Artificial Intelligence In Medicine Application and Limitation

4/3AFWAnPqNn54D1AAEKPXeK6el7RknUNWvzoEk8
L78JJriNDOWPNnWGU

By Morteza Homayounfar

Content

Part 1: AI (45 min)

- Introduction to Neural Networks
  - Multilayer perceptron
  - Convolutional neural networks
  - Recurrent neural networks
  - Popular architectures
- Introduction to Keras and Tensorflow
  - Running a simple code

Content

Part 2: MED (30 min)

- Introduction to Medical data
  - Images
    - CT- scan images
    - MRI and FMRI
    - Ultrasound
  - Signals
    - EMG
    - EEG
    - ECG

Content

Part 3: AI in MED – applications (60 min)

- Lung cancer detection using deep learning
- Motion correction of (f)MRI images using deep learning
- Breast cancer detection in ultrasound
- Infection detection in COVID-19 cases
- Wearable Sensors in Digital Health (Parkinson)
- Wearable Sensors in Digital Health (Active prosthesis)

Content

Part 4: Federated learning & project – limitations (15 min)

- Limitation No.1: Privacy challenge
  - Project No.1. Federated learning
- Limitation No.2: limited dataset challenge
  - Project No.2. Unet based feature engineering

1. AI

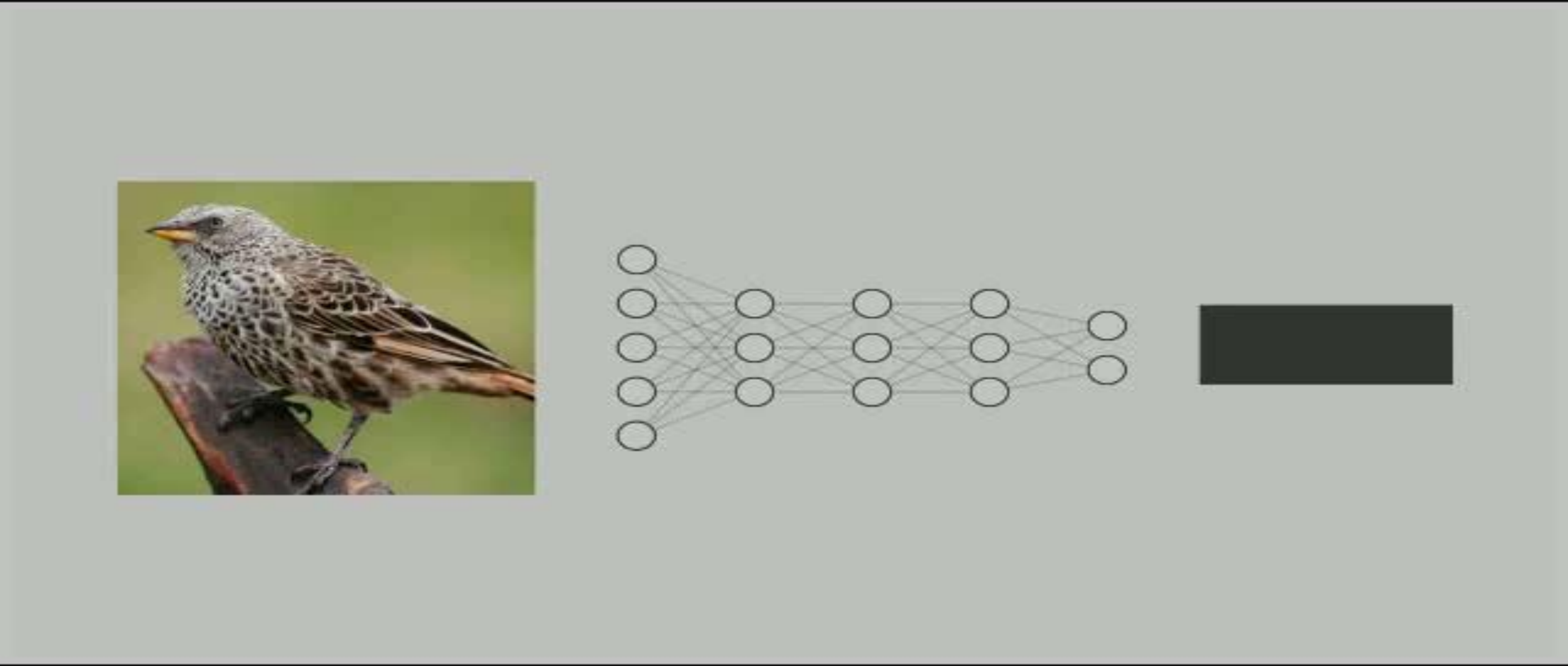
→ **Introduction to Neural Networks**

Multilayer perceptron, Convolutional neural networks, Recurrent neural networks, Popular architectures

→ **Introduction to Keras and Tensorflow**

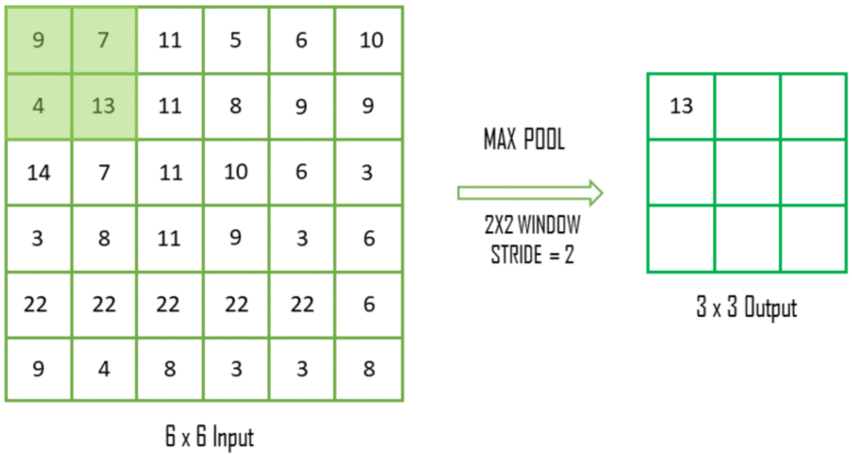
Running a simple code

Main concept! How NNs work?



[TED talk: https://www.ted.com/talks/blaise_aguera_y_arcas_how_computers_are_learning_to_be_creative](https://www.ted.com/talks/blaise_aguera_y_arcas_how_computers_are_learning_to_be_creative)

Filters in CNNs



Q1:

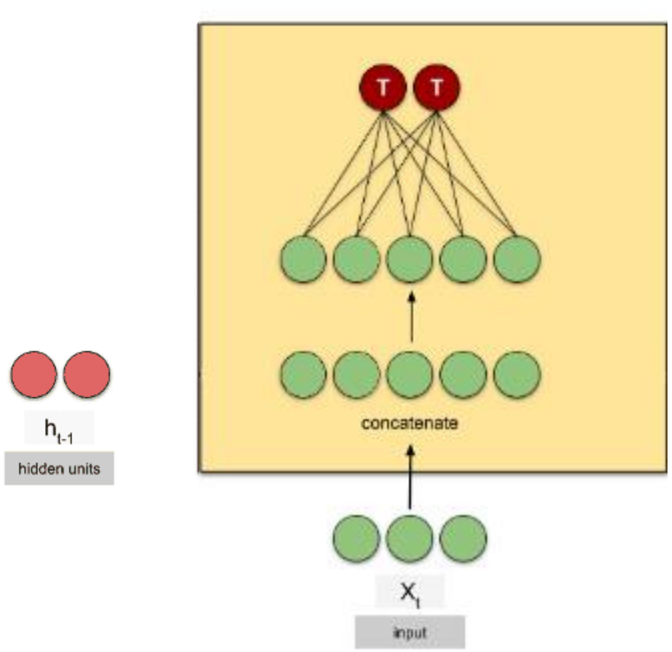
Is it important to change the filters (conv or pooling) behavior based on the inputs?

Q2:

Can we use CNNs instead of RNNs for sequential data?

https://cs231n.github.io/convolutional-networks/

MLPs vs RNNS



https://towardsdatascience.com/animated-rnn-lstm-and-gru-ef124d06cf45

Q3:

How we can use RNNs for image data?

Techniqal view

(برای شبکهٔ پرسپترون تک‌لایه، با نورون‌هایی با تابع غیر خطی پیوسته)

فرضیات اولیه:

n	تعداد نرون‌ها	m	بعد بردارهای ورودی
P	تعداد نمونه‌های تعلیم	p	شمارندهٔ نمونه‌های تعلیم
W	ماتریس n×(m+۱) وزن‌ها	k	شمارندهٔ دفعات تعلیم همهٔ نمونه‌ها
$\bar{d}$	خروجی مطلوب	$f(Y)=\frac{1}{1+e^{-Y}}$	تابع غیر خطی نورون

گام ٤ : اصلاح وزن‌ها:

$$\Delta W \leftarrow \eta \bar{x}^T * [(\bar{d}_p - \bar{y})\bar{y}(1-\bar{y})] + \alpha \Delta W$$

$$W \leftarrow W + \Delta W$$

گام ٥ : محاسبهٔ خطای جمعی دورهٔ تعلیم:

$$E \leftarrow E + \tfrac{1}{2}\sum_{j=1}^{n}(d_j - y_j)^2$$

گام ٦ :اگر p<P ، $p \leftarrow p+1$ و به گام ۳ برو، در غیر این صورت به گام ۷ برو.

گام ۷ : دورهٔ تعلیم کامل شده است.

اگر $E < E_{max}$ ، تعلیم به پایان رسیده است. مقدار k ، وزن‌ها و E را به خروجی بفرست.

اگر $E \geq E_{max}$ ، قرار بده: $E \leftarrow 0;\ \ p \leftarrow 1;\ \ k \leftarrow k+1$

و دورهٔ جدید تعلیم را با رفتن به گام ۳ آغاز کن.

Techniqal view

P : تعداد نمونه‌های دادگان تعلیم

p : شمارندهٔ نمونه‌های دادگان تعلیم ($p = 1,2,\ldots,P$)

k : شمارندهٔ دفعات تعلیم تمامی نمونه‌ها

m : تعداد گره‌ها در ورودی، n : تعداد نورون‌ها در لایهٔ پنهان، l : تعداد نورون‌های خروجی

- نورون‌ها با تابع غیرخطی سیگموئید تک‌قطبی : $f(z) = \frac{1}{\;}$

$$E \leftarrow \sum_{q=1}^{l}\left(d_q - z_q\right)^2 + E$$

•**گام ۴** : سیگنال خطای δ_z و δ_y (در لایهٔ خروجی و لایهٔ پنهان) محاسبه می‌شوند:

$$\delta_y : 1 \times n \quad \text{و} \quad \delta_z : 1 \times l$$

$$\delta_{zq} = (d_q - z_q) z_q (1 - z_q) \qquad q = 1,2,\ldots,l$$

$$\delta_{y_j} = y_j (1 - y_j) \sum_{q=1}^{l} \delta_{zq} W_{jq} \qquad j = 1,2,\ldots,n$$

•**گام ۵** : وزن‌های لایهٔ خروجی اصلاح می‌شوند:

$$\begin{cases} \Delta W_{jq} \leftarrow \eta\, y_j \delta_{zq} + \alpha\, \Delta W_{jq} \\ W_{jq} \leftarrow W_{jq} + \Delta W_{jq} \end{cases} \qquad \begin{cases} q = 1,2,\ldots,l \\ j = 1,2,\ldots,n \end{cases}$$

•**گام ۶** : وزن‌های لایهٔ پنهان اصلاح می‌شوند:

$$\begin{cases} \Delta V_{ij} \leftarrow \eta\, x_i \delta_{yj} + \alpha\, \Delta V_{ij} \\ V_{ij} \leftarrow V_{ij} + \Delta V_{ij} \end{cases} \qquad \begin{cases} j = 1,2,\ldots,n \\ i = 1,2,\ldots,m \end{cases}$$

•**گام ۷** : اگر $p < P$:

$p \leftarrow p + 1$ و برو به مرحلهٔ ۲.

وگرنه برو به مرحلهٔ ۸.

•**گام ۸** : دورهٔ تعلیم کامل شده، (مقدار $\sqrt{\frac{E}{Pl}}$ نسبت به k رسم می‌شود.)

اگر $\sqrt{\frac{E}{Pl}} < E_{max}$ ، تعلیم پایان یافته، V و W و k و E را در خروجی بده.

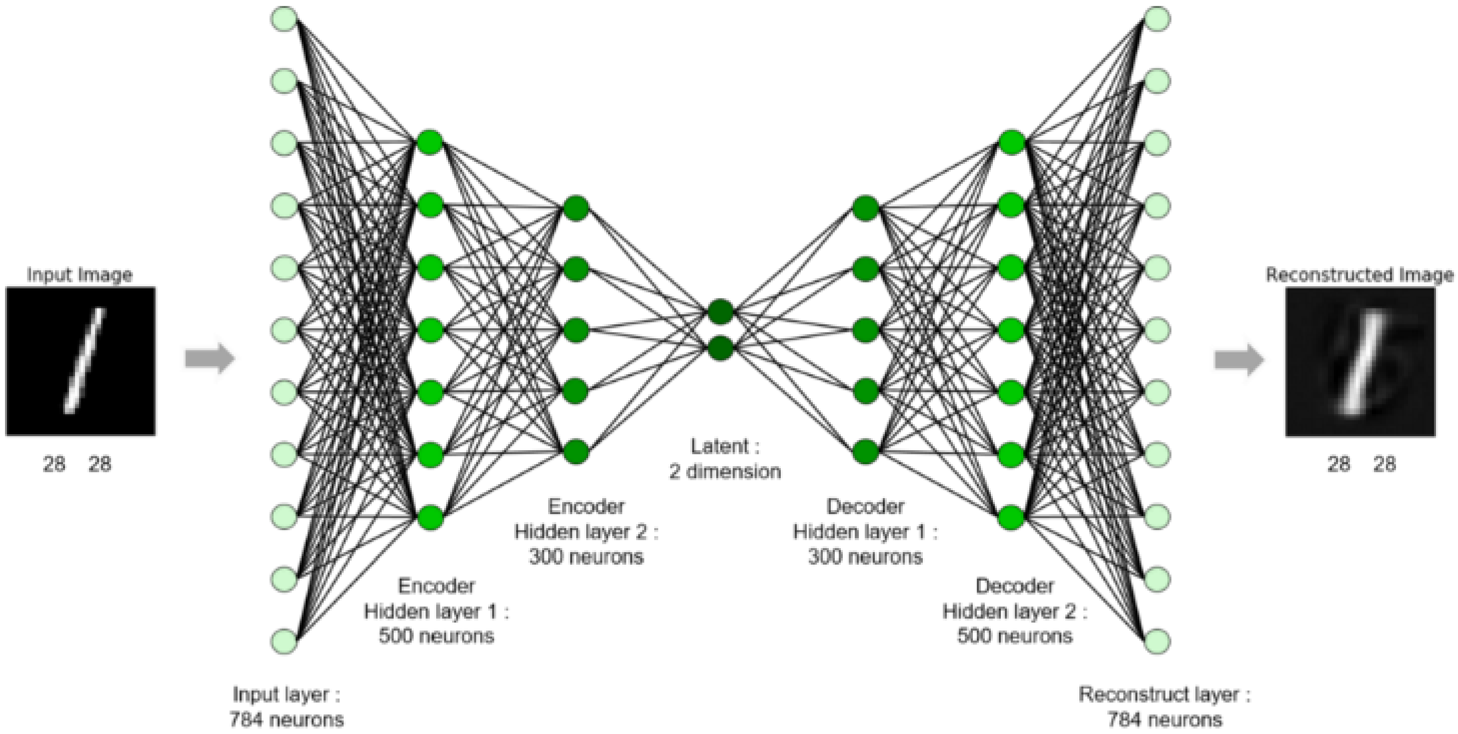
ولی اگر $\sqrt{\frac{E}{Pl}} \geq E_{max}$ ، آنگاه:

$$k \leftarrow k + 1 \quad \text{و} \quad p \leftarrow 1 \quad \text{و} \quad E \leftarrow 0$$

و دورهٔ جدید تعلیم را از مرحلهٔ ۲ مجدداً آغاز کن.

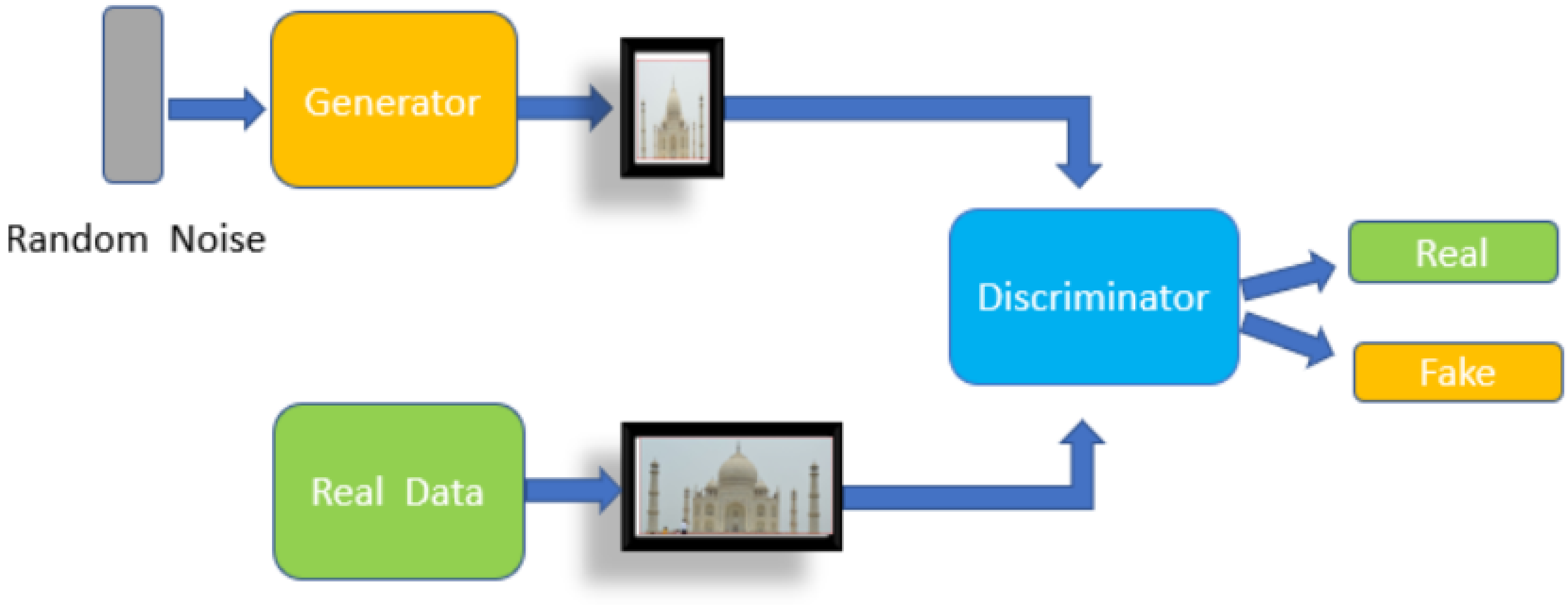
Popular Architectures

AutoEncoder



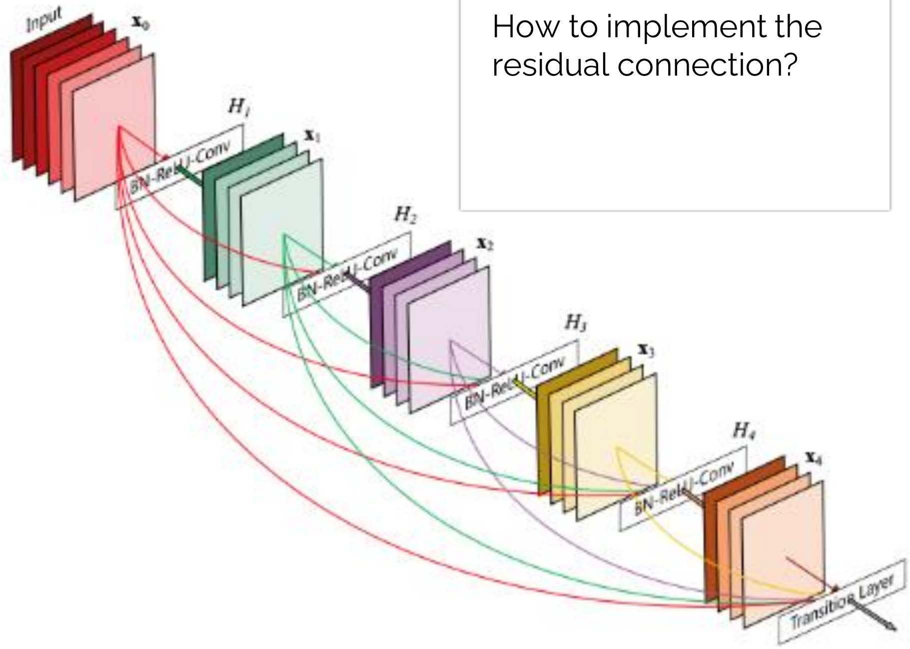
Popular Architectures

GAN



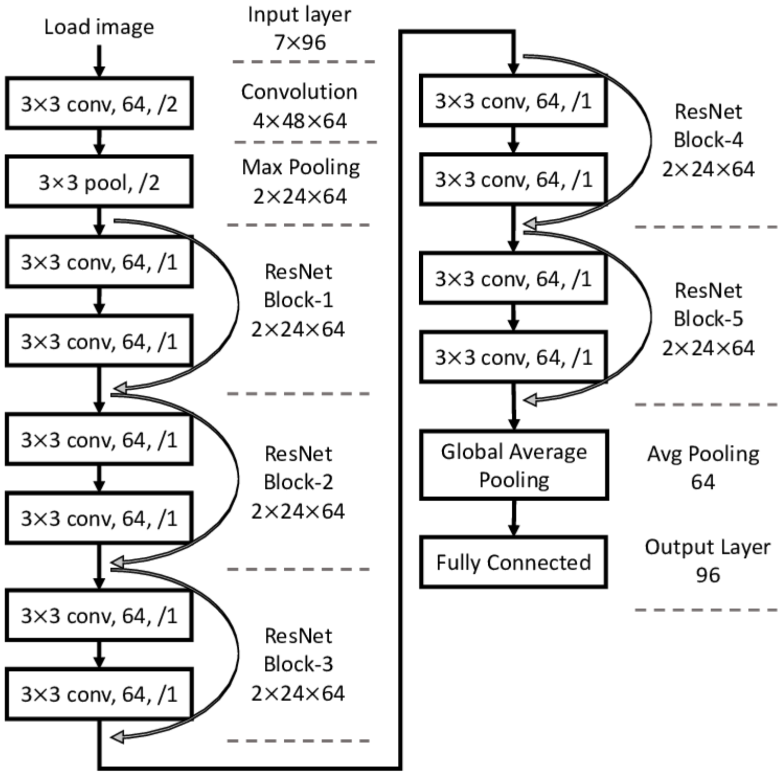
Popular Architectures

Residual blocks



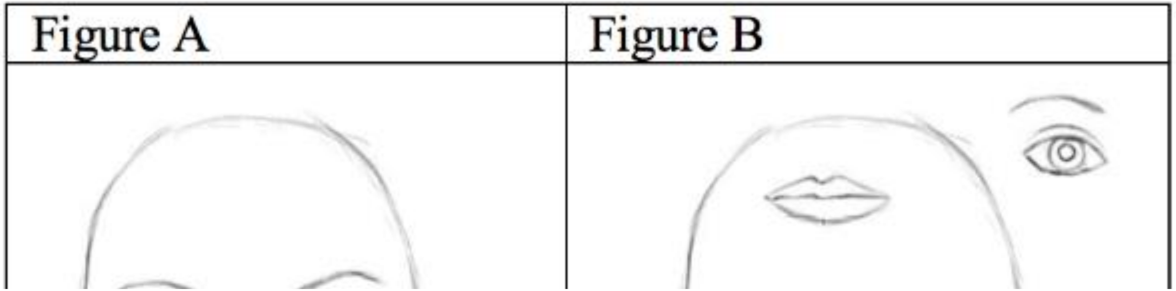
Q4:

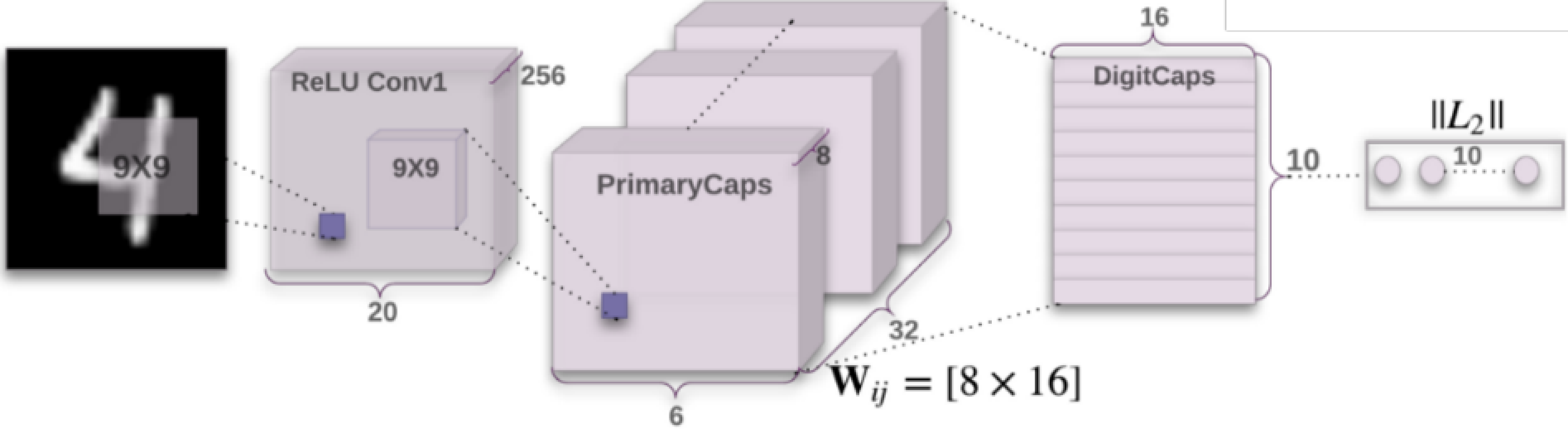
How to implement the residual connection?



Popular Architectures

Capsule network



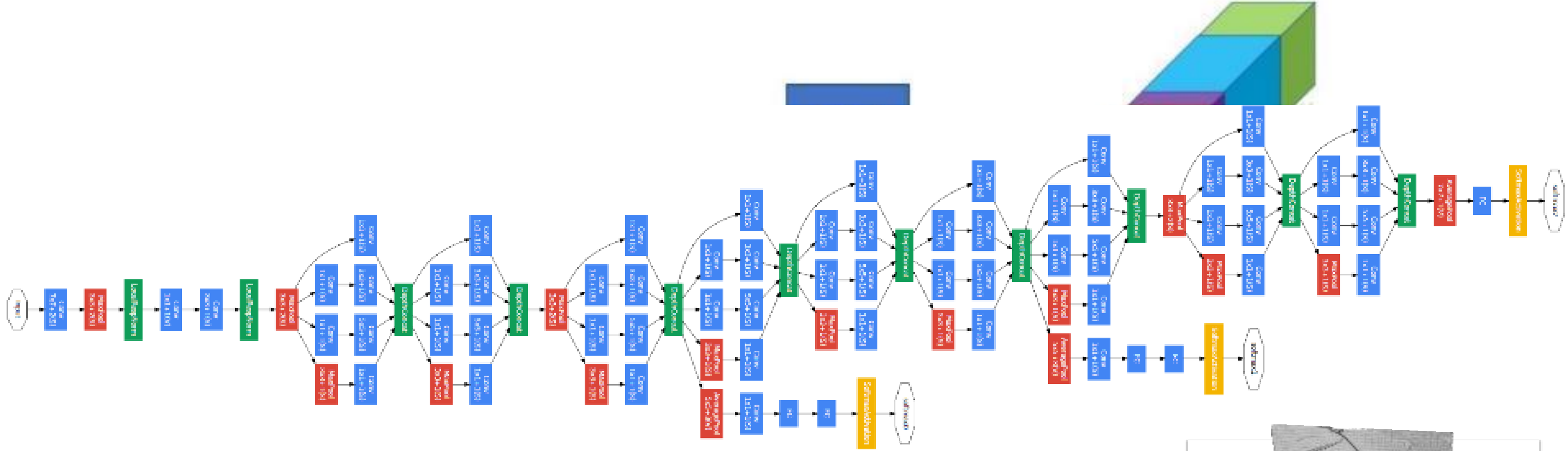


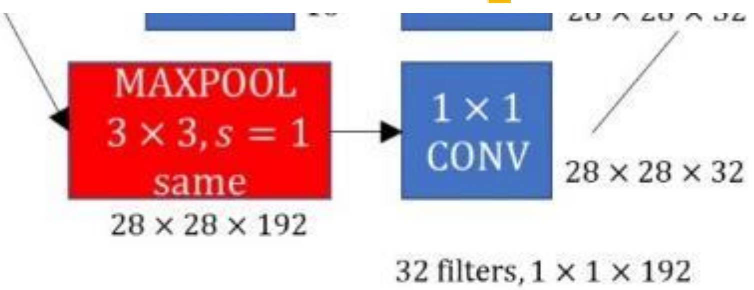
Q5:

What is the main drawback of Capsule network?

Popular Architectures

Inception





Q6:

Why 1×1?

1. AI

- → **Introduction to Neural Networks**

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- → **Introduction to Keras and Tensorflow**

Running a simple code

Frameworks

Keras and tf 1&2

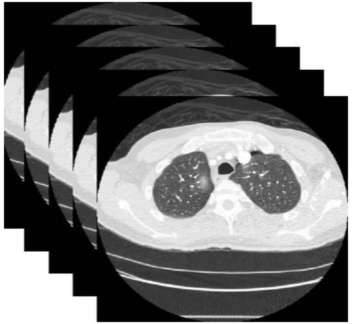
2. Med

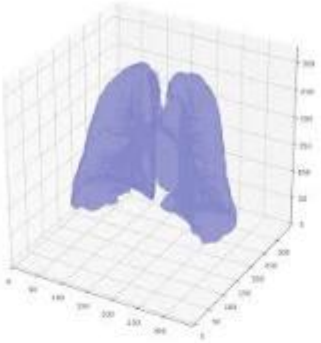
→ **Introduction to Medical data**

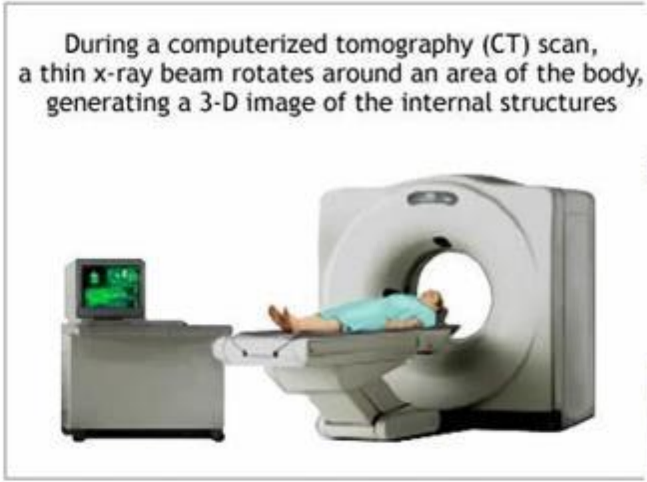
- Images
  - CT- scan images
  - MRI and FMRI
  - Ultrasound
- Signals
  - EMG
  - EEG
  - ECG

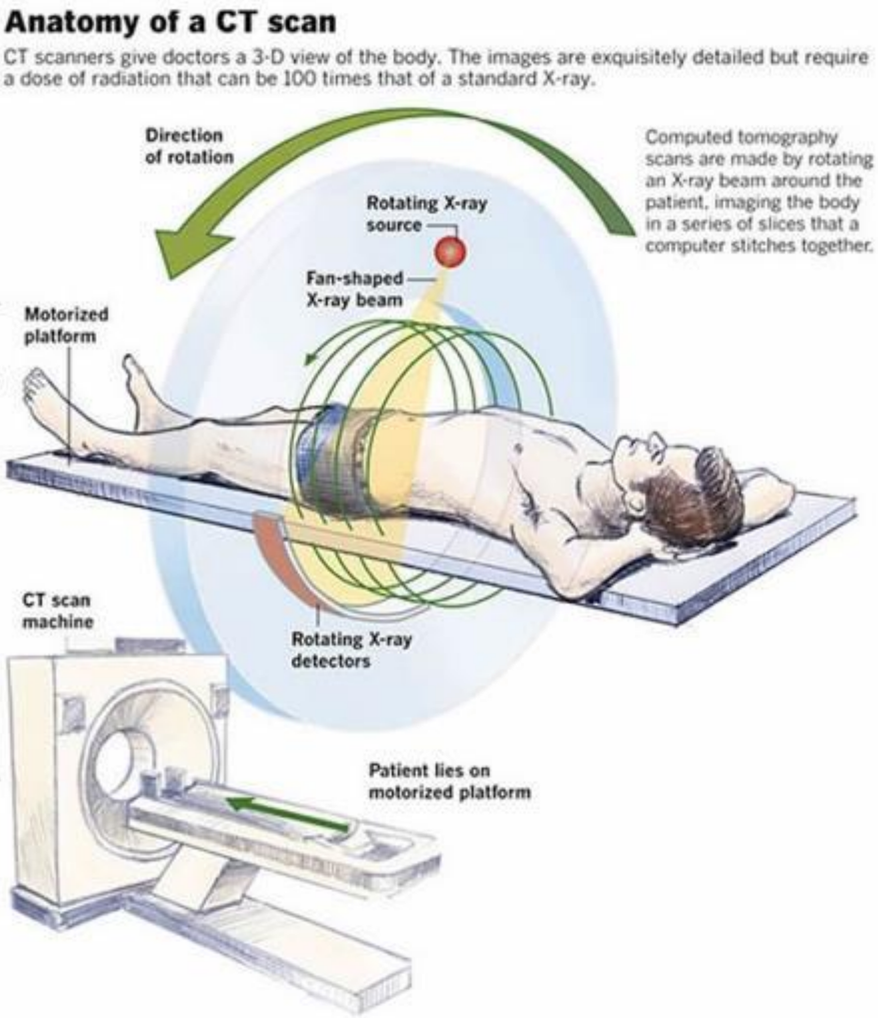
CT-Scan

CT Imaging Overview

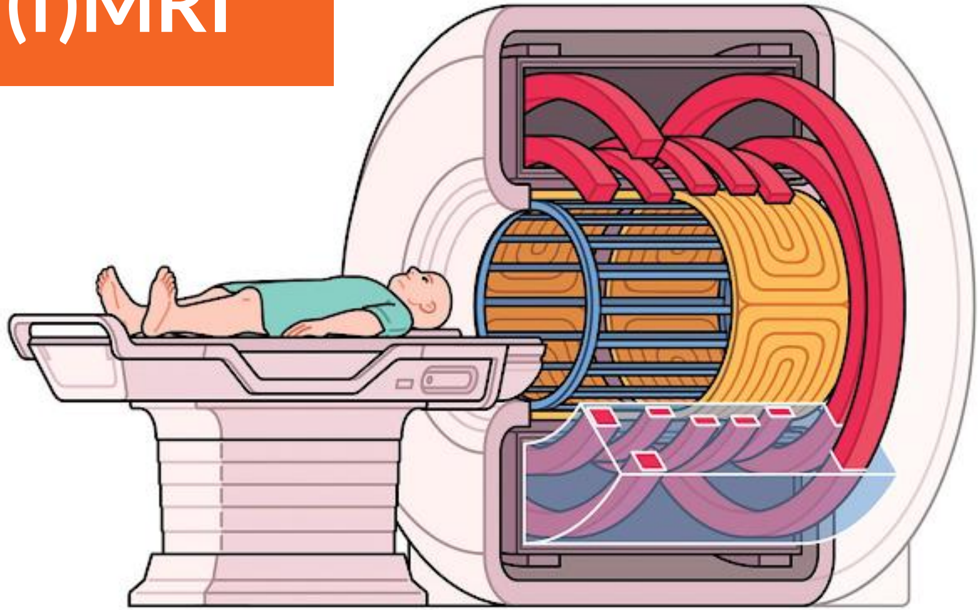


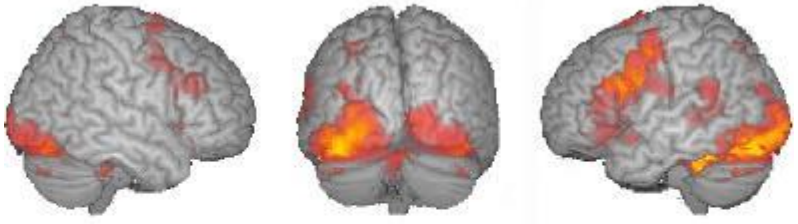


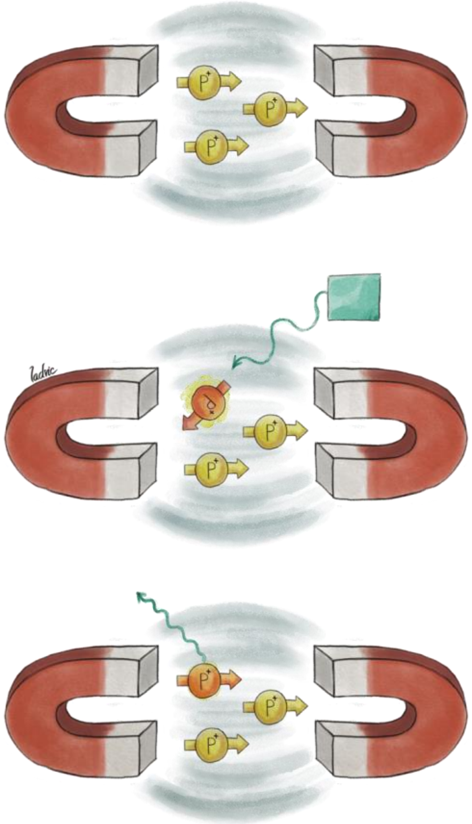




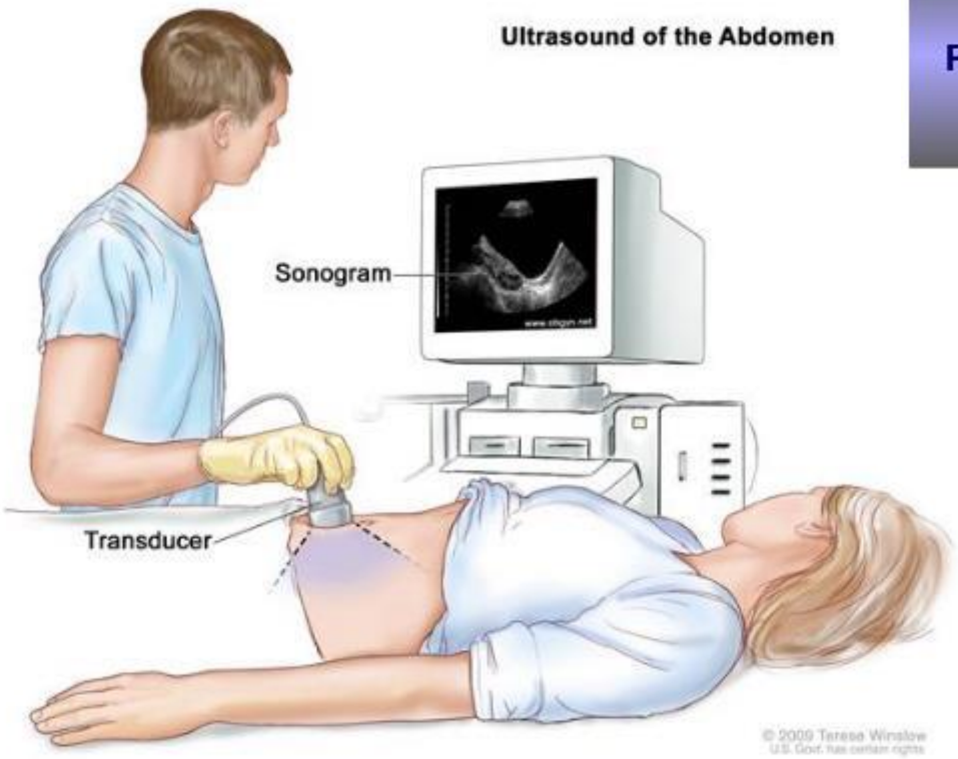
(f)MRI



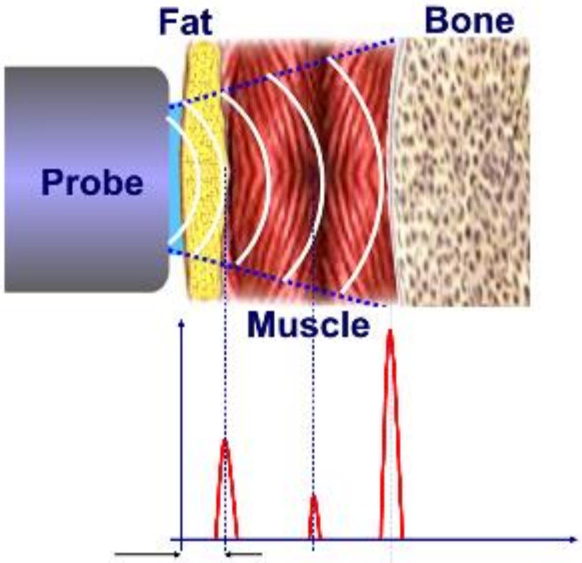




Ultrasound

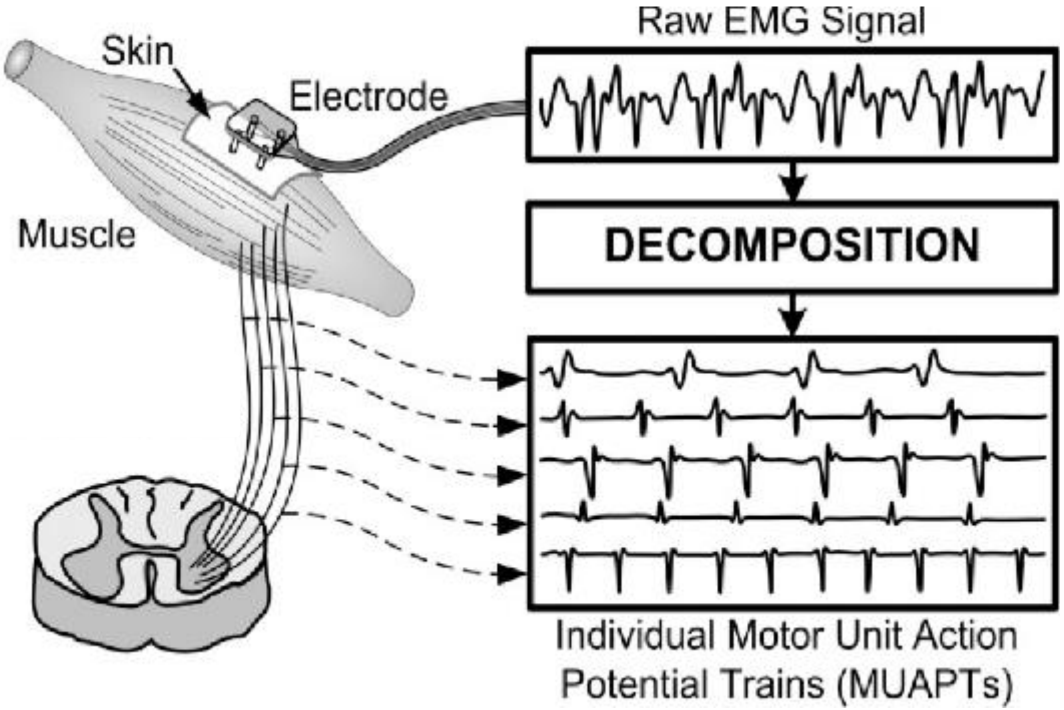


Ultrasound of the Abdomen
Sonogram
Transducer
© 2009 Terese Winslow

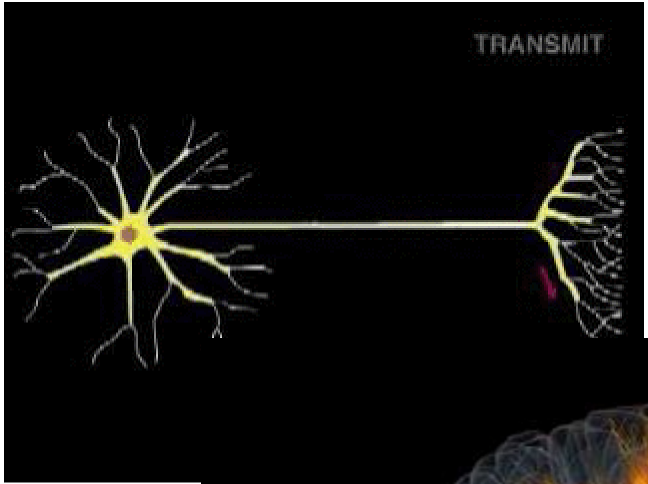


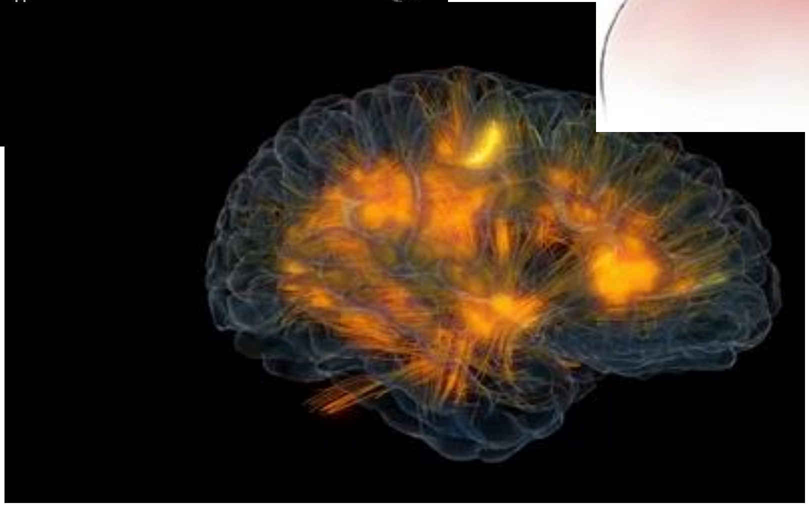
Fat
Bone
Probe
Muscle

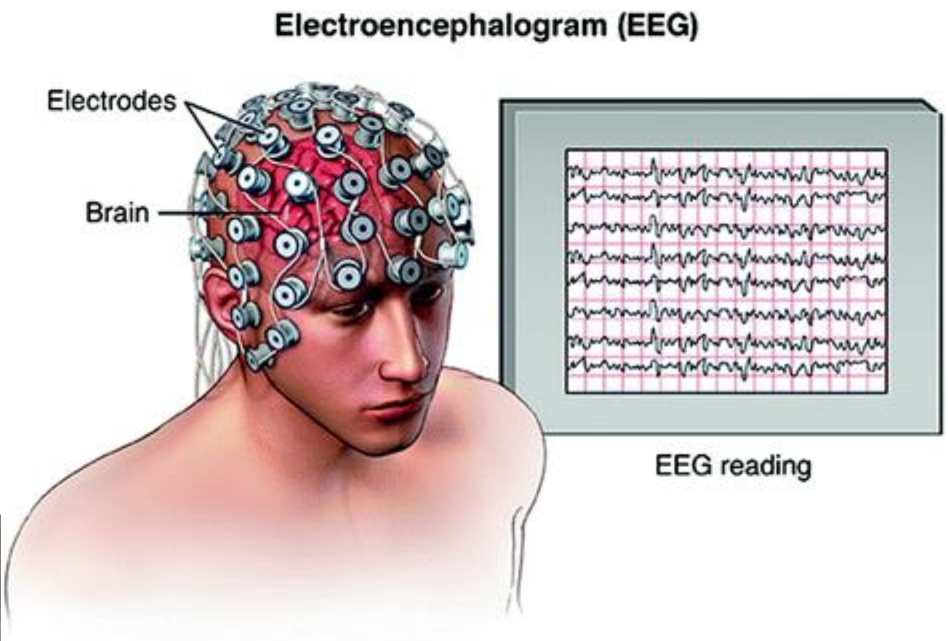
EMG


Skin
Electrode
Muscle
Raw EMG Signal
DECOMPOSITION
Individual Motor Unit Action
Potential Trains (MUAPTs)

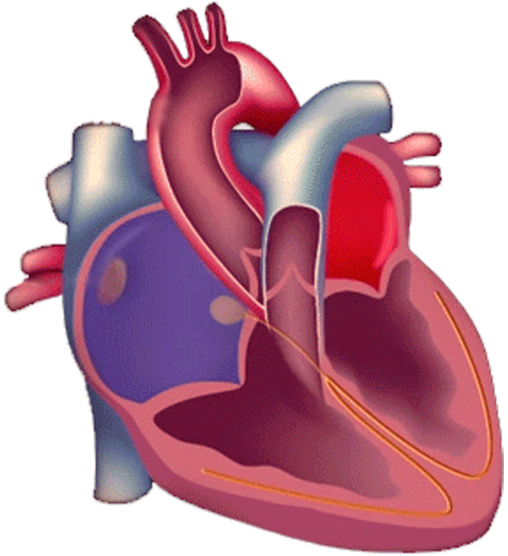
EEG

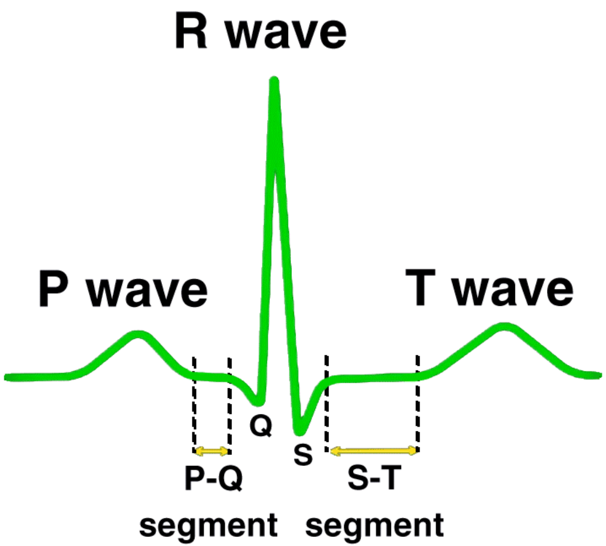

TRANSMIT




Electroencephalogram (EEG)
Electrodes
Brain
EEG reading

ECG





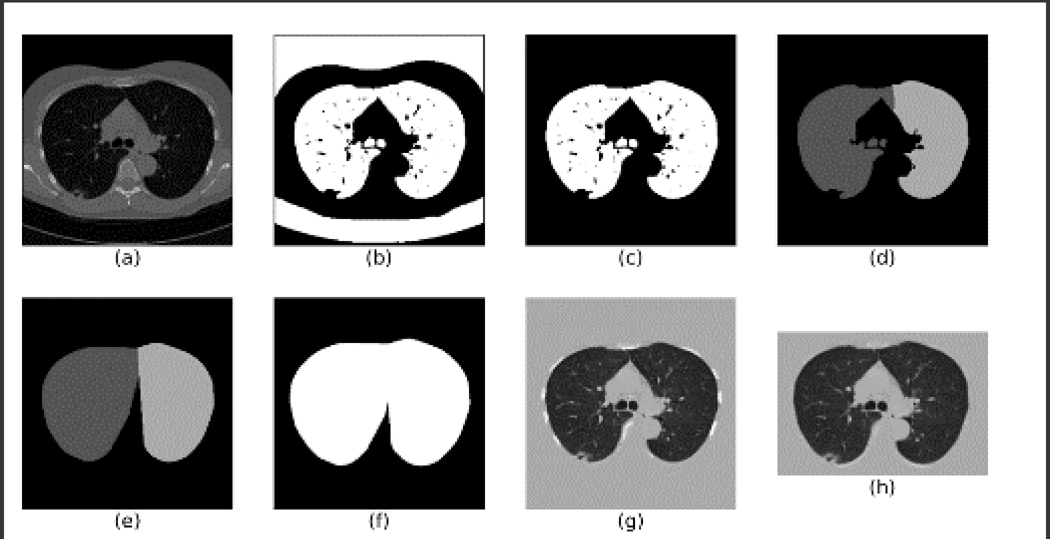
3. AI in MED - applications

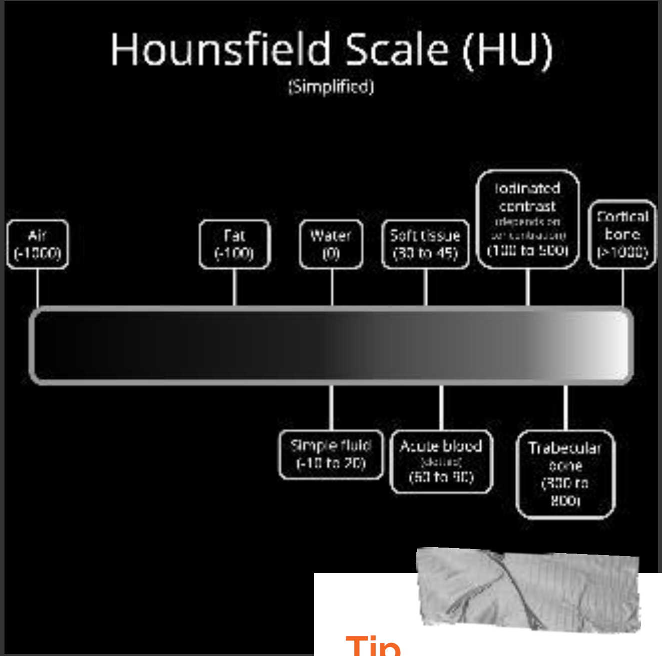
Review related papers in AI in MED

- **Lung cancer** detection using deep learning
- **Motion correction of (f)MRI images** using deep learning
- Breast cancer detection in **ultrasound**
- Infection detection in **COVID-19** cases
- Wearable Sensors in Digital Health (**Parkinson**)
- Wearable Sensors in Digital Health (**Active prosthesis**)

— Lung cancer

How to preprocess CT-scan data?





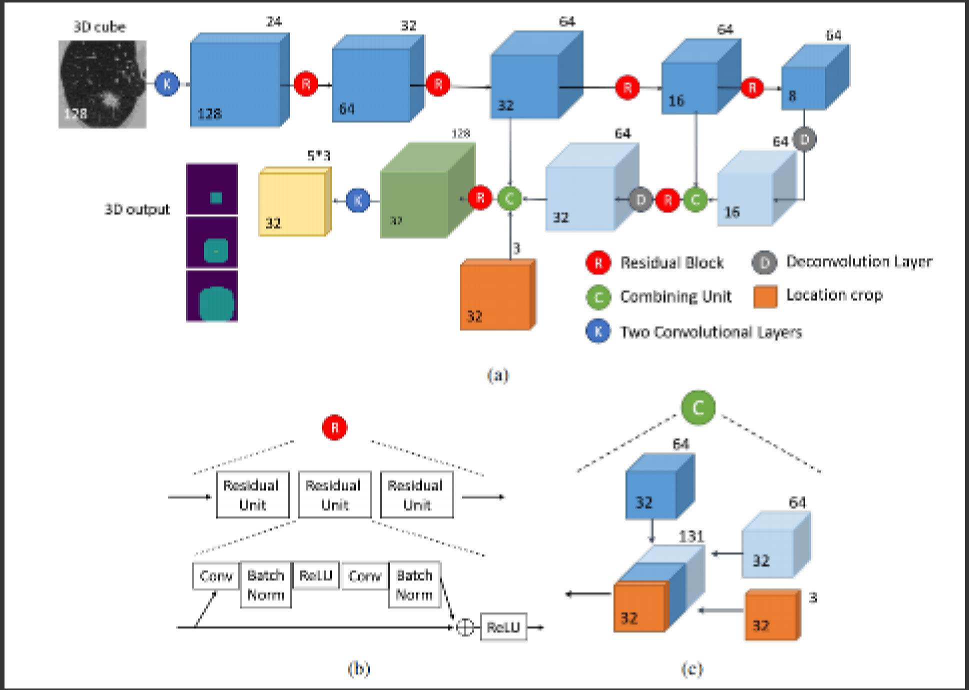
Tip

Lung segmentation using HU thresholding is not recommended!

Use a more intelligent way instead.

[Ream more]()

— Lung cancer models



Tip

Adding medical information (location crop) might be helpful!

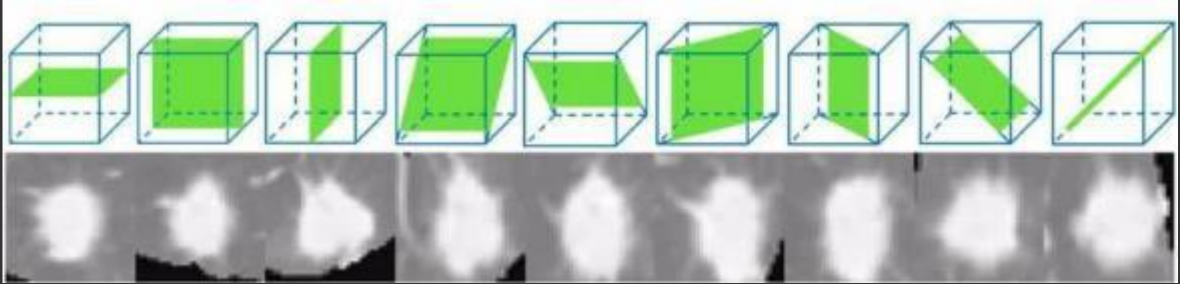
When the input and output of a model are both images, using a U-net based model is recommended.

Residual connection to train a deep model is good for avoiding vanishing gradient.

The size of input patches is a sensitive parameter.

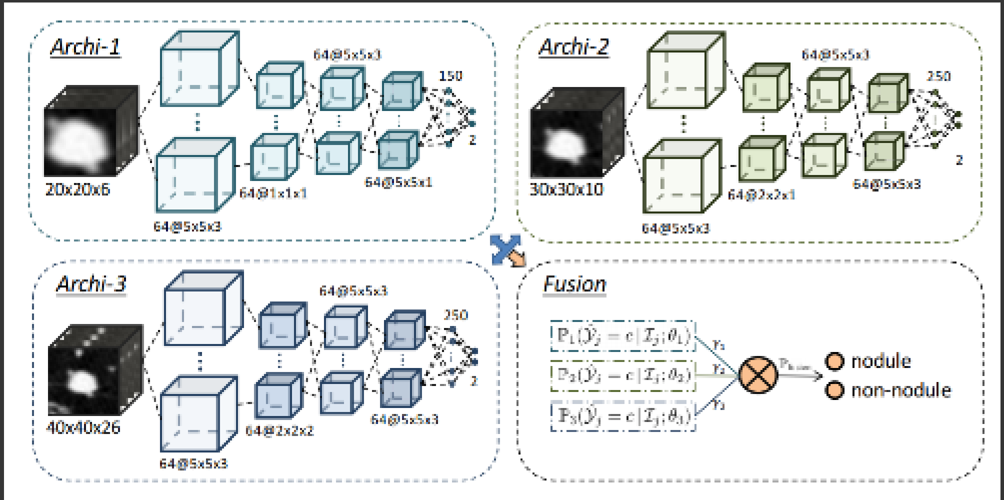
Liao, F., Liang, M., Li, Z., Hu, X., & Song, S. (2019). Evaluate the malignancy of pulmonary nodules using the 3-d deep leaky noisy-or network. *IEEE transactions on neural networks and learning systems*, *30*(11), 3484-3495.

— FP reduction models for lung cancer



Tip

Feature engineering in machine learning is converted to model design in deep learning!



Q

How we can use a network instead of 3 networks?

1- Dou, Q., Chen, H., Yu, L., Qin, J., & Heng, P. A. (2016). Multilevel contextual 3-D CNNs for false positive reduction in pulmonary nodule detection. IEEE Transactions on Biomedical Engineering, 64(7), 1558-1567.

2- Fu, L., Ma, J., Ren, Y., Han, Y. S., & Zhao, J. (2017, March). Automatic detection of lung nodules: false positive reduction using convolution neural networks and handcrafted features. In Medical Imaging 2017: Computer-Aided Diagnosis (Vol. 10134, p. 101340A). International Society for Optics and Photonics.

Limitation & solution

L1. Different size of nodules in lung cancer

L2. High variation in lung's shape of different cases

L3. High false positive rate in lung cancer detection

L4. Large size in inputs (512×512×~300)

S1
Different size of input chunk can improve the result. [Read more]

Q
Is there any other way in model level?

S2
Using a huge dataset to avoid overfitting or learning based on irrelevant features!

Q
Is there anyway in model level?

S3
Using a model to find false positive cases and use it beside of detection model. [Read more]

Q
Any other idea?

S4
- Patch based model.
- Resizing the inputs
- Slice based model

Q
Any other idea?

IDEA!

Using a mixture of anomaly detection and noise reduction tasks using UNET based model.

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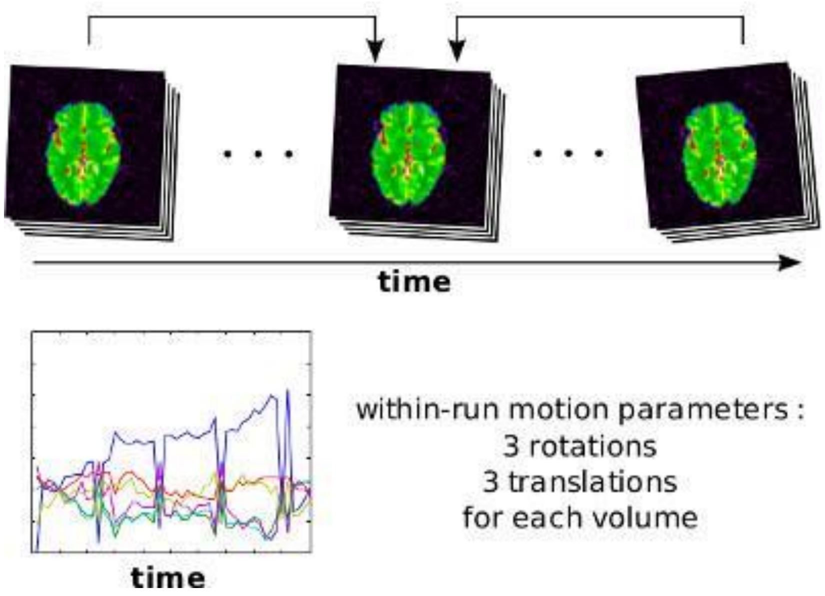
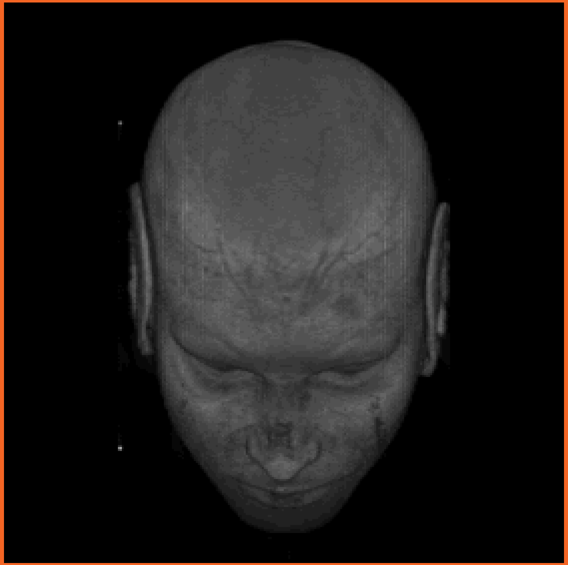
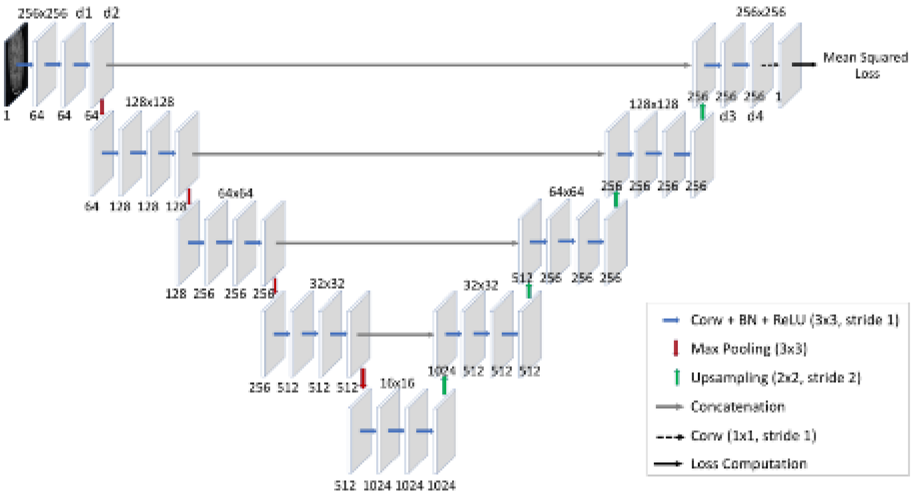
Motion Correction

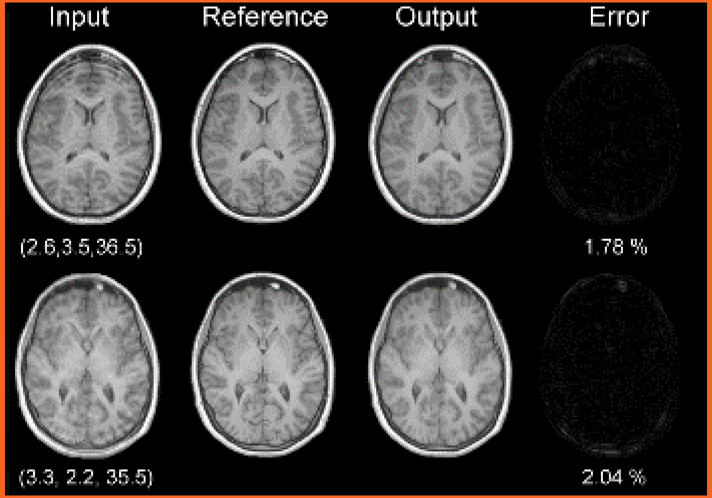
In FMRI





Motion Correction
In FMRI





Q

Ref images get resulted from FSL library. Thus, the best result of deep model is not the perfect one. Can we use an unsupervised model for this?

Pawar, K., Chen, Z., Shah, N. J., & Egan, G. F. (2018). Moconet: Motion correction in 3D MPRAGE images using a convolutional neural network approach. *arXiv preprint arXiv:1807.10831*.

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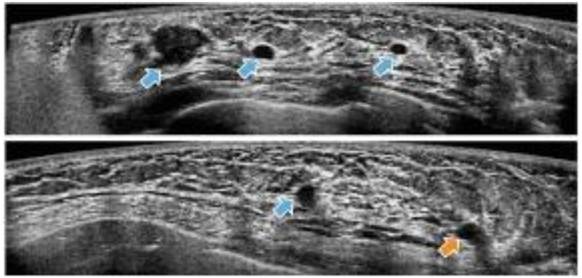
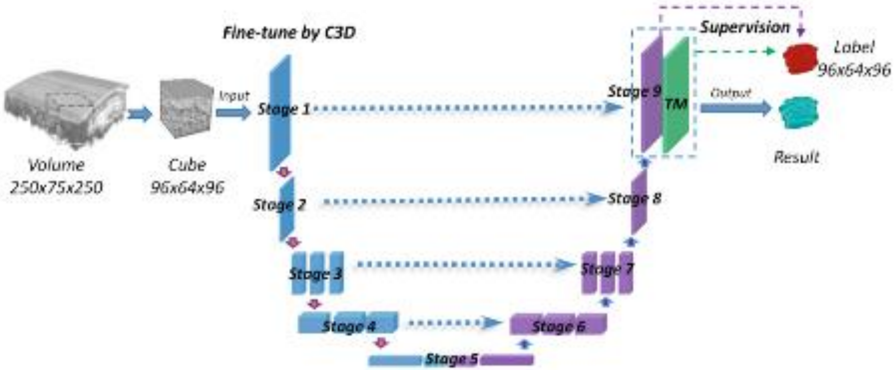
Breast Cancer detection
In Ultrasound





Advantages and Disadvantages

Ultrasound wave is

- safer than other
- Easy to use
- Include high rate of noise

IDEA

- Use registration to improve the noise reduction model

Wang, N., Bian, C., Wang, Y., Xu, M., Qin, C., Yang, X., ... & Ni, D. (2018, September). Densely deep supervised networks with threshold loss for cancer detection in automated breast ultrasound. In International Conference on Medical Image Computing and Computer-Assisted Intervention (pp. 641-648). Springer, Cham.

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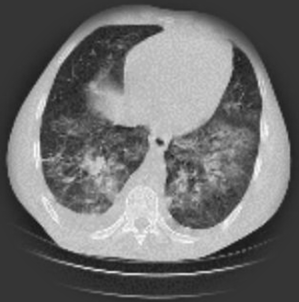
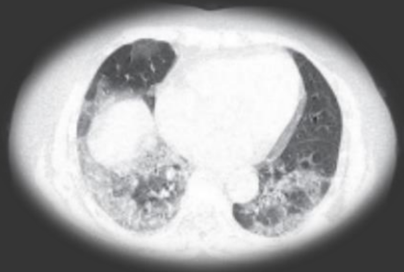
CovidCtNet

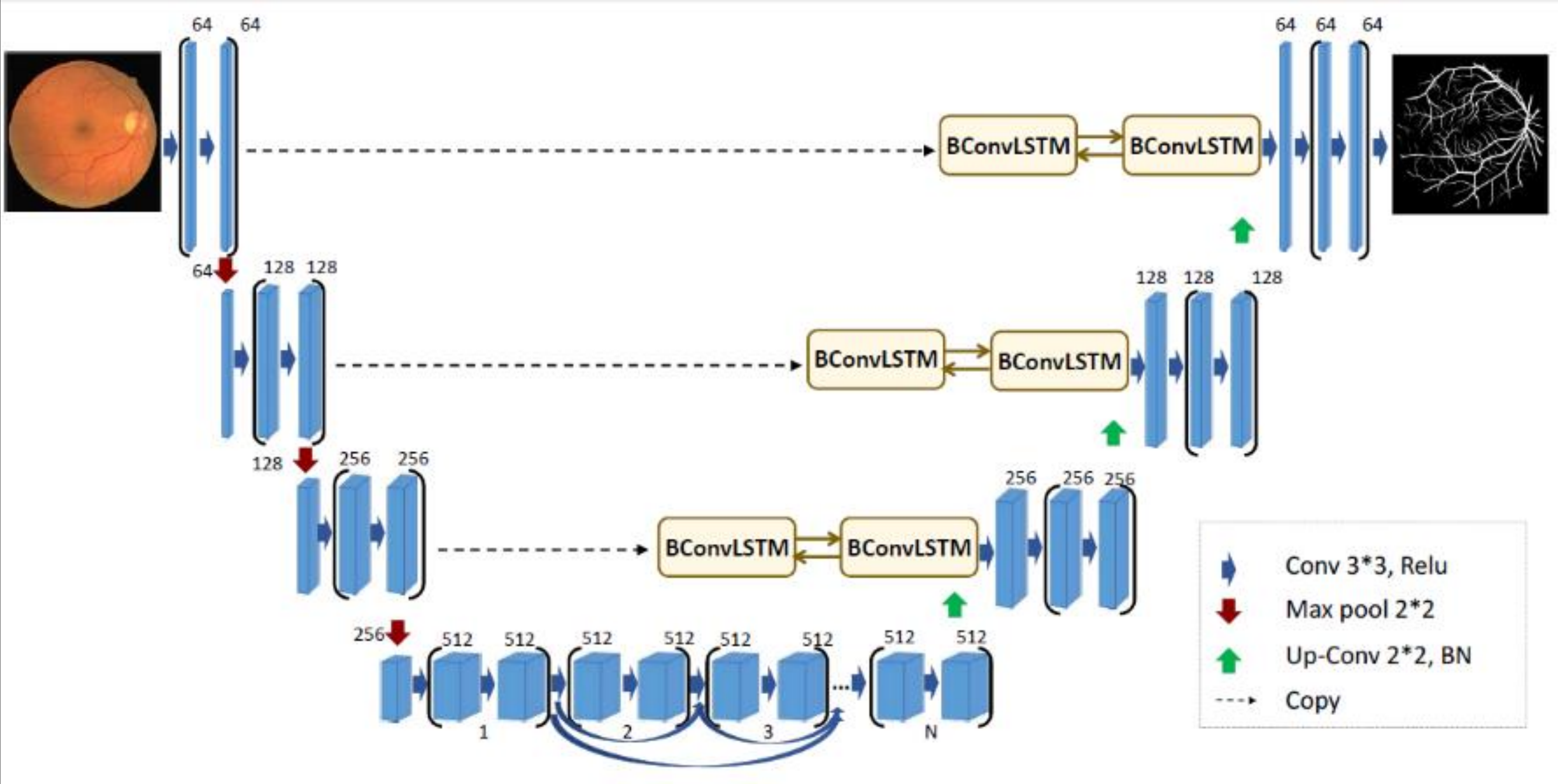




Javaheri, T., Homayounfar, M., Amoozgar, Z., Reiazi, R., Homayounieh, F., Abbas, E., ... & Ghaemi, O. (2020).
Covidctnet: An open-source deep learning approach to identify covid-19 using ct image. arXiv preprint arXiv:2005.03059.

CovidCtNet



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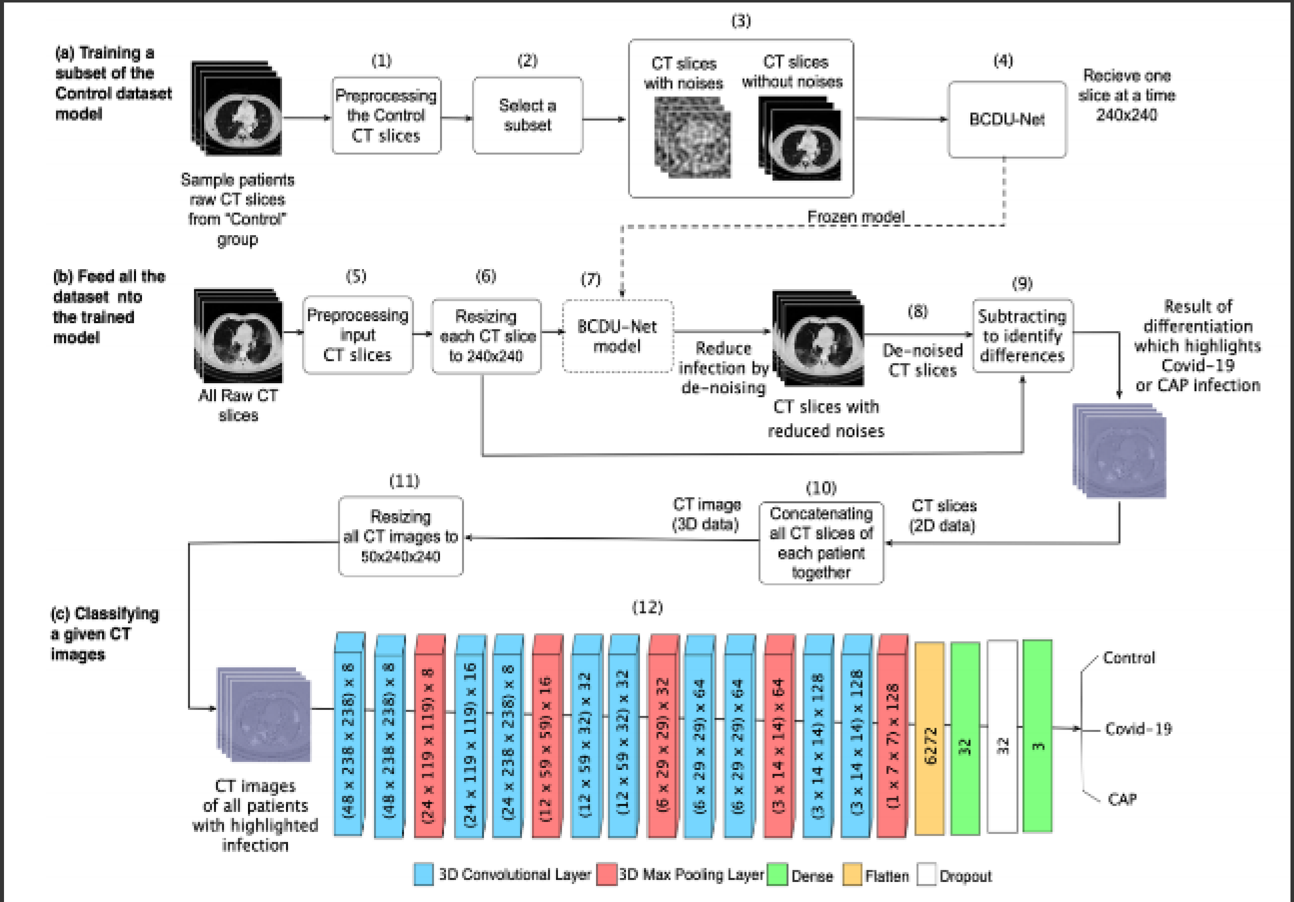
CovidCtNet



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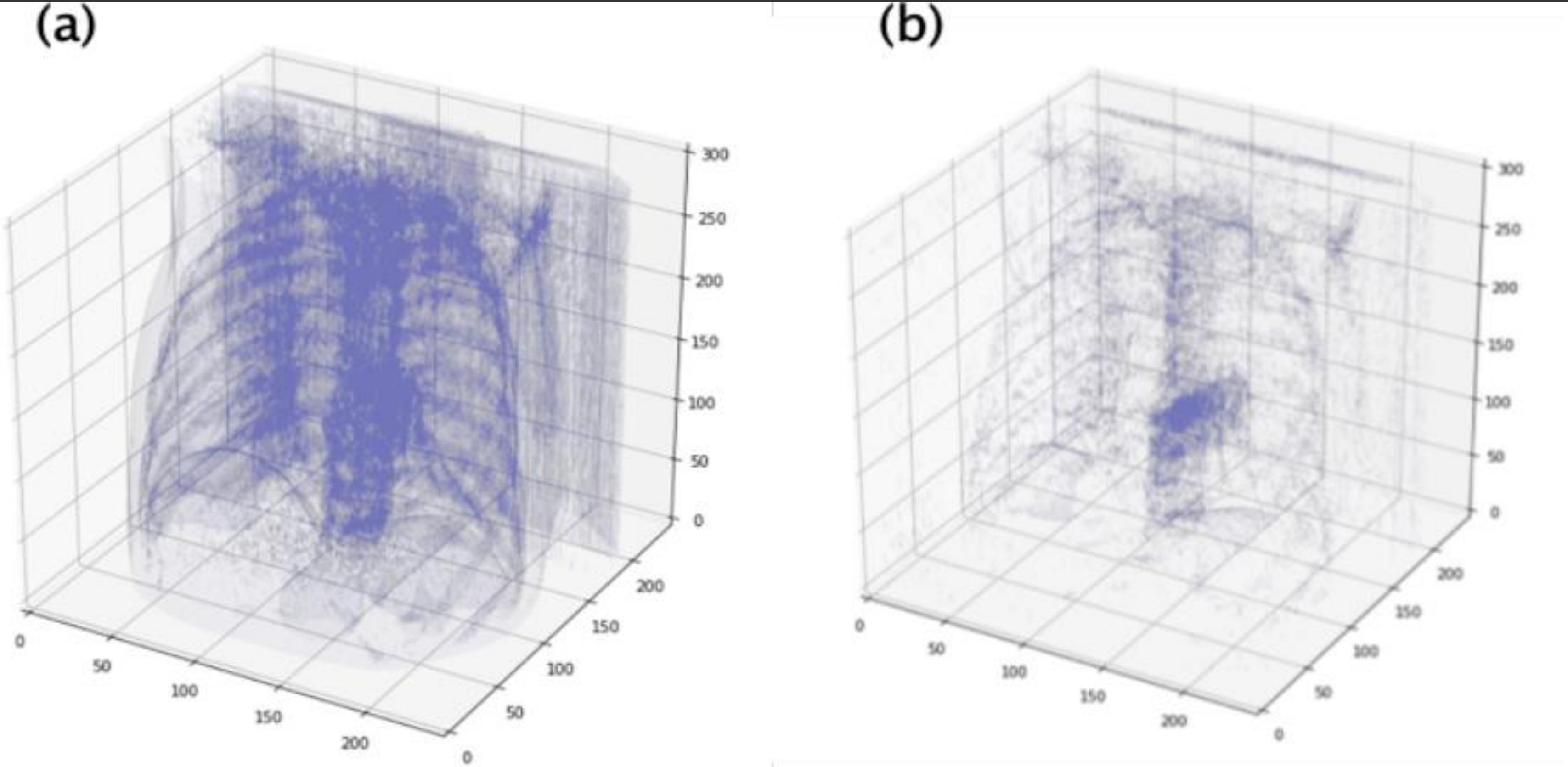

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Limitation & solution

L1. Limited number of data
L2. Extracting infections in CAP cases
L3. Lung segmentation in CAP and COVID cases
L4. Lack of labeled data for infections

S1
Focus on infections

Q
Is there any other unsupervised model for infection extraction?

S4
Use Perlin noise to generate something like infection on CTs

Q
Any other idea?

S3
Using more intelligent way. (need labeled data)

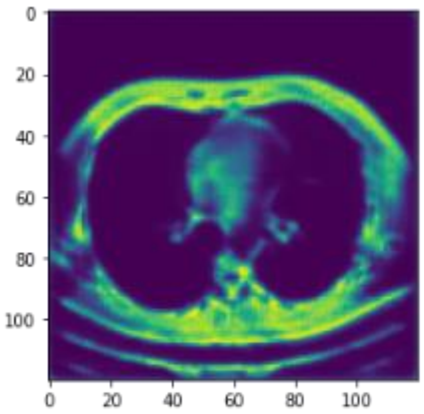
Q
Any other idea?

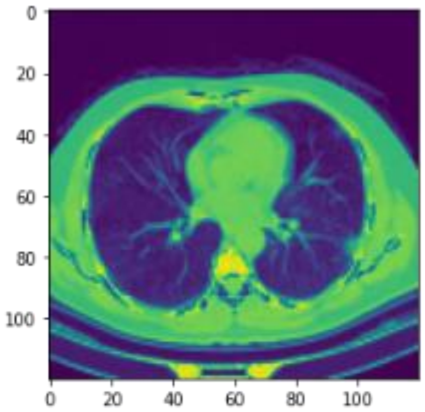
S2
-
We consider them as Non-Covid cases and omit for this stage of the work

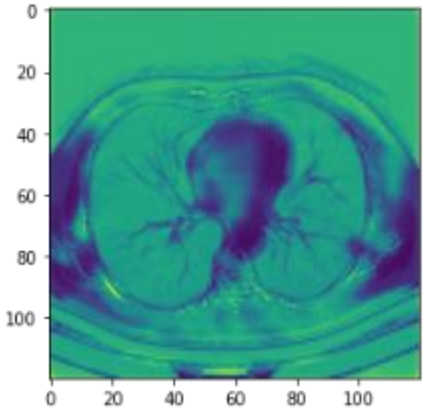
Q
Is there anyway in model level or data level?

Let's code

BCDUNET 4 COVID-19







3. AI in MED - applications

Review related papers in AI in MED

- → **Lung cancer** detection using deep learning
- → **Motion correction of (f)MRI images** using deep learning
- → **Breast cancer** detection in ultrasound
- → Infection detection in **COVID-19** cases
- → Wearable Sensors in Digital Health (**Parkinson**)
- → Wearable Sensors in Digital Health (**Active prosthesis**)

Wearable Sensors in Digital Health

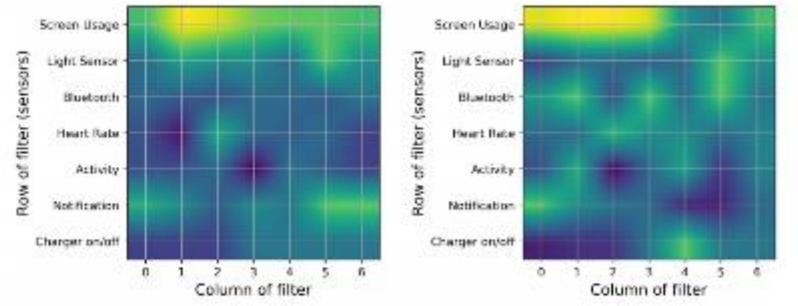
Challenges

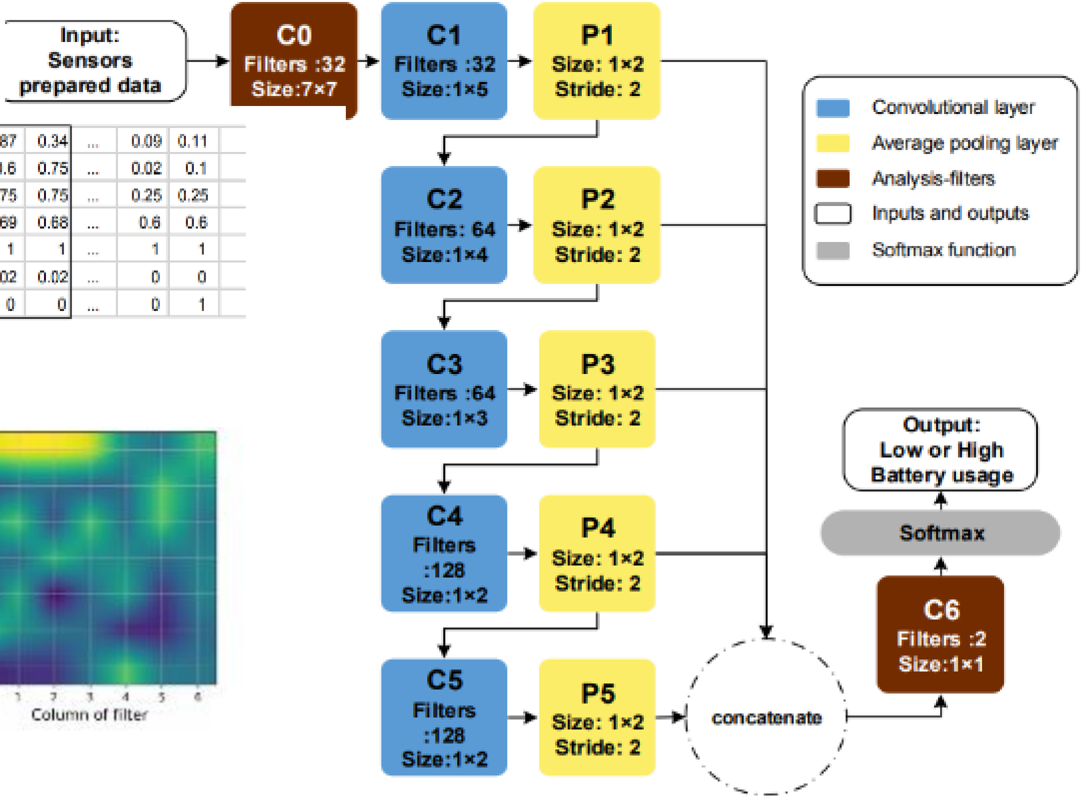
- In-device machine learning
- Data compression
- Federated learning
- Battery utilization
- Explainable models

Wearable Sensors in Digital Health

Input window preparing

screen usage	0.37	0.19	0.23	0.12	0.32	0.1	0.87	0.34	...	0.09	0.11
light sensor	0.01	0.022	0.1	0.03	0.09	0.3	0.6	0.75	...	0.02	0.1
activity	0.25	1	1	0.5	0.5	0.5	0.75	0.75	...	0.25	0.25
heart rate	0.67	0.72	0.74	0.77	0.79	0.8	0.69	0.68	...	0.6	0.6
bluetooth	1	1	1	0	0	1	1	1	...	1	1
notification	0.02	0.02	0	0	0.06	0.06	0.02	0.02	...	0	0
charger on/off	0	0	0	1	1	1	0	0	...	0	1





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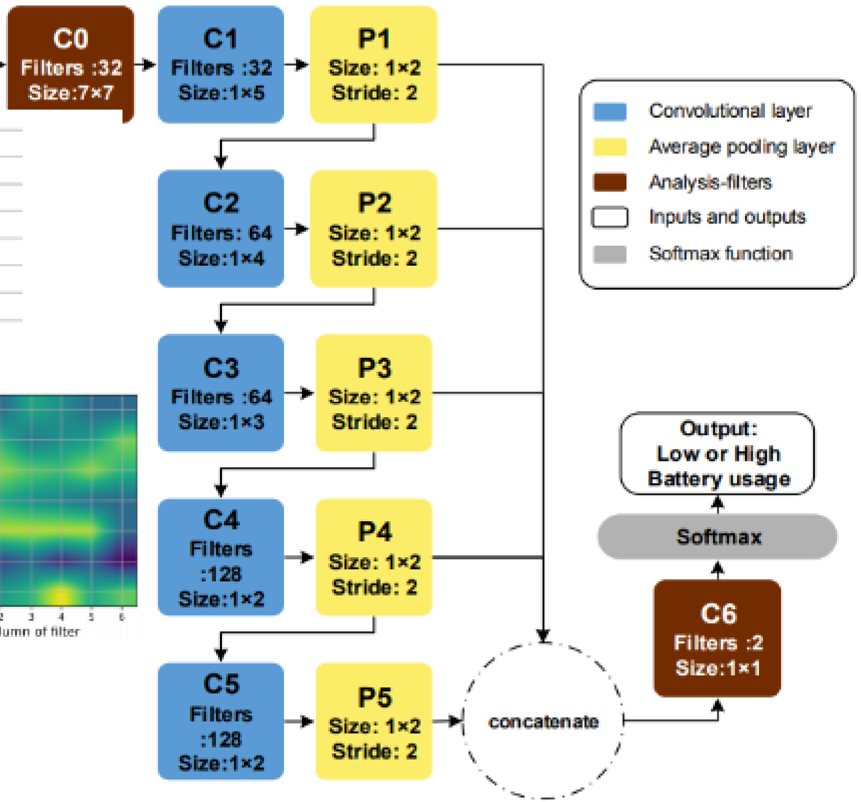
Wearable Sensors in Digital Health



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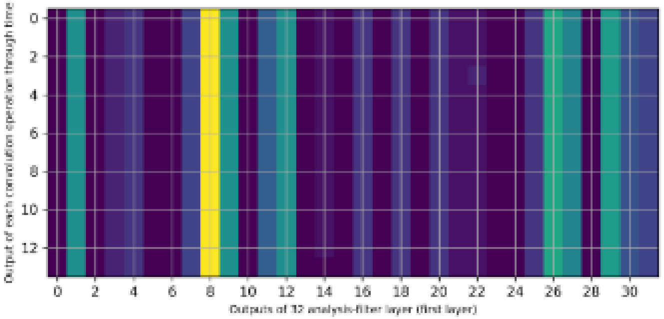

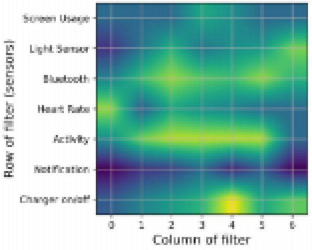

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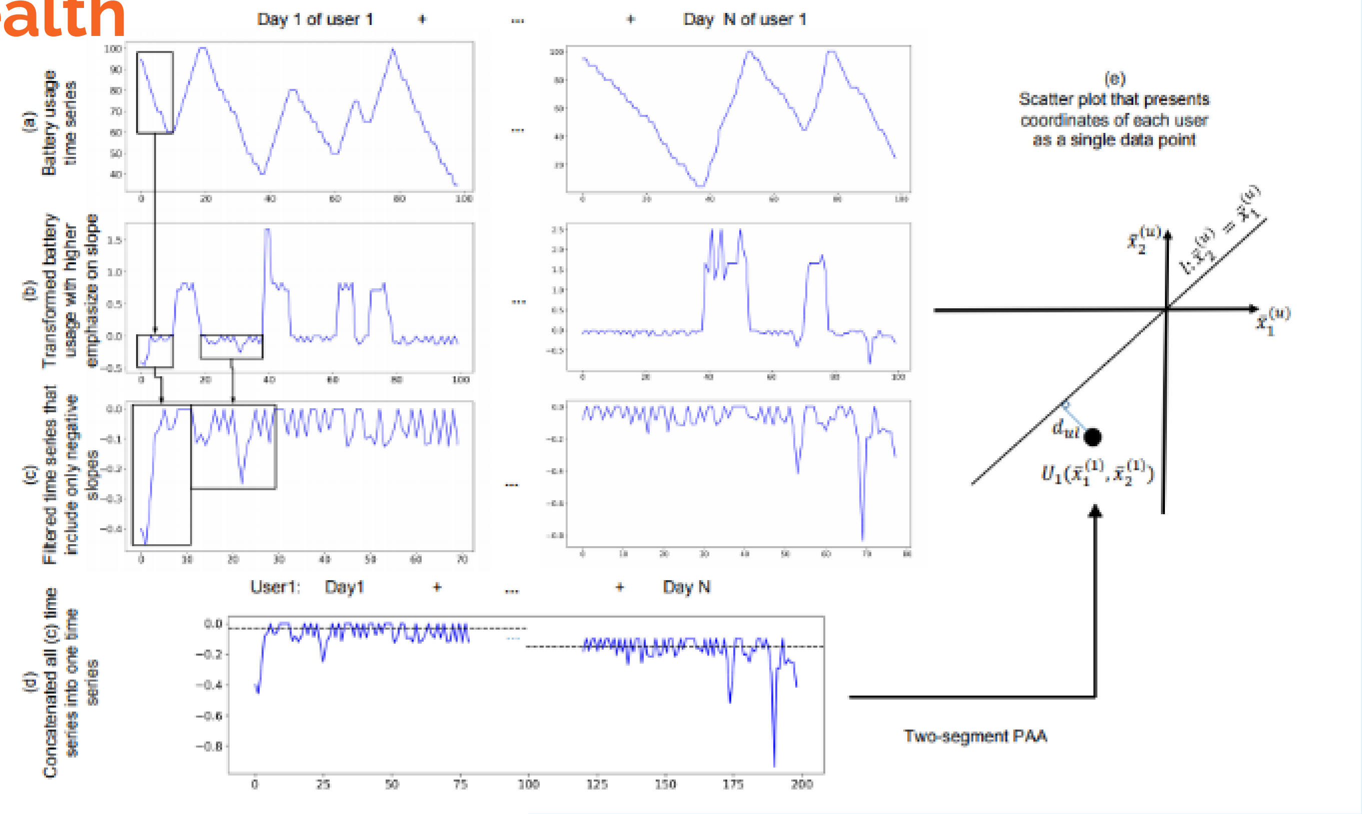
Wearable Sensors in Digital Health



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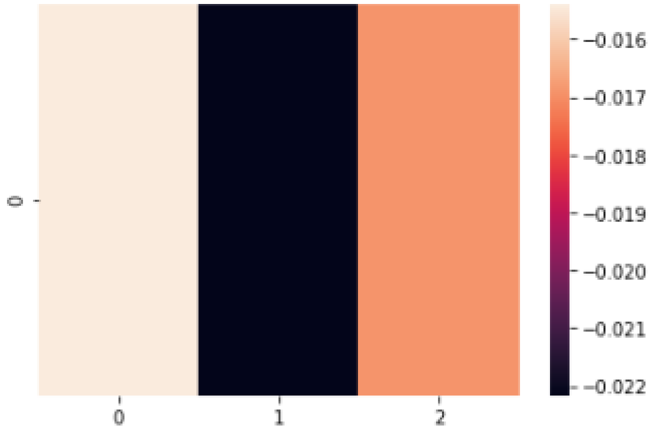
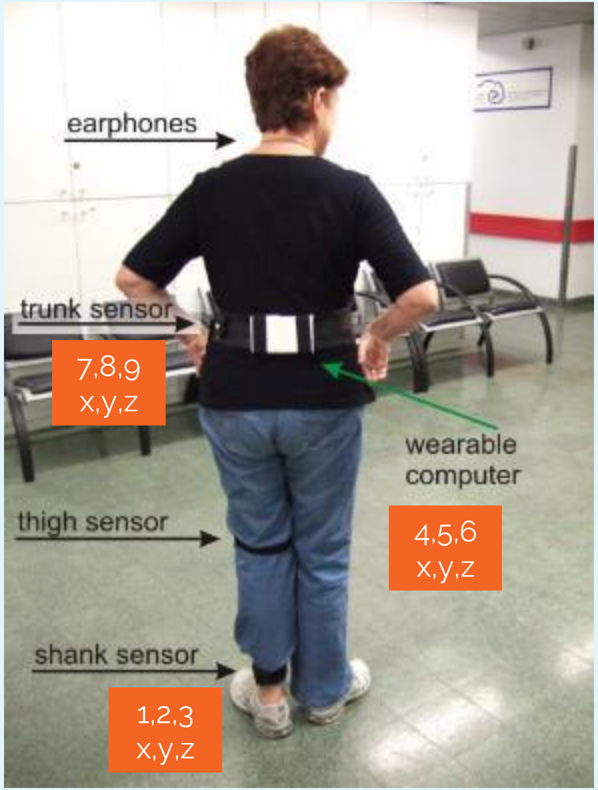
Wearable Sensors in Digital Health (Parkinson)



Average of first layer filter for all cases based on LOSO

Dataset

Daphnet Freezing of Gait



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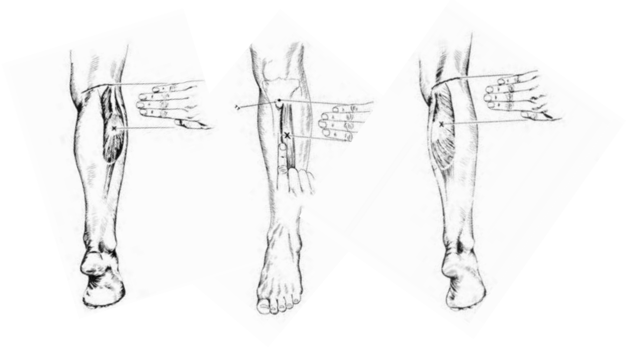
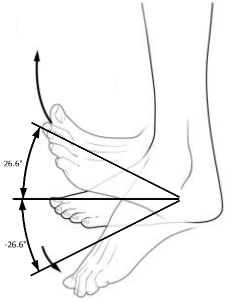
Wearable Sensors in Digital Health (Active prosthesis)

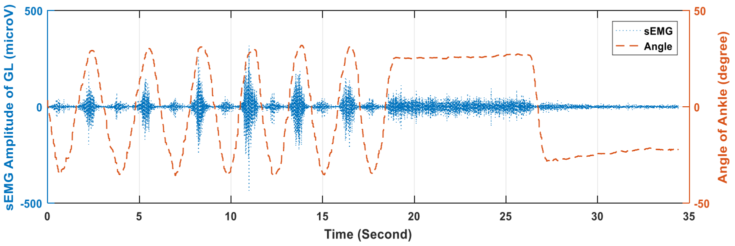


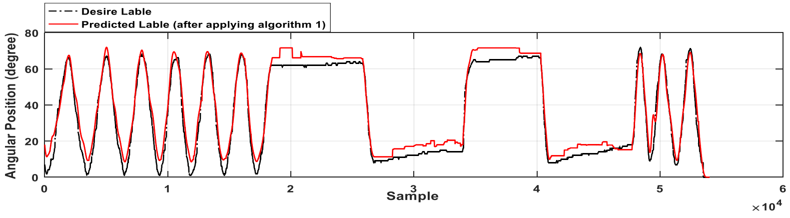


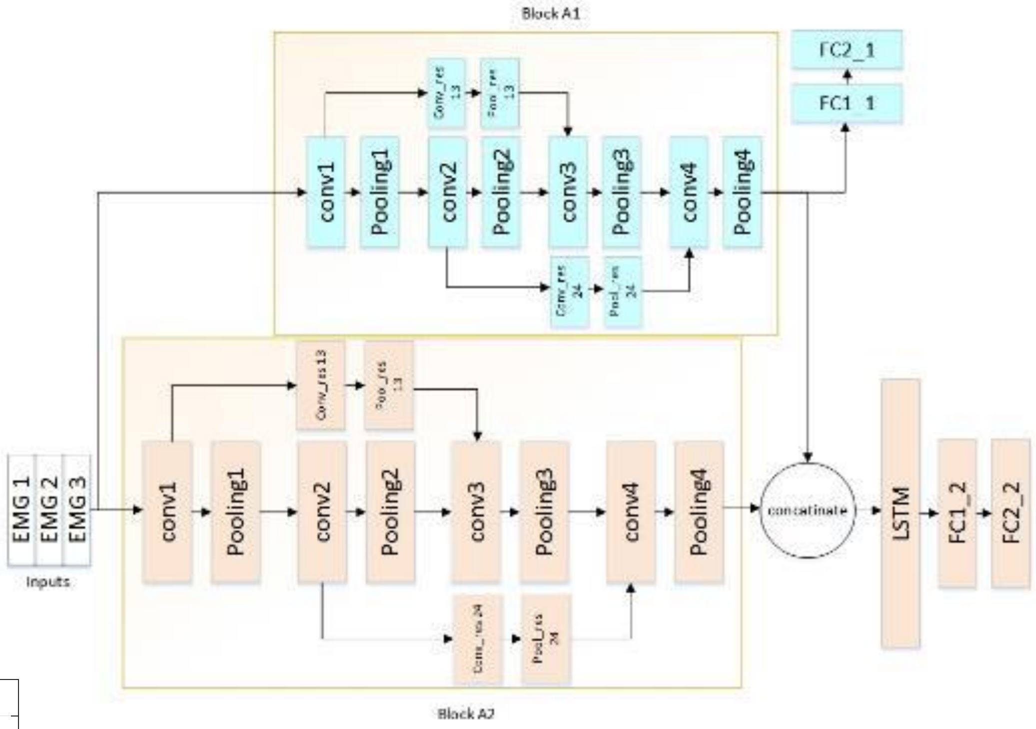
Wearable Sensors in Digital Health (Active prosthesis)

Challenges

- Variation in prediction
- Need to have a high accuracy in degree





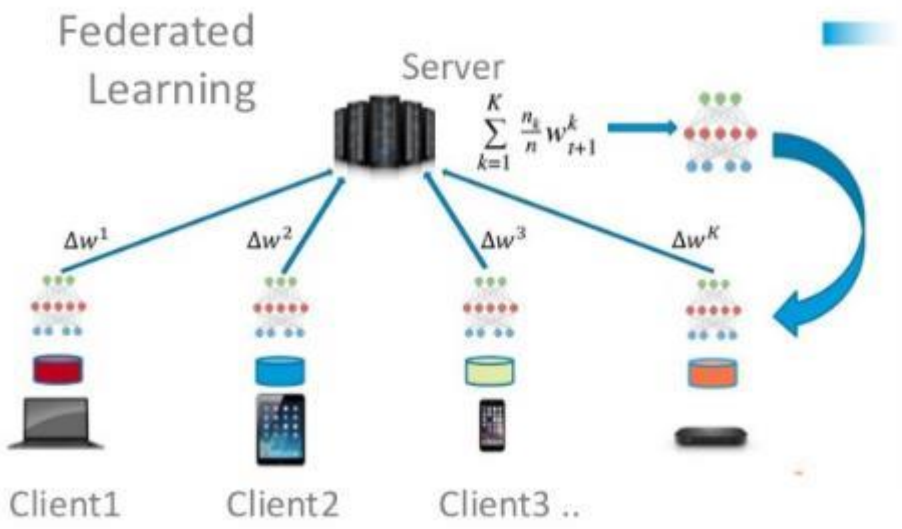


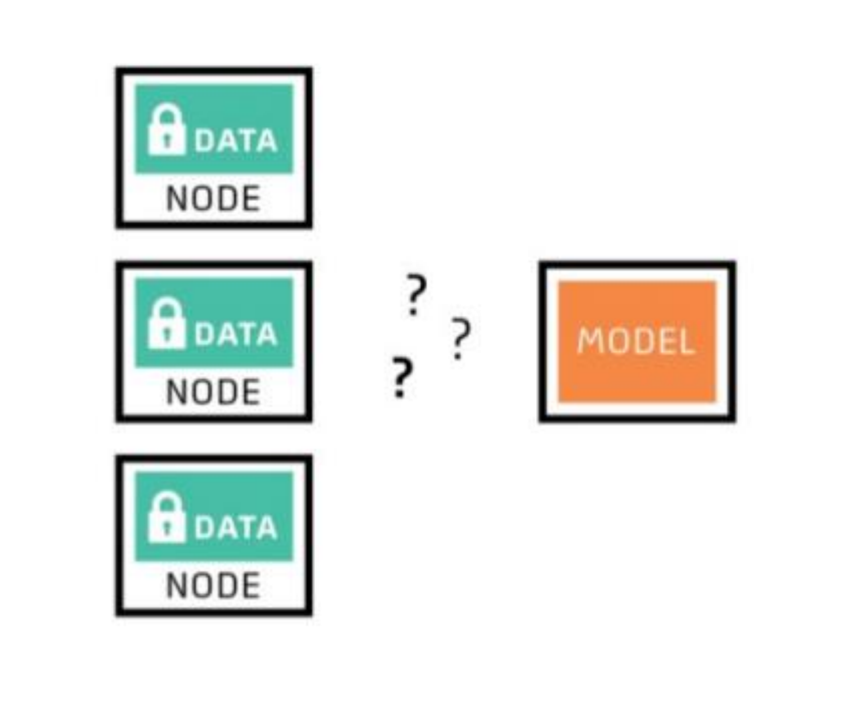
4. Federated learning, limitations & projects

Build confidence around your product or idea by including at least one of the these slides:

- ➔ **Limitation No.1: Privacy challenge**
  Project No.1. An introduction to federated learning
- ➔ **Limitation No.2: limited dataset challenge**
  Project No.2. UNET based model

Privacy and Federated learning





Project No.1 – level: advance

Project No.1. Federated learning for hospitals

Description:
we are going to Implement a denoising AE model on any dataset based on federated learning. The final goal of this project is “being sure the sever model trained and can work on validation dataset”.

Project steps:
- Download your dataset and split them into 3 parts for training and 1 part for validation
- Train each of 3 models on one of splited dataset and save the parameters
- Load 3 models’ parameters and train a server model based on average of parameters of the 3 models.
- Tune the server model to coverage on train set then validate the model on a new part of dataset

Project No.2 – level: advance

Project No.2. focusing on malignant nodule using AE

Description:
In this project, we want to generate a noise like malignant nodule to find them in a lung cancer case to reduce FP rate.

Project steps:
- Download a part of Luna16 dataset
- Preprocess them using this code or this one
- Try to generate a noise like malignant nodule to remove them from lung (using Perlin noise or sth else)
- Test your model with new images and visualize them

A Team for a STARTUP in AI&MED

If you are interested to work in digital health and AI community, please feel free to leave me a massage here:

Mo.homayounfar@gmail.com

Requirements:
- Programming skills (python)
- Basic knowledge of AI
- English communication skills
- No need to have experience on medical data