Artificial Intelligence in Pediatric Surgery: Challenges and Opportunities

Meeting: Service of Pediatric Surgery | HSJ

Porto, Portugal | November 8, 2024

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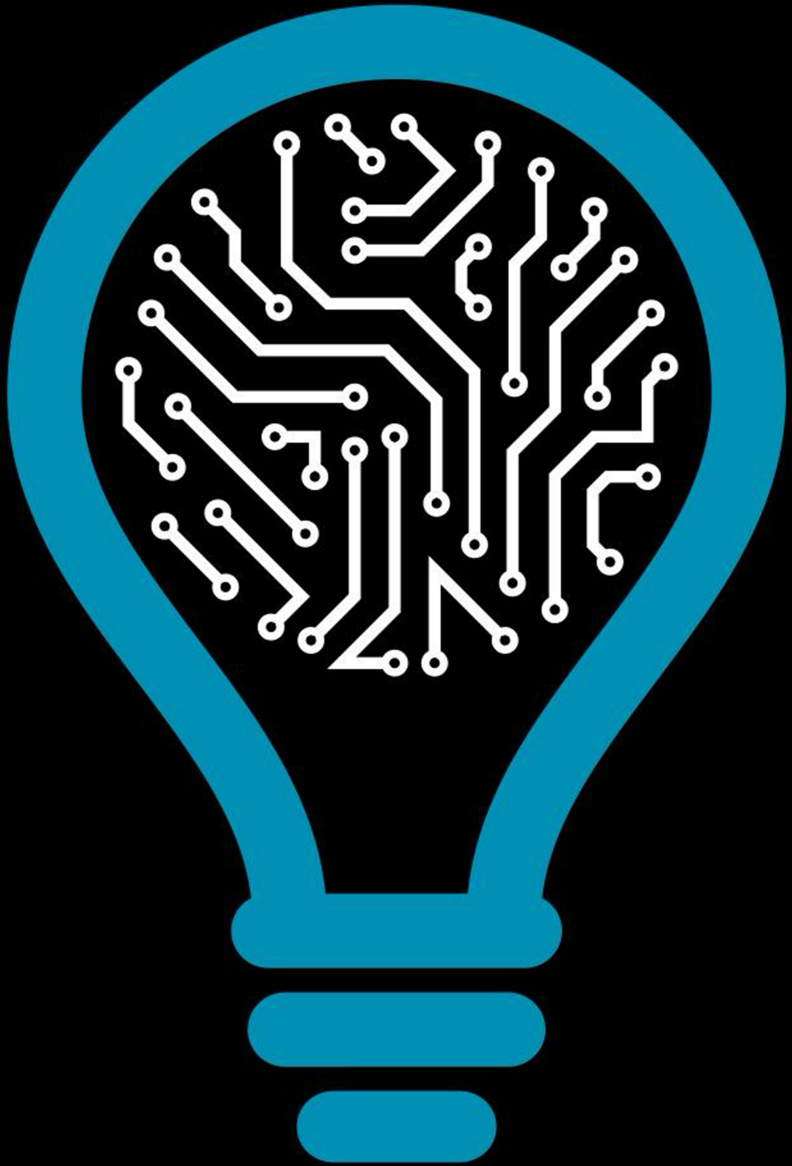

Outline

1. What is Artificial Intelligence?

2. Medical Data: A special use case?

3. Responsible AI: Friend or Foe?

4. AI in Pediatric Surgery: What is the community doing?

1. What is Artificial Intelligence?

Nowadays, we are constantly generating data[1]

- **The paradigm is changing:** most of the daily tasks and services can now be performed with the aid of **digital applications** or **gadgets**
- High-tech companies such as Google, Facebook, Netflix or Amazon **have access to huge amounts of data from several data sources and users**:
  - This phenomenon suggests that the *business of data* will become a **significant sector of the global economy**[2]
  - There are several **open-source data sets with millions of entries** (e.g., ImageNet[3])
- Data is referred as **the new oil**[4]
  - The main impact on humanity is related **to the way data can improve our lives**
  - **A proper management process of the "dark side" of data must be implemented**, but the **advances** in data fuels **are worth the effort**

Sources: [1] https://techjury.net/blog/big-data-statistics/#gref, [2] https://www.forbes.com/sites/gilpress/2020/01/06/6-predictions-about-data-in-2020-and-the-coming-decade/?sh=5cbaadf4fc36, [3] http://www.image-net.org, [4] https://www.forbes.com/sites/forbestechcouncil/2019/11/15/data-is-the-new-oil-and-thats-a-good-thing/?sh=69bb9a407304

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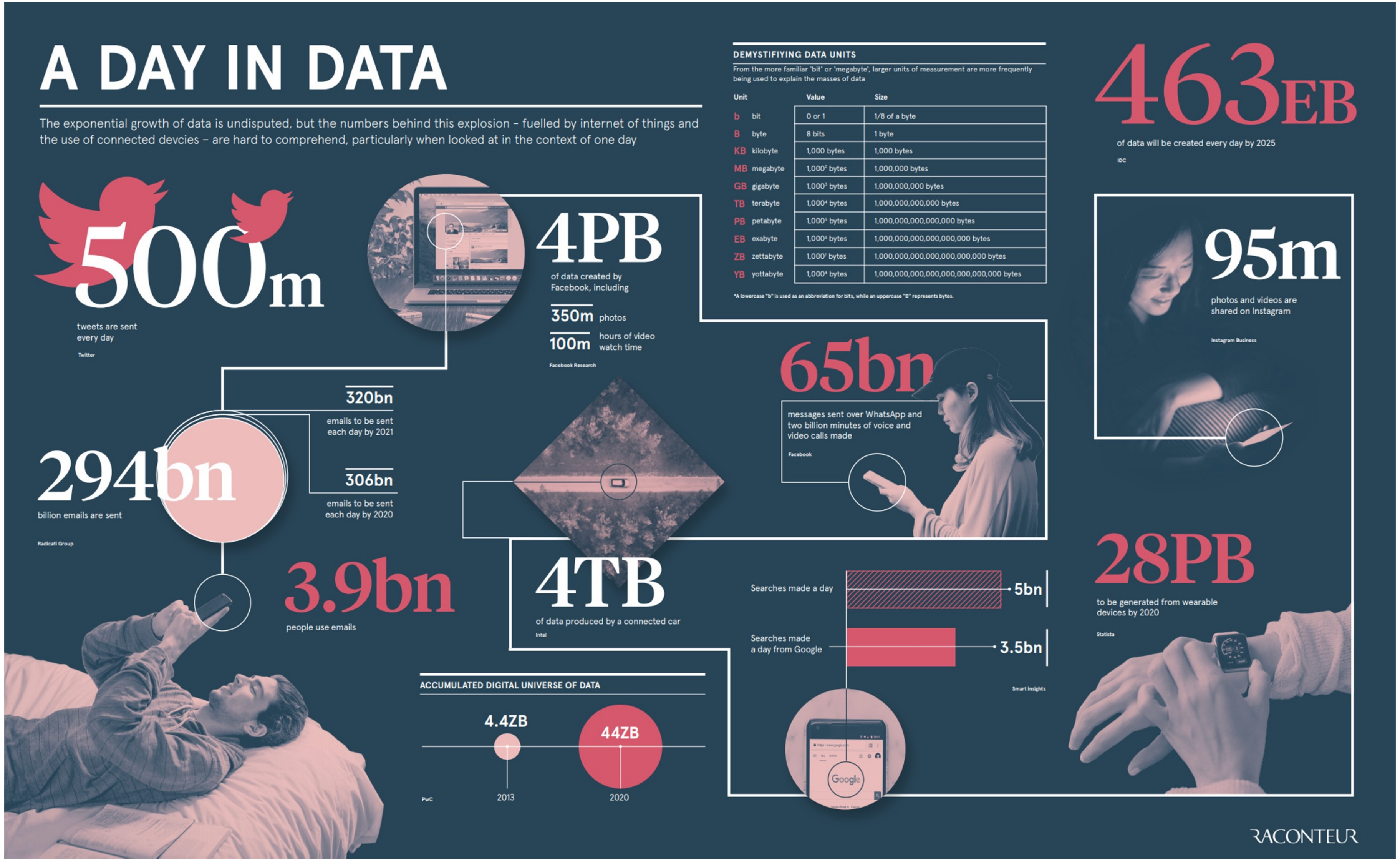
Take a look: A Day in the Wonderful World of Data[1, 2, 3]



Sources: [1] https://www.raconteur.net/infographics/a-day-in-data/, [2] https://www.weforum.org/agenda/2019/04/how-much-data-is-generated-each-day-cf4bddf29f/, [3] https://www.visualcapitalist.com

We have more computational power than ever

- **The fundamental concepts of artificial intelligence and deep neural networks have been around since 1940**[1]
  - Frank Rosenblatt proposed one of the first approaches to the design and training of artificial neural networks: **the Perceptron**[2]

- The development of **powerful computer processing units (CPUs)** and the leveraging of the **graphical processing units (GPUs)**[3] for computation allowed the training of deep and complex algorithms in **"human time"**

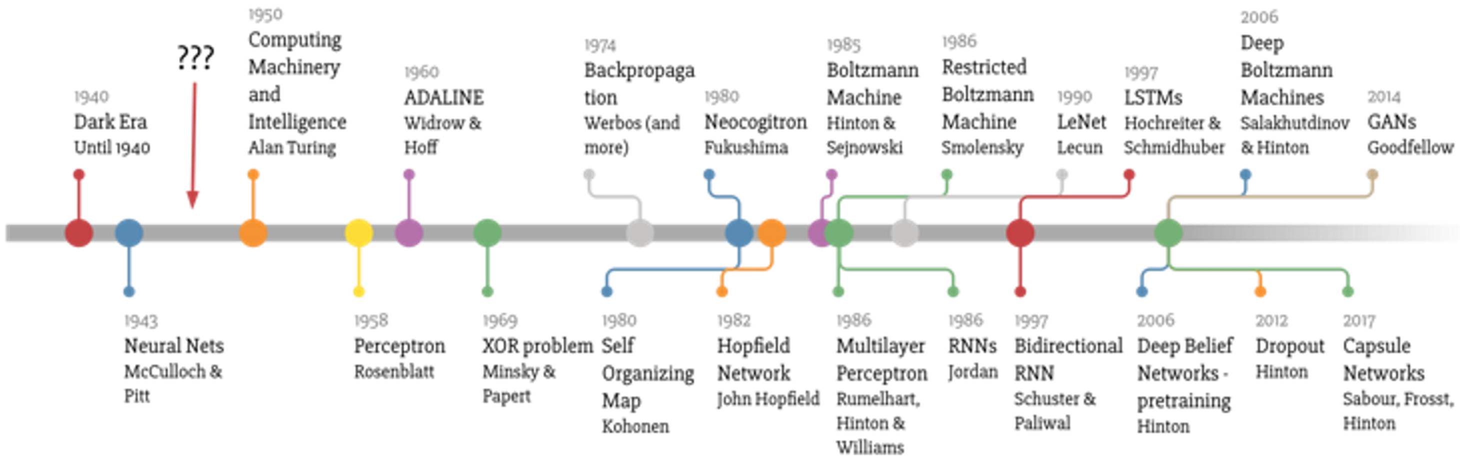


Figure - A (tentative) deep learning timeline (Image from [1])

Sources: [1] https://towardsdatascience.com/a-weird-introduction-to-deep-learning-7828803693b0, [2] Frank Rosenblatt "The perceptron: A probabilistic model for information storage and organization in the brain.", [3] https://www.nvidia.com/en-us/

Technology has been *challenging* human performance...

- There are, at least, two popular events that created a revolution in the History of AI:
  - **In 1997, IBM's Deep Blue beated the Chess World Champion Garry Kasparov**[1]
  - **In 2016, Google's DeepMind AlphaGo learned to play Go alone (i.e., through reinforcement learning policies) and beat the Go World Champion Lee Sedol**[2]

- The two events above are examples of the **(virtually) unlimited boundaries of the application of artificial intelligence** to our daily lives
  - In 2020, Google's DeepMind published a paper in ***Nature*** **suggesting that "its model was able to spot cancer in de-identified screening mammograms with fewer false positives and false negatives than experts"**[3, 4]

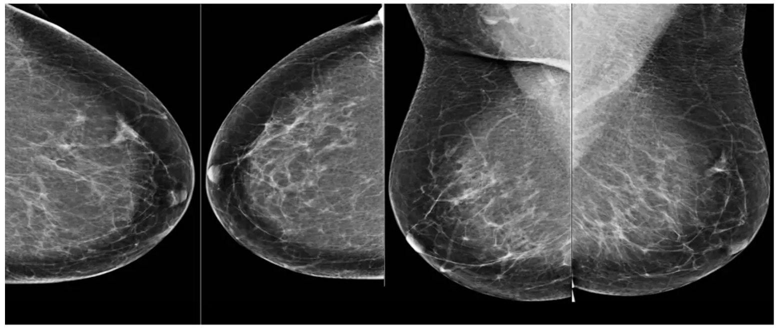


Figure - Medical Image Analysis: Mammograms (Image from [4])

Sources: [1] https://theconversation.com/twenty-years-on-from-deep-blue-vs-kasparov-how-a-chess-match-started-the-big-data-revolution-76882, [2] https://deepmind.com/research/case-studies/alphago-the-story-so-far, [3] https://www.healthcareitnews.com/news/google-ai-platform-aids-oncologists-breast-cancer-screenings, [4] https://www.nature.com/articles/s41586-019-1799-6

Everything seems good except for the lack of transparency

- **The increase of available computational power and the democratised access to a huge amount of data** has leveraged the development of novel artificial intelligence (AI) algorithms and their applications

- Deep learning techniques **have been challenging human performance** at some specific tasks such as cancer detection in biomedical imaging[1] or machine translation in natural language processing[2]

- However, most of these models work as black boxes (i.e., their internal logic is hidden to the user) that receive data and output results **without justifying their predictions in a human understandable way**[3]

Sources: [1] McKinney et al. "International evaluation of an AI system for breast cancer screening", [2] Belinkov and Glass "Analysis Methods in Neural Language Processing: A Survey", [3] Cynthia Rudin "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead"

No worries! We are working on that!

- Even if the models achieve high performances, **it is not trivial to assure that they are learning features that are relevant for that domain** (i.e., **black box** behavior)
    - Machine learning models **are good at extracting correlations**

- While this **may not be an issue in several domains** (e.g., recommendation systems), in others, it is of utmost importance that the **system is capable of transparently showing** the reasons behind its decisions (e.g., healthcare)

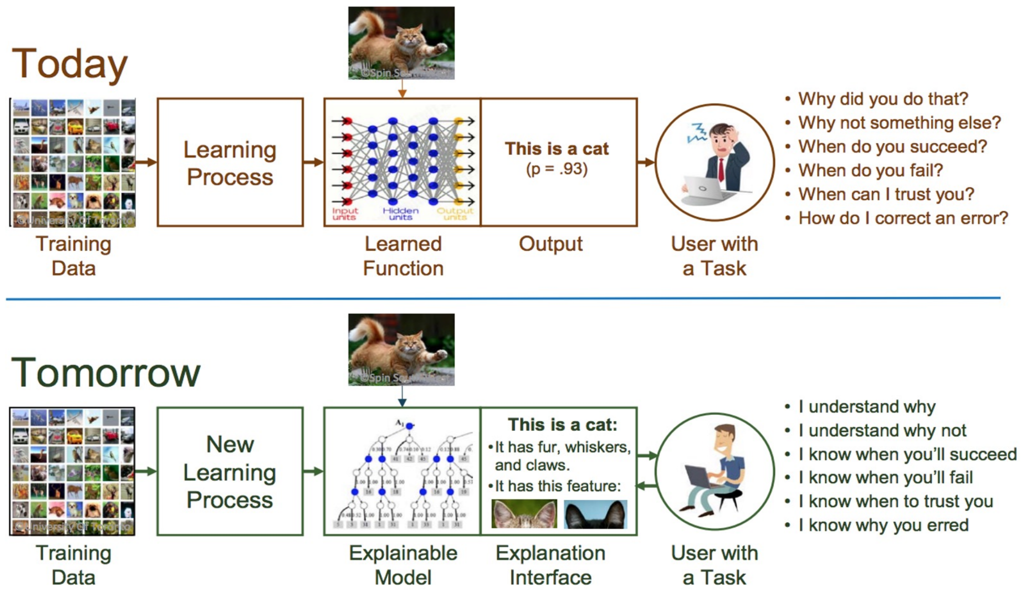


Figure - The future of machine learning algorithms
(Image from [1])

Sources: [1] https://www.cc.gatech.edu/~alanwags/DLAI2016/(Gunning)%20IJCAI-16%20DLAI%20WS.pdf

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Explain it like a Human: Interpretability is the key!

- **Interpretability** is a concept that results from the interaction between several definitions
  - The degree to which a human can **understand the cause of a decision**[1]
  - The degree to which a human can **consistently predict the model's result**[2]

- **Interpretable machine learning** is also related to the **"extraction of relevant knowledge from a machine-learning model concerning relationships either contained in data or learned by the model"**[3]

- Intuitively, the **higher the degree of interpretability** of a model, the **higher the likelihood of a user comprehending its predictions**[4]

- **"Humans have a mental model of their environment that is updated when something unexpected happens. This update is performed by finding an explanation for the unexpected event"**[4]

Sources: [1] Tim Miller "Explanation in artificial intelligence: Insights from the social sciences.", **[2]** Been Kim et al. "Examples are not enough, learn to criticize! Criticism for interpretability.", **[3]** W. J. Murdoch "Definitions, methods, and applications in interpretable machine learning.", **[4]** Christoph Molnar "Interpretable Machine Learning A Guide for Making Black Box Models Explainable"

2. Medical Data: A special use case?

Medical data is multimodal, and that is awesome

- In the clinical context, **it is common to combine several image modalities** during the decision making process (e.g. computed tomography, electroencephalography, magnetic resonance imaging, positron emission tomography)

- Recently, a comprehensive study[1] on data fusion strategies for image classification and segmentation reported that the **network trained with multi-modal images showed superior performance** compared to networks trained with single-modal images, and that **performing image fusion within the network** (e.g., fusing at convolutional or fully connected layers) is generally better than fusing images at the network output (e.g., voting)[1]

Sources: [1] Zhe Guo et al. "Deep Learning-based Image Segmentation on Multimodal Medical Imaging",

Multimodality means that data fusion will play a key role in our lives

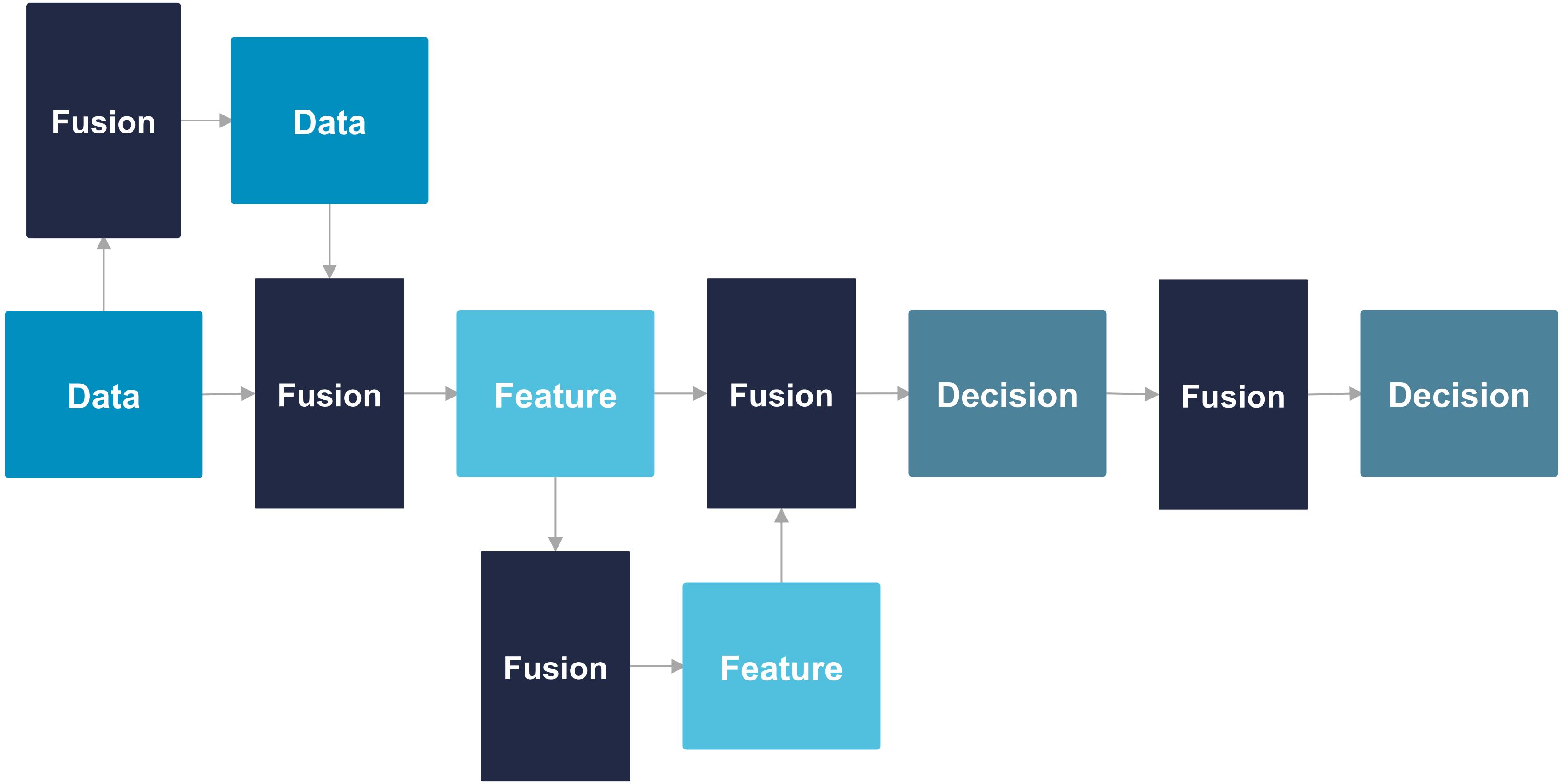


Figure: Different strategies of data fusion[1]

Sources: [1] R. C. Luo et al. "Multisensor fusion and integration: approaches, applications,and future research directions"

The medical world needs human-understandable explanations

- The **black box behavior of deep learning models does not help decision-makers** to have a **clear understanding of their inner-functioning**, thus preventing them to diagnose errors and potential biases or deciding when and how much to rely on these models[1]

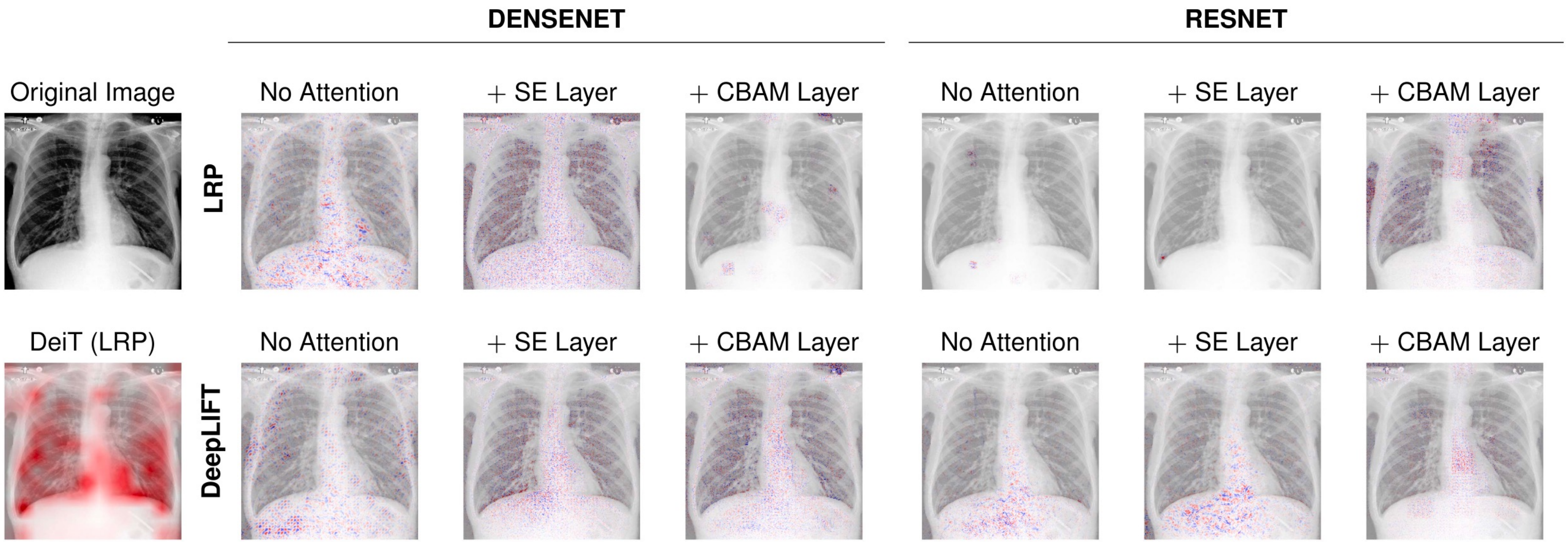
- There has been a huge effort into the **development of post-model strategies** to explain the behavior of black box models, however, the outputs of these algorithms are prone to **subjective evaluation**, **may be misleading**[2] or **fooled**[1]

- Besides, we agree that just being able to obtain explanations is not enough and that we rather need to take into account at the development stage that these methods must **respect specific constraints** that give them the **capability of generating human-understandable explanations** and make decisions based on such premises[3]

Sources: [1] Dylan Slack et al. "Fooling LIME and SHAP: Adversarial Attacks on Post hoc Explanation Methods", **[2]** Zachary C. Lipton "The Mythos of Model Interpretability", **[3]** Cynthia Rudin "Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead"

What do you see?[1]

TABLE 12. **Example of LRP and DeepLIFT *post-hoc* saliency maps for an image of the MIMIC-CXR data set with the label 0 correctly classified as 0 by all models.**



Sources: [1] Tiago Gonçalves et al. "A Survey on Attention Mechanisms for Medical Applications: are we Moving Toward Better Algorithms?"

The healthcare tech market is full of opportunities and requires interpretable artificial intelligence

- Interpretability is already playing its role in the pipelines of machine learning deployment: researchers and developers are **using interpretability techniques to validate and debug** their models before deployment[1, 2]

- Regarding the availability of end-user software that contain **machine learning algorithms for medical applications**, we point to the popularity of:
  - Software for the analysis of volumetric medical images
  - Software for the development and creation of **DICOM pipelines and servers**
  - Software for the **annotation** and **segmentation** of medical images
  - Software for the **automatic classification** of medical images
  - Software for the **automatic analysis of electronic health records** of patients to generate **diagnosis** and **recommendations**

Sources: [1] Umang Bhatt et al. "Explainable Machine Learning in Deployment", [2] Isaac Lage et al. "An Evaluation of the Human-Interpretability of Explanation"

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3. Responsible AI: Friend or Foe?

Responsible AI relies on fundamental principles

- **Responsible AI** is a framework that guides how we should address the challenges around artificial intelligence from both an **ethical, technical and legal** point of view[1]
  - We must resolve ambiguity for where responsibility lies if something goes wrong!

- This framework relies on fundamental principles[2]:
  - **Accountability**
  - **Interpretability**
  - **Fairness**
  - **Safety**
  - **Privacy**

Figure - Responsible AI (Image from [1])

Sources: [1] https://searchenterpriseai.techtarget.com/definition/responsible-AI, [2] https://towardsdatascience.com/what-is-responsible-ai-548743369729

We need to design ethical and fair algorithms

- To facilitate trust (and increase transparency) in AI algorithms it is important to **ensure a priori that these models are interpretable**, and understand how decisions are made in the clinical context

- On the other hand, it is important to understand what the algorithms are already learning and to **evaluate the quality of such explanations** (e.g., understand if the algorithms are extracting relevant features for the clinical context)

- A different dimension of the application of AI in sensitive domains such as healthcare is the **development of ethical and fair algorithms**[1]
    - This strategy is supported by the new European Union’s General Data Protection Regulation (EU-GDPR)[2] which advises that these **algorithms should be able to explain their decisions for the sake of transparency**

Sources: [1] Irene Y. Chen et al. “Treating health disparities with artificial intelligence”, [2] Margot E. Kaminski “The Right to Explanation, Explained”

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While keeping an attentive eye on the technologies that are shaping our lives

- Many entities are already leveraging their data sources to **optimize their inner processes or to develop new services or products**, thus enabling them to achieve a substantial competitive advantage[1]

- In the healthcare context, systems and algorithms need to go through a continuous **pipeline of validation and error assessment**

- Hence, it is **reasonable to accept that these technologies may need to be calibrated** to the data sources of the institutions that are integrating them into their information systems and that these algorithms **may have a continuous learning policy over time**

- Moreover, to assure **transparency, accountability and accessibility**, new regulatory frameworks will have to be developed to allow model adaptations that enable optimal performance while **ensuring reliability and patient safety**[2]

Sources: [1] Lucas Baier et al. "Challenges in the deployment and operation of machine learning in practice",
[2] Farhad Maleki et al. "Machine Learning Algorithm Validation: From Essentials to Advanced Applications and Implications for Regulatory Certification and Deployment"

4. AI in Pediatric Surgery: What is the community doing?

Machine Learning in Pediatric Surgical Clinical Prediction Tools[1]

- **Purpose:** Clinical prediction tools (CPTs) are decision-making instruments utilizing patient data to predict specific clinical outcomes, risk-stratify patients, or suggest personalized diagnostic or therapeutic options. Recent advancements in artificial intelligence have resulted in a proliferation of CPTs created using machine learning (ML) – yet the clinical applicability of ML-based CPTs and their validation in clinical settings remain unclear

- **Conclusions:** While most studies claim significant potential improvements by incorporating ML-based CPTs in pediatric surgical decision-making, both external validation and clinical application remains limited. Further studies must focus on validating existing instruments or developing validated tools, and incorporating them in the clinical workflow

Sources: [1] Bianco et al. "Use of machine learning in pediatric surgical clinical prediction tools: A systematic review"

Machine Learning for Postoperative Complication Prediction[1]

- **Purpose:** Managing children undergoing cardiac surgery with cardiopulmonary bypass (CPB) presents a significant challenge for anesthesiologists. Machine Learning (ML)-assisted tools have the potential to enhance the recognition of patients at risk of complications and predict potential issues, ultimately improving outcomes

- **Conclusions:** The authors developed machine learning-assisted tools that provide an additional perspective and enhance the predictive capabilities of traditional scoring methods. These tools can assist anesthesiologists in making well-informed decisions. Furthermore, they showed the feasibility of creating a practical white-box model. The next steps involve conducting clinical validation and multicenter cross-validation

Sources: [1] Florquin et al. "Pediatric cardiac surgery: machine learning models for postoperative complication prediction"

Using Machine Learning in a Pediatric Surgical Risk Calculator[1]

- **Background:** New methods such as machine learning could provide accurate predictions with little statistical assumptions. The authors seek to develop prediction model of pediatric surgical complications based on pediatric National Surgical Quality Improvement Program (NSQIP)

- **Conclusions:** The authors developed a high-performance and interpretable prediction model of pediatric surgical risk based on novel machine learning techniques and robust pediatric NSQIP data. This tool could potentially be used to improve the quality of surgical care and achieve the goals of complication prevention and data-driven proactive planning

Sources: [1] Bertsimas et al. "High-performance pediatric surgical risk calculator: A novel algorithm based on machine learning and pediatric NSQIP data"

Machine Learning to predict Pediatric Choledocholithiasis[1]

- **Background:** The purpose of this study was to accurately predict pediatric choledocholithiasis with clinical data using a computational machine learning algorithm

- **Conclusions:** This multicenter study uses machine learning for pediatric choledocholithiasis. Nine clinical factors were highly predictive of choledocholithiasis, and a machine learning model trained using medical and laboratory data was able to identify children at the highest risk for choledocholithiasis

Sources: [1] Sachs et al. "Machine learning to predict pediatric choledocholithiasis: A Western Pediatric Surgery Research Consortium retrospective study"

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(The Future of…?) Artificial Intelligence in Pediatric Surgery[1]

- **Context:** The integration of AI into surgical practice holds profound implications for healthcare. Surgery, once characterized solely by the dexterity of surgeons, is now a complicated orchestra of knowledge assimilation, tactful patient work-up and diagnosis formation, skillful technical maneuvering in the operating room, and creative utilization of advanced technology. The last of which now is beginning to incorporate AI to empower surgeons with tools to make more accurate diagnoses, plan surgeries with greater precision, and execute procedures with an increasing level of accuracy

- **Take-home Message:** As technology continues its relentless march forward, the incorporation of AI in pediatric surgery is not just a possibility but a burgeoning reality. The authors explore the transformative impact of AI technology on the field of surgery and pediatric surgery, ushering in an era of precision, efficiency, and improved patient outcomes. The article presents the historical origins of AI, different types of AI, its present applications in pediatric surgery, challenges and limitations, ethical and legal considerations, and potential future developments

Sources: [1] Tsai et al. "Artificial intelligence in pediatric surgery"

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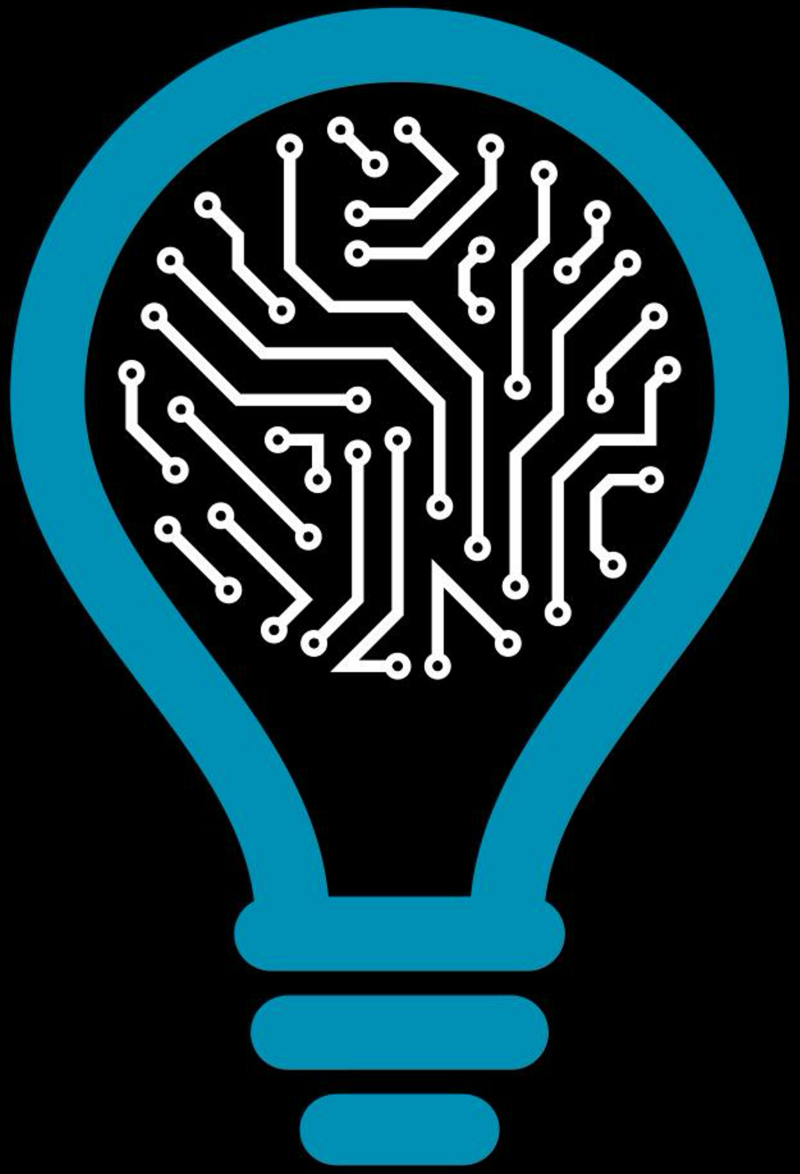

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