Artificial intelligence in Gastroendoscopy

“Improving Health Worldwide”
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FICS, FIAGES, FMAS, FAIMER fellow
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Persistent System Ltd.
Co Authors
Mr. Eric McNeil, Vice President
Mr. Pratap Sanap, Solution Architect
Mr Gunjan Naik
Mr Sudhir Kulkarni, President
Persistent System Ltd.
Future of Medicine
The First Task Watson Addressed was Winning on Jeopardy!
IBM Celebrates the 15th Anniversary of Deep Blue beating Garry Kasparov
NVIDIA Reveals New GPU, GeForce GTX 1080 is Faster than the Titan X
AI in Healthcare

Patient-Facing
- AI Chatbots
  - buoy
  - YouMD
  - medwhat
  - gyant

Wearables & Devices
- QARDIO
  - sino

Personalized Genetics
- rtm
  - cg
day
two

Mental Health
- woobot
  - TouchIn

Drug Discovery
- Exscientia
  - Natural Cycles

Telemedicine
- ada

Lifestyle Management
- Sensely

Disease Management
- AiCure

Medical Records
- AURx

Research
- InfoGenomics

Information & Clinical Trials
- sheds

Genetic Research
- Pathway Genomics

Medical Imaging
- InSight

Hospital
- FOR ward
What is AI and ML?

Computers making decisions in real-world problems

Typical AI System

Apply

Solve

Formulate

MACHINE LEARNING

UNSUPERVISED LEARNING
Group and interpret data based only on input data

CLUSTERING

SUPERVISED LEARNING
Develop predictive model based on both input and output data

CLASSIFICATION

REGRESSION

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Machine Learning Phases

**Training Phase**
- Labels
- Images → Feature Extractor → Features → Machine Learning Algorithm

**Prediction Phase**
- Images → Feature Extractor → Features → Trained Classifier → Label
AI | ML | DL Augments Human Decision-making in Healthcare

Medical imaging example of “AI Augmented” Decision Making

Traditional approach
- Take CT scan
- Data saved in a database
- Image read by a radiologist
- Radiologist highlights anomalies

Potential to apply AI
- Take CT scan
- Data saved in a database
- Image run through an AI trained model for diagnosis
- Anomaly report generated

Human involvement augmented by AI

Slide Source: Dell EMC Consulting

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Image and Signal Processing in Medical Science?

- Bio-Imaging Research, Inc.
- Information about CT scans, ultrasound imaging, MRIs, and more
Big Data in Healthcare

• First time in history extremely Big Data is available

• The Big Data cannot be used by individual physician

• Big Data itself is meaningless, but processing it offers the promise of unlocking novel insights and accelerating breakthroughs in medicine which in turn has the potential to transform current clinical practice

• Explosion in knowledge is beyond use for any capacity

• It would be criminal not use latest processed data/protocol in management of patients

• Artificial Intelligence (AI) in the era of Big Data could assist physicians in shortening processing times and improving the quality of patient care in clinical practice
Limitations of Human Intelligence

- Only 20 percent of the knowledge physicians use to make diagnosis and treatment decisions today is evidence based.
- The result? One in five diagnoses are incorrect or incomplete and
- 1.5 million medication errors are made in the US every year.
- The amount of medical information available is doubling every five years and much of this data is unstructured – often in natural language.
- And physicians simply don't have time to read every journal that can help them keep up to date with the latest advances.
- 81 percent report that they spend five hours per month or less reading journals.
Why AI Getting Popular in Medical Science?

At the rate that technology changes and the rate our knowledge evolves... Enough time has passed to ensure that there is a necessity for a new review

- Are Artificial Intelligence (AI) systems used and useful when applied to critical care?
- Community of computer scientists and healthcare professionals set a research program – Artificial Intelligence in Medicine (AIM) with the aim of revolutionize medicine
- AIM use ‘Machine Learning’ to use and create knowledge
- Machine learning – Computers that can learn from experience
- Use – Stored data used in diagnosis
- Creation – Analyse the relationship within the data to come up with new results
Data Remains to be the Heart of Machine Learning and AI: Data Availability at Biology of Human Systems

Data useful for the practice of precision medicine

- **Social Data**: Personal circumstances, such as living situation and income
- **Device Data**: Information collected from apps that measure fitness and sleeping, electronic inhalers etc
- **Metabolome**: Chemicals which are created, modified and broken down by bodily processes such as enzymatic reactions
- **Transcriptome**: Messages created from DNA to form the template (mRNA) of proteins
- **Genome**: Patient’s complete set of genes ‘written’ in DNA
- **Clinical Data**: Patient’s medical record
- **Exposome**: Impact of the external environment, such as pollution and tobacco smoke etc
- **Microbiome**: Collective name for 100 trillion microscopic bugs living inside us
- **Proteome**: System of proteins, including enzymes, which are the building blocks of the body
- **Epigenetic (MethyloMe)**: The set of nuclear and methylation modifications in a human genome
- **Imaging**: Medical images, such as x-rays, scans, ultrasound

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Epidemiology of Medical Error
BMJ 2000; 320 DOI: https://doi.org/10.1136/bmj.320.7237.774

- The Harvard and Australian studies into medical error remain the only studies that provide population level data on the rates of injuries to patients in hospitals and they identified a substantial amount of medical error.

- In the United States, medical error results in 44,000 – 98,000 unnecessary deaths each year and 1,000,000 excess injuries.

- The Harvard study of medical practice, Brennan et al. reviewed the medical charts of 30,121 patients admitted to 51 acute care hospitals in New York state in 1984.

- They reported that adverse events – Injuries caused by medical management that prolonged admission or produced disability at the time of discharge – occurred in 3.7% of admissions.

- A subsequent analysis of the same data “69% of injuries were caused by errors”
Epidemiology of Medical Error 2

- The quality of Australian health care, a population based study modelled on the Harvard study, investigators reviewed the medical records of 14,179 admissions to 28 hospitals in New South Wales and South Australia in 1995.

- An adverse event occurred in 16.6% of admissions, resulting in permanent disability in 13.7% of patients and death in 4.9%; 51% of adverse events were considered to have been preventable.

Errors often occur when clinicians are inexperienced and new procedures are introduced. Extremes of age, complex care, urgent care, and a prolonged hospital stay are associated with more errors.
The Rise of Artificial Intelligence and the Uncertain Future for Physicians

- Physicians diagnose diseases based on personal medical histories, individual biomarkers, simple scores (e.g., CURB-65, MELD), and their physical examinations of individual patients.

- In contrast, AI can diagnose diseases based on a complex algorithm using hundreds of biomarkers, imaging results from millions of patients, aggregated published clinical research from PubMed, and thousands of physician's notes from Electronic Health Records (EHRs).

- While AI could assist physicians in many ways, it is unlikely to replace physicians in the foreseeable future.

- Let us look at the emerging uses of AI in medicine.
Dermatologist-level Classification of Skin Cancer with Deep Neural Networks: Nature Article

- Andre Esteva\textsuperscript{1 n1}, Brett Kuprel\textsuperscript{1 n1}, Roberto A. Novoa\textsuperscript{2, 3}, Justin Ko\textsuperscript{2}

- Deep convolutional Neural Networks (CNNs)\textsuperscript{4, 5} show potential for general and highly variable tasks across many fine-grained object categories

- Classification of skin lesions using a single CNN, trained end-to-end from images directly, using only pixels and disease labels as inputs

- We train a CNN using a dataset of 129,450 clinical images – two orders of magnitude larger than previous datasets consisting of 2,032 different diseases

- We test its performance against 21 board-certified dermatologists on biopsy-proven clinical images with two critical binary classification use cases: keratinocyte carcinomas versus benign seborrheic keratoses; and malignant melanomas versus benign nevi
Gastro-endoscopy

(a) lowered/closed forceps elevator

(b) raised/open forceps elevator
Types of Endoscopy

- Upper Gastro-endoscopy:
  - For esophagus analysis
  - Inserted thorough Mouth

- Capsule Gastro-endoscopy:
  - For small intestine analysis
  - A capsule has to be taken

- Lower Gastro-endoscopy:
  - For large intestine analysis
  - Inserted from rectum
Data visualization for Endoscopy

- Direct endoscopy: The endoscope has to be immersed in the body and it captures photos of intestinal tract.
- Virtual endoscopy: The intestinal tract has been visualized using CT or MRI images.
Direct visualization

(a) Bubbles

(b) Turbid images

(c) Clear images without pathologies

(d) Polyps
Analysis of Endoscopy Video Using Machine Learning techniques

- Authors: Santosh S. Saraf, G. R. Udupi, and Santosh D. Hajare
- Dataset: Wireless capsule endoscopy

<table>
<thead>
<tr>
<th></th>
<th>Esophagus</th>
<th>Stomach</th>
<th>Duodenum</th>
</tr>
</thead>
<tbody>
<tr>
<td>Knn classification</td>
<td>0.777616</td>
<td>0.695377</td>
<td>0.837956</td>
</tr>
<tr>
<td>SVM (Gaussian)</td>
<td>0.845742</td>
<td>0.73674</td>
<td>0.841363</td>
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<tr>
<td>SVM (Polynomial)</td>
<td>0.86472</td>
<td>0.741606</td>
<td>0.843796</td>
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<tr>
<td>Neural network</td>
<td>0.780535</td>
<td>0.623844</td>
<td>0.774209</td>
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<tr>
<td>Discriminant analysis (quadratic)</td>
<td>0.813139</td>
<td>0.730414</td>
<td>0.854988</td>
</tr>
</tbody>
</table>

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Deep learning analyzes Helicobacter pylori infection by upper gastrointestinal endoscopy images

- Authors: Takumi Itoh, Hiroshi Kawahira, Hirotaka Nakashima, Noriko Yata

<table>
<thead>
<tr>
<th></th>
<th>sensitivity</th>
<th>specificity</th>
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<tr>
<td>Bah A (Statistical)</td>
<td>75%</td>
<td>63%</td>
</tr>
<tr>
<td>Takumi Itoh (Deep learning)</td>
<td>86.7%</td>
<td>86.7%</td>
</tr>
</tbody>
</table>
Deep learning for polyp recognition in wireless capsule endoscopy images

- Authors: Yixuan Yuan and Max Q.-H. Meng
Deep learning for polyp recognition in wireless capsule endoscopy images

- Comparative Results

<table>
<thead>
<tr>
<th></th>
<th>ORA (%)</th>
<th>Bubbles Acc. (%)</th>
<th>Turbid Acc. (%)</th>
<th>Clear Image Acc. (%)</th>
<th>Polyp Acc. (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Li et al.\textsuperscript{10}</td>
<td>81.33 ± 2.07</td>
<td>91.60 ± 3.04</td>
<td>83.90 ± 3.41</td>
<td>84.80 ± 1.01</td>
<td>65.00 ± 2.58</td>
</tr>
<tr>
<td>Silva et al.\textsuperscript{11}</td>
<td>83.42 ± 2.26</td>
<td>92.50 ± 4.67</td>
<td>73.90 ± 2.73</td>
<td>81.40 ± 0.57</td>
<td>85.90 ± 1.14</td>
</tr>
<tr>
<td>Hwang et al.\textsuperscript{13}</td>
<td>88.70 ± 1.21</td>
<td>90.50 ± 3.03</td>
<td>93.30 ± 4.24</td>
<td>1.20 ± 3.97</td>
<td>89.80 ± 2.27</td>
</tr>
<tr>
<td>Limamou et al.\textsuperscript{14}</td>
<td>86.85 ± 1.90</td>
<td>88.00 ± 4.08</td>
<td>9.50 ± 1.02</td>
<td>80.80 ± 2.23</td>
<td>89.10 ± 2.07</td>
</tr>
<tr>
<td>Yuan et al.\textsuperscript{15}</td>
<td>90.02 ± 2.23</td>
<td>90.80 ± 1.99</td>
<td>93.90 ± 4.93</td>
<td>88.70 ± 4.41</td>
<td>86.70 ± 1.32</td>
</tr>
<tr>
<td>Ours</td>
<td>98.00 ± 0.17</td>
<td>99.50 ± 1.75</td>
<td>99.00 ± 0.96</td>
<td>95.50 ± 1.21</td>
<td>98.00 ± 2.11</td>
</tr>
</tbody>
</table>
Angiodysplasia Detection and Localization Using Deep Convolutional Neural Networks

- Authors: Alexey Shvets, Vladimir Iglovikov, Alexander Rakhlin, Alexandr A. Kalinin
- Dataset: MICCAI 2017 Endoscopic Vision SubChallenge: Angiodysplasia detection and localization
- Stage I: Detection
- Stage II: Segmentation
Angiodysplasia Detection and Localization Using Deep Convolutional Neural Networks: Deep learning architecture
Angiodysplasia Detection and Localization Using Deep Convolutional Neural Networks: Results
Computer-aided Detection of Colorectal Polyps at CT Colonography: Prospective Clinical Performance and Third-Party Reimbursement

Ziemlewicz TJ¹, Kim DH¹, Hinshaw JL¹, Lubner MG

An Automatic Gastrointestinal Polyp Detection System in Video Endoscopy Using Fusion of Color Wavelet and Convolutional Neural Network Features

- Authors: Mustain Billah, Sajjad Waheed, and Mohammad Motiur Rahman
An Automatic Gastrointestinal Polyp Detection System in Video Endoscopy Using Fusion of Color Wavelet and Convolutional Neural Network Features
An Automatic Gastrointestinal Polyp Detection System in Video Endoscopy Using Fusion of Color Wavelet and Convolutional Neural Network Features

<table>
<thead>
<tr>
<th>Paper</th>
<th>Used methodology</th>
<th>Used dataset</th>
<th>Accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kodogiannis et al. [3]</td>
<td>Texture + ANFIS</td>
<td>140 images</td>
<td>97%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Park et al. [13]</td>
<td>CNN + CRF</td>
<td>35 videos</td>
<td>86%</td>
<td></td>
<td>85%</td>
</tr>
<tr>
<td>Ribeiro et al. [9]</td>
<td>CNN</td>
<td>100 images</td>
<td>90.96%</td>
<td>95.16%</td>
<td>74.19%</td>
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<tr>
<td>Zhu et al. [7]</td>
<td>CNN + SVM</td>
<td>180 images</td>
<td>80%</td>
<td></td>
<td>79.54%</td>
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<tr>
<td>Alexandre et al. [4]</td>
<td>RGB + XY + SVM</td>
<td>4620 images</td>
<td>94.87%</td>
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</tr>
<tr>
<td>Zou et al. [6]</td>
<td>DCNN</td>
<td>25 videos</td>
<td>95%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Li et al. [5]</td>
<td>Color + shape + MLP</td>
<td>450 images</td>
<td>94.20%</td>
<td>95.07%</td>
<td>93.33%</td>
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<td>Karkanis et al. [1]</td>
<td>CWC + LDA</td>
<td>60 videos</td>
<td>97%</td>
<td></td>
<td>90%</td>
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<tr>
<td>Iakovidis et al. [2]</td>
<td>KL + wavelet + SVM</td>
<td>86 videos</td>
<td>94%</td>
<td></td>
<td></td>
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<tr>
<td><strong>Proposed system</strong></td>
<td><strong>Color wavelet + CNN + SVM</strong></td>
<td><strong>100 videos</strong></td>
<td><strong>98.55%</strong></td>
<td><strong>98.79%</strong></td>
<td><strong>98.52%</strong></td>
</tr>
</tbody>
</table>
Computer-aided Detection in Computed Tomography Colonography with Full Fecal Tagging: Comparison of Standalone Performance of 3 Automated Polyp Detection Systems

- Authors: Patrick A. Hein, Lasse D. Krug, Valentina C. Romano, Sonja Kandel, Bernd Hamm, Patrik Rogalla.
Computer-aided Detection in Computed Tomography Colonography with Full Fecal Tagging: Comparison of Standalone Performance of 3 Automated Polyp Detection Systems
CAD in Medical imaging

- Detection of lung nodules on PA and lateral chest radiographs
- Detection of vertebral fractures on lateral chest radiograph
- Detection of intracranial aneurysms in MRA
- Detection of interval changes in successive whole-body bone scans
- Detection of breast cancer by use of mammograms
Large Scale Automated Reading of Frontal and Lateral Chest X-Rays using Dual Convolutional Neural Networks

- Authors: Jonathan Rubin, Deepan Sanghavi, Claire Zhao, Kathy Lee, Ashequl Qadir, Minnan Xu-Wilson
Large Scale Automated Reading of Frontal and Lateral Chest X-Rays using Dual Convolutional Neural Networks

<table>
<thead>
<tr>
<th>Finding</th>
<th>Individual PA+Lateral</th>
<th>DualNet PA+Lateral</th>
<th>Individual AP+Lateral</th>
<th>DualNet AP+Lateral</th>
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</thead>
<tbody>
<tr>
<td>Atelectasis</td>
<td>0.760</td>
<td>0.766</td>
<td>0.675</td>
<td>0.671</td>
</tr>
<tr>
<td>Cardiomegaly</td>
<td>0.835</td>
<td>0.840</td>
<td>0.752</td>
<td>0.755</td>
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<tr>
<td>Consolidation</td>
<td>0.642</td>
<td>0.632</td>
<td>0.625</td>
<td>0.623</td>
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<tr>
<td>Edema</td>
<td>0.723</td>
<td>0.734</td>
<td>0.757</td>
<td>0.749</td>
</tr>
<tr>
<td>Effusion</td>
<td>0.735</td>
<td>0.757</td>
<td>0.701</td>
<td>0.733</td>
</tr>
<tr>
<td>Fibrosis</td>
<td>0.638</td>
<td>0.761</td>
<td>0.552</td>
<td>0.610</td>
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<tr>
<td>Hernia</td>
<td>0.716</td>
<td>0.815</td>
<td>0.701</td>
<td>0.758</td>
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<tr>
<td>Infiltration</td>
<td>0.746</td>
<td>0.748</td>
<td>0.590</td>
<td>0.773</td>
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<tr>
<td>Mass</td>
<td>0.656</td>
<td>0.692</td>
<td>0.574</td>
<td>0.581</td>
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<tr>
<td>No Finding</td>
<td>0.746</td>
<td>0.758</td>
<td>0.727</td>
<td>0.734</td>
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<tr>
<td>Nodule</td>
<td>0.527</td>
<td>0.568</td>
<td>0.549</td>
<td>0.527</td>
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<tr>
<td>Pleural Thickening</td>
<td>0.687</td>
<td>0.687</td>
<td>0.571</td>
<td>0.629</td>
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<tr>
<td>Pneumonia</td>
<td>0.596</td>
<td>0.625</td>
<td>0.571</td>
<td>0.593</td>
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<tr>
<td>Pneumothorax</td>
<td>0.659</td>
<td>0.706</td>
<td>0.577</td>
<td>0.621</td>
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<tr>
<td>Average</td>
<td>0.690</td>
<td>0.721</td>
<td>0.637</td>
<td>0.668</td>
</tr>
</tbody>
</table>
Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists

- Authors: Pranav Rajpurkar, Jeremy Irvin, Robyn L. Ball
Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists
Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists

Table 1. Radiologists and algorithm AUC with CIs.

<table>
<thead>
<tr>
<th>Pathology</th>
<th>Radiologists (95% CI)</th>
<th>Algorithm (95% CI)</th>
<th>Algorithm – Radiologists Difference (99.6% CI)²</th>
<th>Advantage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Atelectasis</td>
<td>0.808 (0.777 to 0.838)</td>
<td>0.862 (0.825 to 0.895)</td>
<td>0.053 (0.003 to 0.101)</td>
<td>Algorithm</td>
</tr>
<tr>
<td>Cardiomegaly</td>
<td>0.888 (0.863 to 0.910)</td>
<td>0.831 (0.790 to 0.870)</td>
<td>-0.057 (-0.113 to -0.007)</td>
<td>Radiologists</td>
</tr>
<tr>
<td>Consolidation</td>
<td>0.841 (0.815 to 0.870)</td>
<td>0.893 (0.859 to 0.924)</td>
<td>0.052 (-0.001 to 0.101)</td>
<td>No difference</td>
</tr>
<tr>
<td>Edema</td>
<td>0.910 (0.886 to 0.930)</td>
<td>0.924 (0.886 to 0.955)</td>
<td>0.015 (-0.038 to 0.060)</td>
<td>No difference</td>
</tr>
<tr>
<td>Effusion</td>
<td>0.900 (0.876 to 0.921)</td>
<td>0.901 (0.868 to 0.930)</td>
<td>0.000 (-0.042 to 0.040)</td>
<td>No difference</td>
</tr>
<tr>
<td>Emphysema</td>
<td>0.911 (0.866 to 0.947)</td>
<td>0.704 (0.567 to 0.833)</td>
<td>-0.208 (-0.508 to -0.003)</td>
<td>Radiologists</td>
</tr>
<tr>
<td>Fibrosis</td>
<td>0.897 (0.840 to 0.936)</td>
<td>0.806 (0.719 to 0.884)</td>
<td>-0.091 (-0.198 to 0.016)</td>
<td>No difference</td>
</tr>
<tr>
<td>Hernia</td>
<td>0.985 (0.974 to 0.991)</td>
<td>0.851 (0.785 to 0.909)</td>
<td>-0.133 (-0.236 to -0.055)</td>
<td>Radiologists</td>
</tr>
<tr>
<td>Infiltration</td>
<td>0.734 (0.688 to 0.779)</td>
<td>0.721 (0.651 to 0.786)</td>
<td>-0.013 (-0.107 to 0.067)</td>
<td>No difference</td>
</tr>
<tr>
<td>Mass</td>
<td>0.886 (0.856 to 0.913)</td>
<td>0.909 (0.864 to 0.948)</td>
<td>0.024 (-0.041 to 0.080)</td>
<td>No difference</td>
</tr>
<tr>
<td>Nodule</td>
<td>0.899 (0.869 to 0.924)</td>
<td>0.894 (0.853 to 0.930)</td>
<td>-0.005 (-0.058 to 0.044)</td>
<td>No difference</td>
</tr>
<tr>
<td>Pleural thickening</td>
<td>0.779 (0.740 to 0.809)</td>
<td>0.798 (0.744 to 0.849)</td>
<td>0.019 (-0.056 to 0.094)</td>
<td>No difference</td>
</tr>
<tr>
<td>Pneumonia</td>
<td>0.823 (0.779 to 0.856)</td>
<td>0.851 (0.781 to 0.911)</td>
<td>0.028 (-0.087 to 0.125)</td>
<td>No difference</td>
</tr>
<tr>
<td>Pneumothorax</td>
<td>0.940 (0.912 to 0.962)</td>
<td>0.944 (0.915 to 0.969)</td>
<td>0.004 (-0.040 to 0.051)</td>
<td>No difference</td>
</tr>
</tbody>
</table>
Generative Adversarial Training for MRA Image Synthesis Using Multi-Contrast MRI

- Authors:
  - Sahin Olut
  - Yusuf H. Sahin
  - Ugur Demir
  - Gozde Unal
Generative Adversarial Training for MRA Image Synthesis Using Multi-Contrast MRI
Automated Whole-Body Bone Lesion Detection for Multiple Myeloma on 68Ga-Pentixafor PET/CT Imaging Using Deep Learning Methods

- Authors: Lina Xu, Giles Tetteh, Jana Lipkova
Automated Whole-Body Bone Lesion Detection for Multiple Myeloma on 68Ga-Pentixafor PET/CT Imaging Using Deep Learning Methods

- Authors: Lina Xu, Giles Tetteh, Jana Lipkova
Detecting and classifying lesions in mammograms with Deep Learning

• Authors:
  • Dezső Ribli
  • Anna Horváth
  • Zsuzsa Unger
  • Péter Pollner
  • István Csabai

Figure 1. The outline of the Faster R-CNN model for CAD in mammography.
Detecting and classifying lesions in mammograms with Deep Learning
Case Studies:
IBM Watson In Action
The Science Behind Watson

- Watson understands natural language, breaking down the barrier between people and machines
- The system then generates hypotheses – recognizing that there are different probabilities of various outcomes
- See how Watson "learns," tracking feedback – learning from success and failure – to improve future responses
• Watson enables processing of text, speech and images (...correlate to use cases in healthcare around understanding medical literature/patient records; interactions between caregivers and patients, etc.; analysis of images such as X-ray, MRI, simple cameras)

• Watson can be trained on domain-specific and organization-specific content

• Watson enables anytime-anywhere “augmented intelligence” via the cloud, so existing healthcare software can be enhanced without major re-writes

• Watson enables intelligent interaction with devices (IoT) for enhanced care delivery in hospital, post-discharge care, clinical trials, etc.

• Watson enables the use of predictive modeling which can be applied to disease progression, payer pricing models, medication adherence models, etc.
MEDICAL: “Smart Speaker” in Patient Suite

Problem/Opportunity
• A leading US hospital in US wanted to improve patient stays and reduce patient anxiety
• Need to reduce doctor visits and automate status updates

Solution: IBM Watson text-to-speech (and back)
• Smart Speaker near patient bed asks predefined questions
• Speech-to-text API returns responses based on context
• Response is sent to device using text-to-speech API in audio format
• Patient controls appliances in room by voice command on Samsung SmartThings Hub and cloud platform

Benefits
• Patient experience and satisfaction increased
• Daily doctor visits decreased
• Staff and housekeeping interactions improved

Persistent Systems Toolkit
• IBM Bluemix, Samsung SmartThings Cloud platform, Node-Red
• Conversation API, speech-to-text & text-to-speech APIs
MEDICAL: Oncology Statistical Analytics Reporting

Problem/Opportunity

- Develop a dashboard showing different statistics for cancer patients
- Used information to treat and advise the patients in a more informed way based on the symptoms and other similar cases

Solution: IBM Watson text-to-speech (and back)

- Use Watson Analytics to crawl and analyze structured and unstructured oncology data
- Identify relationships among entities
- Deliver clear, understandable data visualizations for doctor & patient

Benefits

- Reduce patient fear, confusion and anxiety
- Provide actionable intelligence to caregivers to suggest possible treatments
- Deliver customized results based on patient demographics

Persistent Systems Toolkit

- IBM Watson Analytics
- Dash DB
Watson Tackles Cancer

- Watson was tested on 1,000 cancer diagnoses made by human experts. In 99% of them, Watson recommended the same treatment as the oncologists.
- In 30% of the cases, Watson also found a treatment option the human doctors missed.
- Some treatments were based on research papers that the doctors had not read — more than 160,000 cancer research papers are published a year.
- Other treatment options surfaced in new clinical trials the oncologists had not yet seen announced on the web.
Success Stories of AI Systems

Cancer:
- Somashekhar et al. demonstrated that the IBM Watson for oncology would be a reliable AI system for assisting the diagnosis of cancer through a double-blinded validation study.19
- Esteva et al analysed clinical images to identify skin cancer subtypes.

Neurology:
- Bouton et al. developed an AI system to restore the control of movement in patients with quadriplegia
- Farina et al tested the power of an offline man/machine interface that uses the discharge timings of spinal motor neurons to control upper-limb prostheses

Cardiology:
- Dilsizian and Siegel discussed the potential application of the AI system to diagnose the heart disease through cardiac image.3
- Arterys recently received clearance from the US Food and Drug Administration (FDA) to market its Arterys Cardio DL application, which uses AI to provide automated, editable ventricle segmentations based on conventional cardiac MRI images.23
Conclusion

- Real time knowledge is available first time in history
- Better than any guidelines.
- AI is expensive
- MD Anderson spent $65 million on IBM Watson platform and still to use
Artificial Intelligence for the Real World

Don't start with moon shots.

by Thomas H. Davenport and Rajeev Ronanki

Artificial Intelligence for the Real World

Don’t start with moon shots.

BY THOMAS H. DAVENPORT AND RAJEEV RONANKI
i-Doctor
Intelligent Drug Dispensing ATM Based on Symptom-based Algorithm
i-Doctor Introduction

i-Doctor, is an attempt to go beyond current telemedicine model and support Indian citizens to get affordable health care services within their vicinity.

- **Patient’s Interaction**
- **Intelligent Diagnosis**
- **Medicine Dispensing**

**Point of Care devices**

**Intelligent Systems in Action**
The rise of the machines has already begun

**50+ Clinical Conditions**

**100+ Medicines**

**Battery backed i-Doctor System**

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i-Doctor Methodology

Biometric Authentication

Collect readings from easily configurable Point of care devices

Patients Data

Intelligence System Questionnaire to Diagnose Clinical Condition

Battery backed i-Doctor System

Payment Gateway

Generate Prescription

Emergency Situation

Follow-up call

Weighing Scale

Thermometer

Camera

ECG

BP

Oeterxim

Drug Dispensing Machine

Call Doctor/Ambulance/Hospital

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Future Of Medicine
i-Doctor Robot
SkinSense

- Components used for prediction:
  - **Multiple QSAR models** built using large publicly available data on sensitizers (of various potency classes) & non-sensitizers
  - **Structural similarity** to known sensitizers and non-sensitizers
  - Presence of **sub-structure(s)** associated with skin sensitization reaction mechanisms

- Integrated statistical & mechanistic approaches that helped achieve improved prediction performance & coverage
Key Features

- Predict skin sensitization potential of molecules
- Identify protein-reactive groups & skin sensitization mechanism of molecules
- Validated & compared against unbiased dataset with accuracy = 75.32%, CCR = 74.36%, sensitivity = 70% & specificity = 78.72%
- Accepts standard input formats (eg. SMILES, SDF) and allows drawing of structures
Definition of Health in Ayurveda

One whose doshas, agni, functions of doshas and malas are in state of equilibrium, who has cheerful atman, mind, intellect and sense organs is designated as healthy.
The gist, as we can make out, is that individual body constitution analysis or ‘Prakriti’ analysis, as mentioned in Ayurveda, is very essential for positive health of mankind in times to come.

In today's era
Global Focus is on

PERSONALISED MEDICINE
Interventions from Samhita and Opinions of experts

- Samadosha
- Samagni
- Sama Dhatu
- Mala Kriya

Clusters of Ayurvedic Entity

Interventions

Real-time Management of Patients

Monitoring Parameter's

Modern Medicine Ayurveda

Outcome

Machine learning

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Cognitive Domain Analysis of available interventions specific to clusters

- Clinical picture
- Radiology
- Receptor status
- Laboratory Data

Clusters of Disease with all data in Permutation

Interventions

All Data that was used for cluster analysis

Monitoring Parameter's

Outcome

Real-time Management of Patients

Morbidity, Mortality, Survival, Quality of Life

Machine learning

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Thank You!