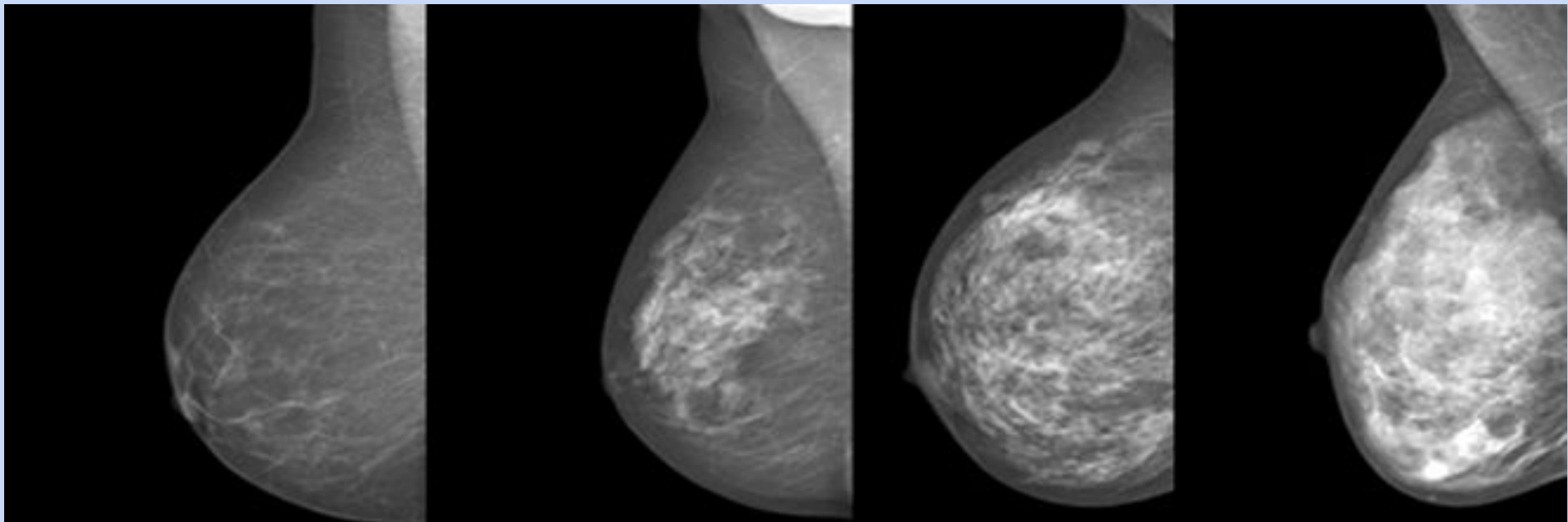


Early Stage Breast Cancer Detection in the Age of Computers

A review
Dennis Amphan & Simon Jenner

Introduction

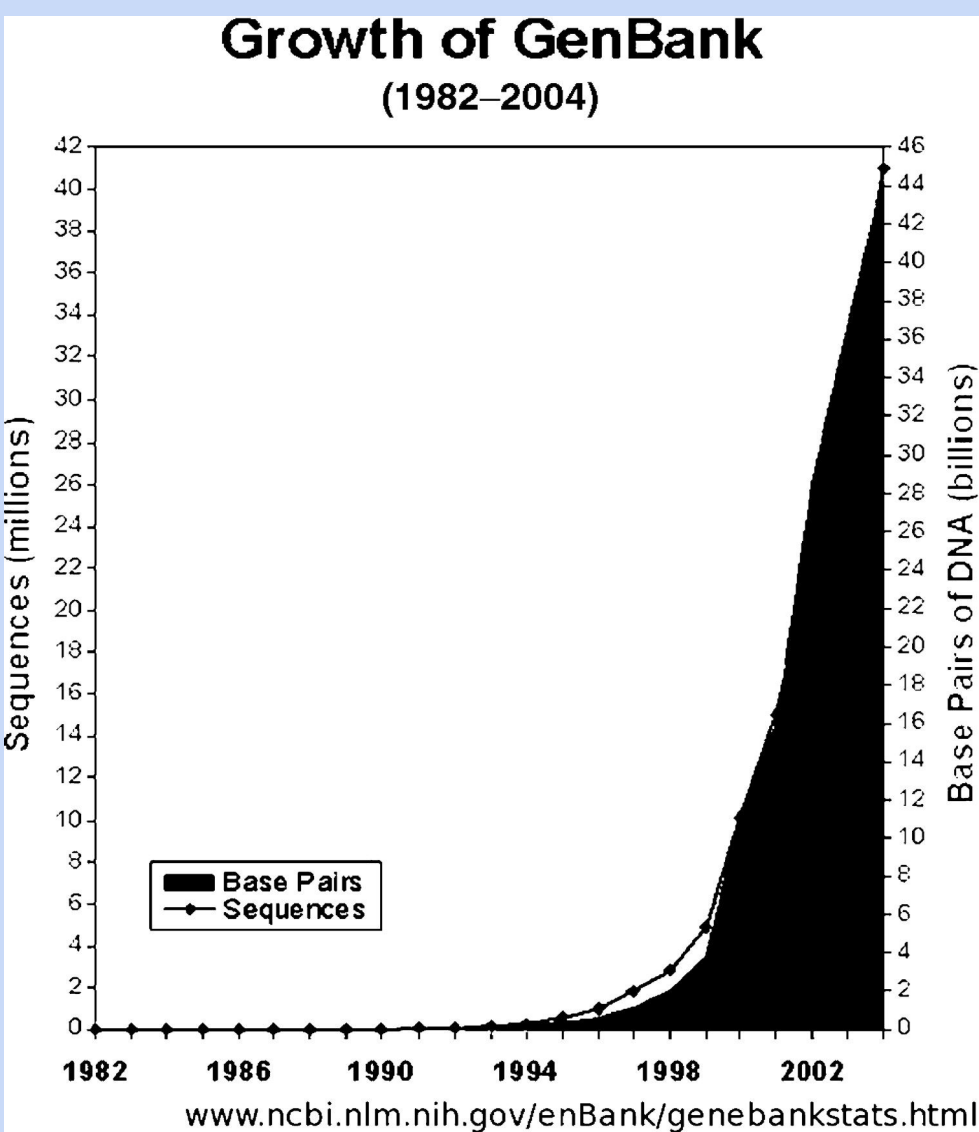
Breast cancer is the most common cancer type in the world and finding it in an early stage to get treatment is one of the most important strategies in order to prevent death. Today's methods for diagnosis (in the early stages) are heavily dependent on image analysis from image data, often X-ray images from mammograms. Recent studies have suggested flaws in this method of diagnosis, as the density of breast tissue can vary drastically between patients and smaller tumours can easily be missed in more dense breast tissue.



Source: <https://brostcancerforbundet.se/om-brostcancer/diagnostik/tata-brost/>

Image Based Models (CNN)

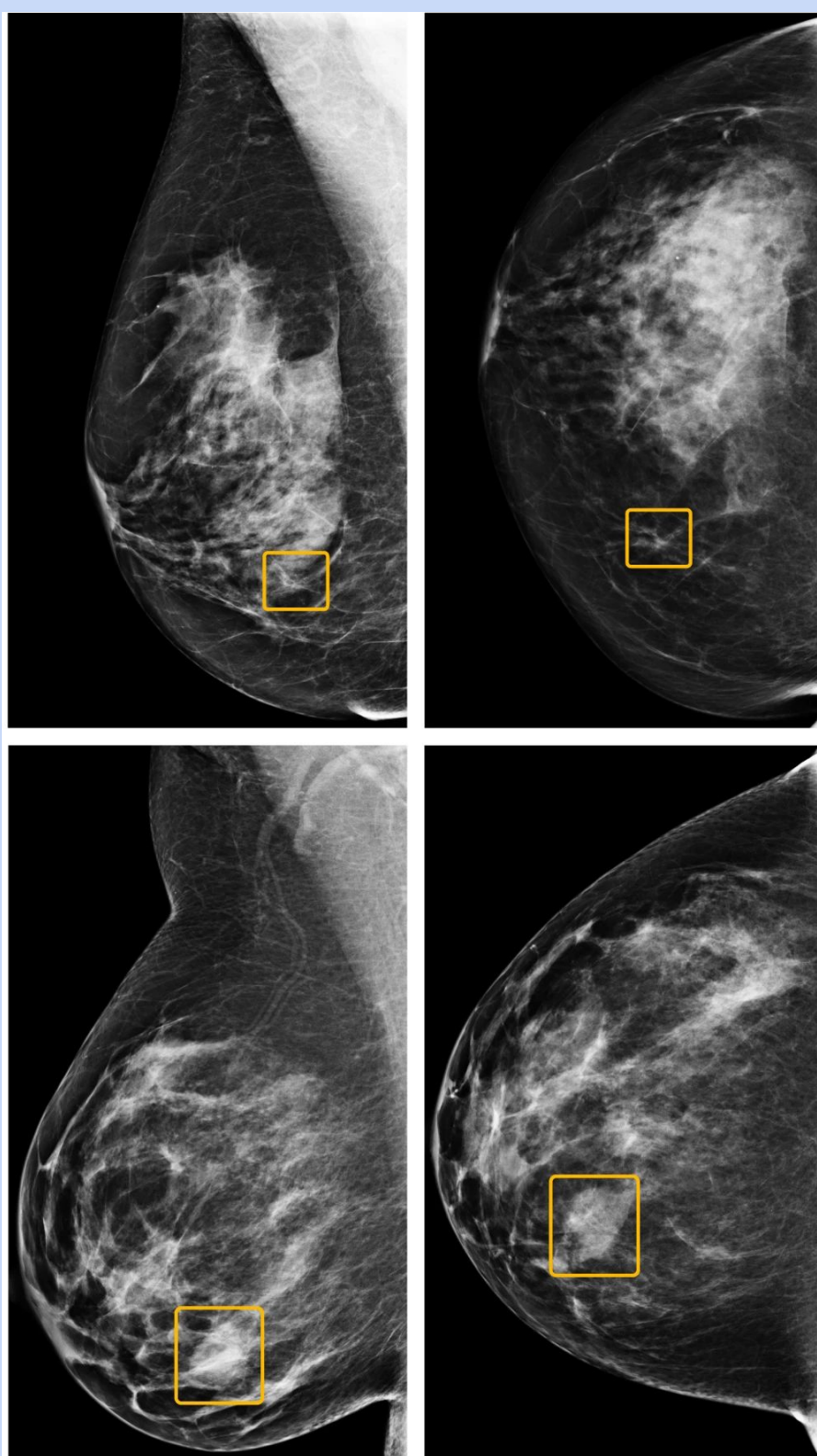
- Good results, similar performance as radiologist
- Easily built on existing methods
- Not reliable on dense tissue



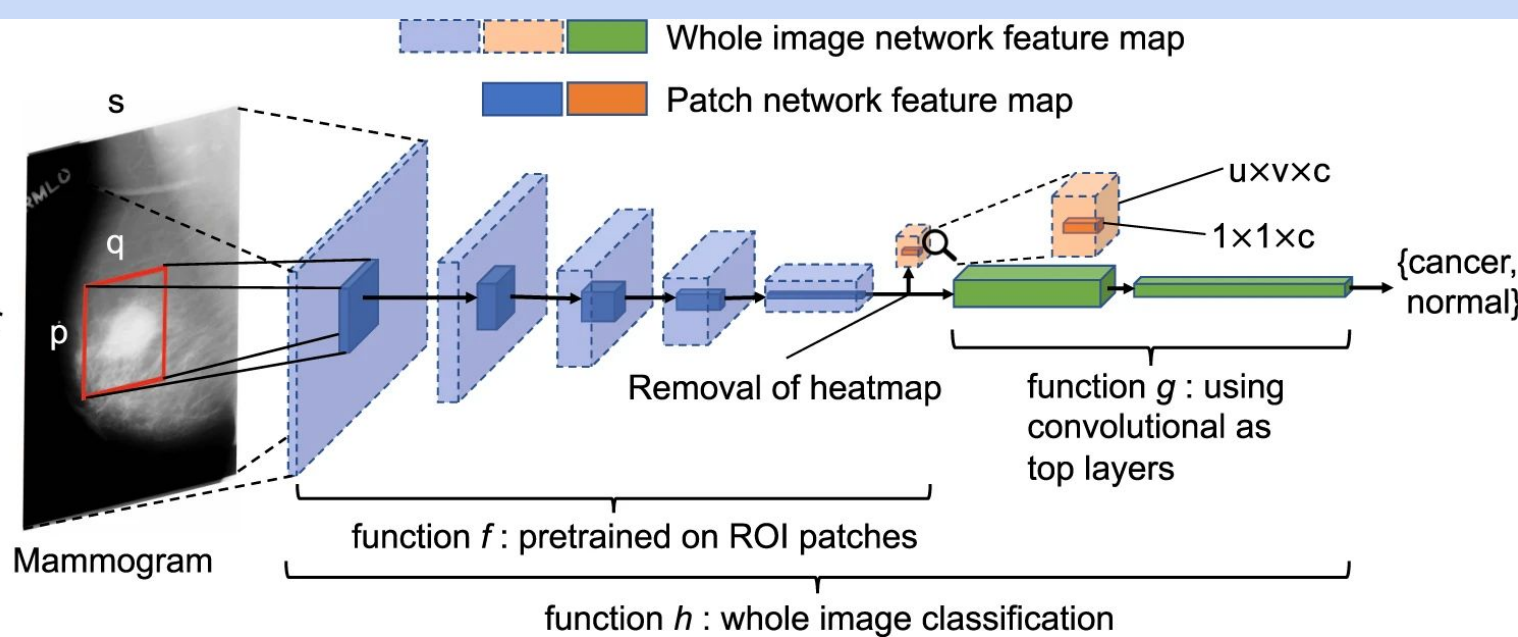
In recent years the number of genes in the GenBank has increased drastically



Source: <https://www.embopress.org/doi/full/10.15252/msb.20156651>



Source: <https://www.nature.com/articles/s41586-019-1799-6>



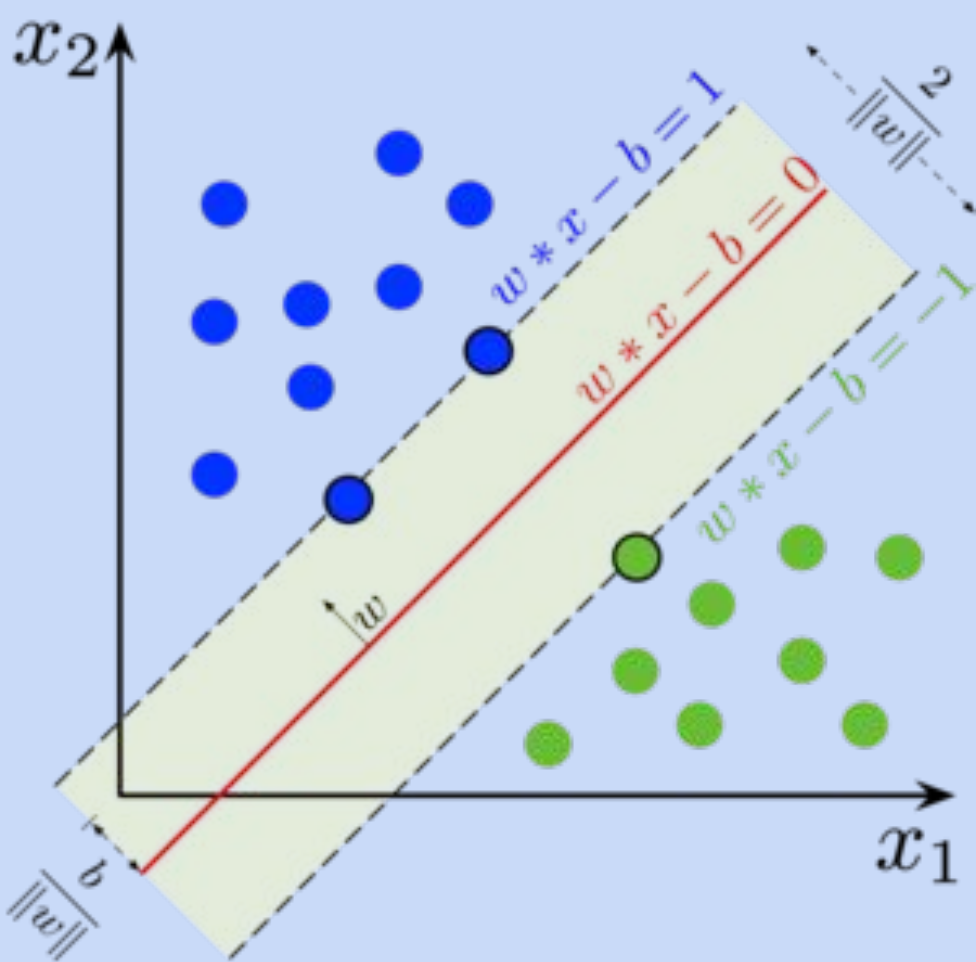
Source: <https://www.nature.com/articles/s41598-019-48995-4>

Top images were miss classified by 6 radiologists, but correctly classified by the model. The bottom two were the other way around.

Results

Method	Accuracy	Sensitivity	Specificity	AUC
Mammography	89.3%	97%	64.5%	0.75
SVM - Biomarker	98.82(± 0.34)%	97.69(± 0.88)%	83.80(± 4.64)%	0.96
ANN - Biomarker	97.36(± 0.34)%	98.32(± 0.32)%	89.59(± 3.53)%	0.99
CNN - Mammography	—	56.24%	84.29%	0.91

- Both methods using biomarkers provide better result
- Non ICT-method (standard mammography yields the lowest overall performance
- Double reading with AI yield same result as two radiologists.



Support vector machines could act as a suitable method for cancer diagnosis.

Source: https://upload.wikimedia.org/wikipedia/commons/thumb/7/72/SVM_margin.png/1024px-SVM_margin.png

Conclusion

- Black box nature makes it hard to fully integrate deep neural networks.
- More interpretable models for bioinformatic data, SVM.
- Combining neural networks with existing methods is a good way to keep transparency.
- Meanwhile a great potential for saving in on time and resources.
- More efficient workflow.
- Could remove the need for radiation exposure.

HI2010 Medical Informatics and Communication Systems

transparent way than traditional methods².



private to protect the patient.²

Implementations:

There are several possibilities to design a blockchain network for different purposes (Table 1). Requirements for healthcare applications are Ethereum^{5,6}, Multichain^{7,8} and Hyperledger^{9,10}.

Table 1: Relevant Features to design a blockchain for healthcare applications ⁴.

Relevant Features	Options and implications	
Network permission (NP)	Permissioned (P)	Authorized participants
	Permissioned-less (PL)	Public participation
Consensus protocol (CP)	Proof of Work (PoW)	High intense demand algorithm suitable for PL
	Proof of Stake (PoS)	Low intense demand algorithm
	Mining Diversity	Low intense demand algorithm designed for P healthcare networks
	Kafka	Low energy consumption based on major voted. Requires higher time while the network grows
Special Hardware (SH)	Yes/No	If yes, hardware specifications should be specified before
Smart Contract Support (SC)	Yes/No	Required if the network contains autonomous operations like health insurance payments

Ethereum ^{4,5}			
• NP:	Permissioned	Permissioned-less	
• CP:	PoW	Pos	
• SH:	No	No	
• SC:	Yes	Yes	

MultiChain ^{4,7}			
• NP:	Permissioned		
• CP:	PoW Mining	Diversity	
• SH:	No		
• SC:	Yes		

Hyperledger ^{4,9}			
• NP:	Permissioned		
• CP:	Kafka		
• SH:	Yes		
• SC:	Yes		

Case 1: Health Records

Information spread over multiple centers Transform patient data sharing and information interoperability patient data control (🔒 🦋 📡), worldwide institutions EHR access (📡 🦋 📡), patient confidence (🔒), professional selective access (🔒 🦋) Akiri12 (company), omniPHR2 (architecture), MedRec2,3,13 (architecture)	Problems in healthcare supply chain due to its complexity and global connectivity Introduce supply chain transparency Supply chain optimization (📡 🦋 📡), customer and professional confidence (🔒 🦋) IBM+ Sonoco18 (company), FarmaTrust19 (company)
→ Problem: → Goal: → Blockchain11: → Example:	→ Problem: → Goal: → Blockchain17: → Example:

Case 4: IoT-Based Healthcare Monitoring

	Dr. Robin Dr. Smith	On Monday he goes to the pharmacy and asks for Dr. Smith's prescription.	After finishing the pills after a week, he goes again to the pharmacist and asks for Dr. Robin's prescription.	The pharmacists is surprised. That face is familiar to him.			Tom has a very unhealthy lifestyle.		His doctor recommends him, to track his heart activity with a smartwatch for while.		The smartwatch collects a lot of data, which Tom wants to show his doctor the next visit.		Before Tom can visit the doctor, he has a heart attack and must go to the hospital.
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→ Problem:	Abuse of drug prescription because of an incomplete feedback between prescription writers and fillers
→ Goal:	Close the loop between prescription writers and filler
→ Blockchain^{14,15}:	Unique prescription identifier (🔒), patient prescription history (🔒👤), true information sharing (🔒👤👤), constant information checkup (🔒👤👤)
→ Example:	BlockVerify ¹⁶ (Company)

Blockchain offers a lot of improvements and benefits, as explained above. However, the technology is still new and its pilot studies exist, but there is still a lot of research that must be conducted to solve the current existing challenges.^{2,24}

The diagram illustrates six key challenges in blockchain technology, each represented by a teal box with a white icon and a list of specific issues:

- Security** (Lock icon):
 - Risk of unauthorized access of data^{2,24}
- Privacy** (Eye icon):
 - Keeping track of data could reveal patient^{1,24}
- Scalability** (Graph icon):
 - Large amount of patient data is collected with time
 - processing large amount of data in real-time difficult¹
- Costs** (Coins icon):
 - High implementation and electricity costs²⁴
 - Significant cost savings with several years^{2,4}
- Standardization** (Document with checkmark icon):
 - Technical challenges to standardize and transfer medical data to blockchain^{2,25}
- Hardware** (Computer monitor and tower icon):
 - Computing power is limited²
 - Risk of temporary outage²⁴

How Dr. Pikachu Helps You to Get Healthy

Tim Flück and Zhaoyuan Wan

Definition and Introduction

According to Deterning et al. „Gamification“ can be defined as „the use of game design elements in non-game contexts“. Gamification plays an ever growing role in the health care sector among other fields like business or engineering. Such tools are primarily used for prevention and training purposes but also support treatments for example in the area of mental health by motivating the user to keep up a workout routine or adhere to an overall healthier behaviour.

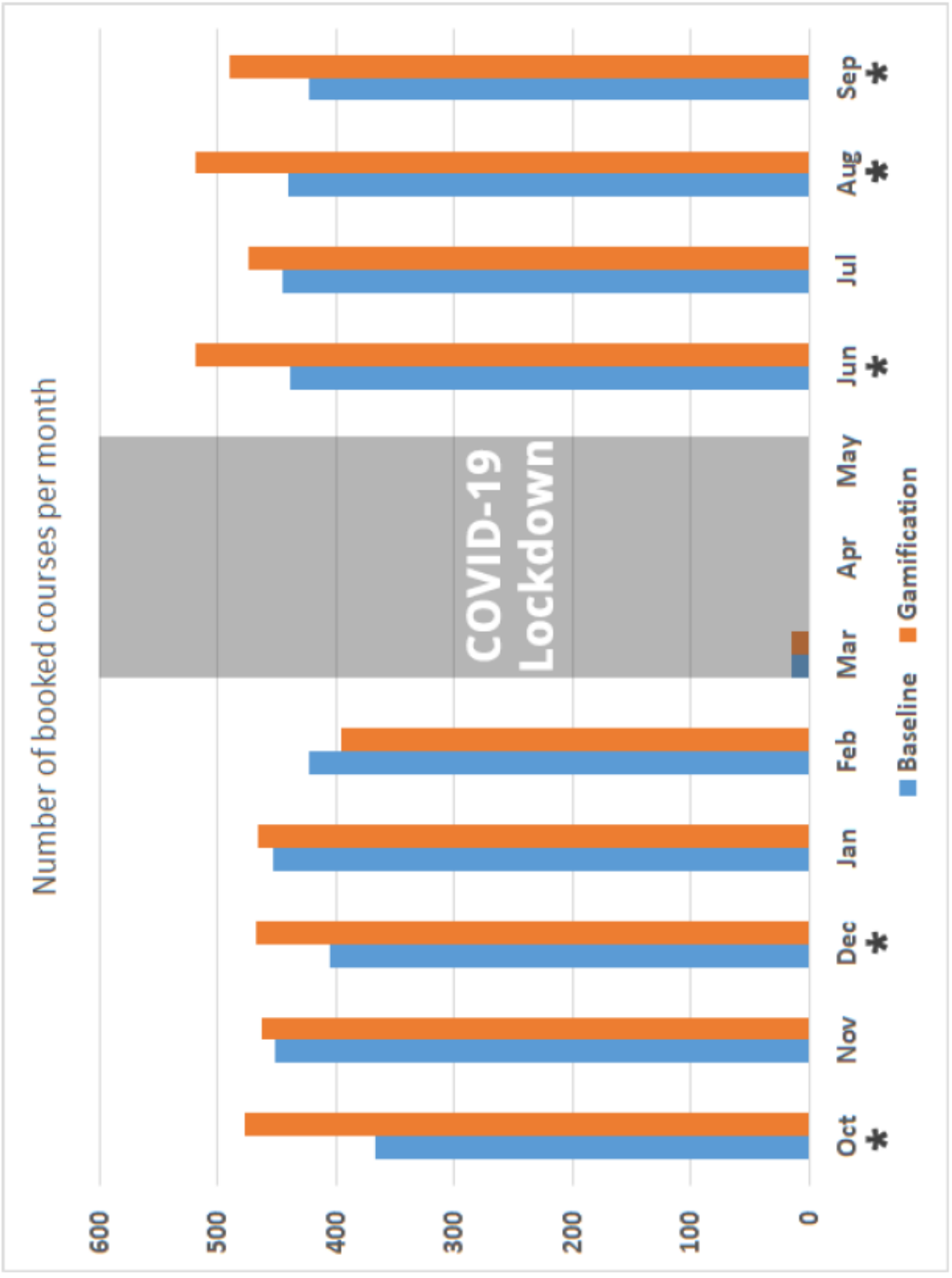
As technology gets better and almost every person has a smartphone nowadays, mobile health applications and its use of gaming elements are an easy and relatively cheap way to reach a lot of people and have an impact on public health interventions and healthy behaviour in general.

Market Overview

Before smartphones were widely available, most gamification of health was used in web-based applications like ayogo.com where children were rewarded when they entered information about their diabetes into an application.

In the beginning of the 2010s, almost everybody had a smartphone and the numbers of mobile health apps increased dramatically. One of those apps that included a high level of gamification was MyFitnessPal, which is still one of the most used Health Apps today.

With the development of AR technology, games like Ingress and Pokemon Go emerged. Although they were not initially designed for health purposes, their gameplay had inspired their players to take more physical activities, which in turn improved public health.



Comparison between the number of booked gym courses per month of people before (baseline) and after (Gamification) the use of Gamification in their workout.

Source: „A long-term investigation on the effects of (personalized) gamification on course participation in a gym“. Altmeyer et al.

Effectiveness

In the early 2010s there was no industry standard concerning gamification and the effectiveness of such mobile health interventions were not properly documented. In recent years, more and more studies with randomized control trials examined the impact of gamification on the user and how the user could profit. Though proper evaluation protocols are still lacking.

Promising results occurred primarily in of the field of fitness and mental health. While short-term studies showed that the higher the inclusion of game-like features the more popular the app is, long term studies also showed that the adherence to a workout regime is higher when gamification elements are involved. Increased adherence was also documented in studies with mental health apps, where adherence and easy access to treatment is especially important. These findings prove the potential of gamification in health care.



Pokemon GO logo

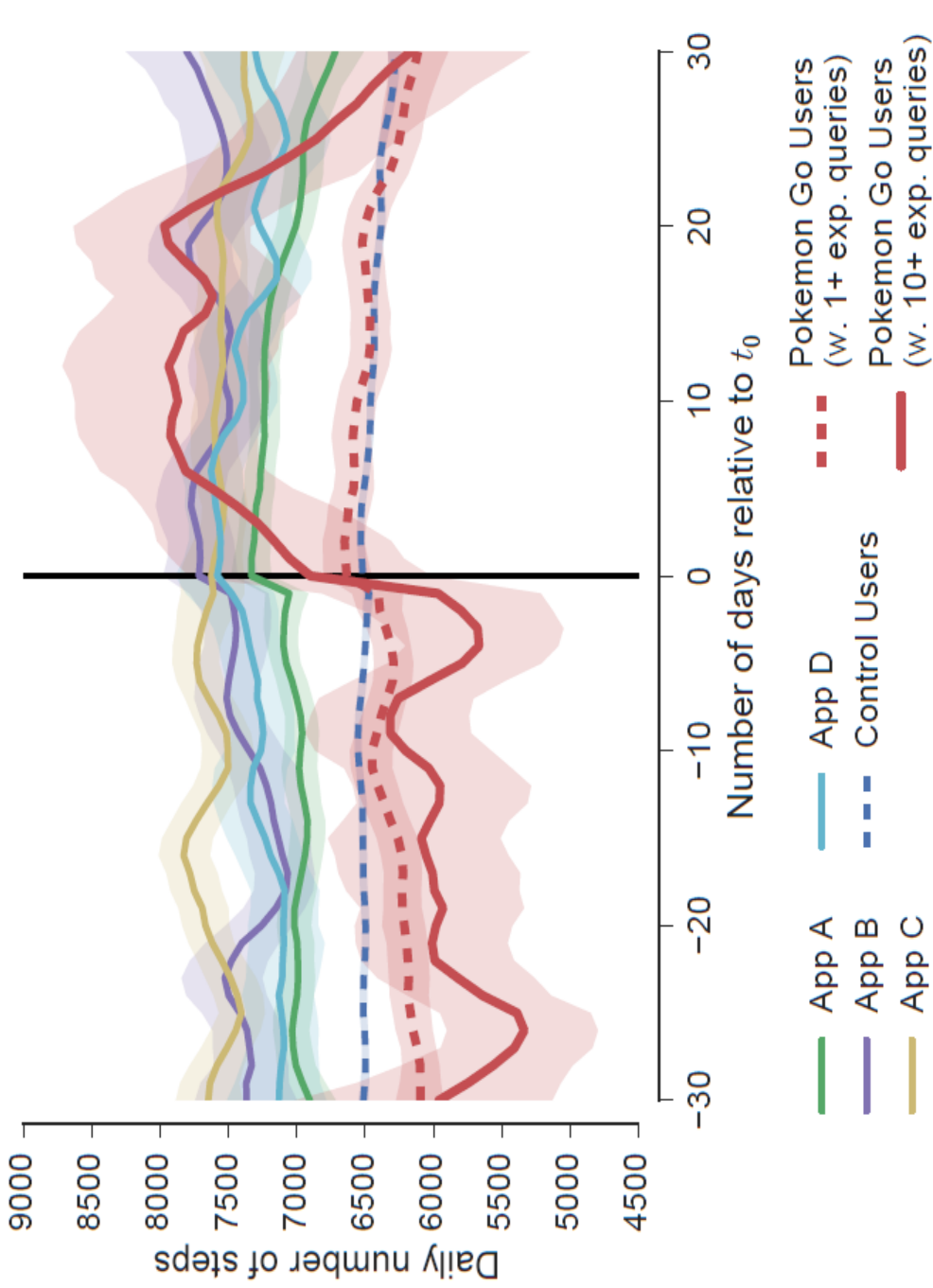
Source: <https://lofrev.net/pokemon-go-logo-pictures/> (11.10.2021)

Features

Gamified apps and AR games are frequently developed on smartphones because of their technical features. With GPS and inbuilt accelerometers, the users' physical movements can be conveniently measured and monitored on their mobile phones.

However, those sensing systems are nothing new. The 'game elements' should be the real focus. A typical feature of gamification is that many health apps have implemented achievement systems and ranking systems (leaderboards) to motivate their users with senses of accomplishment and competition.

In AR games like Ingress and Pokémon GO, the players' real-world location directly decides their avatars' location in the game world. Hence it becomes natural for the players to take physical activities since it is the way to make progress in the game.



Comparison of the activity level of Pokemon Go users before and after they use the app and other consumer health apps

Source: „Influence of Pokémon Go on Physical Activity: Study and Implications“. Althoff et al.

START

GAMIFICATION TO TACKLE CHILD OBESITY

- 1 **Gamification** = applying gaming principles, game design techniques, and game mechanics to non-game applications in order to improve clinical outcomes.

Obesity

= abnormal or excessive fat accumulation that presents a risk to health

BMI > 30

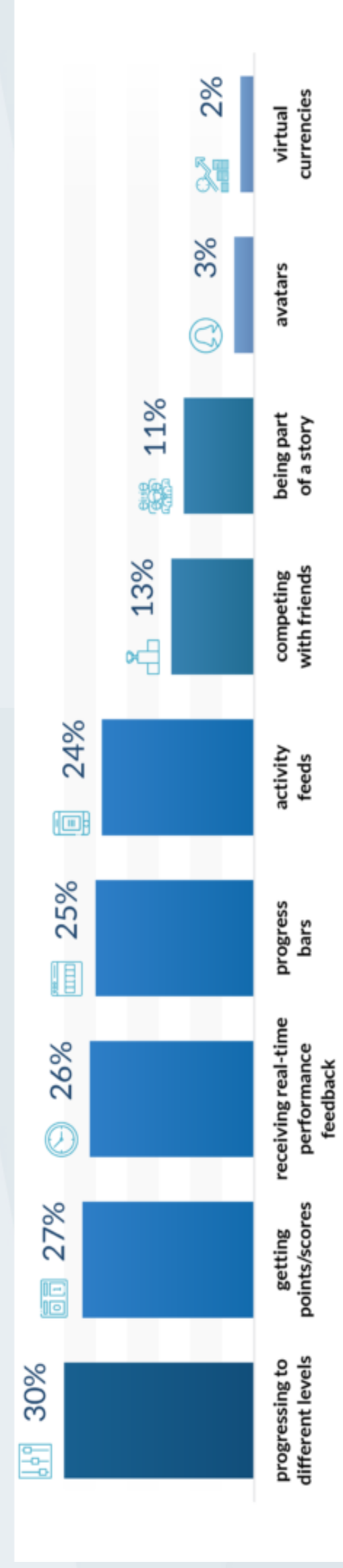
17,2% of children around the world have obesity

more deaths worldwide than underweight

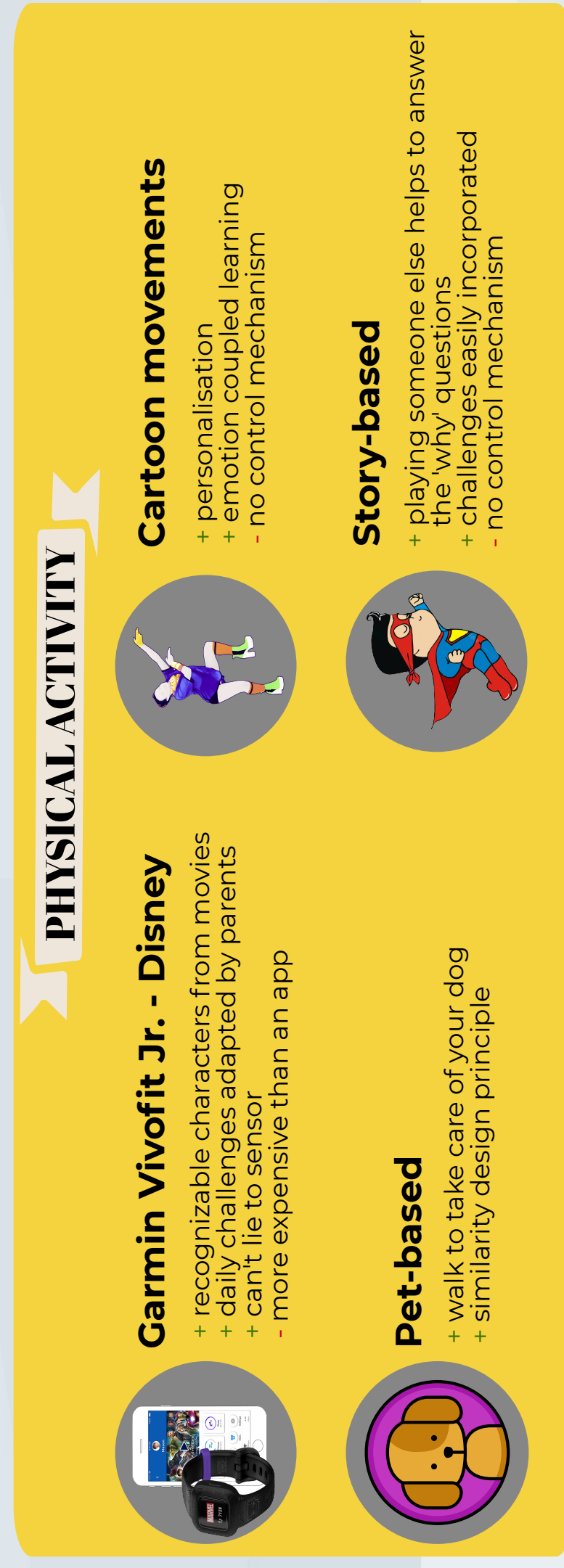
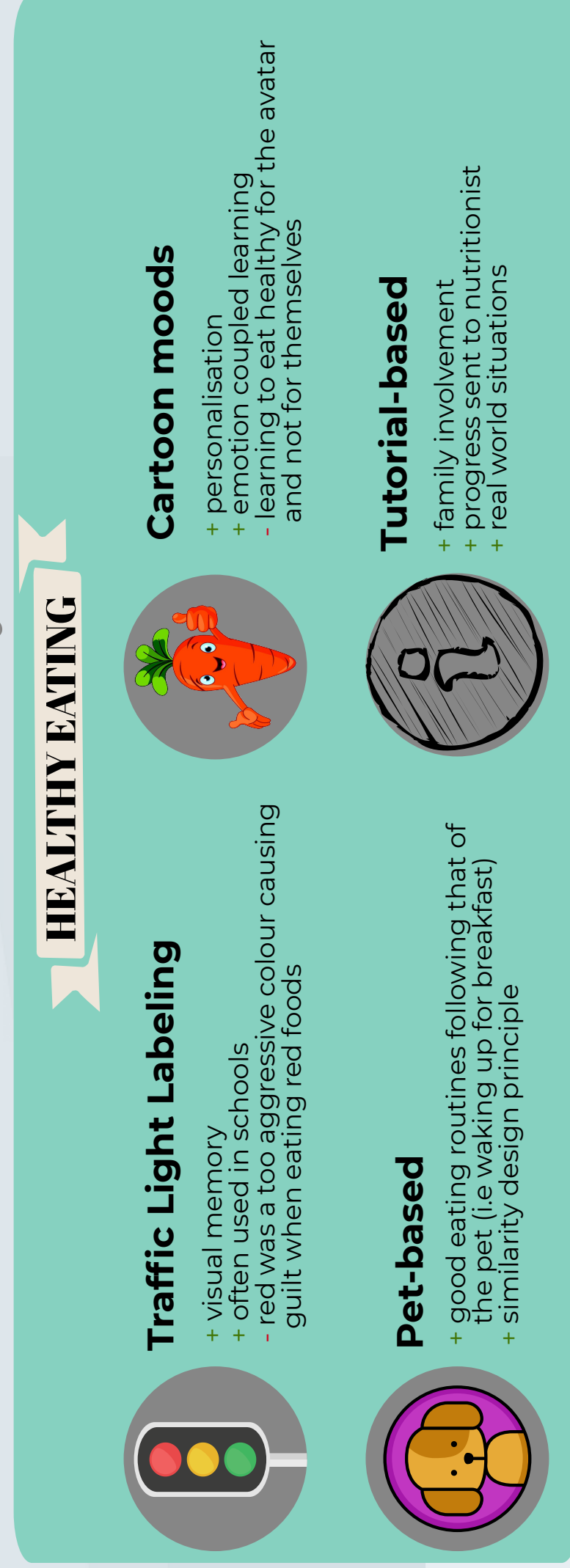
2 Game Design Elements for Children Health Apps



PREFERRED GAMIFICATION STRATEGIES

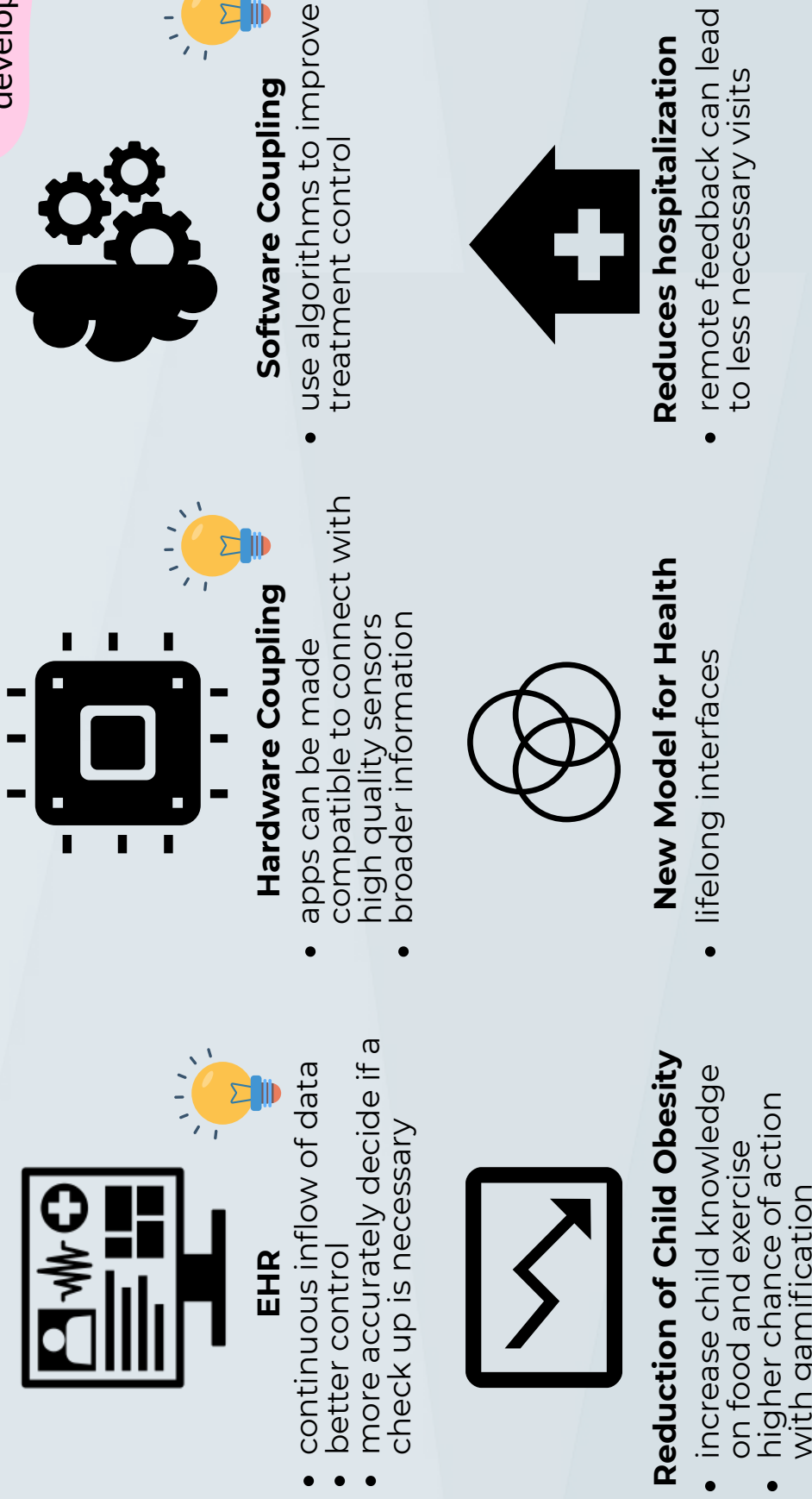


5 Game Aspects for Obesity

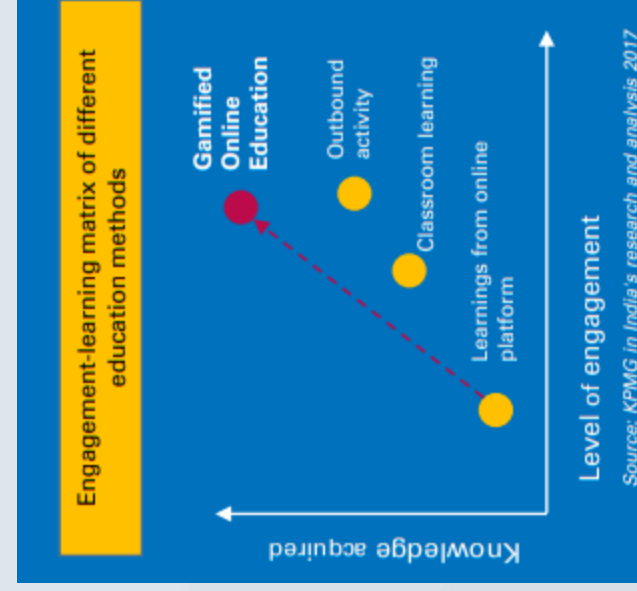
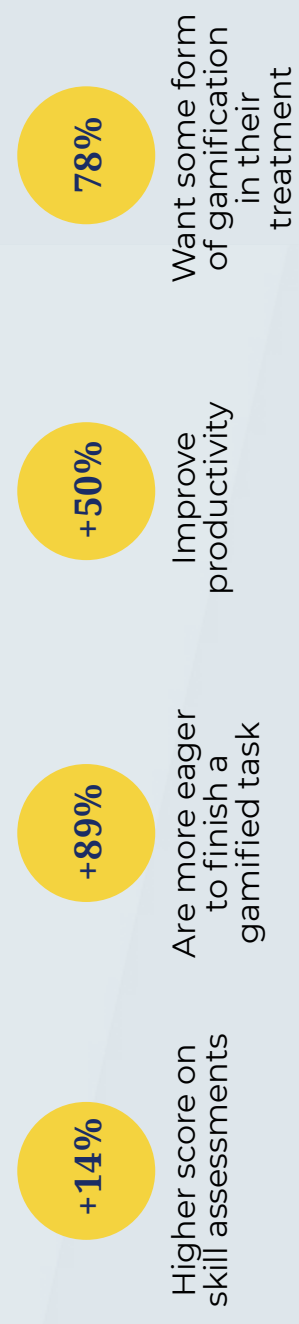


6 Role and Impact

ON MEDICAL INFORMATION AND COMMUNICATION SYSTEMS AND THE HEALTH CARE SYSTEM



7 Some Numbers



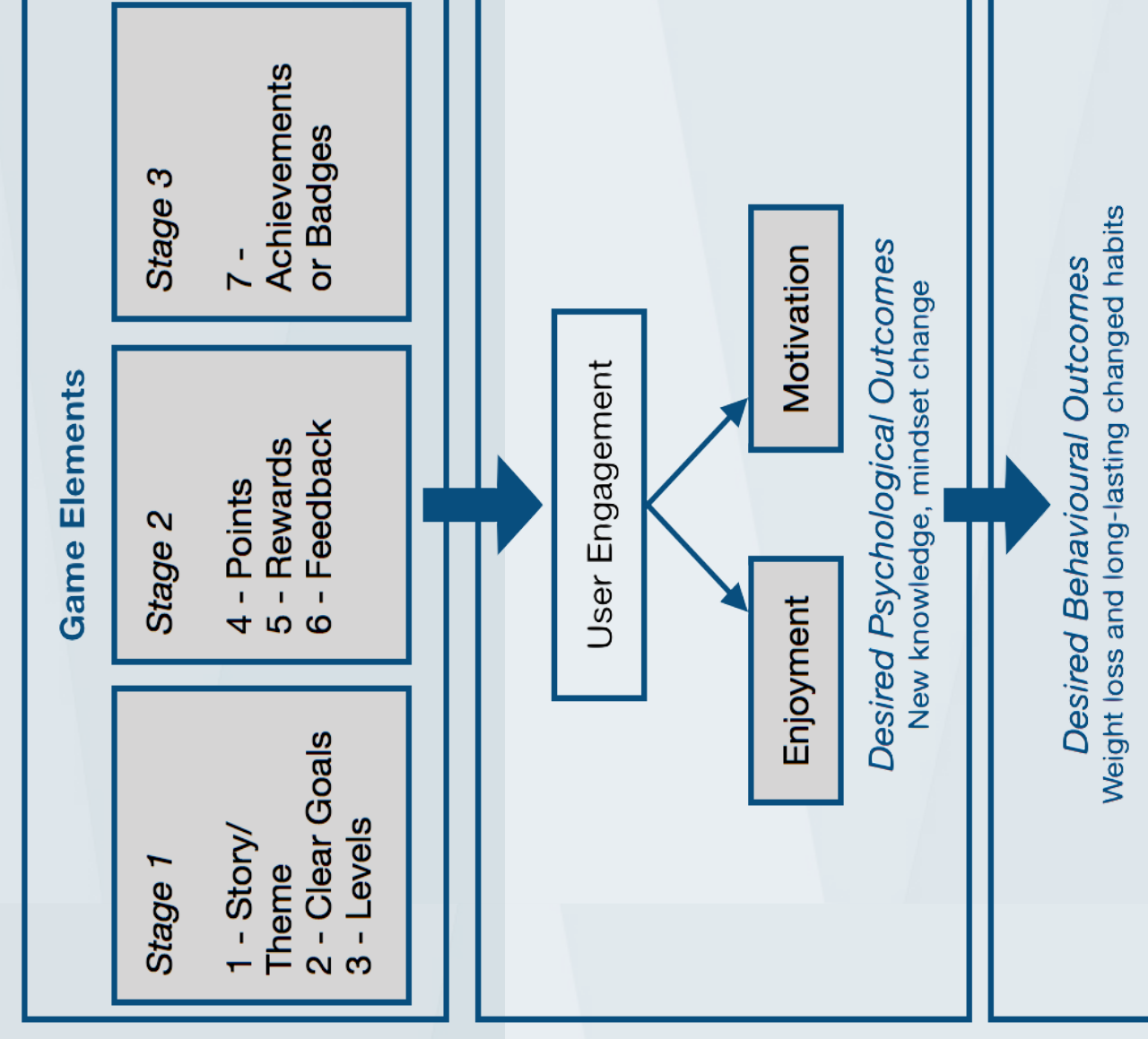
In general, research shows that most children want games and it improves the outcome of the healthcare.

3 Other Gamification Techniques

Gamification is not necessarily the use of an app! There are other ways of turning 'annoying' tasks into something fun.



4 Gamification Model



8 Conclusion

If implemented in an interactive way, gamification of health care apps can be an effective way to treat child obesity. Certain elements are very important to keep the children engaged, like a story, progress bars and real-time feedback. This can lead to psychological and behavioural outcomes, which in the case of obesity is changed food and exercise habits and eventually weight loss. Implementing these new habits can be achieved in different ways. For food, some tested methods are traffic light labeling and cartoon moods. For exercise, pets and stories are often used. If the real-life control can be improved, these apps can have life changing effects for many children around the world.

STOP

The biggest breakthrough in the medicine history

Minha Choi, Yanis Aeschlimann

Medical Engineering, KTH Royal Institute of Technology, Stockholm, Sweden

Introduction

- 1956**
 - The term 'Artificial Intelligence' firstly used
 - The first program including AI launched

Not achieved good result with Machine Learning

- 2000**
 - Deep learning performs good enough
 - Tried to be used in medicine

- 2017**
 - Deep learning network deployed in many clinical practices (detect lesions, diagnosis, medical reports)

- Definition of AI, ML and DL**



Fig. 1 Meaningful definition of AI^[2]

Biomarker discovery

- Biomarker?**
 - A measurable indicator of a normal or abnormal biological process or response
 - Omic biomarker**
 - e.g.) Trisomy 21 (Down's syndrome)
 - : Genetic signature to predict the status of disease
- It is impossible for researchers to manually analyse and interpret a vast amount of data

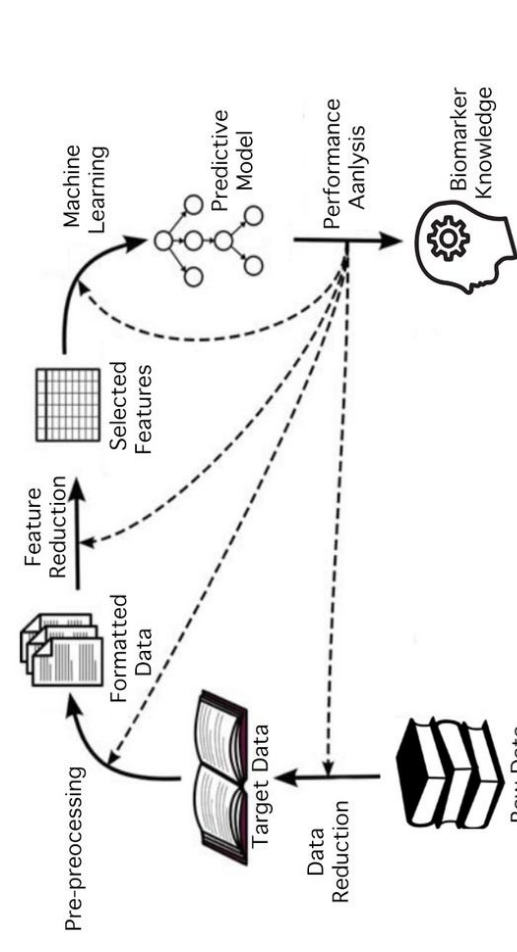


Fig. 4 ML for Biomarker Discovery^[3]

- Non-omic biomarker**
 - e.g.) Neural excitement signal
 - : Can facilitate the development of interface for prosthetic control

Concept of main networks

- Convolutional Neural Network (CNN)**
- Purpose:**
 - Classification task
- Components:**
 - Input layer: images
 - First inner layers: Convolutional layers
 - Last inner layers: neural layers
 - output layer: neural layer with number of neurons equals to the number of class.

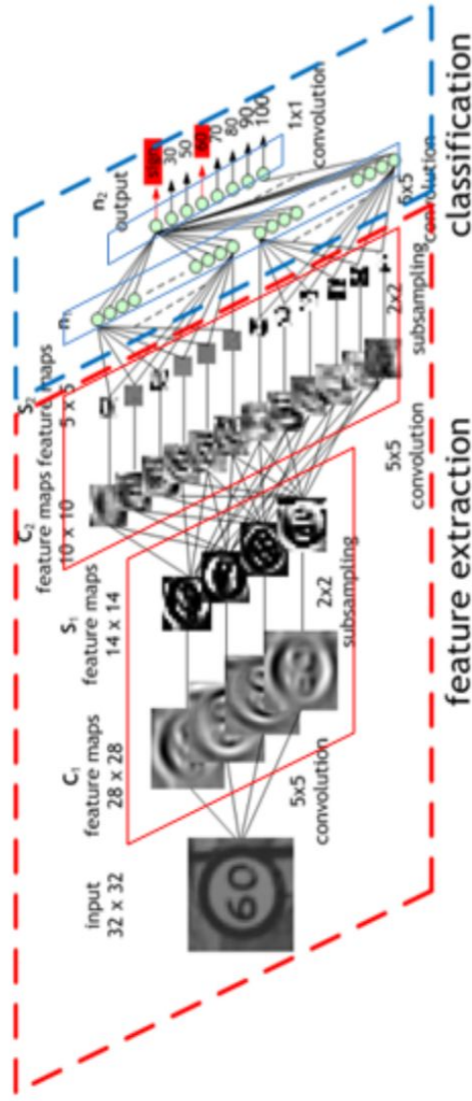


Fig. 2 CNN structure^[6]

- Weights of the neurons and of the convolutional masks are set randomly.
- During training step, the outputs are compared with the groundtruth and all the weights are adjusted.
- The validation step aims at assessing the model, but the weights are not changed anymore.

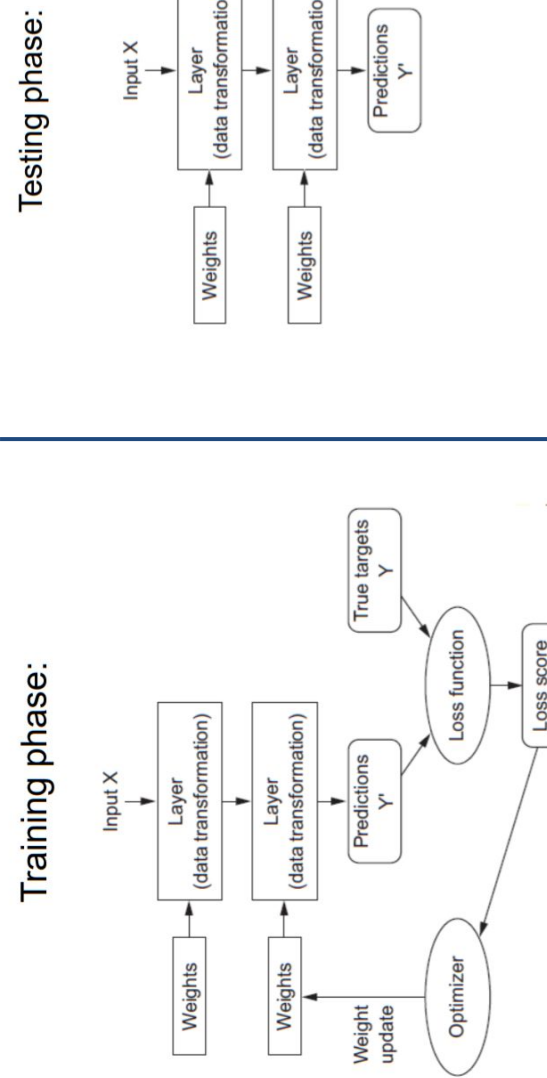


Fig. 3 Training and Testing phase^[6]

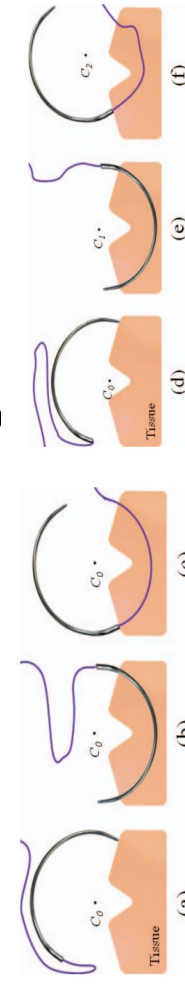
- Fully Convolutional Network (FCN)**
- Purpose:**
 - Segmentation task
- Components:**
 - Input layer: images
 - Inner layers: Convolutional layers
 - output layer: images

The convolutional layers are used to extract features from images, whereas neural layers try to mimic the human brain with sort of neurons all connected on each other.

Autonomous Robotic Surgery

- Robotic systems controlled by AI**
 - Industry : Commonly used
 - Medical surgery : Robotically 'assisted' → But started to change

- Autonomous Suturing robot**



< Fig. 10-1 Motion control concept^[4]

- Autonomous Cochleostomy**
 - Cochlear implantation drilling robot

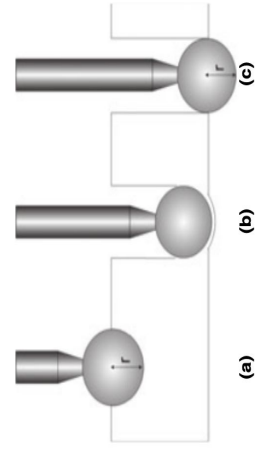


Fig. 6 States of drilling process^[5]

- Have better consistency
 - Minimize the damage

Challenges

- Ethical problem**
 - What can be done legally
 - What an organization would like to do
 - Ethical problem?
 - What can be done technically
- Environmental problem**
 - e.g.) Higher demand for semiconductors

Fig. 11 An ethical position^[1]

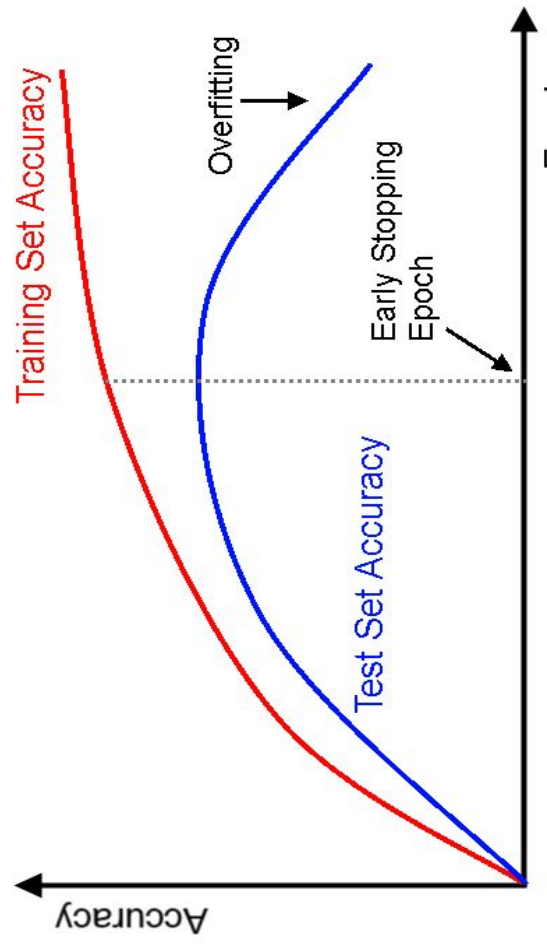


Chart 5. The overfitting problem.^[2]

Image Based Diagnosis

The most widely used technologies : X-ray, MRI, CT, PET

- Radiology**
 - Detection of lung nodules
 - Diagnosis of pulmonary tuberculosis & lung disease
 - Breast-mass identification
 - Employed 'transfer learning'

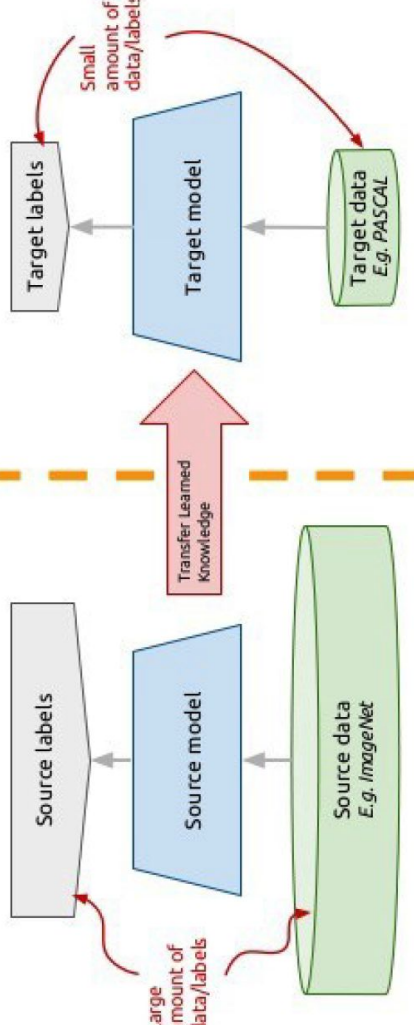


Fig. 6 Transfer Learning concept^[6]

- Dermatology**

ABCDE's of Melanoma : criteria of skin cancer

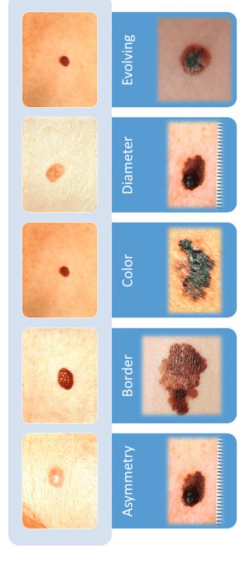


Fig. 7 ABCDE's rule^[7]

Recently, finalized diagnostic model can be deployed on mobile devices

- Ophthalmology**

Detection of DR(Diabetic Retinopathy), glaucoma

→ Capture the image of retina with Fundus photography

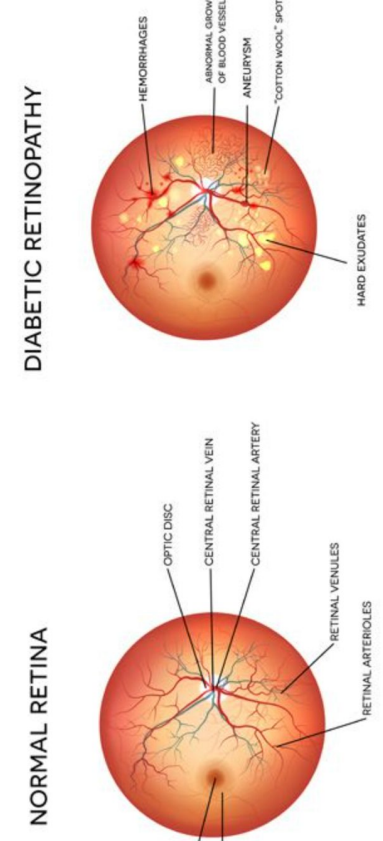


Fig. 8 Normal vs DR retina image^[8]

- Pathology**

Detection of many different cancers (prostate, breast) → Interpreting the slides under a microscope

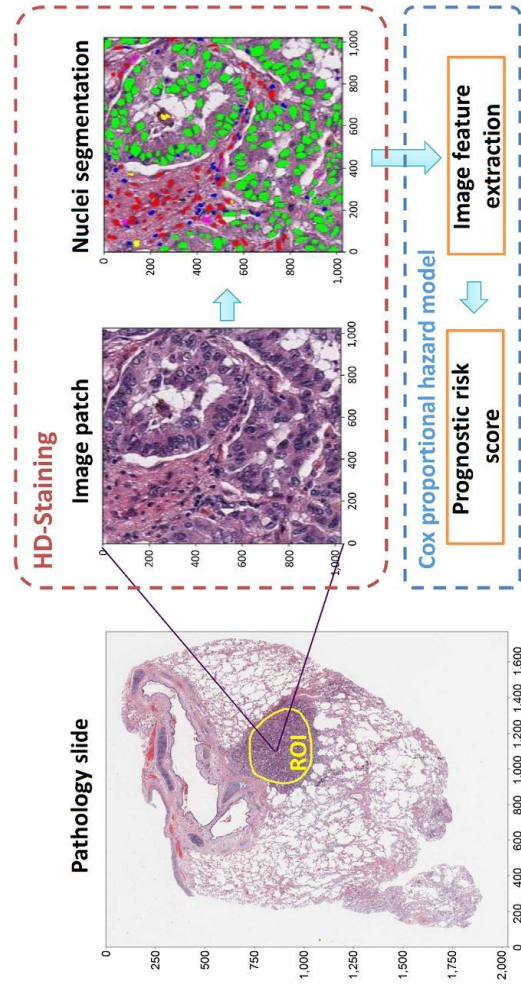


Fig. 9 Flow chart of pathology image analysis^[9]

Contact

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Wireless sensor networks play an important role in designing effective mobile healthcare (mHealth) systems to manage healthcare. Body sensor network (BSN), also known as body area sensor network (BASN), is a sensor network whose nodes are biosensors either implanted in, worn on, or close to human bodies. BASN can facilitate self-monitoring, allowing patients to avoid hospitalisation. and improving the healthcare sector. It can provide long-term health monitoring without disrupting a patient's privacy and is used in vital signs monitoring, home care monitoring, clinical monitoring and sports health.



HSP: Healthcare Service Provider. *M*: Mobile staff member.
CN: Controller Node. *SN*: Super Node.

Fig. 2: Architecture of an mHealth system [2]

Data from various sensor nodes is transmitted to a special node called super sensor node, with more storage capabilities. The data collected by the super sensor nodes is sent to a local controller node. The controller node is responsible for collecting all patients' data and sends them to the healthcare provider's medical server through public networks. Two main biometric authentication approaches for intra-BAN communication have been compared here - ECG fiducial point based and IPI based. Both methods use heart rate variability as a shared source of entropy for cryptographic key generation.

Mutual authentication:	A secure process where both entities verify the identity of each other before communication.
Anonymity:	The identity of the node / user needs to be anonymous to maintain patient privacy.
Unlinkability:	Consecutive transactions / sessions should not be linkable by an adversary.
Reliability:	Proposed systems need quality of service and fault tolerance.
Secure management:	A console is needed for a coordinator to add and remove nodes securely.
Integrity:	Check if the data received has been altered.
Freshness:	Ensure the newness of data (timestamp).

* Anonymity and unlinkability are applicable mainly to Tier 2 and 3 communication

Fig. 3: Biometric authentication in intra-BAN communication [5]

The process begins with both the sensor node and super sensor node measuring their respective parameters of the heart. The algorithm then extracts HRV parameters (mentioned in the table) and uses it as an entropy source to generate the shared key. Standard cryptographic methods can be implemented for key exchange and initial secure communication. The sequence similarity is quantified as a distance measure to authenticate the device and evaluate the method. The table below summarises some works from literature.

Ref.	Parameters	Modeling
[6]	NN interval, SDNN, RMSSD, pNN50	Hash function with message
[1], [9]	RR, RQ, RS, RP, RT interval	Multiple fiducial point binary sequence generation
[8]	QRS axis, QT-interval, ST-level, and T-wave abnormalities	Wavelet domain Hidden Markov Model
[3]	Inter pulse interval	μ and σ of IPI array
[4]	Inter pulse interval	Finite monotonic increasing sequences generation cyclic block encoding
[5]	IPI from ECG and PPG	Hamming distance of generated binary sequence

Metric	Inter Pulse Interval based	ECG Fiducial based
Computation cost	Lower	Higher
Energy cost	Lower	Higher
Data duration	~30 sec	~30 sec
Randomness of source	Lower	Higher
Synchronisation errors	Higher	Lower

Synchronisation in measurement - The pulse wave has a slightly different timing based on the location of measurement, leading to synchronisation difficulties.

Requirement of circulatory sensing in every node - Since every node needs to measure the heart rhythm in some way, it may lead to redundant sensors increasing the cost, size and complexity.

The increased adoption of wearable devices in consumer electronics and healthcare has created scope for continuous long term monitoring. By aggregating and synchronising multi-modal sources of data from the body, there is great potential to improve the quality of data recorded by automatically filtering noisy values or annotating mismatch timestamps, etc. This information could prove useful to better sensor design as well analytics. Due the privacy concerns with medical data, it is instrumental to have a secure communication interface - although classical cryptographic methods exist using hardware random number generation algorithms, biometric authentication techniques offer an alternative approach that utilizes the shared pool of information in the heart beat. It also offers the added benefit that it cannot be "sniffed" remotely, requiring physical contact with the subject to access the information.

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