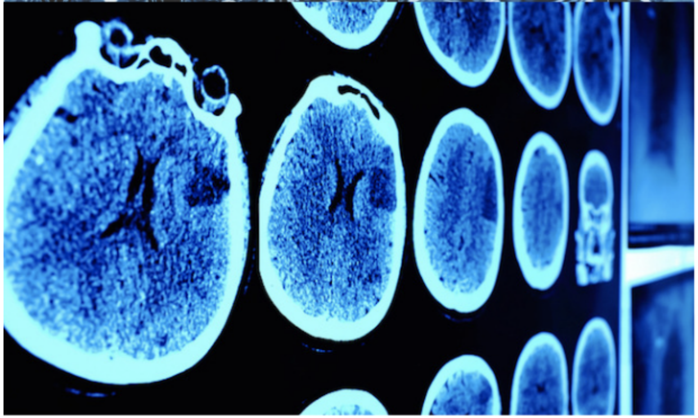
Week 9

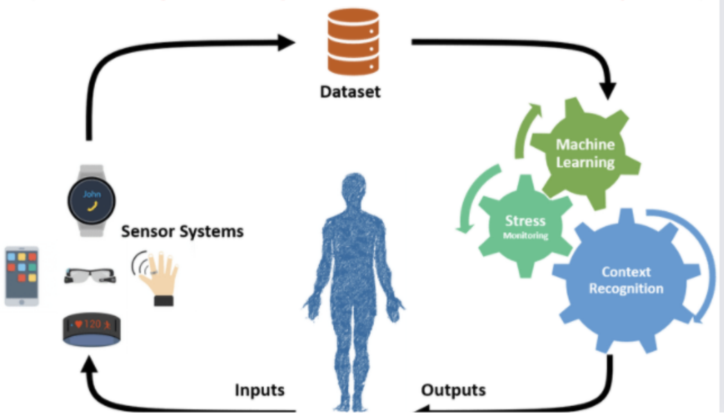
Open topics discussion Project presentations Final project due

Medical Imaging









MRI Scanner

MRI Interpretability and Diagnosis

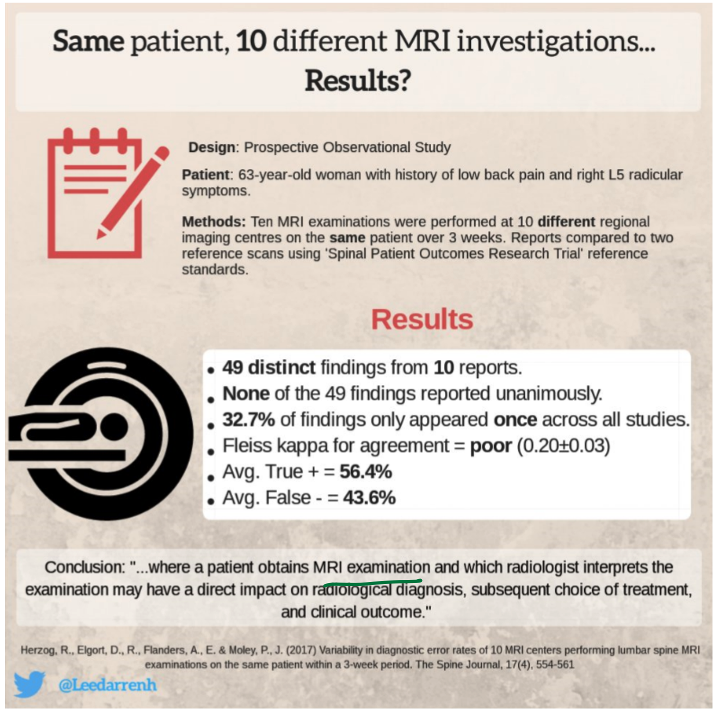
MRI

Interpolating

Scanner

High Res (T7)

Mid Res (T3)



Variability in diagnostic error rates of 10 MRI centers performing lumbar spine MRI examinations on the same patient within a 3-week period. 2017

MRI Interpretability and Diagnosis

Conclusion

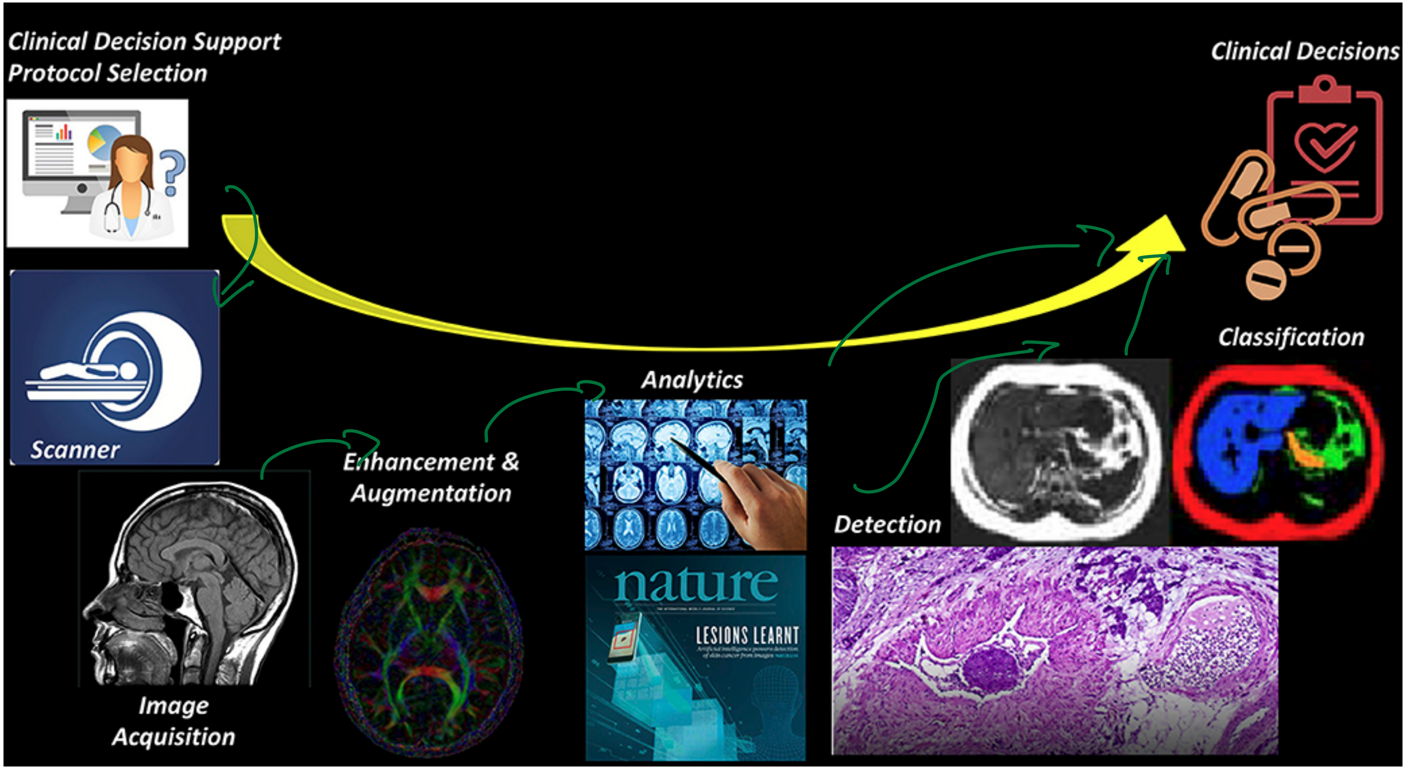
This study found marked variability in the reported interpretive findings and a high prevalence of interpretive errors in radiologists' reports of an MRI examination of the lumbar spine performed on the same patient at 10 different MRI centers over a short time period. As a result, the authors conclude that where a patient obtains his or her MRI examination and which radiologist interprets the examination may have a direct impact on radiological diagnosis, subsequent choice of treatment, and clinical outcome.

Variability in diagnostic error rates of 10 MRI centers performing lumbar spine MRI examinations on the same patient within a 3-week period. 2017

(Semi) Automating Diagnostics based on Medical Imaging

1. This motivates the need for more automated analytics of the imaging with good accuracy.
2. Automated analytics can augment a Radiologists' understanding of a scan (e.g. MRI) and make for a more accurate diagnosis

The pipeline for MRI diagnostics



AI for MRI Diagnostics

1. **Downstream Tasks - Diagnostics/Detection:** Using CV techniques for detection and segmentation of anatomical structures and the detection of lesions, such as hemorrhage, stroke, lacunes, microbleeds, metastases, aneurysms, primary brain tumors, and white matter hyperintensities.

Have been around

Cancer

Separate classifier

AI for MRI Diagnostics

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2. **Upstream Tasks:** Image Acquisition, Image Enhancement - Think super resolution (More recent).

2000 papers in 2018 on Imaging AI

5% DL

1.5T Fast (Low Res Image)

7T Slow

AI for MRI Diagnostics

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2. **Upstream Tasks:** Image Acquisition, Image Enhancement - Think super resolution (More recent).
3. **Upstream Tasks:** Lowering radiation and contrast dose - Potentially saving complications due to radiation and time!

Better for patients

DL archs

inference

1. **NLP:** RNN, LSTM, Transformers and BERT archs used

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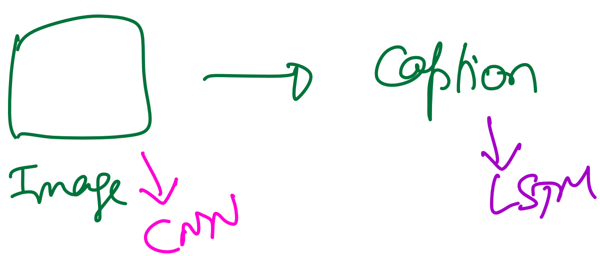
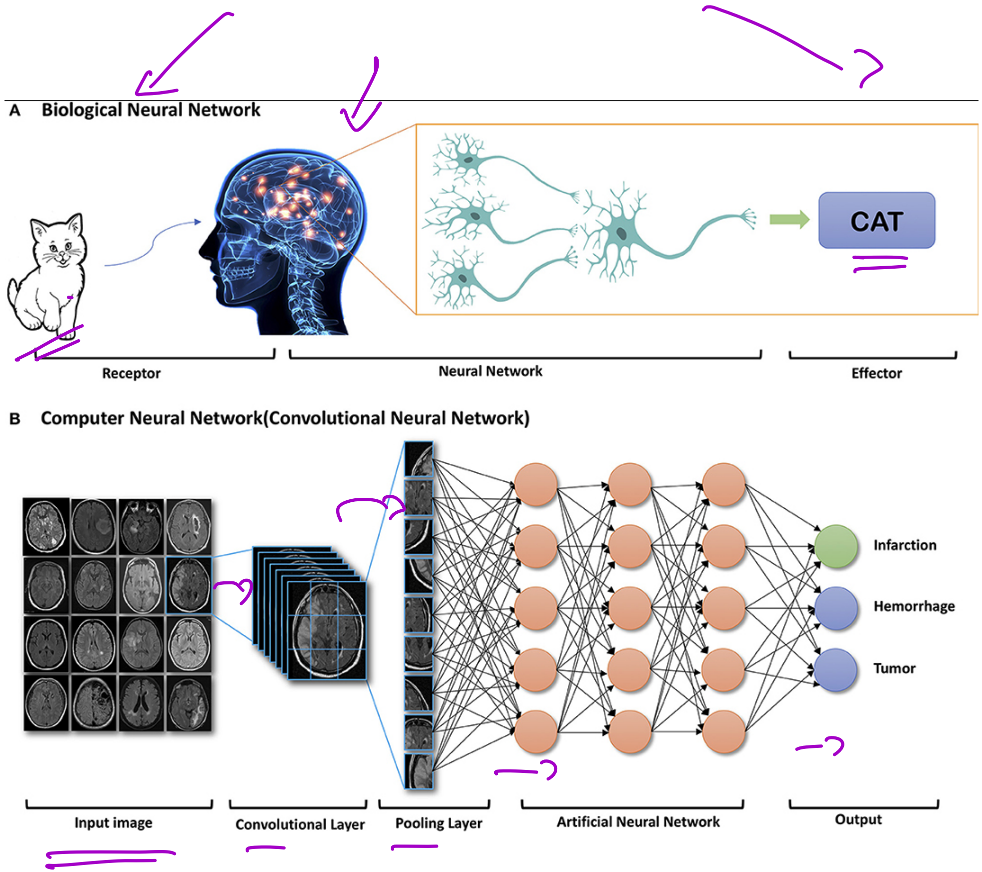
2. **Imaging:** CNN primarily for image feature extraction, etc but can be mixed with LSTM for sequence of images, for example.

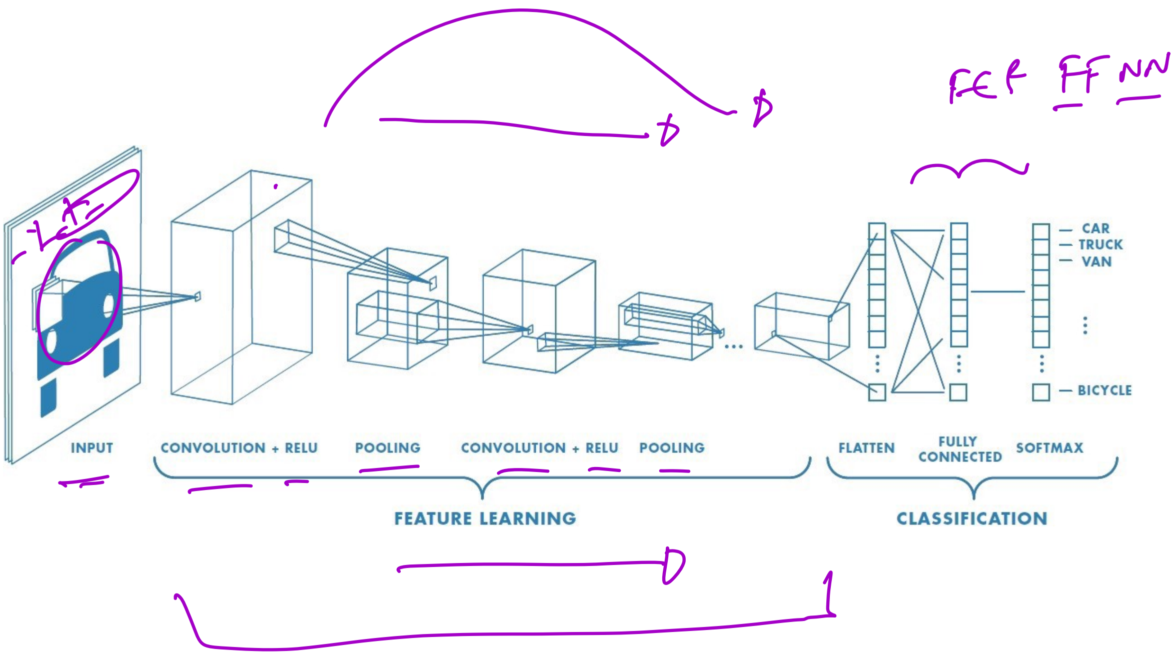
Conv. Neural Network



CNN for MRI Analytics



CNNs


FCF FFNN
CAR
TRUCK
VAN
BICYCLE
INPUT
CONVOLUTION + RELU
POOLING
CONVOLUTION + RELU
POOLING
FLATTEN
FULLY CONNECTED
SOFTMAX
FEATURE LEARNING
CLASSIFICATION

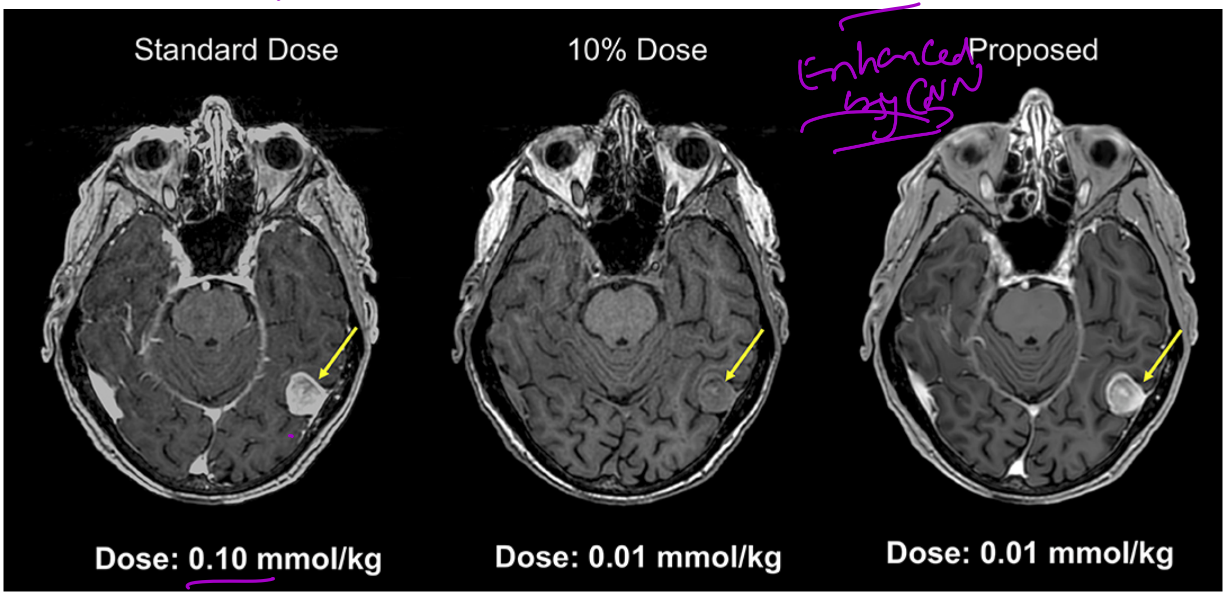
Application: Reducing contrast dose in MRIs

1. Gadolinium-based contrast agents (GBCAs) have become indispensable in routine MR imaging

↳ Deposits in the body

↳ Fibrosis/health issue

High Res



Enhanced by CNN

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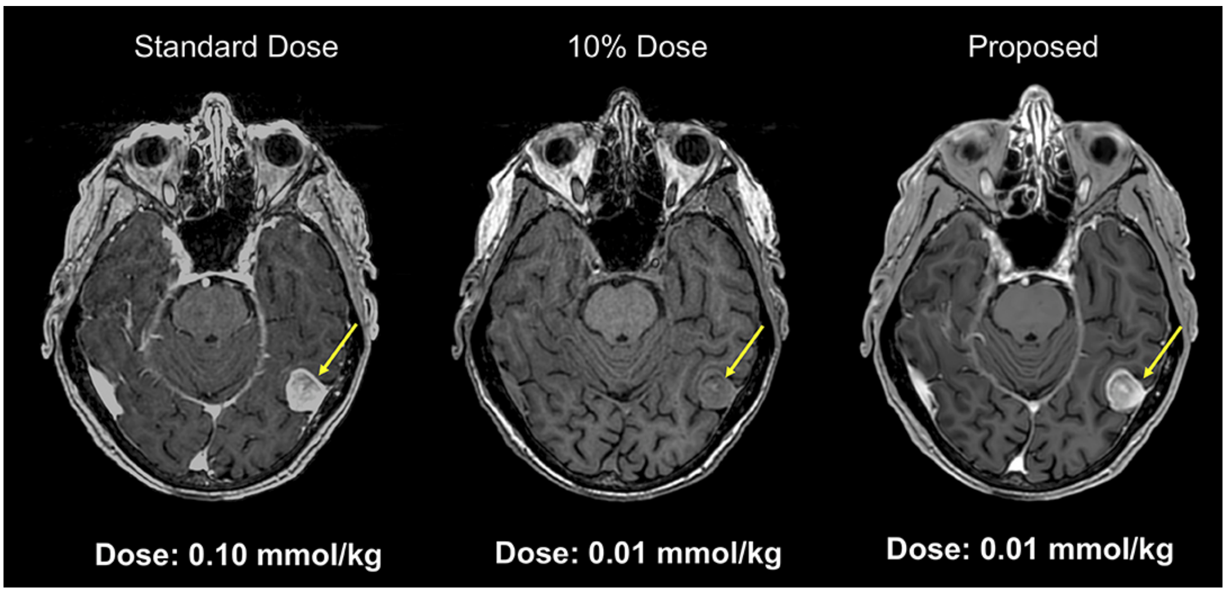

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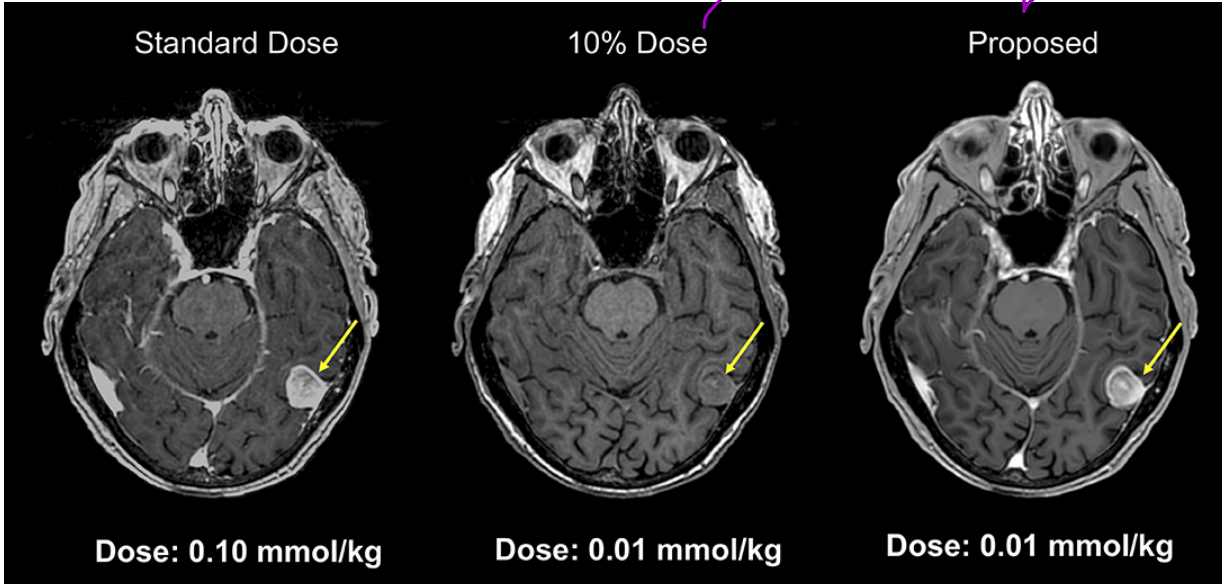
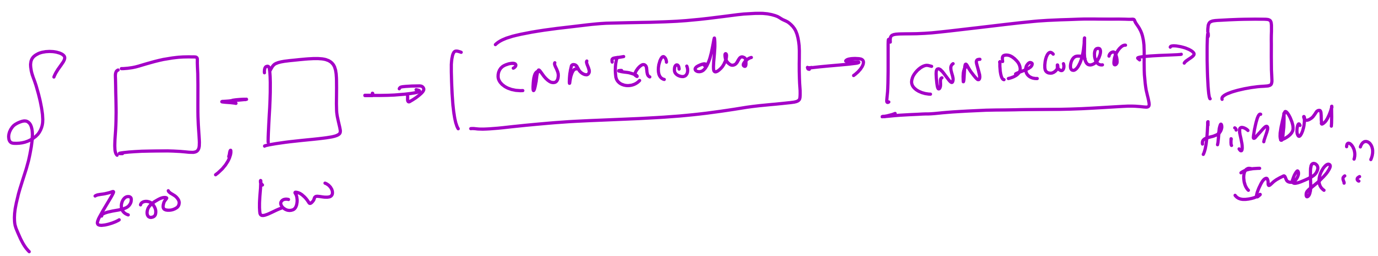
3. Can reduced contrast dose MRI along with deep learning help reconstruct full dose MRI?



Breakout 1 Discussion

Describe the ML model

Can reduced contrast dose MRI along with deep learning help reconstruct full dose MRI? Given a zero contrast MRI, low dose MRI and full dose MRI images of the same patients - What Deep learning model would you use, which kind of an architecture and what are the inputs/outputs to the model - So it can help learn to reconstruct full dose MRI?



CT Scan

Application: Reducing radiation in CT scans

Radiation dose comparison, according to the FDA

Diagnostic Procedure	Typical Effective Dose (mSv)[1]	Number of Chest X rays (PA film) for Equivalent Effective Dose[2]	Time Period for Equivalent Effective Dose from Natural Background Radiation[3]
Chest x ray (PA film)	0.02	1	2.4 days
Skull x ray	0.1	5	12 days
Lumbar spine	1.5	75	182 days
I.V. urogram	3	150	1.0 year
Upper G.I. exam	6	300	2.0 years
Barium enema	8	400	2.7 years
CT head	2	100	243 days
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1. Lower Radiation in CT means lower image quality
2. Higher Radiation in CT is a health hazard

Application: Reducing radiation in CT scans

Original image | Noisy image | Denoised image

(uniform Gaussian Noise!?)

some artifacts washed out!!

useful

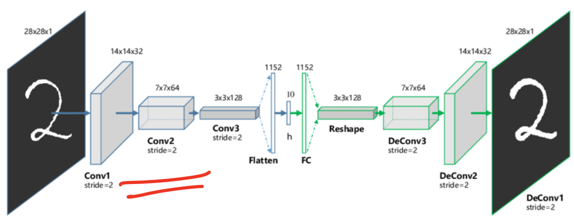
1. Standard image processing techniques lead to waxy images

Application: Reducing radiation in CT scans

Original image Noisy image Denoised image

1. Standard image processing techniques lead to waxy images
2. Use of encoder-decoder CNN to remove noise in images. What does this remind you off?

Denoising AutoEncoder!



Application: Reducing radiation in CT scans

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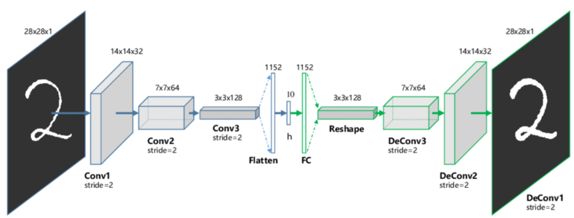
2. Use of encoder-decoder CNN to remove noise in images. What does this remind you off?
3. Autoencoder CNN to remove noise!



Application: Reducing radiation in CT scans

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2. Study showed artifacts (noisy) in low dose CT were removed after passing through the CNN encoder-decoder trained on this data

Artifacts → Noisy → Removed

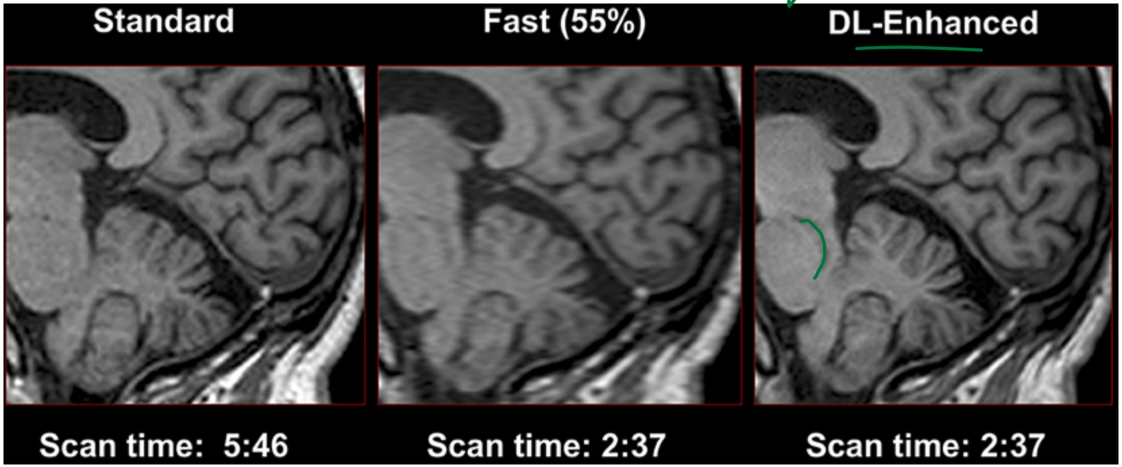
Artifacts → Good → Preserve!

Application: Reducing radiation in CT scans

1. **Interesting CT example:** Pass in low-dose CT scan as input and regular dose CT scan as output. What does the model learn?
2. Study showed artifacts in low dose CT were removed after passing through the CNN encoder-decoder trained on this data
3. **Super-resolution:** Can use generic super resolution methods as well to increase resolution of CT image for better diagnosis.

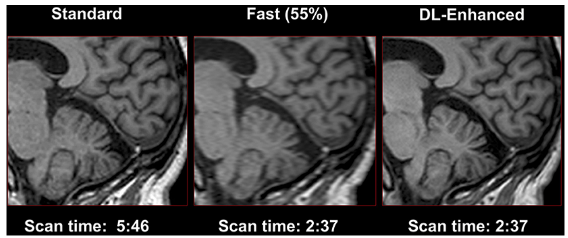
Super-resolution of MRI scans

3T-MRI scans are faster but low resolution, 7T-MRI scans are slower but high resolution. More time = More exposure to radiation!



– Save time
– Save radiation

Breakout 2 Discussion



Describe a DL model for Super-resolution

What Deep Learning Model Architecture would be suitable and perform well for super-resolution of fast MRI scans? Discuss the components of the arch, its inputs and outputs.

Input:- Fast MRI Image
output:- Standard MRI
Arch:- CNN Encoder-Decoder

Deep Learning Challenges for Imaging

1. Ethical considerations in diagnostics with DL

with an AI
→ people ask questions??

Deep Learning Challenges for Imaging

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2. Trust issues?

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5. Need for big data with DL vs costs and feasibility of data acquistion!
6. Data Augmentation. Pros and Cons??

References

1. Variability in diagnostic error rates of 10 MRI centers performing lumbar spine MRI examinations on the same patient within a 3-week period. 2017
2. Applications of Deep Learning to Neuro-Imaging Techniques. 2019