AI applications in healthcare

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About me

Louis Abraham

- Education: École polytechnique, ETH Zurich
- Experience:
  - Quant @ BNP Paribas
  - Deep learning @ EHESS / ENS Ulm
  - Data protection @ Qwant Care

Non-exhaustive list of current and potential AI applications in medicine

- Basic biomedical research
  - Automated experiments
  - Automated data collection
  - Gene function annotation
  - Prediction of transcription factor binding sites
  - Simulation of molecular dynamics
  - Literature mining

Non-exhaustive list of current and potential AI applications in medicine

- Translational research
  - Biomarker discovery
  - Drug–target prioritization
  - Drug discovery
  - Drug repurposing
  - Prediction of chemical toxicity
  - Genetic variant annotation

Non-exhaustive list of current and potential AI applications in medicine

- Clinical practice
  - Disease diagnosis
  - Interpretation of patient genomes
  - Treatment selection
  - Automated surgery
  - Patient monitoring
  - Patient risk stratification for primary prevention

The success of automated medical-image diagnosis

- Radiology
  - detection of lung nodules using computed tomography images
  - diagnosis of pulmonary tuberculosis and common lung diseases with chest radiography
  - breast-mass identification using mammography scan
- Dermatology
  - dermatologist-level accuracy in diagnosing skin malignancy trained on 129,450 clinical images
- Ophthalmology
  - expert level in referable diabetic retinopathy and diabetic macular oedema identification trained using 128,175 retinal images
- Pathology
  - detection of prostate cancer from biopsy specimens
  - identification of breast cancer metastasis in lymph nodes
  - detection of mitosis in breast cancer
  - net deficit of more than 5,700 full-time equivalent pathologists by 2030

Other domains

- Genome interpretation
  - Deep learning outperforms conventional methods
- Biomarker discovery

A few examples from the PhysioNet challenge

- clinical databases
- library of publications
- software
- challenge

PhysioNet 2000: Detecting and quantifying apnea based on the ECG

(Goldberger et al. 2000)

- 70 recordings of ECG signal digitized at 100 Hz with 12-bit resolution, continuously for approximately 8 hours split in training and test dataset
- 1 label per minute
- 2 tasks: detection per patient and detection per minute
- results: 100% and 90% accuracy

PhysioNet 2000: Detecting and quantifying apnea based on the ECG

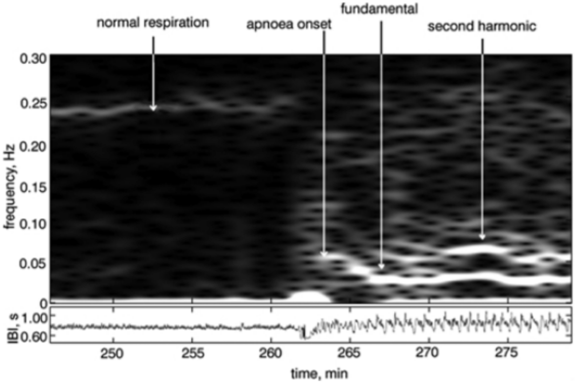

Fig. 2 *Visual detection of one method is illustrated: periods of apnoea were visually identified by looking at spectrogram (McNames and Fraser, 2000) in 0.02–0.08 Hz range. A lot of energy in this region was indicative that signal contained apnoea. Frequency range of normal respiration was also inspected to see if there was a periodic pattern. This 40-year-old male had an apnoea/hypopnoea index of 33 events per hour*

PhysioNet 2004: Spontaneous Termination of Atrial Fibrillation

(Moody 2004)

- Is it possible to predict if (or when) an episode of atrial fibrillation will end spontaneously?
- 80 one-minute recordings of two simultaneously recorded ECG signals
- 3 classes
  - N: non-terminating AF
  - S: terminates one minute after the end of the record
  - T: terminates immediately after the end of the record
- Training 10N+10S+10T, Test A 15N+15T, Test B 10S+10T
- results: 97% and 100% accuracy
- similar method: simple signal processing

PhysioNet 2016: Classification of Normal/Abnormal Heart Sound Recordings

(Liu et al. 2016)

- 4,430 recordings taken from 1,072 subjects, totalling 233,512 heart sounds
- Additional data: subject demographics (age and gender), recording information, synchronously recorded signals (such as ECG), sampling frequency and sensor type used
- 3 labels: Normal, AF, Noisy
- 2 metrics: **Se**nsitivity (detecting abnormal) and **Sp**ecificity (detecting normal)

PhysioNet 2016: Classification of Normal/Abnormal Heart Sound Recordings

Rank	Entrant	*Se*	*Sp*	*MAcc*	Method note
1	Potes *et al.*	0.9424	0.7781	0.8602	AdaBoost & CNN
2	Zabihi *et al.*	0.8691	0.8490	0.8590	Ensemble of SVMs
3	Kay & Agarwal	0.8743	0.8297	0.8520	Regularized Neural Network
4	Bobillo	0.8639	0.8269	0.8454	MFCCs, Wavelets, Tensors & KNN
5	Homsi *et al.*	0.8848	0.8048	0.8448	Random Forest + LogitBoost
6†	Maknickas	0.8063	0.8766	0.8415	Unofficial entry - no publication
7	Plesinger *et al.*	0.7696	0.9125	0.8411	Probability-distribution based
8	Rubin *et al.*	0.7278	0.9521	0.8399	Convolutional NN with MFCs
17†	Voting of top N=38 algorithms	0.7120	0.9015	0.8068	Simple mode
43†	Sample entry	0.6545	0.7569	0.7057	See section 3

Table 3. Final scores for the top 8 of 48 entrants, the example algorithm provided and a simple voting approach. Best performances of competition entrants are in bold. † denotes an unofficial entry. MFCC = Mel Frequency Cepstral Coefficients. NN = Neural Network. SVM = Support Vector Machine. CNN = Convolutional NN. KNN = K Nearest Neighbors.

Quite a variety of approaches

PhysioNet 2018: You Snooze, You Win

(Ghassemi et al. 2018)

- 1,983 polysomnographic recordings
- Clinical features and 13 signals
- detect arousals

PhysioNet 2018: You Snooze, You Win

Rank	Entrant	AUPRC
1	Howe-Patterson, Pourbabaee & Benard	0.54
2	Kristjánsson, Þráinsson, Ragnarsdóttir, Marinósson, Gunnlaugsson, Finnsson, Jónsson, Helgadóttir, & Ágústsson	0.45
3	He, Wang, Liu, Zhao, Yuan, Li, & Zhang	0.43
4	Varga, Görög, & Hajas	0.42
5	Patane, Ghiasi, Scilingo, & Kwiatkowska	0.40
6	Miller, Ward, & Bambos	0.36
6	Warrick & Homsi	0.36
8	Bhattacharjee, Das, Choudhury, & Banerjee	0.29
8	Szalma, Bánhalmi, & Bilicki	0.29
10	Parvaneh, Rubin, Samadani, Prakash, & Katuwal	0.21
11	Plešinger, Nejedly, Viscor, Andrla, Halámek, & Jurák	0.20
12	Zabihi, Rad, Särkkä, Kiranyaz, Katsaggelos, & Gabbouj	0.19
13	Schellenberger, Shi, Mai, Wiedemann, Steigleder, Eskofier, Weigel, & Kölpin	0.14
14	Li, Cao, Zhong, & Pan	0.10
15	Jia, Yu, Yan, Zhao, Xu, Hu, Wang, & You	0.10
16	Shen	0.07
	Unofficial entries	
–	*Li & Guan* †	0.55
–	*Bilal, Khan, Khan, Qureshi, Saleem, & Kamboh* †	0.15
–	*Wang, Wang, & Li* †	0.07

Table 3. Final scores for the 19 teams in the Challenge. † denotes unofficial entries.

The top approaches used neural networks

Conclusion

- Older systems are still not widely used
- Increase in dataset sizes
- AI is meant to complement, not replace doctors

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