Deep Learning in Healthcare

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Computational biology - deep learning

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Better Medicine
for everyone
Cat
Cat
Cat

Representation
Cat

Representation
Machine Learning

Representation

Cat

Not a cat
A mostly complete chart of Neural Networks

©2016 Fjodor van Veen - asimovinstitute.org
1.2 million images
1000 categories
Errors

2010 2011

28% 26%

http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/
Errors

28% 26% 16%

2010 2011 2012

AlexNet (A. Krizhevsky et al. 2012)

http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/
IMAGENET

AlexNet (A. Krizhevsky et al. 2012)

Errors

28% 26% 16% 12% 7% 3% <3%


http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/
Errors

<table>
<thead>
<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Errors</td>
<td>28%</td>
<td>26%</td>
<td>16%</td>
<td>12%</td>
<td>7%</td>
<td>3%</td>
<td>&lt;3%</td>
</tr>
</tbody>
</table>

AlexNet (A. Krizhevsky et al. 2012)

Hypothetical super-dedicated fine-grained expert ensemble of human labelers

http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/
Different breeds

The same breed

Hypothetical super-dedicated fine-grained expert ensemble of human labelers

AlexNet (A. Krizhevsky et al. 2012)

https://www.semanticscholar.org/paper/Fine-grained-Categorization-Short-Summary-of-our-E-G%C3%B6ring-Freytag/0f3b7d252c236d47cf4185fd81bbb40767baf3d8
أنا سعيدة بمناسبة زيارتك. الطقس سوف يكون جميل عندما تصل.

نعم، وأنا أيضاً سعيد. من فضلك اخبرني عمما احضر معني.
Atari

Go
9,600,000 people die from cancer a year.

Economic burden of cancer is over 1,160,000,000,000 USD.
How about medical field?
Medicine is complex
Medicine is really complex
Medicine is massive
Super rapid growth

Deep Learning
Deep Learning  Super rapid growth
Deep Learning  Super rapid growth

COVID19
6000 participants at NeurIPS 2016 in Barcelona
6000 participants at NeurIPS 2016 in Barcelona.
54,037 participants at RSNA 2016
Medicine is weird
Bloodletting
Bloodletting

Soothing
Bloodletting

Soothing

Lobotomy
Nevertheless...
Trends in cancer survival

Year
1970
2010

Skin
Breast
Prostate
Bowel
Kidney
Leukaemia
Myeloma
Ovarian
Pancreatic
## Merck Molecular Activity Challenge 2012

<table>
<thead>
<tr>
<th>#</th>
<th>Team Name</th>
<th>Kernel</th>
<th>Team Members</th>
<th>Score</th>
<th>Entries</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>gggg</td>
<td></td>
<td></td>
<td>0.49409</td>
<td>20</td>
</tr>
<tr>
<td>2</td>
<td>DataRobot</td>
<td></td>
<td></td>
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<td>37</td>
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<td>0.48209</td>
<td>88</td>
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<tr>
<td>4</td>
<td>Gangnam Style</td>
<td></td>
<td></td>
<td>0.48158</td>
<td>43</td>
</tr>
<tr>
<td>5</td>
<td>Luxtorpeda</td>
<td></td>
<td></td>
<td>0.48154</td>
<td>35</td>
</tr>
</tbody>
</table>
Patients are about to see a new doctor: artificial intelligence

Artificial Intelligence could put lawyers and doctors OUT of a job in FIVE YEARS' time

Will Robots Take Over Our Jobs In Healthcare?

IBM's Watson AI Recommends Same Treatment as Doctors in 99% of Cancer Cases

Digital Diagnosis: Intelligent Machines Do a Better Job Than Humans

Computer Program Beats Doctors at Distinguishing Brain Tumors from Radiation Changes

Robots will destroy our jobs but not ready for it

Two-thirds of Americans believe robots will soon be done by humans but 80% also believe their jobs will be
Diabetic Retinopathy
Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Skin Cancer
Dermatologist-level classification of skin cancer with deep neural networks
Diabetic Retinopathy
Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

Skin Cancer
Dermatologist-level classification of skin cancer with deep neural networks
Diabetic Retinopathy

NORMAL VISION
Vision remains intact
Diabetic Retinopathy

NORMAL VISION
Vision remains intact

DIABETIC RETINOPATHY
Vision is obstructed by macular edema
Diabetic Retinopathy

NORMAL Vision

DIABETIC RETINOPATHY
Vision is obstructed by macular edema
Diabetic Retinopathy

NORMAL
Vision is clear

DIABETIC
Vision is obstructed
Diagnostics done manually
9 - 12 minutes per patient

- Normal retina
- Retinopathy

- Macula
- Optic disk
- Hemorrhage
- Aneurysms
128,175 images for training
54 US licensed ophthalmologists
128,175 images for training
54 US licensed ophthalmologists
Classify into healthy, mild, and severe
Sample annotation

1st doctor  2nd doctor  3rd doctor  4th doctor

Healthy  Disease
Sample annotation

1st doctor  2nd doctor  3rd doctor  4th doctor

Healthy  Disease
Sample annotation

1st doctor  2nd doctor  3rd doctor  4th doctor

Healthy

Disease
Sample annotation

1st doctor  2nd doctor  3rd doctor  4th doctor

Healthy

Disease
Sample annotation

1st doctor  2nd doctor  3rd doctor  4th doctor

Major vote is used

Healthy

Disease
Sample annotation

Algorithm might only *marginally* outperform doctors

Healthy

Disease
Algorithm vs Ophthalmologists
Algorithm vs Ophthalmologists

AUC of 97.4%
Algorithm vs Ophthalmologists

The black curve is ROC for the **Deep Learning** algorithm

AUC of **97.4%**
Algorithm vs Ophthalmologists

The black curve is ROC for the Deep Learning algorithm.

Points on ROC are performances of individual ophthalmologists.

AUC of 97.4%
Algorithm vs Ophthalmologists

The black curve is ROC for the **Deep Learning** algorithm.

Points on ROC are performances of individual **ophthalmologists**.

Performances are very **similar**.

AUC of **97.4%**
Algorithm vs Ophthalmologists

Deep Learning algorithm can operate in **any point** on the **curve**

AUC of **97.4%**
Deep Learning algorithm can operate in **any point** on the curve.

Algorithm vs Ophthalmologists

High specificity mode (diagnosis)

AUC of **97.4%**
Algorithm vs Ophthalmologists

High sensitivity mode (screening)

High specificity mode (diagnosis)

Deep Learning algorithm can operate in any point on the curve

AUC of 97.4%
Algorithm vs Ophthalmologists

High sensitivity mode (screening)

High specificity mode (diagnosis)

Deep Learning algorithm can operate in **any point** on the **curve**

While **ophthalmologists**’s mode is **fixed** by experience

AUC of **97.4%**
Diabetic Retinopathy
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Skin Cancer
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Skin Cancer
Dermatologist-level classification of skin cancer with deep neural networks
Difference in survival rates is drastic

90% VS 14%
LESIONS LEARNT
Artificial intelligence powers detection of skin cancer from images
PAGES 35 & 115
129 450 images for training set
129 450 images for training set

21 board-certified dermatologists
Skin disease
Non-neoplastic
Benign
Malignant
Dermal
Epidermal
Melanocytic
Inflammatory
Genodermatosis
Epidermal
Dermal
Melanocytic
Epidermal
Dermal
Melanoma
Lymphoma
Google Inception v3
Google Inception v3
Algorithm vs Dermatologists
Algorithm vs Dermatologists

Carcinoma:
135 images

Dermatologists (25)

AUC of 96%
Algorithm vs Dermatologists

Carcinoma: 135 images
Dermatologists (25)

Each of the cases was verified by biopsy

AUC of 96%

Sensitivity, %
Specificity, %
Algorithm vs Dermatologists

Carcinoma: 135 images
Dermatologists (25)

AUC of 96%
Algorithm vs Dermatologists

Carcinoma: 135 images

Dermatologists (25)

Performance of the algorithm was compared to dermatologists

AUC of 96%
Algorithm vs Dermatologists

Performance of the algorithm was compared to dermatologists.

Average dermatologist’s performance was marked as +

Carcinoma: 135 images
Dermatologists (25)

Specificity, %
Sensitivity, %

AUC of 96%
Performance of the algorithm was compared to dermatologists. Average dermatologist’s performance was marked as +

Carcinoma: 135 images

Dermatologists (25)

AUC of 96%
Algorithm vs Dermatologists

Carcinoma: 135 images
Dermatologists (25)
AUC of 96%

Melanoma: 130 images
Dermatologists (22)
AUC of 94%

Melanoma: 111 images
Dermatologists (21)
AUC of 91%
Algorithm vs Dermatologists

Across all biopsy verified datasets Deep Neural Network was superior

Carcinoma: 135 images
Dermatologists (25)
AUC of 96%

Melanoma: 130 images
Dermatologists (22)
AUC of 94%

Melanoma: 111 images
Dermatologists (21)
AUC of 91%
Diabetic Retinopathy
Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs
https://jamanetwork.com/journals/jama/fullarticle/2588763

Skin Cancer
Dermatologist-level classification of skin cancer with deep neural networks
https://www.nature.com/nature/journal/v542/n7639/full/nature21056.html
Few more interesting applications
Diagnosing Parkinson from voice
(Al-Fatlawi et al., 2016)
Diagnosing Parkinson from voice (Al-Fatlawi et al., 2016)

Predicting subsequent hospitalisation (Choi et al., 2016)
Diagnosing Parkinson from voice (Al-Fatlawi et al., 2016)

Detection of hypoglycemic episodes in children (San et al., 2016)

Predicting subsequent hospitalisation (Choi et al., 2016)
Diagnosing Parkinson from voice (Al-Fatlawi et al., 2016)

Detection of hypoglycemic episodes in children (San et al., 2016)

Predicting subsequent hospitalisation (Choi et al., 2016)

Pain estimation from video (Zhou et al., 2016)
Application of Deep Learning for Recognizing Infant Cries

Chuan-Yu Chang, Jia-Jing Li
National Yunlin University of Science & Technology, Taiwan
E-mail: chuanyu@yuntech.edu.tw

Abstract—Crying is a way which infants express their needs to their parents. In general, parents often feel worried and anxious when infant crying. For realizing the reason of baby crying, this paper presents an automatic infant crying recognition method. Crying is convert to spectrogram. A convolutional neural networks (CNN) based deep learning is then adopted to train and classify the crying into three categories including hungry, pain, and sleepy. Experimental results shows that the proposed method achieves high classification accuracy.

I. INTRODUCTION
In recent years, deep learning with capability of high-level abstraction had been widely applied to image recognition and speech recognition [4]. There are many deep learning algorithms had been proposed such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.
Application of Deep Learning for Recognizing Infant Cries

Jia-Jing Li

Abstract

In recent years, several deep learning algorithms had been proposed, such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.
Application of Deep Learning for Recognizing Infant Cry

Jia-Jing Li

Sleep

Abstract

In this paper, we present a new approach to recognizing infant cry using deep learning techniques. The proposed method employs deep neural networks to classify different types of infant cries accurately.

Deep learning algorithms have been proposed such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). These deep learning algorithms have applied to many applications successfully.

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.
Application of Deep Learning for Recognizing Infant Cries

Jia-Jing Li

Abstract

The proposed system uses the performance of neural networks to recognize infant cries. The system is trained using the baby's cry, and it shows that the proposed approach is effective in recognizing infant cries.

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.

Algorithms had been proposed such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.
Application of Deep Learning for Recognizing Infant Cries

Jia-Jing Li
Institute of Biomedical Engineering & Technology, Taiwan
department@institute.edu

Abstract

In this work, the application of deep learning algorithms had been proposed such as restricted Boltzmann machine (RBM), convolutional neuron networks (CNN), deep belief networks (DBN), and deep neuron networks (DNN). Those deep learning algorithms have applied to many applications successfully.

Fig. 1. (a) is a normal neural network, (b) adopted dropout learning in the neural network.

After the analysis of the package of the baby cry, the network won the train dataset. Furthermore, the testing dataset shows that the neural network has adopted dropout learning.
Seems like revolution did not happened
Why Deep Learning has not revolutionised medicine yet?
Chart of possible reasons why deep learning may fail to revolutionise medicine

<table>
<thead>
<tr>
<th>Likelihood</th>
<th>Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Highly likely</td>
<td>Not nice, but ok</td>
</tr>
<tr>
<td>Unlikely</td>
<td>Terrible consequences</td>
</tr>
</tbody>
</table>
We may fail to compose large enough datasets
We may fail to compose large enough datasets.

Collecting data in medicine is very expensive.
We may fail to compose large enough datasets

- Collecting data in medicine is very expensive
- Medical data is often protected (for a good reason)
We may fail to compose large enough datasets
We may fail to compose large enough datasets
We may fail to compose large enough datasets
We can build a model that can distinguish them from other objects. We may fail to compose large enough datasets.
We can build a model that can distinguish them from other objects.

We may fail to compose large enough datasets.
We may fail to compose large enough datasets

We can build a model that can distinguish them from other objects

We cannot build a robust representation for all of them
We can build a model that can distinguish them from other objects.

We cannot build a robust representation for all of them.

We would need a separate ImageNet for each type.

We may fail to compose large enough datasets.
Medical Image Net

Possible solution

Featured Goals

- Data migration/federation/honest broker
- Linkage to EMR and multi-omics
- Cohort discovery tools
- Image viewing software
- Governance
- Image classification and annotation

http://langlotzlab.stanford.edu/projects/medical-image-net/
Medical Image Net

A petabyte-scale, cloud-based, multi-institutional, searchable, open research diagnostic imaging studies for developing intelligent image analysis systems.

Featured Goals

- Data migration/federation/honest broker
- Linkage to EMR and multi-omics
- Cohort discovery tools
- Image viewing software
- Governance
- Image classification and annotation

Stanford Medicine
Chart of possible reasons why deep learning may fail to revolutionise medicine

- Unlikely
- Highly likely

Effect

Not nice, but ok
Terrible consequences

Data
How doctors diagnose melanomas?
How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college.
How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college.

Melanomas are **Asymmetrical**
How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college.

- **Melanomas are Asymmetrical**
How doctors diagnose melanomas?

There is an ABCD rule they learned in college.

- Melanomas are Asymmetrical.
- Their Borders are uneven.
How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college:

- Melanomas are **Asymmetrical**
- Their **Borders** are uneven
How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college

- **Melanomas are Asymmetrical**
- **Their Borders are uneven**
- Colour can be patchy and variegated
How doctors diagnose melanomas?

There is a ABCD rule they learned in college:

- Melanomas are **Asymmetrical**
- Their **Borders** are uneven
- Colour can be patchy and **variegated**
How doctors diagnose melanomas?

There is a ABCD rule they learned in college:

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- Their **Borders** are uneven
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How doctors diagnose melanomas?

There is a **ABCD** rule they learned in college:

- Melanomas are **Asymmetrical**
- Their **Borders** are uneven
- **Colour** can be patchy and variegated
- Their **Diameter** is usually > 6 millimetres
How doctors diagnose melanomas?

There is an **ABCD** rule they learned in college:

- **Melanomas are Asymmetrical**
- Their **Borders** are uneven
- **Colour** can be patchy and variegated
- Their **Diameter** is usually > 6 millimetres
How **computers** diagnose melanomas?
How **computers** diagnose melanomas?
How **computers** diagnose melanomas?
How **computers** diagnose melanomas?
EXPLAINABLE ARTIFICIAL INTELLIGENCE: UNDERSTANDING, VISUALIZING AND INTERPRETING DEEP LEARNING MODELS

Wojciech Samek\textsuperscript{1}, Thomas Wiegand\textsuperscript{1,2}, Klaus-Robert Müller\textsuperscript{2,3,4}

classify image

Black Box AI System

Rooster

don prediction $f(x)$

input $x$

heatmap

Al system’s decision is based on these pixels

explain prediction

Why explainability?

Verify predictions
Identify flaws and biases
Learn about the problem
Ensure compliance to legislation

Explanation methods

\textbf{LRP:} Decomposition

$\sum_i R_i = f(x)$

(how much does each pixel contribute to prediction)

\textbf{SA:} Partial derivatives

$R_i = \left| \frac{\partial}{\partial x_i} f(x) \right|$

(how much do changes in each pixel affect the prediction)

Chart of possible reasons why deep learning may fail to revolutionise medicine

Likelihood

Unlikely

Highly likely

Interpretability

Data

Effect

Not nice, but ok

Terrible consequences
Your computer
Your computer

ACCCTTAAGGAGATCCTT
TAACCGAACCTCACCCTT
AAGGAGATCCTTTAACCG
CCCTTTTATTCTATTACGT
Read 3.5 B more…
Gene Technology

Your computer

Genome

Read 3.5 B more…
Genome Technology

Schizophrenia - 0.15%
Diabetes      - 0.05%
Cancer        - 0.01%

Your computer

Gene Technology

Genome

ACCCCTTAAGGAGATCCTTT
TAACCGAACCTCACCCTTT
AAGGAGATCCTTTAACCG
CCCTTTTATTCCTATTACGT
Read 3.5 B more…
Risks

- Schizophrenia: 0.15%
- Diabetes: 0.05%
- Cancer: 0.01%

Gene Technology

Your computer

ACCCTTAAGGAGATCCTTT
TAACCGAACCCTCACCCCT
AAGGAGATCCCTTTAACC
CCCTTTTATTCTATTACGT
Read 3.5 B more…

Risks

- Schizophrenia: 0.15%
- Diabetes: 0.05%
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Gene

Your computer
Risks

Genome

Schizophrenia - 0.15%
Diabetes - 0.05%
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Gene Technology

Your computer

ACCCTTAAGGAGATCCTT
TAACCGAACCTCACCCTT
AAGGAGATCCTTTAACC
CCCTTTTATTCTATTACGT
Read 3.5 B more…
ACCCTTAAGGAGATCCTTT
TAACCGAACCTCACCCTTT
AAGGAGATCCTTTAACCG
CCTTTTATTCTCTATTACGT

Your computer

Application

Cool company

Gene Technology

Schizofrenia - 0.15%
Diabetes      - 0.05%
Cancer         - 0.01%

Genome

Risks

Read 3.5 B more…
Your computer

Application

Gene Technology
- Schizophrenia - 0.15%
- Diabetes - 0.05%
- Cancer - 0.01%

Cool company

Risks
- Schizophrenia - 0.15%
- Diabetes - 0.05%
- Cancer - 0.01%

Genome

ACCCTTAAGGAGATCCTT
TAACCGAACCTCACCCTT
AAGGAGATCCTTTAACC
CCCTTTTATTCCCTATTACGT
Read 3.5 B more…
ACCCTTAAGGAGATCCTT
TAACCGAACCTCACCCTT
AAGGAGATCCTTTAACCG
CCCTTTTATTCCTATTACGT
Read 3.5 B more…
Encrypting your genome

Your computer

ACCCTTAAGGAGATCCTT
TAACCGAACCTCACCCTT
AAGGAGATCCTTTAACCG
CCCTTTTATTCTATTACGT
Read 3.5 B more…
Encrypting your genome

Your computer

Read 3.5 B more
Encrypted genome

Your computer

Gene Technology

Read 3.5 B more…
Your computer

Encrypted genome

Gene Technology

#@$!@@# - #@%
#@$(@(%% & - ?@@#%$
$@))#^%? - ?@@%
Your computer

Decrypt your risks with your private key

Gene Technology

Encrypted risks

Encrypted genome
Your computer

Decipher your risks with your private key

Gene Technology

Encrypted genome

Schizofrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%

Encrypted risks

#@$!@# - #@%#
#@$(%&&& - ?@#%$
$@))#^%? - ?@%
Your computer

Decrypted genome

Gene Technology

Gene Technology

and start panicking changing your lifestyle

Schizophrenia - 0.15%
Diabetes - 0.05%
Cancer - 0.01%

Decrypt your risks with your private key

Encrypted risks

Encrypted risks

Encrypted genome
Chart of possible reasons why deep learning may fail to revolutionise medicine

- **Likelihood**
  - Highly likely
  - Unlikely

- **Effect**
  - Not nice, but ok
  - Terrible consequences

- **Interpretability**
- **Data**
- **Privacy**

Read 3.5 B more…
Houdini: Fooling Deep Structured Prediction Models

Moustapha Cisse, Yossi Adi, Natalia Neverova, Joseph Keshet

(Submitted on 17 Jul 2017)
Chart of possible reasons why deep learning may fail to revolutionise medicine.
Chart of possible reasons why deep learning may fail to revolutionise medicine

- **Likelihood**
  - Highly likely
  - Unlikely

- **Effect**
  - Not nice, but ok
  - Terrible consequences

- **Factors**
  - Interpretability
  - Data
  - Privacy
  - Regulations
  - Adversarial attacks
Device is allowed!

International standards

Notified body

FDA

Ethics committee

CE

Clinical studies
Chart of possible reasons why deep learning may fail to revolutionise medicine

- **Interpretability**
- **Data**
- **Regulations**
- **Privacy**
- **Adversarial attacks**

Likelihood
- Highly likely
- Unlikely

Effect
- Not nice, but ok
- Terrible consequences
Chart of possible reasons why deep learning may fail to revolutionise medicine

Despite all of this...
How can you join the fight?
Heart failure

35% risk of death in first year after diagnosis

Volume of blood pumped out of the ventricle per beat
Total volume of blood in ventricle at end diastole

Ejection fraction (%)
The measurement of how much blood the left ventricle pumps out on a beat by beat basis.

Team: Mari-Liis Allikivi, Elena Sügis, Dmytro Fishman

http://www.datasciencebowl.com/competitions/transforming-how-we-diagnose-heart-disease/
Heart failure

35% risk of death in first year after diagnosis

Team: Mari-Liis Allikivi, Elena Sügis, Dmytro Fishman

http://www.datasciencebowl.com/competitions/transforming-how-we-diagnose-heart-disease/
Turning Machine Intelligence Against Lung Cancer

Team: Lauri Listak
Supervisor: Dmytro Fishman

Turning Machine Intelligence Against Lung Cancer

Team: Lauri Listak
Supervisor: Dmytro Fishman

Turning Machine Intelligence Against Lung Cancer

20% of lung cancer deaths can be reduced with early detection
High False Positives rates lead to interventional treatments, additional costs and patient anxiety.

20% of lung cancer deaths can be reduced with early detection.
The 2021 Kidney and Kidney Tumor Segmentation Challenge

Computational biology - deep learning

William Jones$*, Kaur Alasoo$*, Dmytro Fishman£*, Leopold Parts$@

$Wellcome Trust Sanger Institute, Hinxton, UK
£Institute of Computer Science, University of Tartu, Estonia
*These authors contributed equally to this work
@To whom correspondence should be addressed: leopold.parts@sanger.ac.uk (Leopold Parts)
References


• Opportunities and obstacles for deep learning in biology and medicine by Ching et al. (http://www.biorxiv.org/content/biorxiv/early/2017/05/28/142760.full.pdf)

• Computational biology - deep learning by William Jones, Kaur Alasoo, Dmytro Fishman et al. (https://doi.org/10.1042/ETLS20160025)
That's all Folks!

BIIT
dmytro@ut.ee