Healthcare Cyber-Physical System (H-CPS)

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Outline

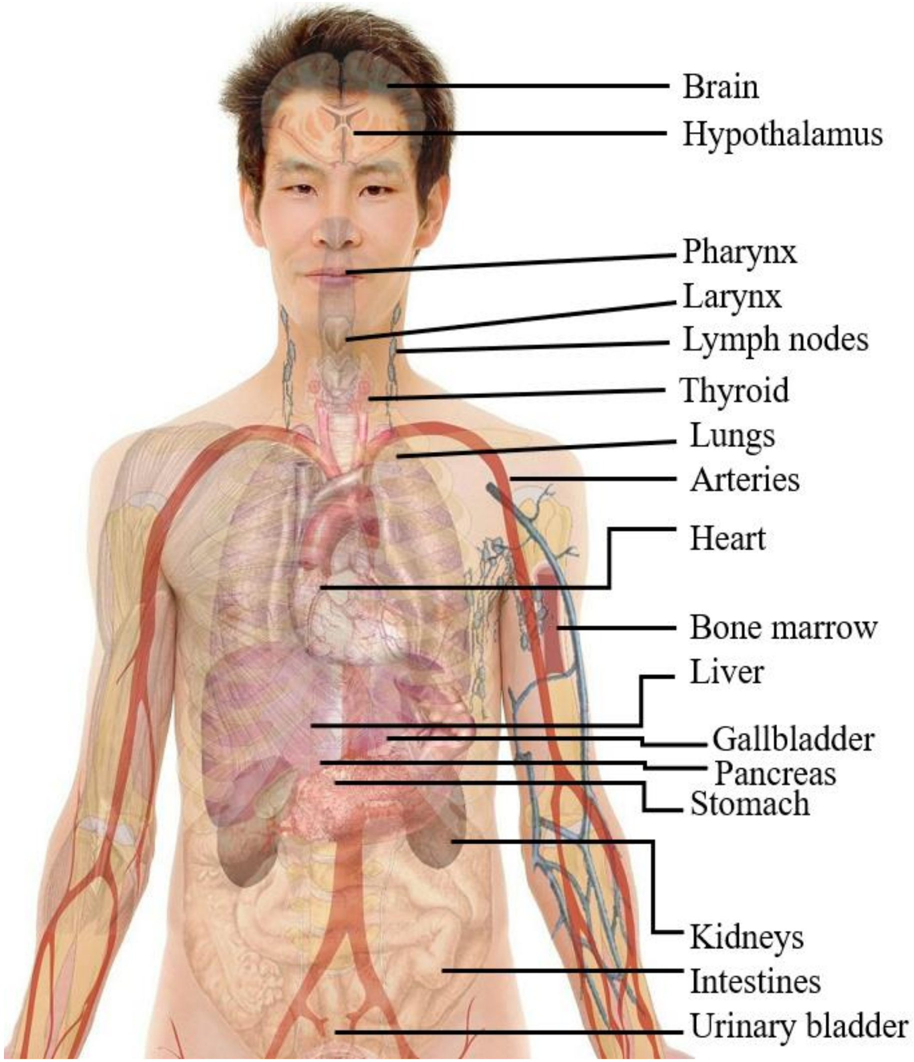
- Healthcare → Smart Healthcare
- Smart Healthcare - Characteristics
- Smart Healthcare - Components
- Smart Healthcare - Examples
- Smart Healthcare - Challenges
- Conclusions and Future Directions

Healthcare
to
Smart Healthcare

Human Body and Health

Human Body

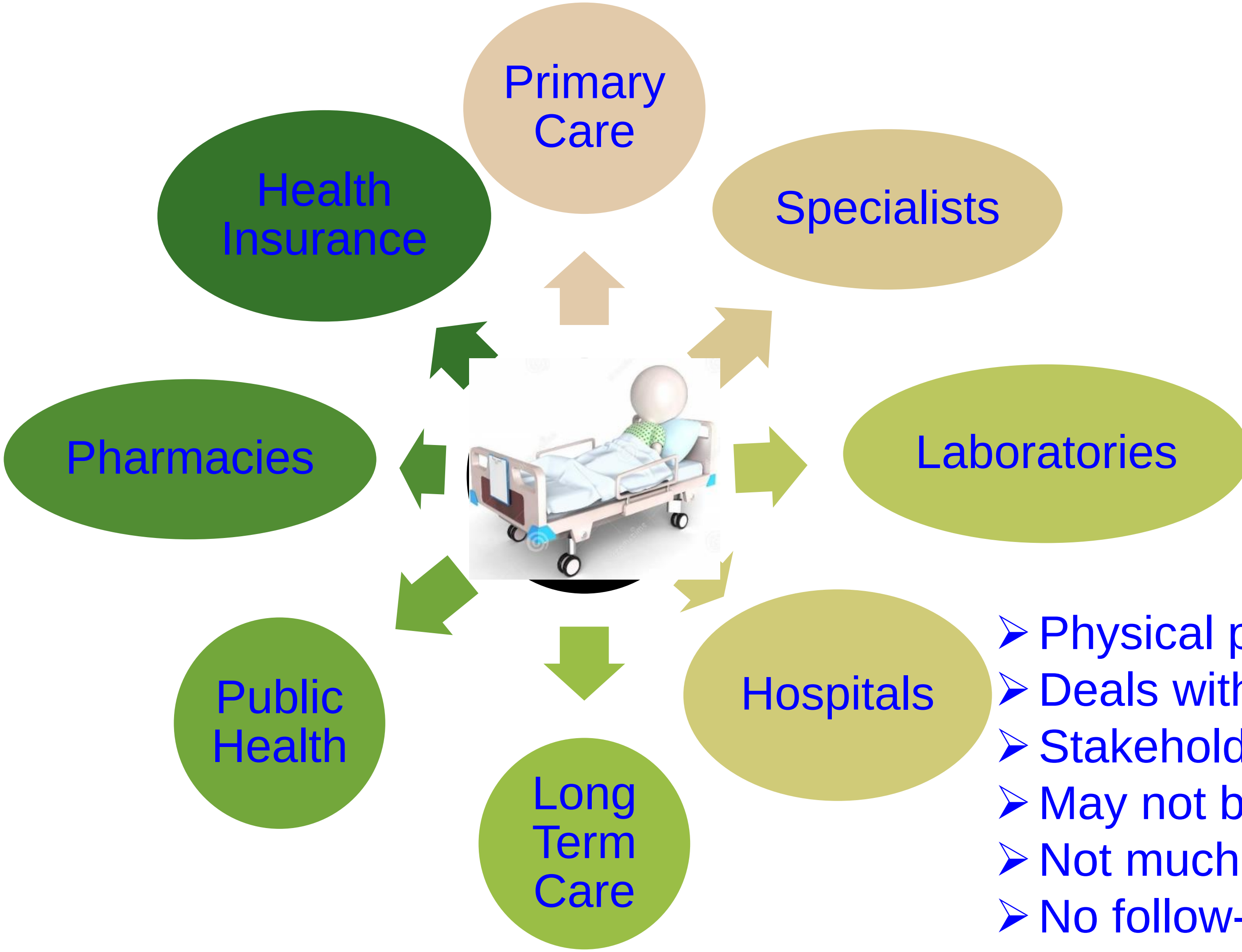
- From an engineering perspective, the human body can be defined as a combination of multi-disciplinary subsystems (electrical, mechanical, chemical …).



Health

- Human health is a state of complete physical, mental and social well-being.

Traditional Healthcare



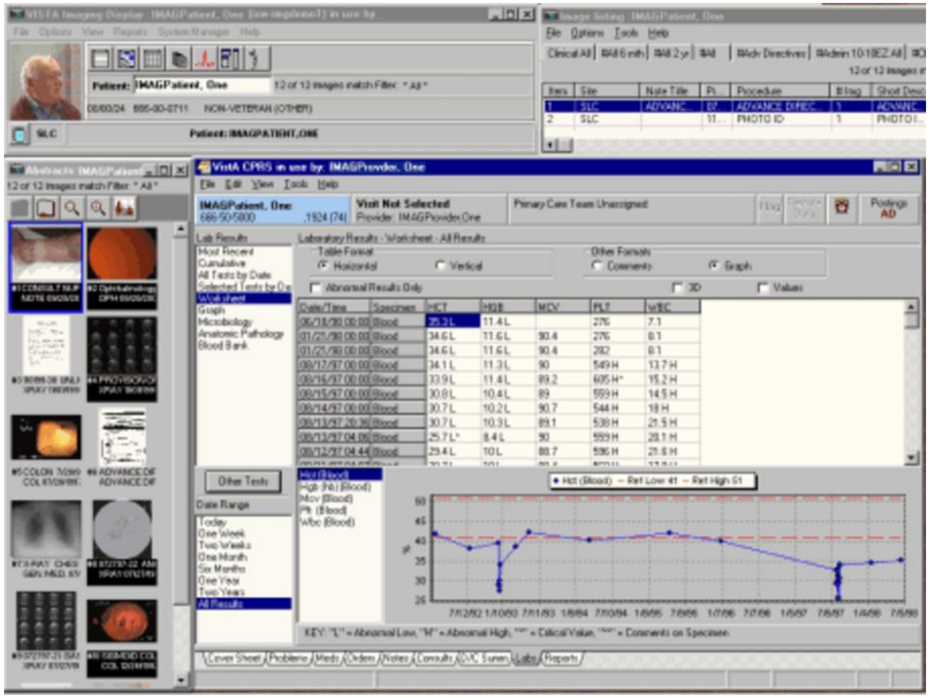
- Physical presence needed
- Deals with many stakeholders
- Stakeholders may not interact
- May not be personalized
- Not much active feedback
- No follow-up from physicians

Telemedicine

Telemedicine is the use of telecommunication and information technology to provide clinical health care from a distance.

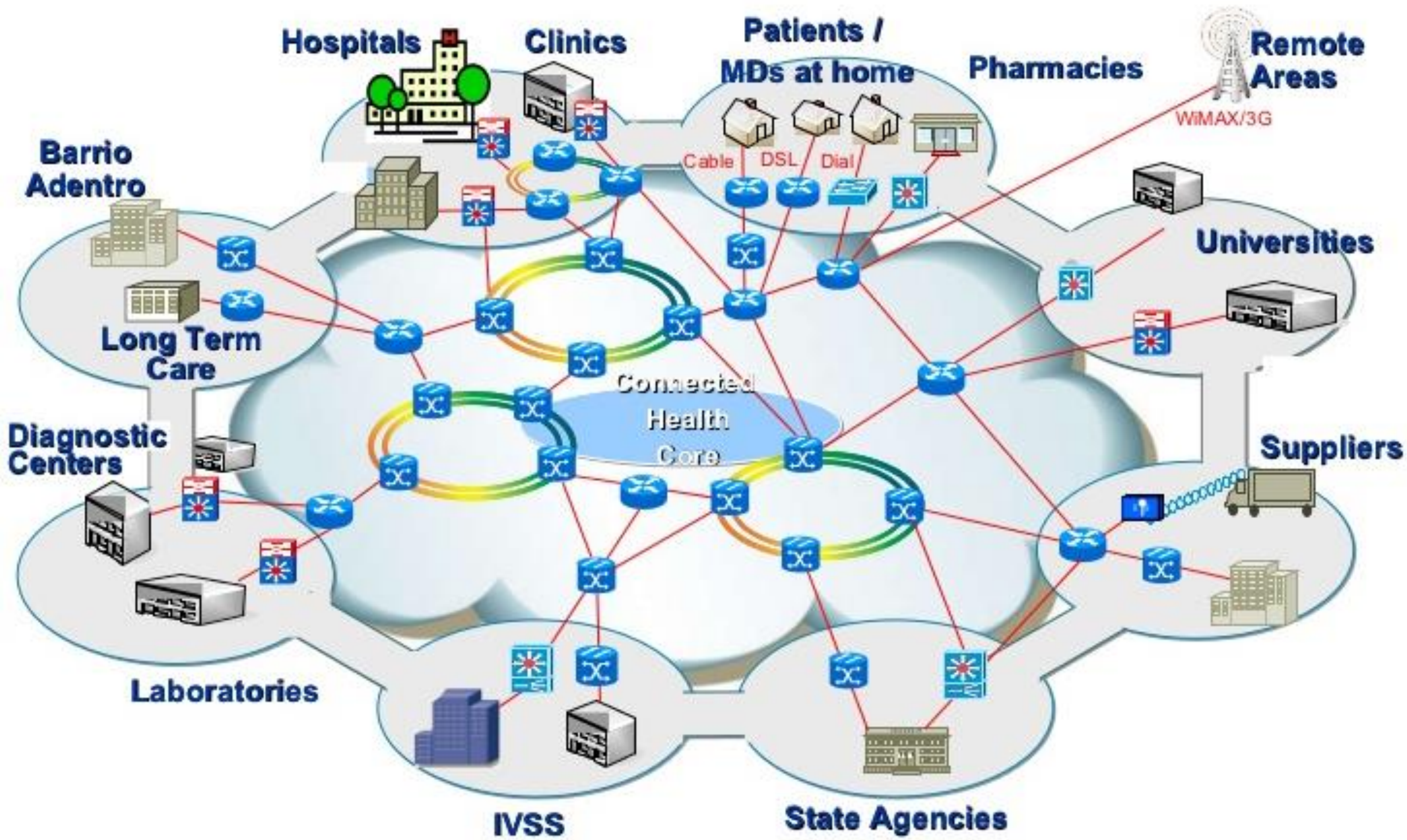
Electronic Health (eHealth)

- eHealth: The use of information and communication technologies (ICT) to improve healthcare services.



Source: W. O. Nijeweme-d'Hollosy, L. van Velsen, M. Huygens and H. Hermens, "Requirements for and Barriers towards Interoperable eHealth Technology in Primary Care," *IEEE Internet Computing*, vol. 19, no. 4, pp. 10-19, July-Aug. 2015.

Connected Health (cHealth)



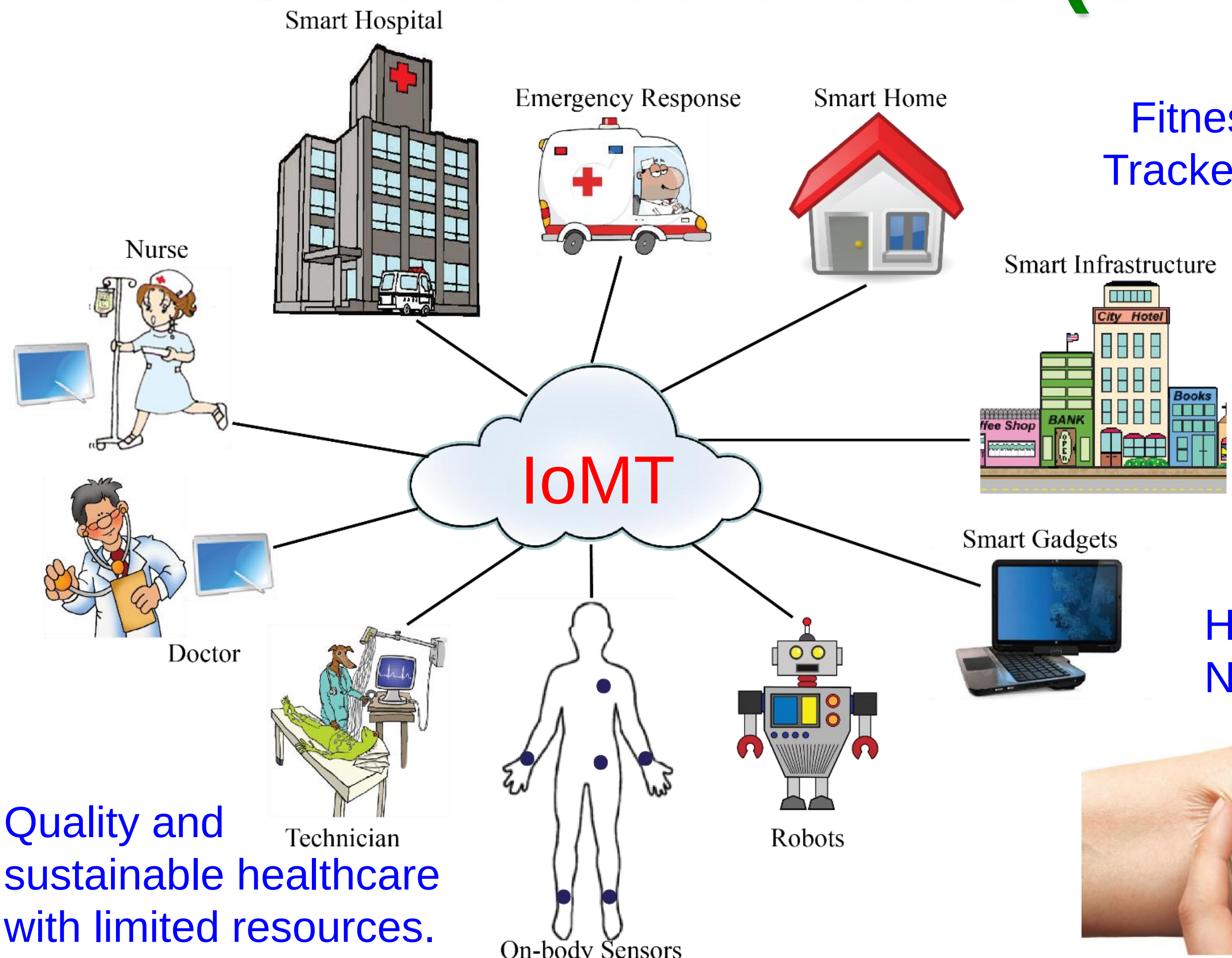
Source: https://www.slideshare.net/tibisay_hernandez/connected-health-venfinal

Mobile Health (mHealth)

- mHealth: Healthcare supported by *mobile devices* that uses mobile telecommunications and multimedia technologies for the delivery of healthcare services and health information.

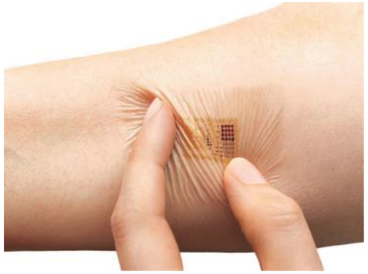
Source: H. Zhu, C. K. Wu, C. H. KOO, Y. T. Tsang, Y.Liu, H. R. Chi, and K. F. Tsang, "Smart Healthcare in the Era of Internet-of-Things", *IEEE Consumer Electronics Magazine*, vol. 8, no. 5, pp. 26-30, Sep 2019.

Smart Healthcare (sHealth)



Fitness Trackers

Headband with Embedded Neurosensors



Embedded Skin Patches

Sethi 2017: JECE 2017

Quality and sustainable healthcare with limited resources.

Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, “Everything You Wanted to Know about Smart Health Care”, *IEEE Consumer Electronics Magazine (MCE)*, Vol. 7, Issue 1, January 2018, pp. 18-28.

Smart Healthcare

Healthy Living

- Fitness Tracking
- Disease Prevention
- Food monitoring

Home Care

- Mobile health
- Telemedicine
- Self-management
- Assisted Living

Acute Care

- Hospital
- Specialty clinic
- Nursing Home
- Community Hospital

Internet of Medical Things (IoMT)

Frost and Sullivan predicts smart healthcare market value to reach US$348.5 billion by 2025.

January 2018

Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, “Everything You Wanted to Know about Smart Health Care”, *IEEE Consumer Electronics Magazine (MCE)*, Vol. 7, Issue 1, January 2018, pp. 18-28.

Smart Healthcare - Characteristics

What is Smart Healthcare?

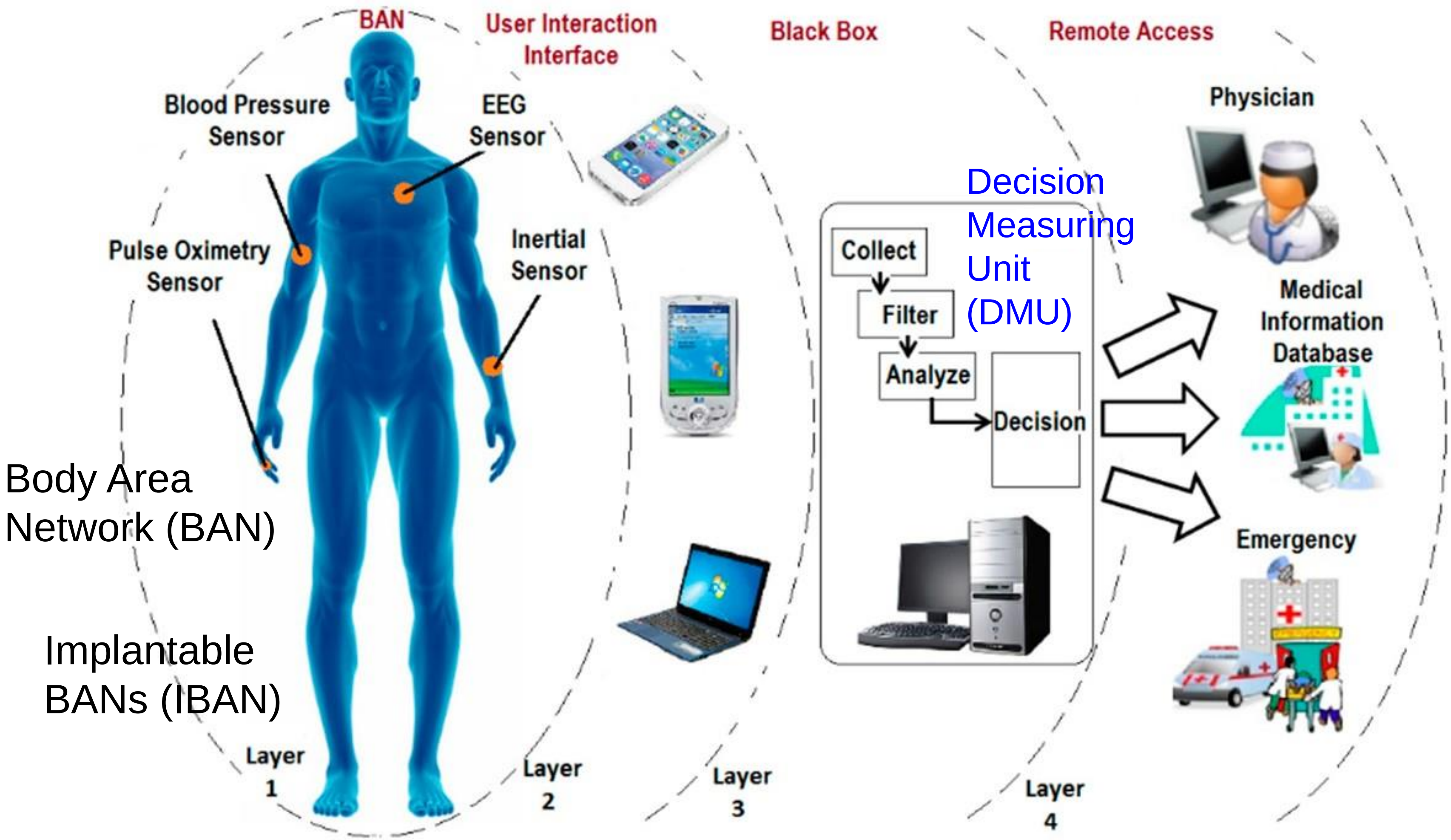
Smart Healthcare ←
Conventional Healthcare
+ Body sensors
+ Smart Technologies
+Information & Communication Technology (ICT)
+ AI/ML

Internet of Medical Things (IoMT) | Internet of Health Things (IoHT)

Healthcare Cyber-Physical Systems (H-CPS)

Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "Everything You Wanted to Know about Smart Health Care", *IEEE Consumer Electronics Magazine (MCE)*, Volume 7, Issue 1, January 2018, pp. 18-28.

Smart Healthcare - 4-Layer Architecture



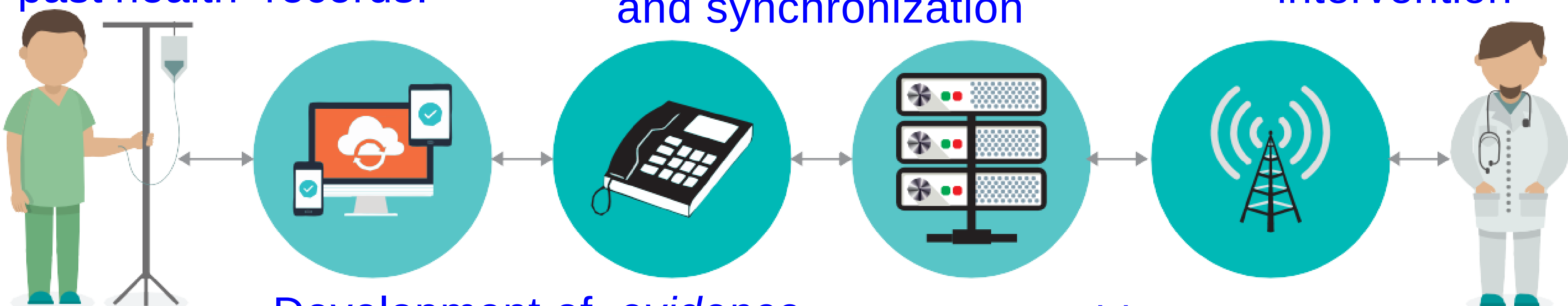
Source: M. Ghamari, B. Janko, R.S. Sherratt, W. Harwin, R. Piechockic, and C. Soltanpur, "A Survey on Wireless Body Area Networks for eHealthcare Systems in Residential Environments", *Sensors*, 2016. 16(6): p. 831.

IoMT based H-CPS

Patient-specific care with *context* and enabled through past health records.

Improved inter-device connection and synchronization

Real-time *tracking* and intervention



Patient

Development of *evidence-based guidelines* which can helpful to incorporate the local intelligence in future machine.

Data driven health *prediction*

Healthcare Provider

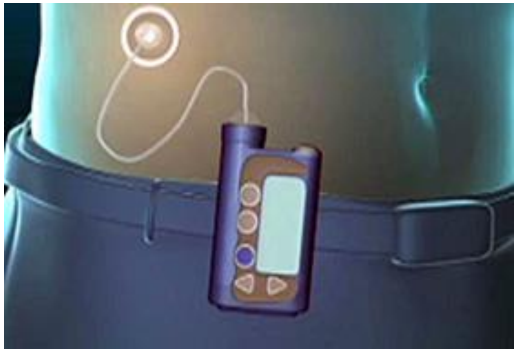
Healthcare Cyber-Physical Systems (CPS)

Source: Y. Shelke and A. Sharma, "Internet of Medical Things", 2016, Aranca, https://www.aranca.com/knowledge-library/special-reports/ip-research/the-internet-of-medical-things-iomt, Last Visited 10/18/2017.

Wearable Medical Devices (WMDs)

Fitness Trackers

Headband with Embedded Neurosensors

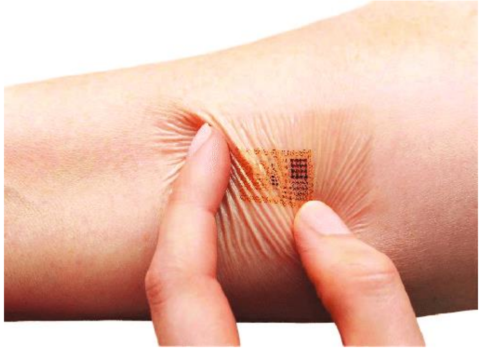


Source: https://www.webmd.com

Insulin Pump

Source: https://www.empatica.com/embrace2/

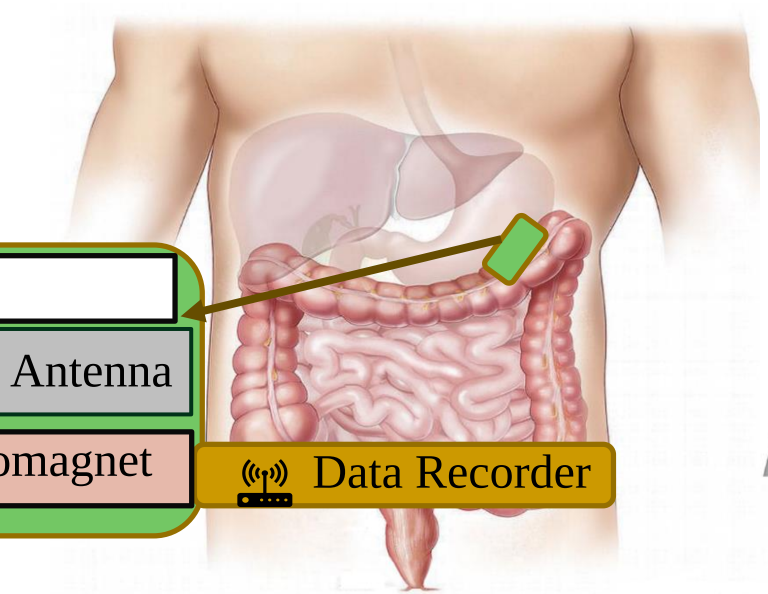
Medical grade smart watch to detect seizure

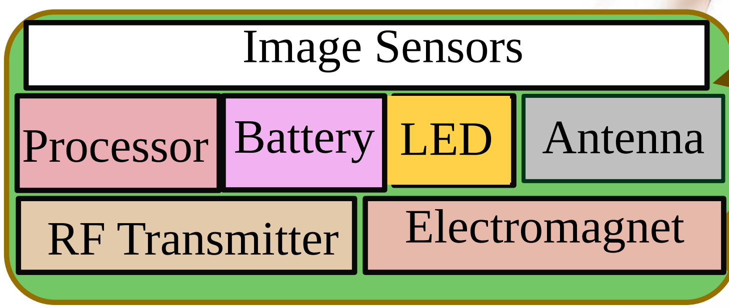


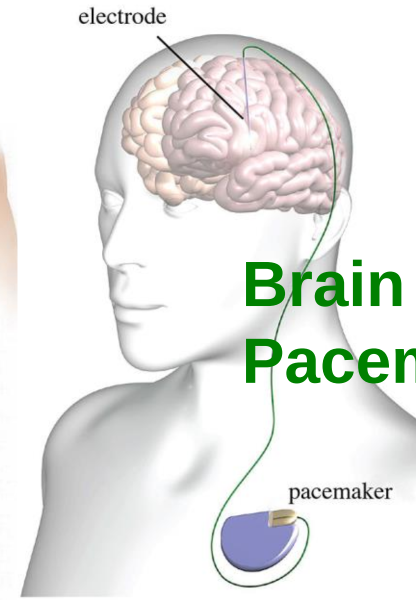
Embedded Skin Patches

Implantable Medical Devices (IMDs)

Pill Camera







Brain Pacemaker

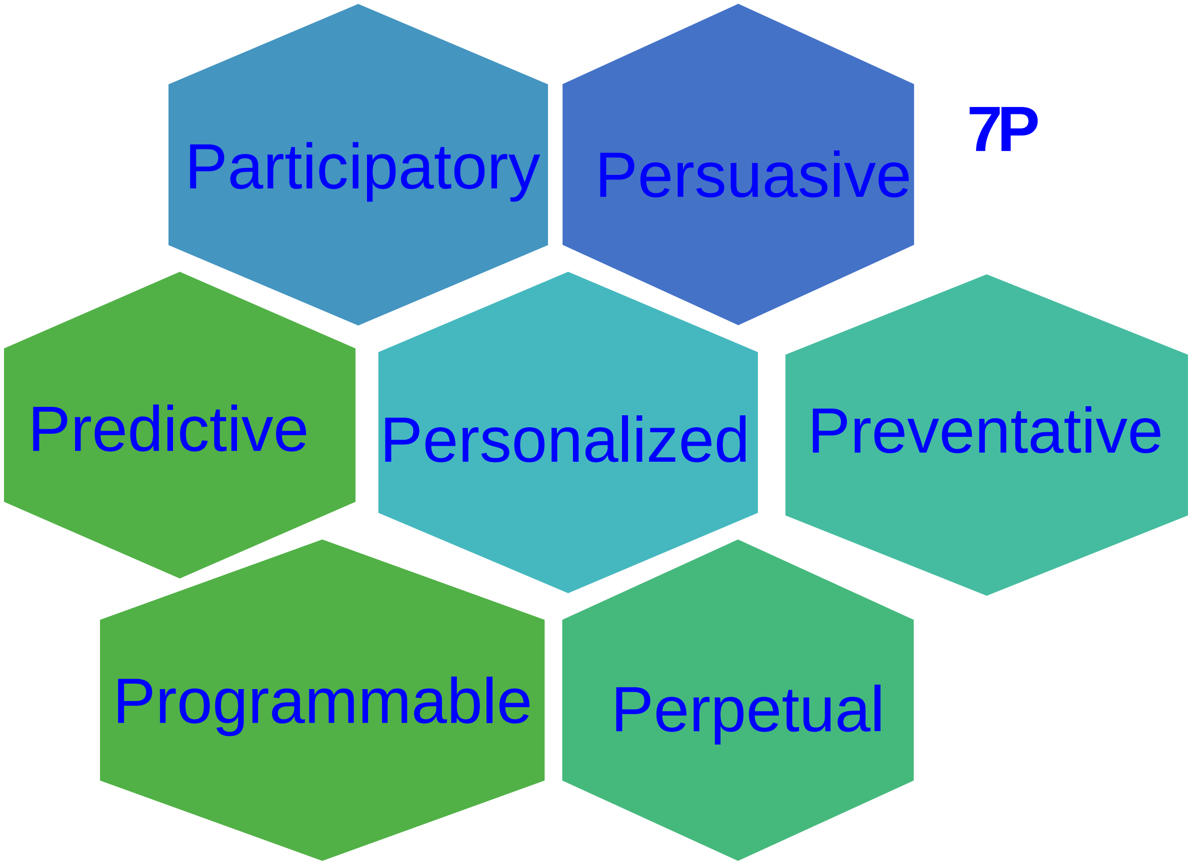
Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "*Everything You Wanted to Know about Smart Health Care*", IEEE Consumer Electronics Magazine (MCE), Volume 7, Issue 1, January 2018, pp. 18-28.

Collectively:
Implantable and Wearable Medical Devices (IWMDs)

Implantable MEMS Device

Source: http://web.mit.edu/cprl/www/research.shtml

Smart Healthcare – 7Ps



Source: H. Zhu, C. K. Wu, C. H. KOO, Y. T. Tsang, Y.Liu, H. R. Chi, and K. F. Tsang, "Smart Healthcare in the Era of Internet-of-Things", *IEEE Consumer Electronics Magazine*, vol. 8, no. 5, pp. 26-30, Sep 2019.

Smart Healthcare - Tasks

Smart Healthcare - Tasks

Daily Healthcare | **Clinical Boundary** | **Clinical Healthcare**

(ii) Daily Diagnosis

- Wearable Medical Sensor (WMS)-based diagnosis

(i) Daily Prevention

- Fitness checkup
- Activity tracking
- Emotion analysis
- Disease risk prediction

(v) Daily Treatment

- Out-patient therapy
- Ambient healthcare
- Disease status monitoring
- Precision medicine

(iii) Clinical Diagnosis

- Physician variance reduction
- Personalized diagnosis

(iv) Clinical Treatment

- Treatment plan selection
- Treatment method evaluation
- In-patient monitoring
- Precision medicine

Source: Hongxu Yin, Ayten Ozge Akmandor, Arsalan Mosenia and Niraj K. Jha (2018), "Smart Healthcare", *Foundations and Trends® in Electronic Design Automation*: Vol. 12: No. 4, pp 401-466. http://dx.doi.org/10.1561/1000000054

IoMT Advantages & Limitations

Advantages

Patients/Users
- Real-time interventions in emergency
- Cost reduction
- Reduced morbidity and financial burden due to less follow up visits

Healthcare Service Providers
- Optimal utilization of resources
- Reduced response time in emergency

Manufacturers
- Standardization/compatibility and uniformity of data available
- Capability to sense and communicate health related information to remote location

Limitations

Technical Challenges
- Security of IoT data - hacking and unauthorized use of IoT
- Lack of standards and communication protocols
- Errors in patient data handling
- Data integration
- Need for medical expertise
- Managing device diversity and interoperability
- Scale, data volume and performance

Market Challenges
- Physician compliance
- Data overload on healthcare facility
- Mobile hesitation
- Security policy compliance

Source: Y. Shelke and A. Sharma, "Internet of Medical Things", 2016, Aranca, https://www.aranca.com/knowledge-library/special-reports/ip-research/the-internet-of-medical-things-iomt, Last Visited 10/18/2017.

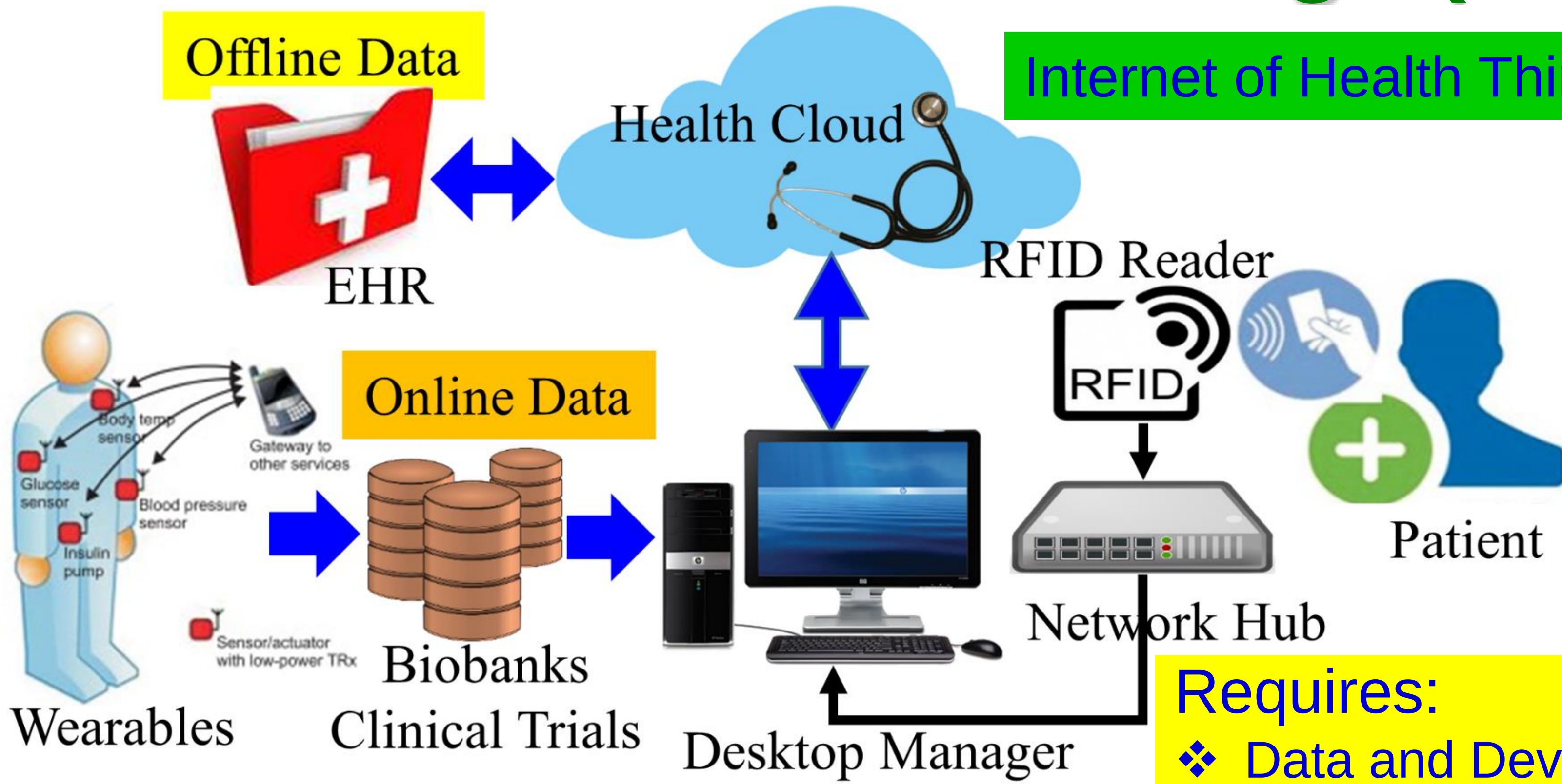
Smart Healthcare - Architectures

Problem?

- Sensors should be connected to each other All The Time !!
- Perform data analytics and deploy cloud based solutions in small computing devices.
- Sensors can be in-vitro or in-vivo: small battery size.
- Due to these reasons, optimizations in terms of security, energy requirements, size, and performance is required.

Smart Healthcare - Components

Internet of Medical Things (IoMT)



Internet of Health Things (IoHT)

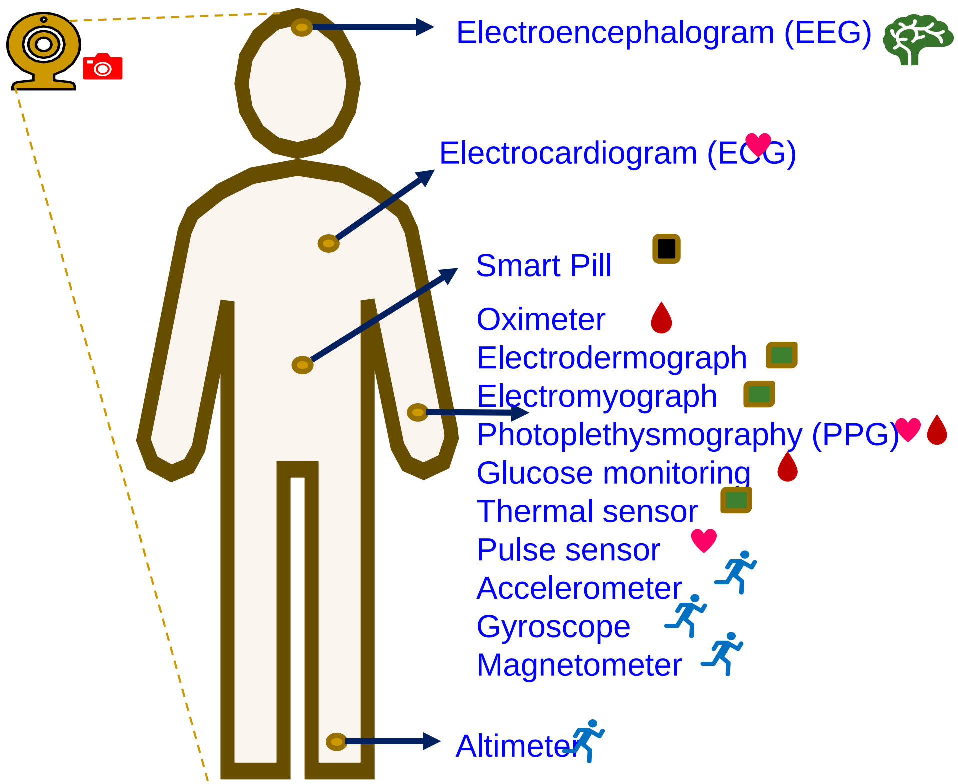
Requires:

- ❖ Data and Device Security
- ❖ Data Privacy

IoMT is a collection of medical sensors, devices, healthcare database, and applications that connected through Internet.

Source: http://www.icemiller.com/ice-on-fire-insights/publications/the-internet-of-health-things-privacy-and-security/
Source: http://internetofthingsagenda.techtarget.com/definition/IoMT-Internet-of-Medical-Things

Smart Healthcare Sensors



Types of Sensors

- Brain related applications
- Imaging applications
- Heart related applications
- Skin related applications
- Blood related applications
- Ingestible sensors
- Motion Detection

Smart Healthcare Communication

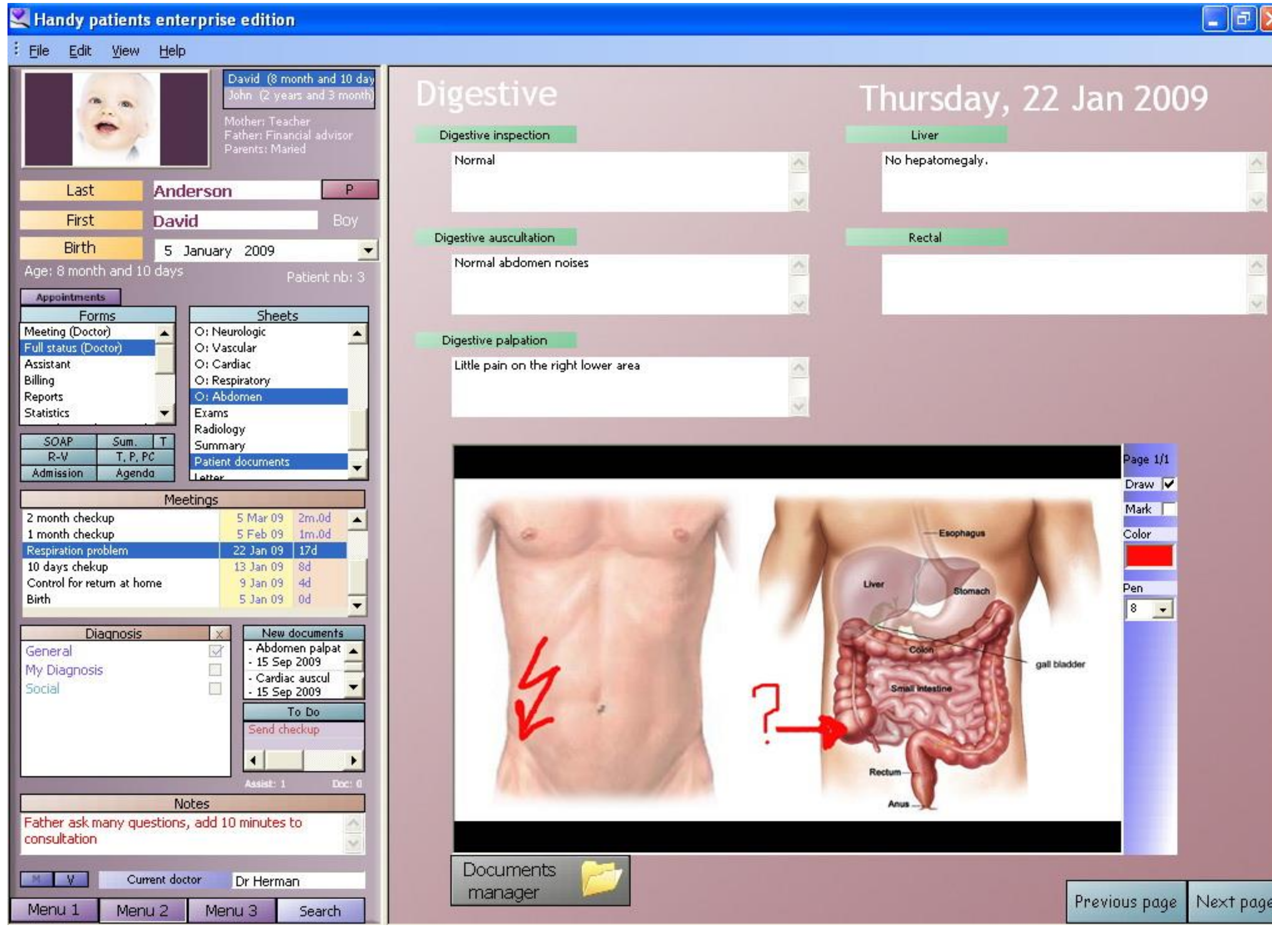
Technology	Frequency Band	Data Rate	Range	Transmission Power
Bluetooth 4.0 (LE)	2.4 GHz	50–200 Kbps	30 m	~10 mW
Zigbee	868 MHz/ 915 MHz/ 2.4 GHz	20–250 Kbps	30 m	30 mW
ANT	2400-2485 MHz	1 Mbps	Up to 10 m	0.01–1 mW
IEEE 802.15.6	2,360-2,400/ 2,400-2,483.5 MHz UWB: 3–10 GHz HBC: 16/27 MHz	NB: 57.5–485.7 Kbps UWB: 0.5–10 Mbps	1.2 m	0.1 μW
Medical Implant Communications Service (MICS)	402-405 MHz	Up to 500 Kbps	2 m	25 μW

Source: V. Custodio, F.J. Herrera, G. López, and J. I. Moreno, "*A Review on Architectures and Communications Technologies for Wearable Health-Monitoring Systems*", *Sensors*, 2012. 12(10): p. 13907-13946.

Electronics Health Record (EHR)

Electronic Health Record (EHR) is the systematized collection of health information of individuals stored in a digital format.

Created by various health providers such as hospitals and clinics.



Electronic Medical Record (EMR)

Smart Healthcare - Framework

Smart Healthcare - System and Data Analytics : To Perform Tasks

Systems & Analytics
- Health cloud server
- Edge server
- Implantable Wearable Medical Devices (IWMDs)

Machine Learning Engine

Data
- Physiological data
- Environmental data
- Genetic data
- Historical records
- Demographics

Systems & Analytics
- Clinical Decision Support Systems (CDSSs)
- Electronic Health Records (EHRs)

Machine Learning Engine

Data
- Physician observations
- Laboratory test results
- Genetic data
- Historical records
- Demographics

Source: Hongxu Yin, Ayten Ozge Akmandor, Arsalan Mosenia and Niraj K. Jha (2018), "Smart Healthcare", *Foundations and Trends® in Electronic Design Automation*, Vol. 12: No. 4, pp 401-466. http://dx.doi.org/10.1561/1000000054

Machine Learning (ML)

Supervised ML

- Data instance: features + label
- Data instance sets: training, testing
- Inference: Mathematical Model

Enhancement Techniques

- Ensemble method: base vs. meta
- Feature filtering: redundant vs. informative

Source: Hongxu Yin, Ayten Ozge Akmandor, Arsalan Mosenia and Niraj K. Jha (2018), "Smart Healthcare", *Foundations and Trends® in Electronic Design Automation*, Vol. 12: No. 4, pp 401-466. http://dx.doi.org/10.1561/1000000054.

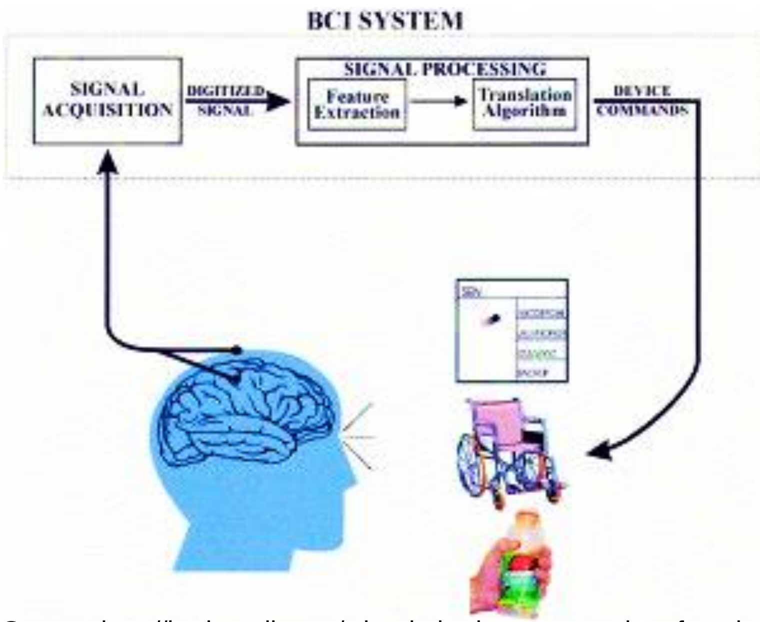
Brain Computer Interface (BCI)

"Currently, people interact with their devices by thumb-typing on their phones. A high-bandwidth interface to the brain would help achieve a symbiosis between human and machine intelligence and could make humans more useful in an AI-driven world."

-- Neuralink - neurotechnology company - Elon Musk.

Sources: http://brainpedia.org/elon-musk-wants-merge-human-brain-ai-launches-neuralink/

BCI - Applications



Source: http://brainpedia.org/what-is-brain-computer-interface-bci/

BCI Allows paralysis patients move a wheelchair

Source: http://brainpedia.org/brain-computer-interface-allows-paralysis-als-patients-type-much-faster/

BCI Allows paralysis patients to Type

- BCI Types
  - Based on Location
    - Non-invasive
    - Semi-invasive
    - Invasive
  - Based on Signal
    - EEG
    - MEG
    - fNIR
    - fMRI

Virtual Reality in Healthcare

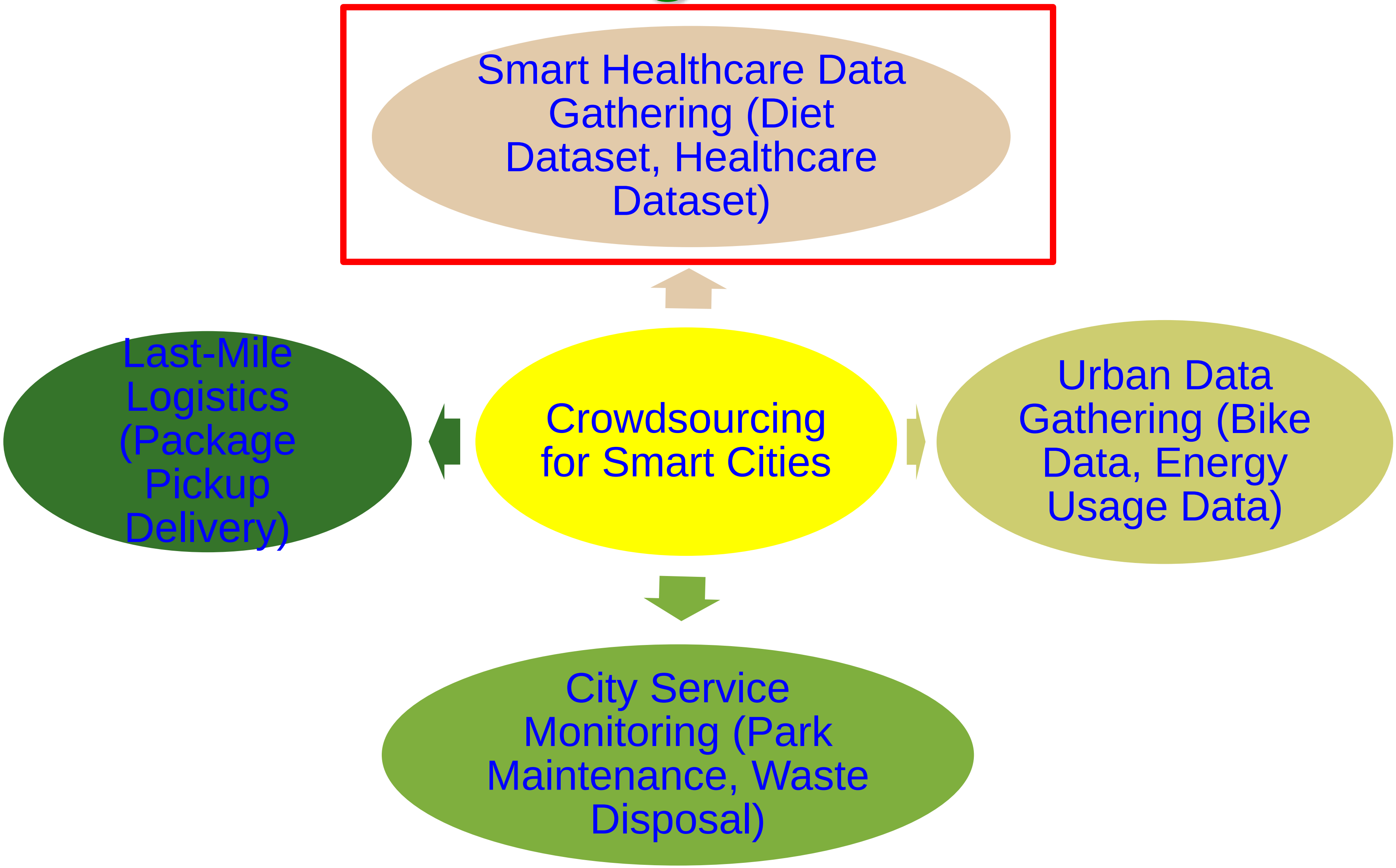
Source: https://touchstoneresearch.com/tag/applied-vr/

In Surgery

Source: http://medicalfuturist.com/5-ways-medical-vr-is-changing-healthcare/

For Therapy

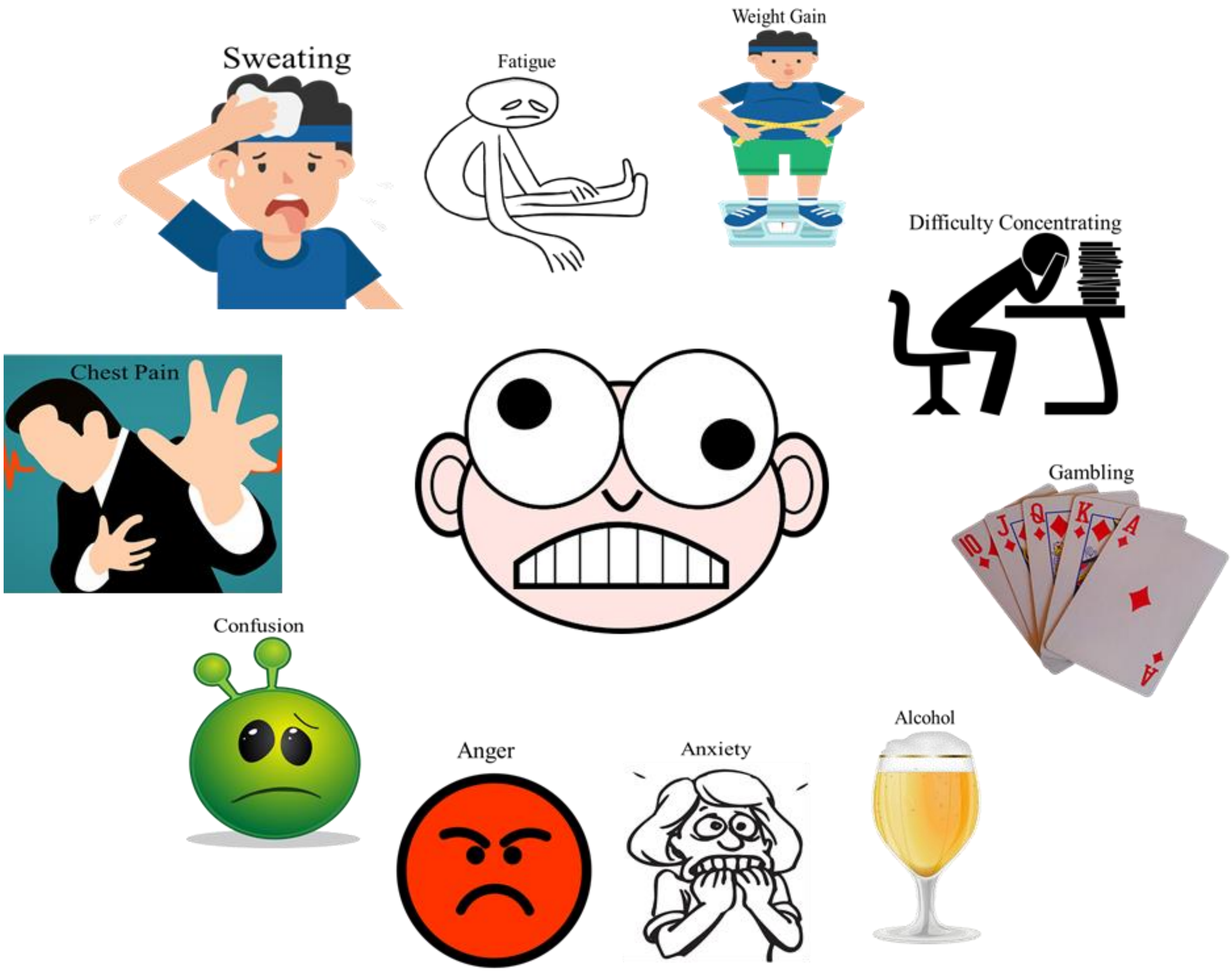
Crowdsourcing for Smart Cities



Smart Healthcare – Specific Examples

Smart Electronic Systems Laboratory (SESL)
UNT DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING College of Engineering
EST. 1890

Symptoms of Stress

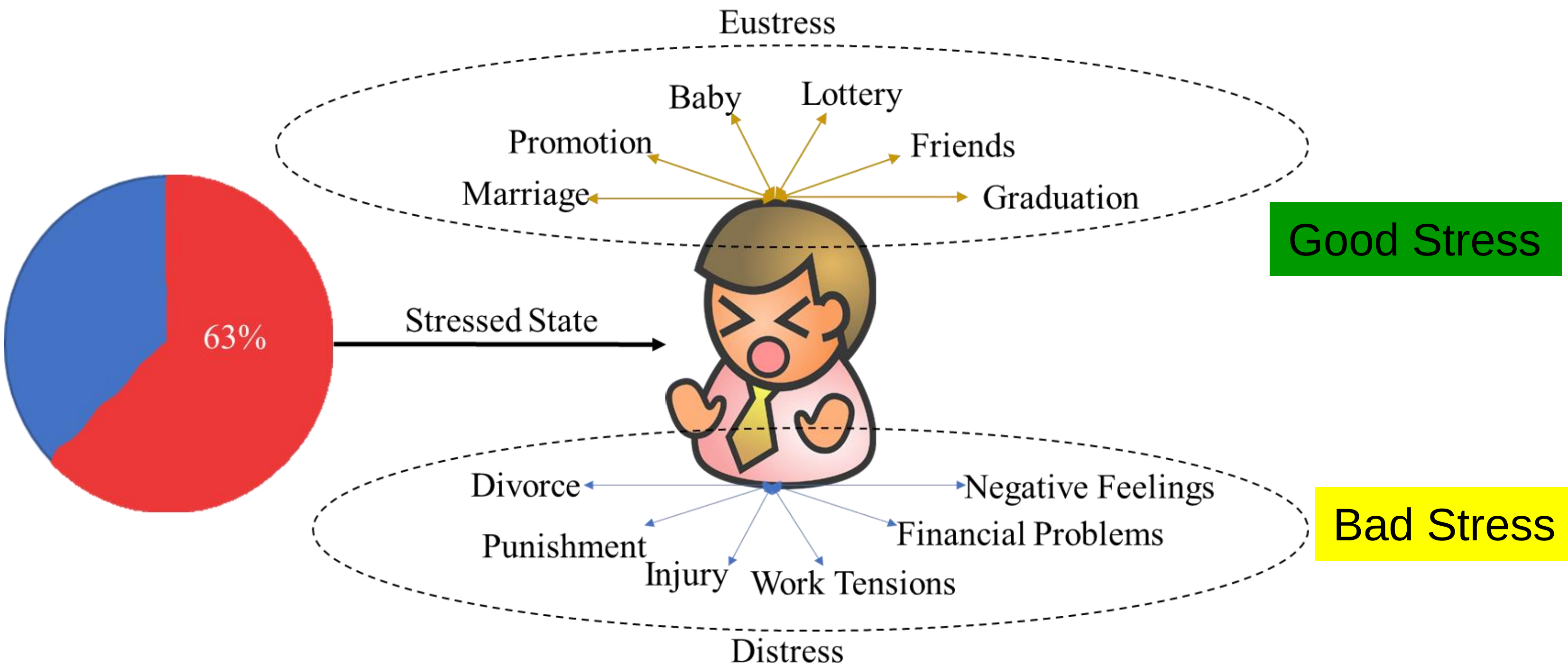


Stress is a Global Issue

- In major global economies - 6 in 10 workers experiencing increased workplace stress.
- In USA: 75% of adults reported experiencing moderate to high levels of stress. 1 out of 75 people may experience panic disorder.
- In Australia: 91% of adults feel stress in at least one important area of their lives.
- In UK: An estimated 442,000 individuals, who worked in 2007/08 believed that they were experiencing work-related stress
- Depression is among the leading causes of disability worldwide. 25% of those with depression world-wide have access to effective treatments → 75% don't have.

Source: http://www.gostress.com/stress-facts/

What is Stress?



- Stress is the relationship between a person and a situation, which adversely impacts the happiness and health of the sufferer or physiological reactions.
- Stress can be divided into two parts: stressor and reaction.
- Stressor is the activity or effect that triggers a change in the physiological parameter values of the human body.
- Reaction is the deviation of these parameter values from their normal levels.

Why Stress Needs to be Resolved?

When there is an encounter with sudden **stress**, your brain floods your **body** with chemicals and hormones such as adrenaline and cortisol.

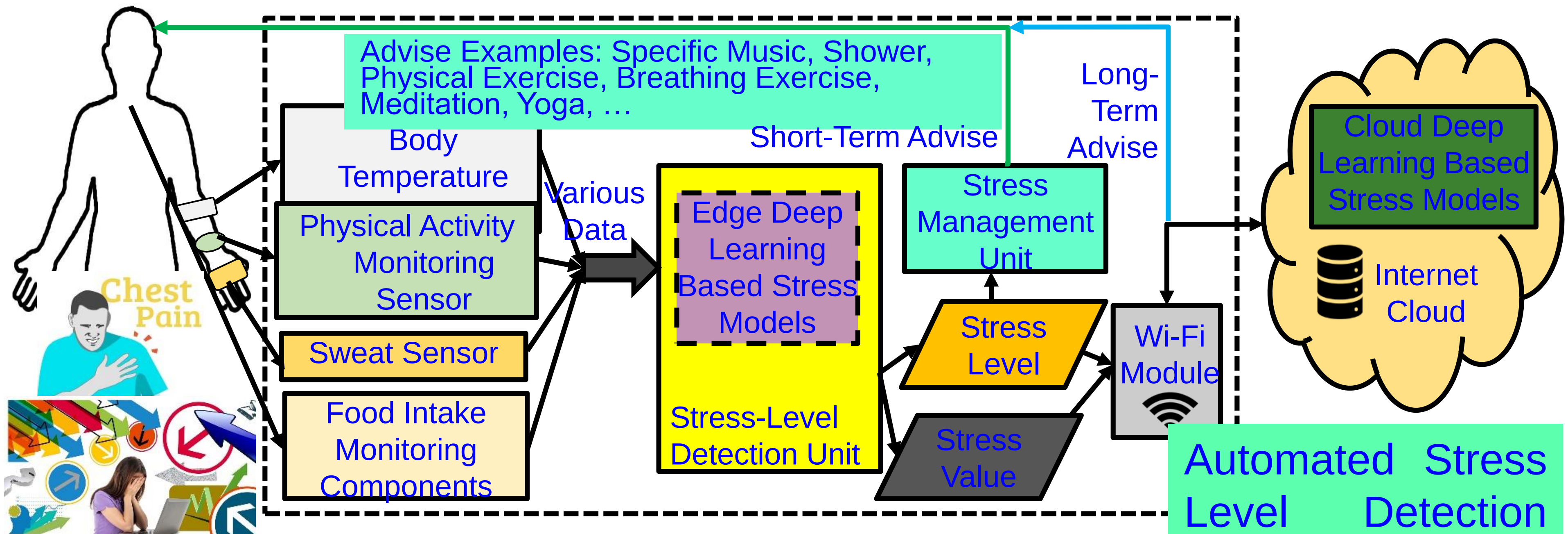
- Lack of Energy
- Type 2 Diabetes
- Osteoporosis
- Mental cloudiness (brain fog) and memory problems
- A weakened immune system, leading to more vulnerable to infections

Distress

Eustress

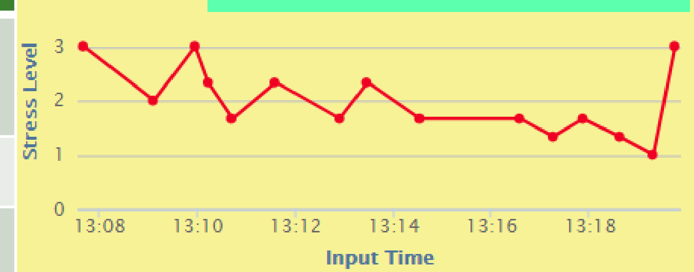
Stress is the body's reaction to any change that requires an adjustment or response.

Smart Healthcare - Stress Monitoring & Control



Automated Stress Level Detection and Management

Sensor	Low Stress	Normal Stress	High Stress
Accelerometer (steps/min)	0-75	75-100	101-200
Humidity (RH%)	27-65	66-91	91-120
Temperature ℉	98-100	90-97	80-90



Source: L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, No 4, Nov 2019, pp. 474--483.

Consumer Electronics Devices – Can Provide Data for Stress Detection

Brand	Device	Signals	RTI	Ambulant
Empatica	E4 wristband	PPG, GSR, HR, ACC, ST	Yes	Yes
Garmin	Vivosmart	HR, HRV, ACC	Yes	Yes
Zephyr	BioHarness 3.0	HR, HRV, GSR, ACC, ST	Yes	Yes
iMotions	Shimmer 3+ GSR	GSR, PPG	Yes	No
BIOPAC	Mobita Wearable	ECG, EEG, EGG EMG, and EOG	Yes	No

GSR = Galvanic Skin Response, HR = Heart Rate, ACC = Acceleration, ST = Skin Temperature, HRV = Heart Rate Variability, PPG = Photoplethysmograph, RTI = Real Time Implementation

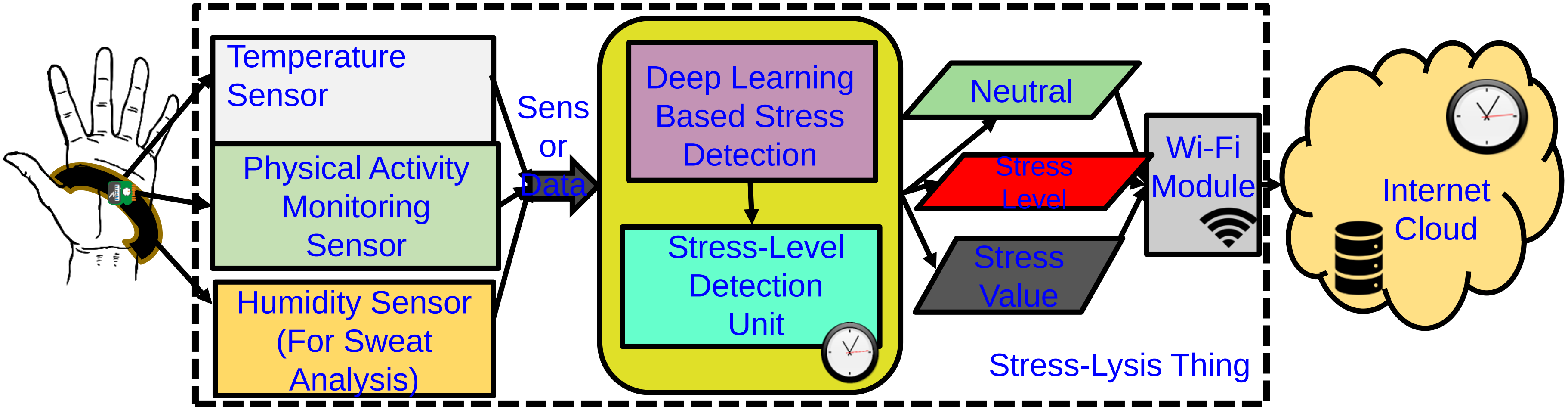
Source: R. K. Nath, H. Thapliyal, A. Caban-Holt, and S. P. Mohanty, "Machine Learning Based Solutions for Real-Time Stress Monitoring", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 9, XX, No. YY, ZZ 2020, DOI: 10.1109/MCE.2020.2993427.

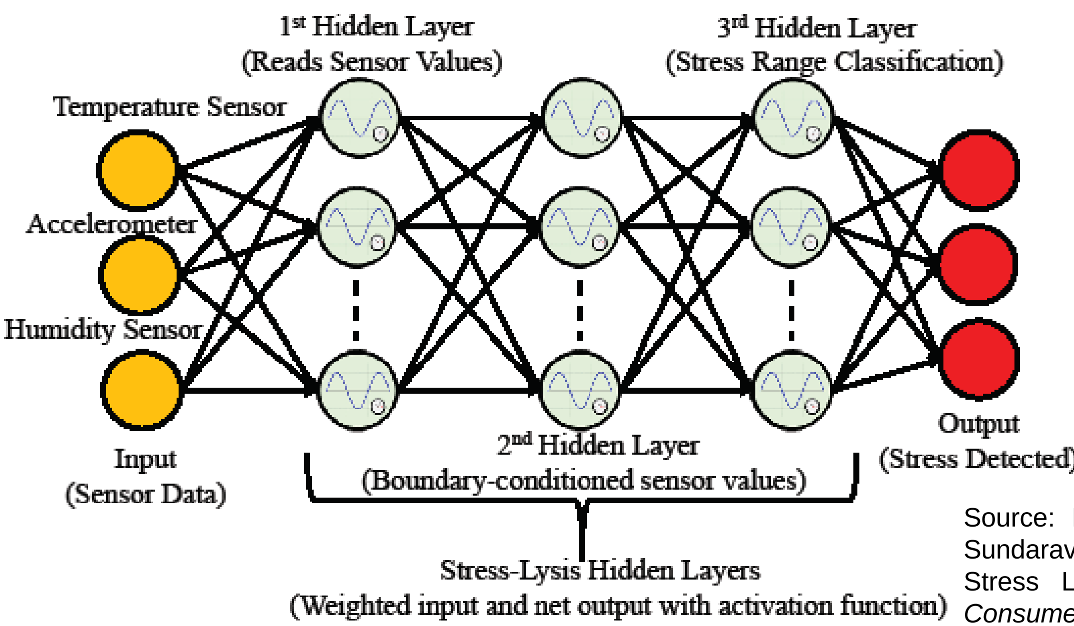
Stress-Lysis: Research Question

- How to have an accurate and rapid Stress Level Detection system that *acquires and models sensor data, and detects stress level* at the user end (at *IoT-Edge*) and stores the data at the cloud end (at *IoT-Cloud*)?

Source: L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-Lysis: A DNN-Integrated Edge Device for Stress Level Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE*), Vol 65, No 4, Nov 2019, pp. 474--483.

Stress-Lysis: From Physiological Signals





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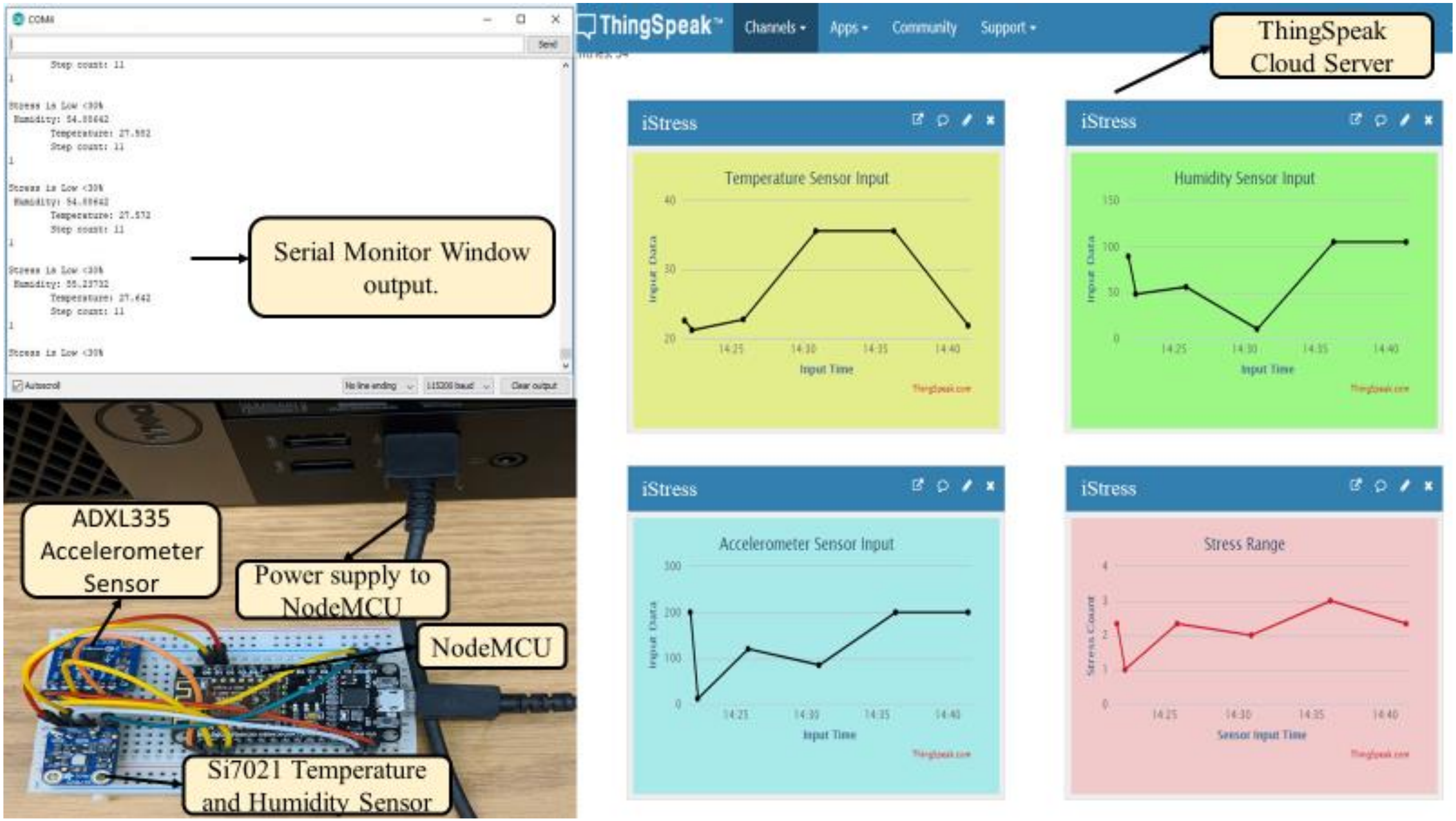
Stress-Lysis: Experiments



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Smart-Pillow: Research Question

- How to have a non-invasive, optimized, IoT enabled system which detects the stress level variations based on the sleeping parameters, analyses the data at the user end (at *IoT-Edge*) and stores the data at the cloud end (at *IoT-Cloud*)?

Source: Mohanty iSES 2018: "Smart-Pillow: An IoT based Device for Stress Detection Considering Sleeping Habits", in *Proc. of 4th IEEE International Symposium on Smart Electronic Systems (iSES)* 2018.

Consumer Electronics Sleep Trackers

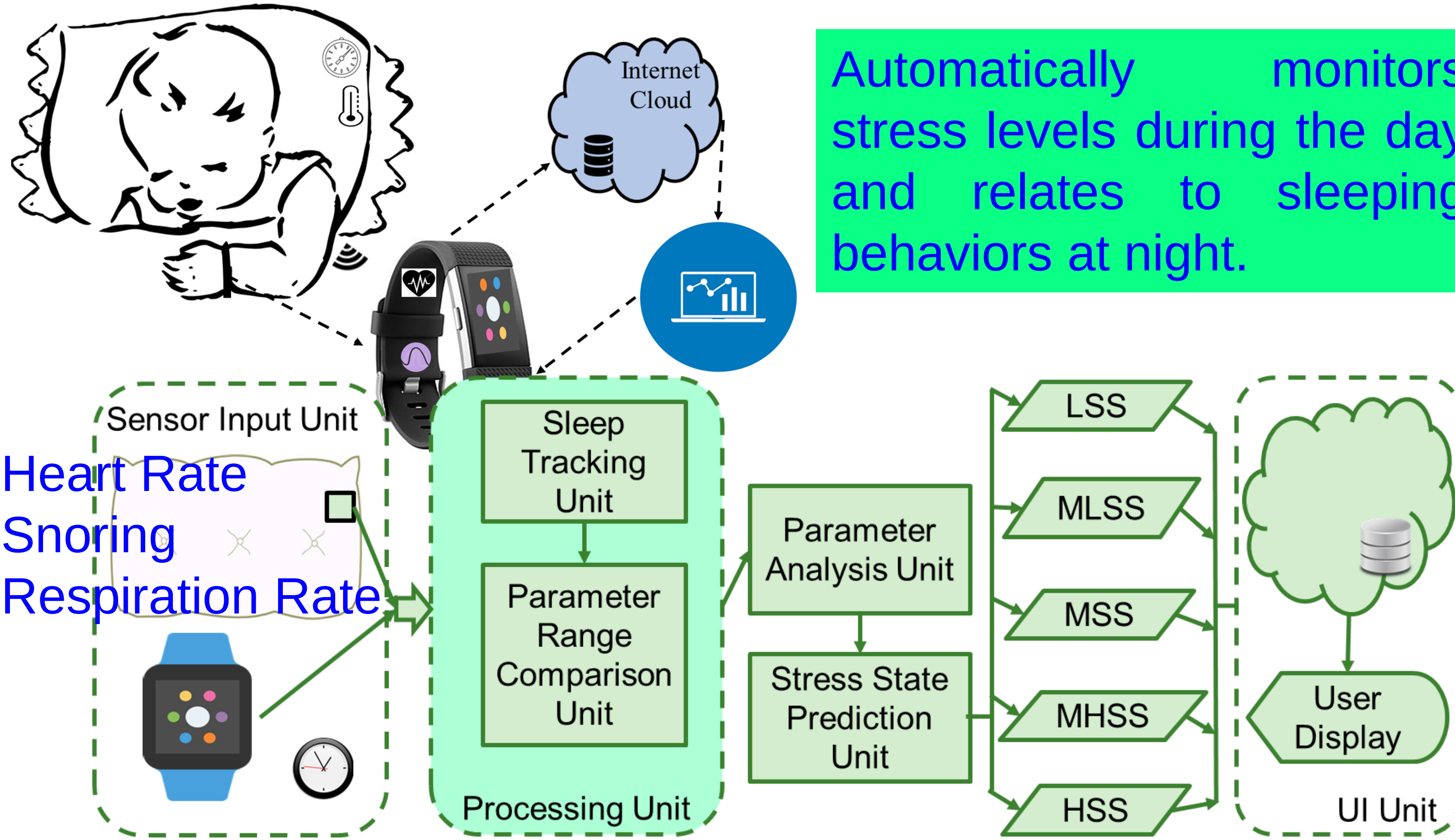
Consumer Products	Approach	Features	Drawbacks
Fitbit [34]	Wearable	Heart rate monitor, sleep stages monitor. Has techniques to improve the sleep score.	Relationship between stress and sleep is not discussed.
SleepScore Max [36]	Non-wearable	Invisible radio wave sleep tracking	Does not manage stress with sleep.
Nokia Sleep [38]	Non-wearable	Uses Ballistocardiography sensor	Does not explain the relationship with stress with sleep.
Xiaomi Mi Band 3 [31]	Wearable	Pulse Monitor	No information on importance of quality sleep.
Eversleep [32]	wearable	Snoring and breathing interruptions	No explanation on the relationship between stress and sleep.
Beddit [35]	Non-wearable	Monitors snoring	Doesn't consider other possible features.
Eight [37]	Non-Wearable	Humidity, temperature, heartbeat, breathing rate	No data on how it is important to have a good sleep.
Dreem [33]	Wearable	Simulates slow brain waves	It doesn't consider other features; Does not manage stress with sleep.
Muse [26]	Wearable	Simulates brain waves	No understanding of the importance of quality sleep.

Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: A Blockchain-Enabled, Privacy-Assured Framework for Stress Detection, Prediction and Control Considering Sleeping Habits in the IoMT", *arXiv Computer Science*, arXiv:2007.07377, July 2020, 38-pages.

Smart Healthcare – Smart-Pillow

Automatically monitors stress levels during the day and relates to sleeping behaviors at night.

Heart Rate
Snoring
Respiration Rate

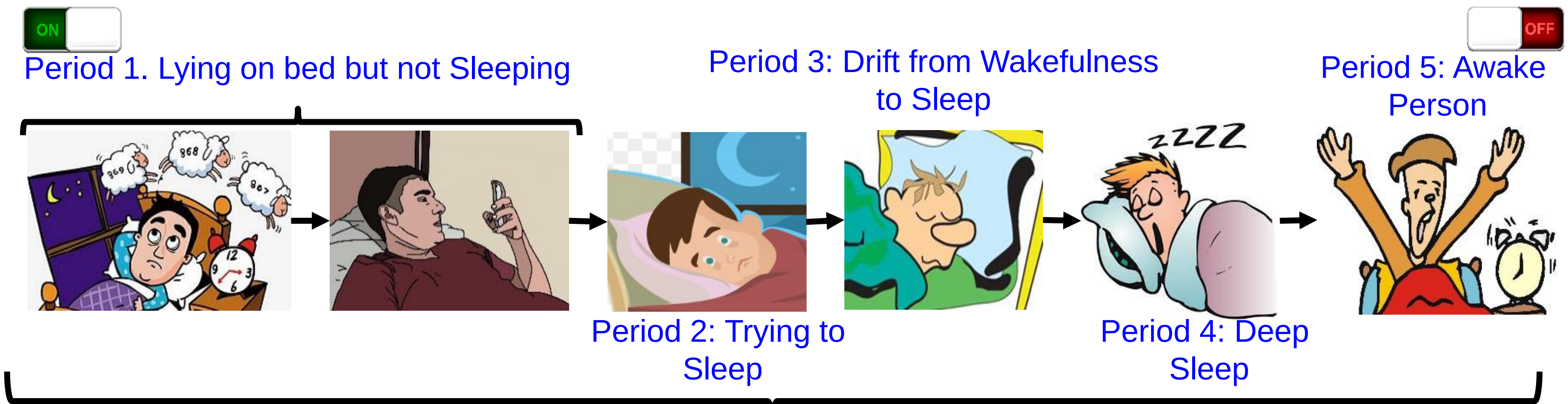


Source: Mohanty iSES 2018: “Smart-Pillow: An IoT based Device for Stress Detection Considering Sleeping Habits”, in *Proc. of 4th IEEE International Symposium on Smart Electronic Systems (iSES)* 2018.

Smart-Yoga Pillow (SaYoPillow) – Sleeping Pattern

Person On Pillow:
Physiological Sensor Data Monitoring Starts

Person Off Pillow:
Physiological Sensor Data Monitoring Ends



Transitions of a person drifting into non-rapid eye movement (NREM) followed by rapid eye movement (REM) to Awake State.

Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: A Blockchain-Enabled, Privacy-Assured Framework for Stress Detection, Prediction and Control Considering Sleeping Habits in the IoMT", *arXiv Computer Science*, arXiv:2007.07377, July 2020, 38-pages.

Parameter Ranges

Snoring Range (dB)	Respiration Rate (bpm)	Heart Rate (bpm)	Stress State
50-60	17-19	54-57	LSS
60-70	19-21	57-60	MLSS
70-80	21-22	60-64	MSS
80-89	23-25	65-70	MHSS
90+	25+	70+	HSS

Smart-Pillow - simple fuzzy logic-based design finds classify stress to 5 levels

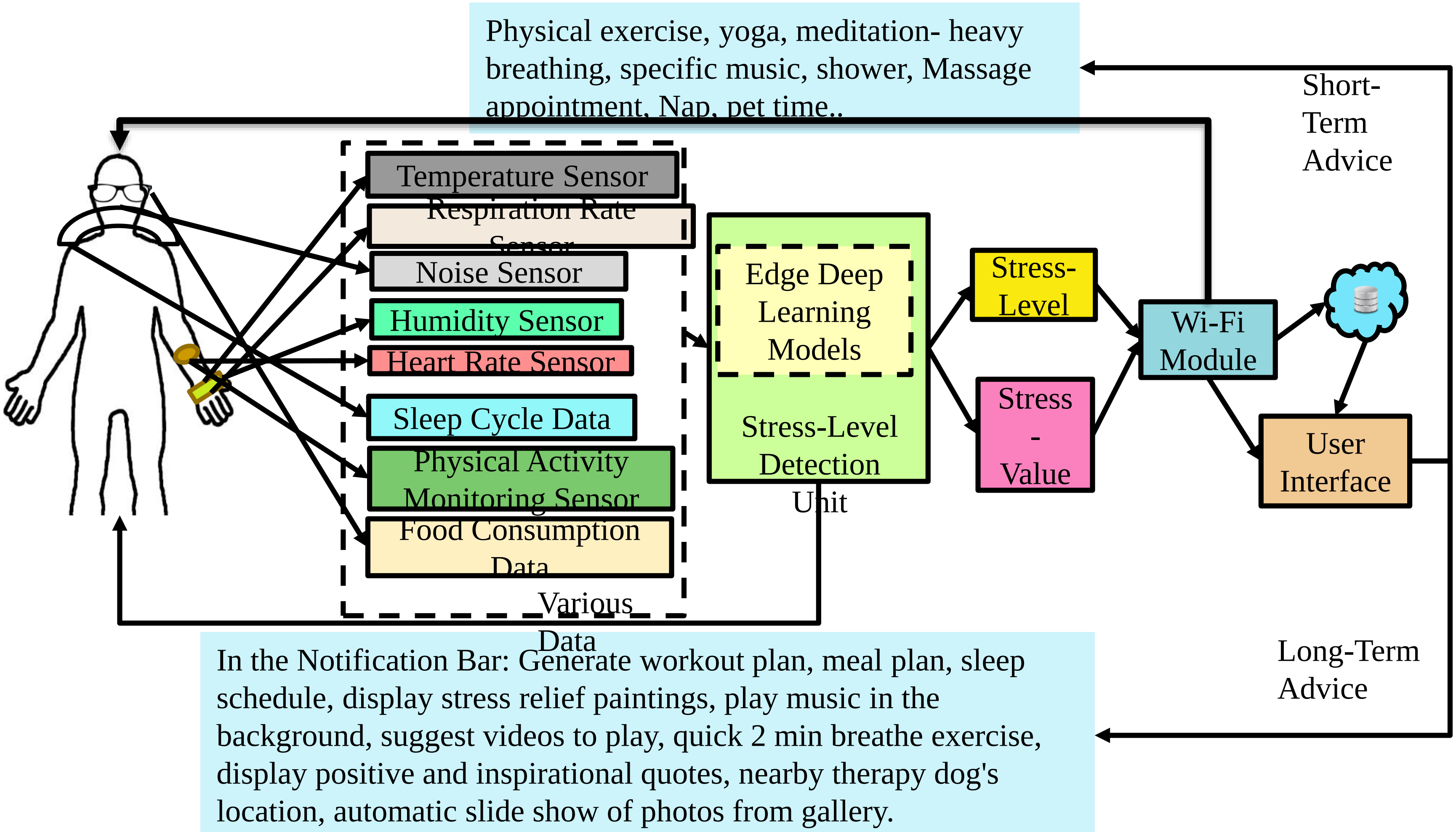
SaYoPillow – Uses deep learning for 96% accuracy with blockchain based security features

iFeliz: Research Question

- How to have an accurate and rapid **Stress Control** system at the user end (at ***IoT-Edge***) and stores the data at the cloud end (at ***IoT-Cloud***)?

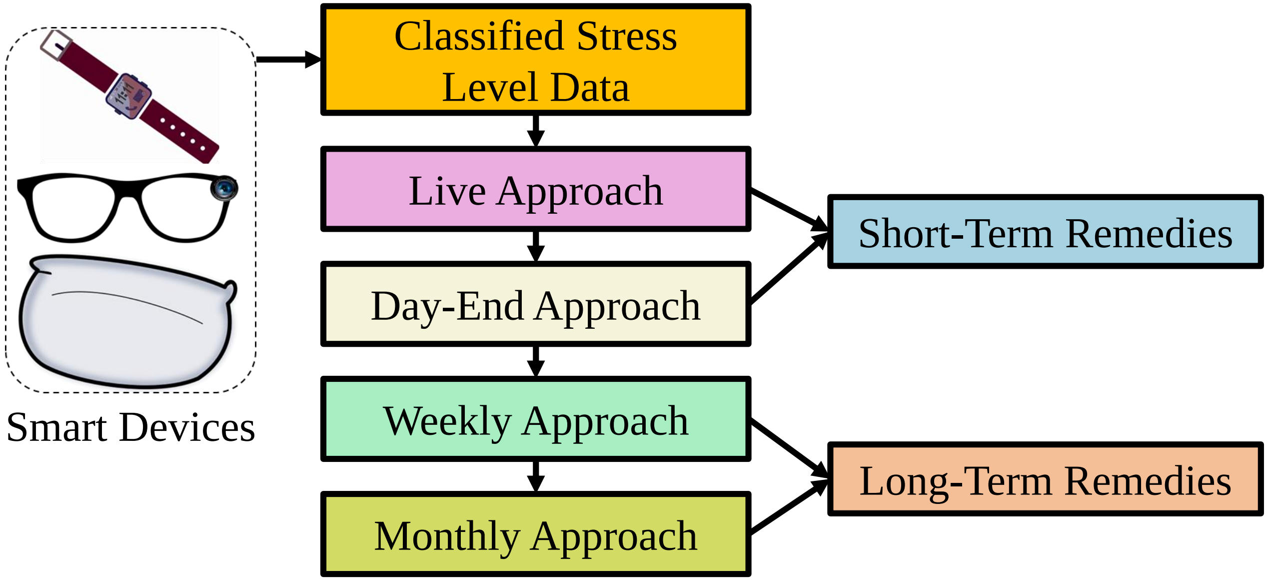
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference*, 2020, pp. Under Review.

iFeliz: Proposed System



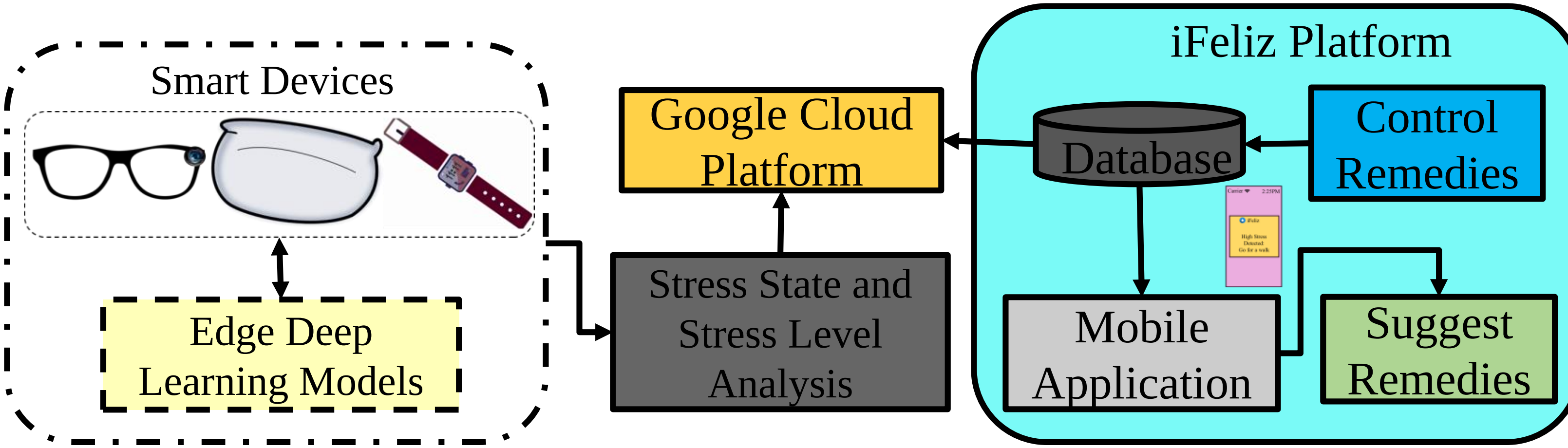
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference*, 2020, pp. Under Review.

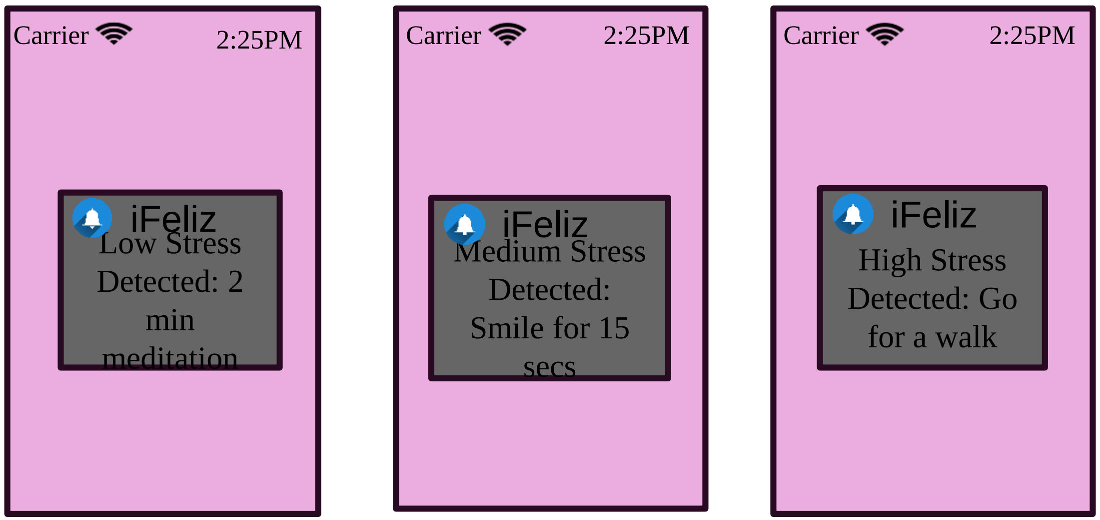
iFeliz: Stress Control Approaches



Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference*, 2020, pp. Under Review.

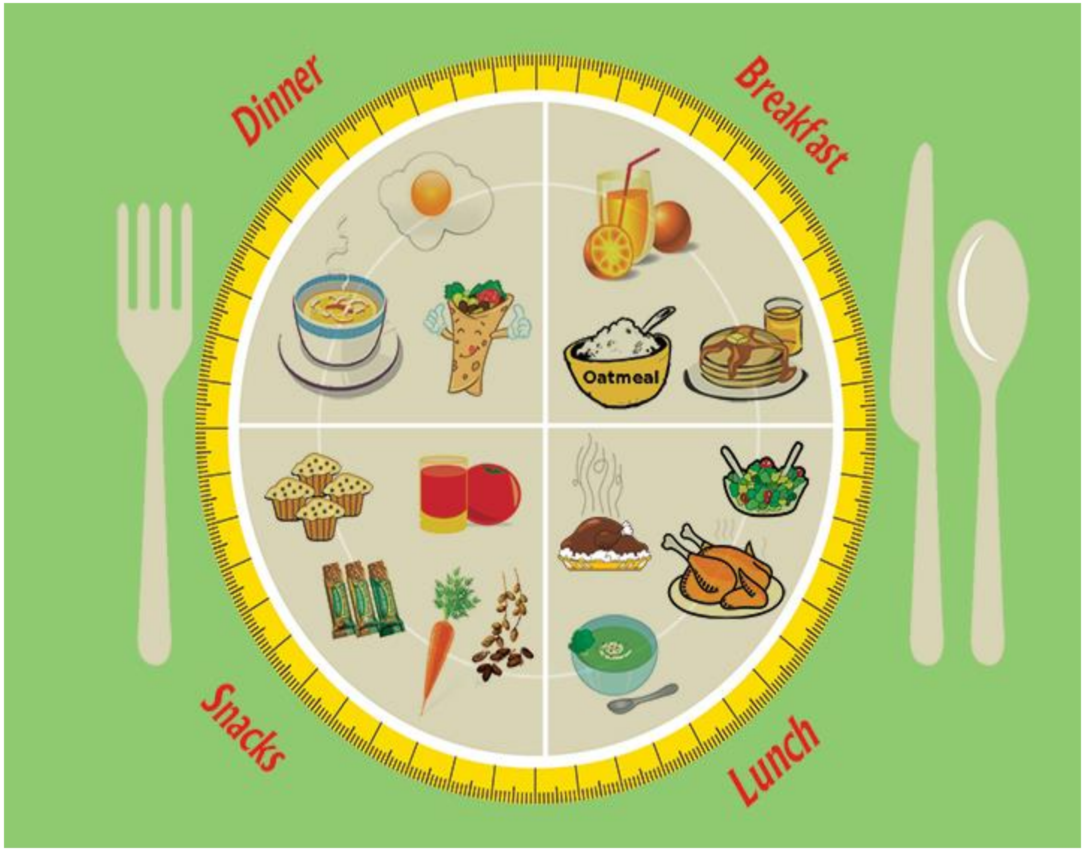
iFeliz: Prototyping





Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference*, 2020, pp. Under Review.

Automatic Food Intake Monitoring and Diet Management is Important



Imbalance Diet is a Global Issue

- Imbalanced diet can be either more or fewer of certain nutrients than the body needs.
- In 2017, 11 million deaths and 255 million disability-adjusted life-years (DALYs) were attributable to dietary risk factors.
- Eating wrong type of food is potential cause of a dietary imbalance:
  - Psychiatric disorders
  - Coronary heart disease
  - High blood pressure
  - Obesity
  - Tooth decay
  - Diabetes

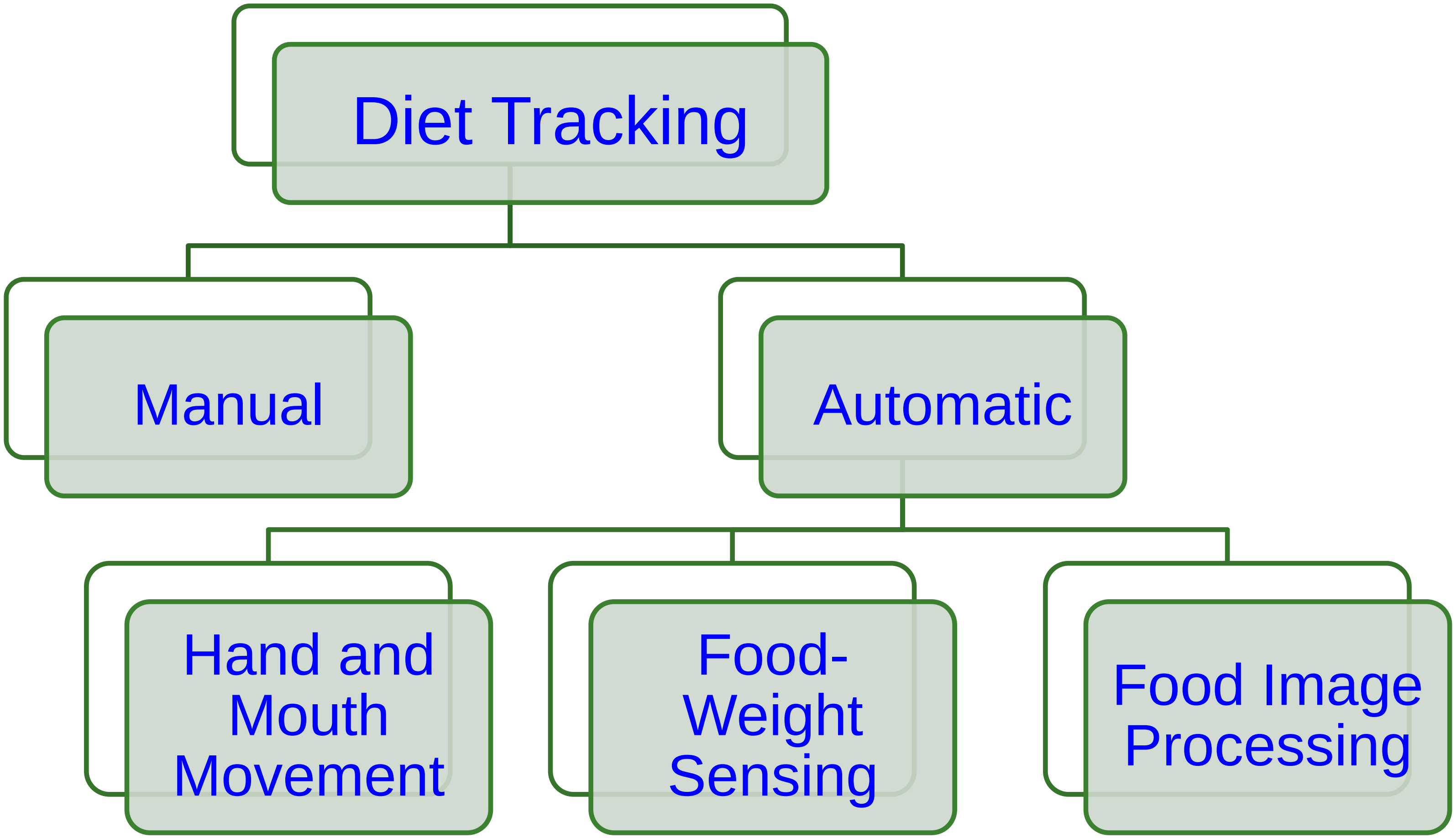
Source: https://obesity-diet.nutritionalconference.com/events-list/imbalanced-diet-effects-and-causes
https://www.thelancet.com/article/S0140-6736(19)30041-8/fulltext

Food Tracking Apps

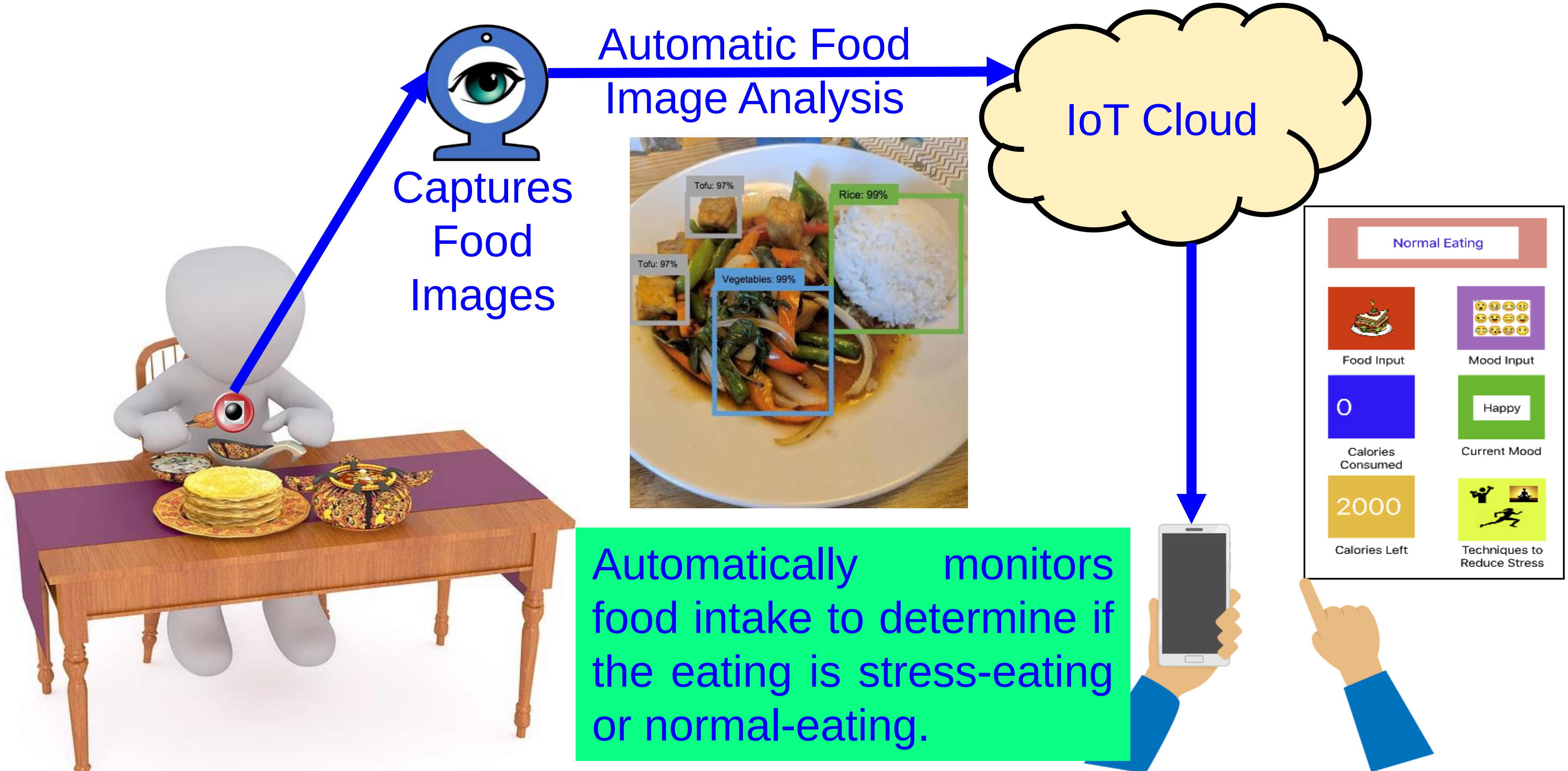
Table 1. Overview of popular food tracking approaches and their capabilities.

App Name	Downloads	Reviews	Rating	Input Method: Image	Food-Label in Image: Auto	Food-Label in Image: Manual	Food-Label in Image: Crowd Sourced	Manual	Scanning	Speech	Database search	Calories	Nutrition
MyFitnessPal	50 M	2 M	4.6					X	X			X	
FatSecret	10 M	268 k	4.5					X	X			X	X
My Diet Coach	10 M	144 k	4.4					X				X	
Lose it	10 M	77 k	4.4	X				X	X			X	
MyPlate	1 M	31 k	4.6					X	X			X	X
mynetdiary	1 M	31 k	4.5					X				X	X
Macros	500 k	3 k	4.5					X	X			X	
Cron-o-meter	100 k	1 k	4.2					X					
Eating Habit	100 k	549	4	X		X						X	
21 day Fix	100 k	470	3.7					X				X	
Bite Snap	50 k	2k	4.7	X								X	X
MealLogger	50 k	225	3.5	X				X				X	X
EatRight	10 k	220	4.5					X				X	
Keto Meal Plan	10 k	19	2.6								X		
YouAte	10 k			X									
KudoLife	1 k	11	3.4								X	X	X
Calorific	19		3.2								X		
Ate				X				?				?	?
Foodlog				X	X			X				X	

Diet Tracking Approaches



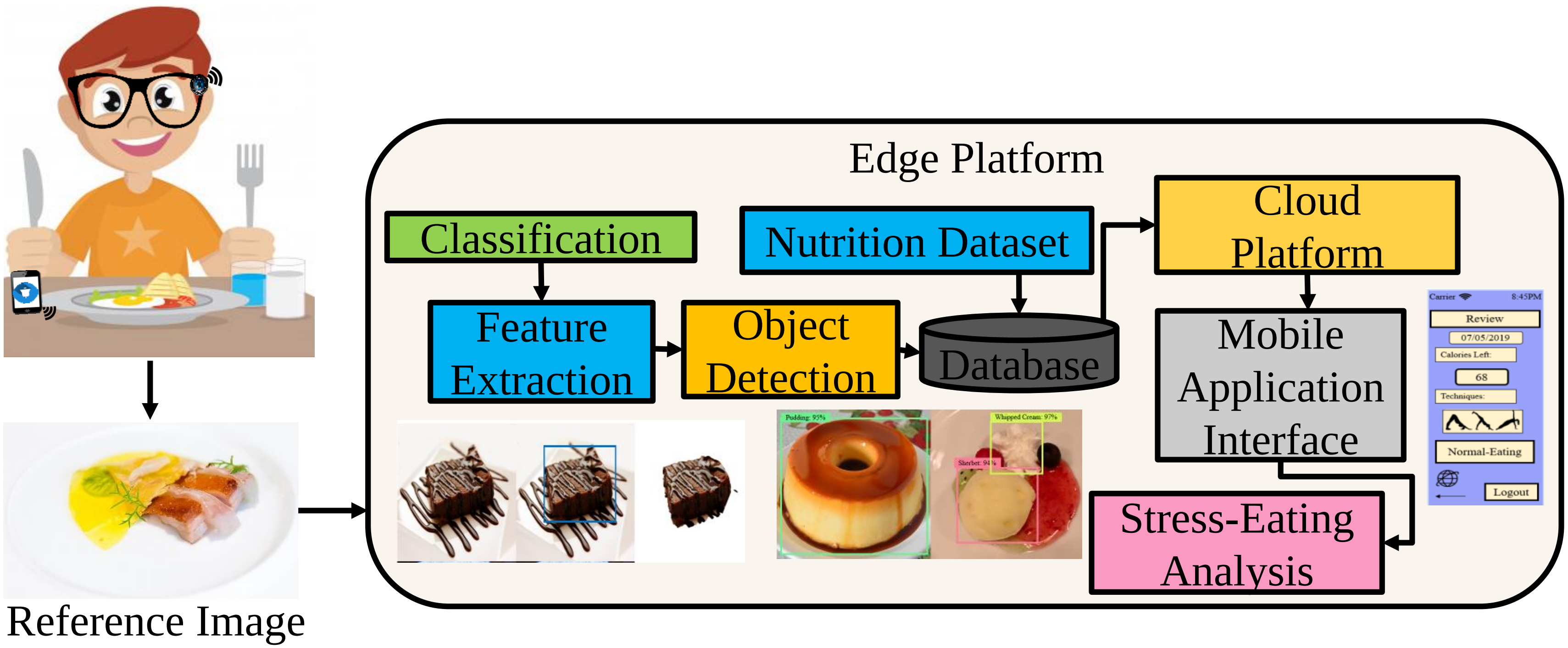
Smart Healthcare – Diet Monitoring



Accuracy of detecting food - 97%

Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, “iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT”, *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare – iLog



iLog- Fully Automated Detection System with 98% accuracy.

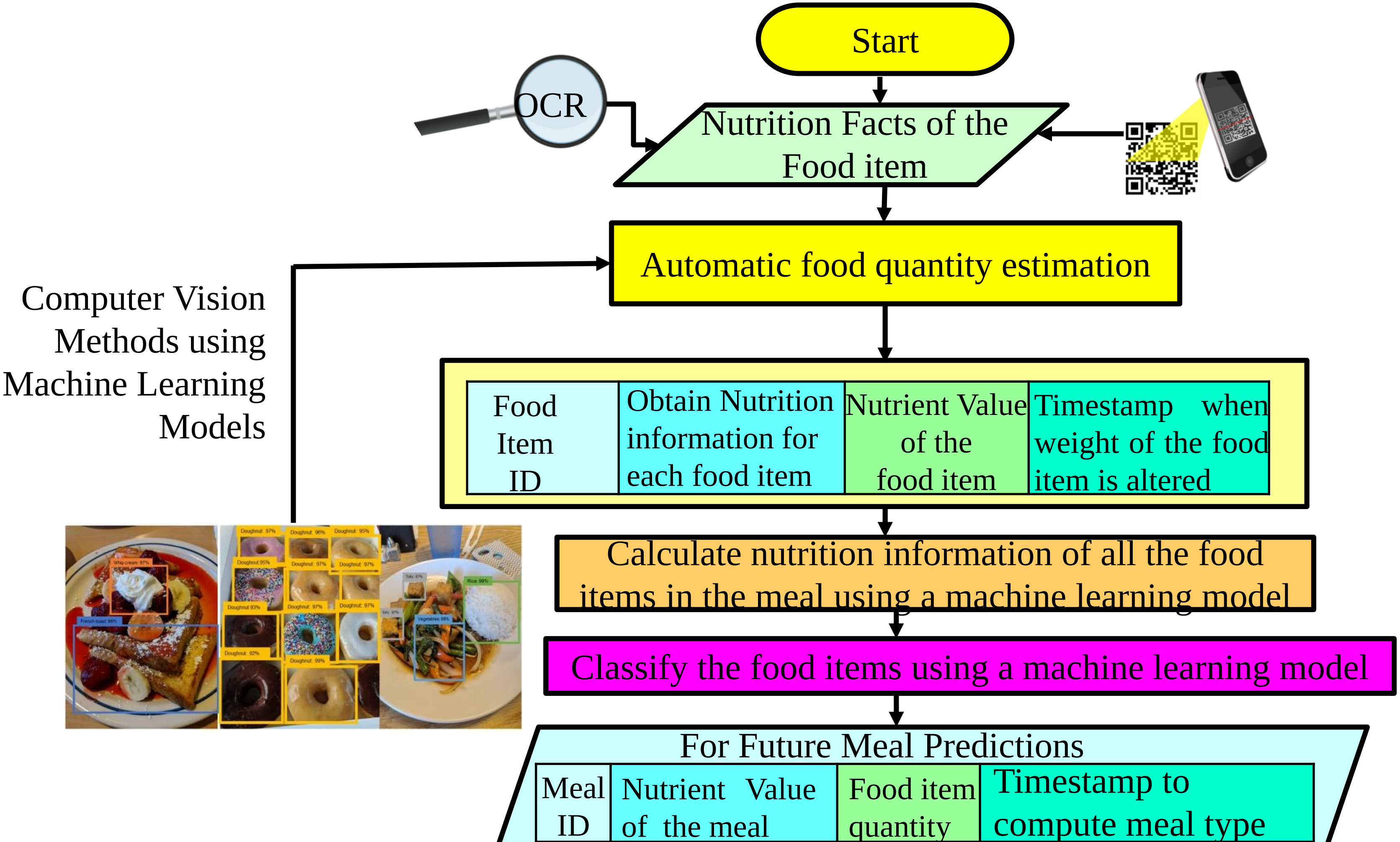
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare – iLog

The data collected is sent to the Firebase Database in which the calorie count is generated by using a dataset with calories and sugars count of individual items from data.gov.

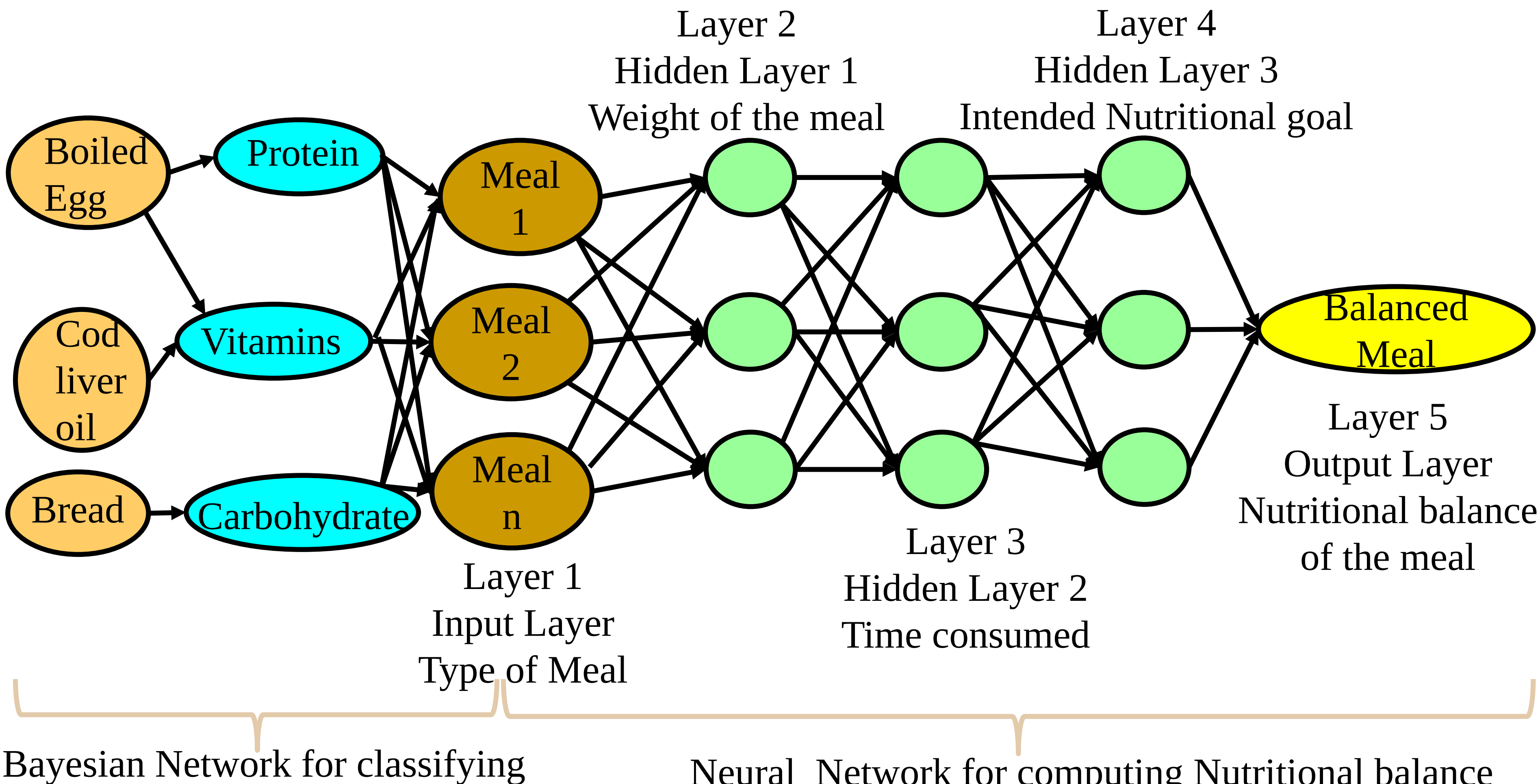
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare – Diet Prediction



Source: P. Sundaravadivel, K. Kesavan, L. Kesavan, **S. P. Mohanty**, and E. Kougianos, “Smart-Log: A Deep-Learning based Automated Nutrition Monitoring System in the IoT”, *IEEE Transactions on Consumer Electronics*, Vol 64, Issue 3, Aug 2018, pp. 390-398.

Smart Healthcare – Diet Prediction



Prediction (Automated) accuracy of Smart-Log - 98.6%

Source: P. Sundaravadivel, K. Kesavan, L. Kesavan, S. P. Mohanty, and E. Kougianos, "Smart-Log: A Deep-Learning based Automated Nutrition Monitoring System in the IoT", *IEEE Transactions on Consumer Electronics (TCE)*, Volume 64, Issue 3, August 2018, pp. 390--398.

Epileptic Seizure

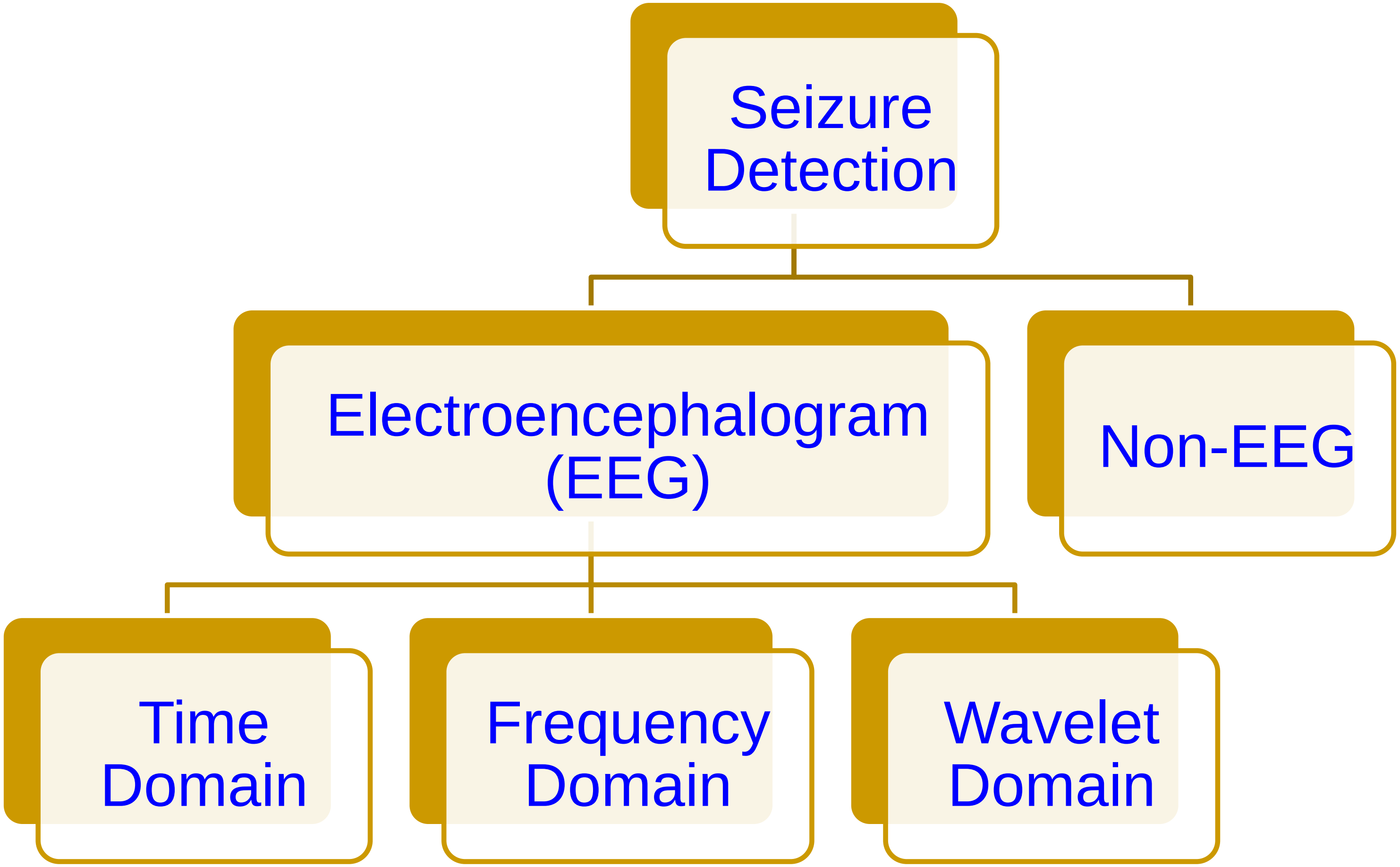
- A seizure is an abnormal activity in the nervous system which causes its sufferers to lose consciousness and control.

Epileptic Seizure Has Global Impact

- Up to 1% of the world's population suffers from epilepsy.
- Epilepsy is the fourth most common neurological disease after migraine, stroke, and Alzheimer's.
- Individuals can suffer a seizure at any time with potentially disastrous outcomes including a fatal complication called "Sudden Unexpected Death in Epilepsy" (SUDEP).

Source: https://www.epilepsy.com/learn/about-epilepsy-basics/epilepsy-statistics

Seizure Detection Methods



Seizure Detection Methods – Non-EEG

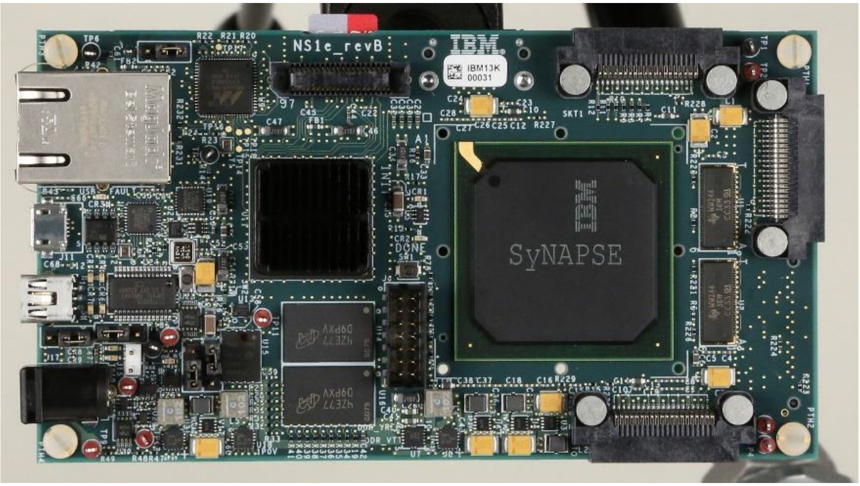
			DETECTION METHODS							
			Audio	Video	Electro-magnetic waves	ACM/ gyro/ magneto	Electrodes	Plethys-mograph (volume)	Pressure	Tempe-rature
NON-EEG SEIZURE MANIFESTATIONS	Motor	Body	bed noise	optical or thermal camera	radio, infrared or microwaves	bed or body attached	EMG		pressure mat for bed vacancy	
		Eye(lid)		optical camera			EOG/EMG			
	Auto-nomic	HR	PCG	thermal camera	radio or microwaves (BCG)	BCG	ECG	PPG		
		BP						PPG		
		SpO_2			infrared waves of oximeter					
		Respira-tion	neck	thermal camera	radio or microwaves chest, infrared waves of oximeter/ capnograph	ACM/ magneto chest	EMG, EDR, impedance pneumograph chest, electrodes for pO_2/CO_2	RIP chest	pneumo-tachograph airflow	thermo-couple airflow
		Sweating					ohm/ galvanometer			
		Vomiting/ salivation/ coughing	audio phone				humidity meter			
		Inconti-nence					humidity meter			
	Vocalizations		audio phone							
	Fever			thermal camera	radio waves					sticker

ACM = accelerometer, BP = blood pressure,
ECG = electrocardiography,
EDR = ECG-derived respiration,
EMG = electromyography,
EOG = electro-oculography,
gyro = gyroscope, HR = heart rhythm, magneto = magnetometer,
PCG = phonocardiography,
pO_2/CO_2 = partial pressure oxygen/carbon dioxide,
PPG = photoplethysmography,
RIP = Respiratory Inductance Plethysmography, SpO_2 = blood oxygenation.

Source: https://www.seizure-journal.com/article/S1059-1311(16)30114-5/fulltext

IBM's Implantable Seizure Detector

- The TrueNorth chip is postage stamp-sized and consumes over 1,000 times less power than a conventional processor of similar size.



Source: http://uberveillance.squarespace.com/?category=health_care

Consumer Electronics for Seizure Detection

Source: https://spectrum.ieee.org/the-human-os/biomedical/diagnostics/this-seizuredetecting-smartwatch-could-save-your-life

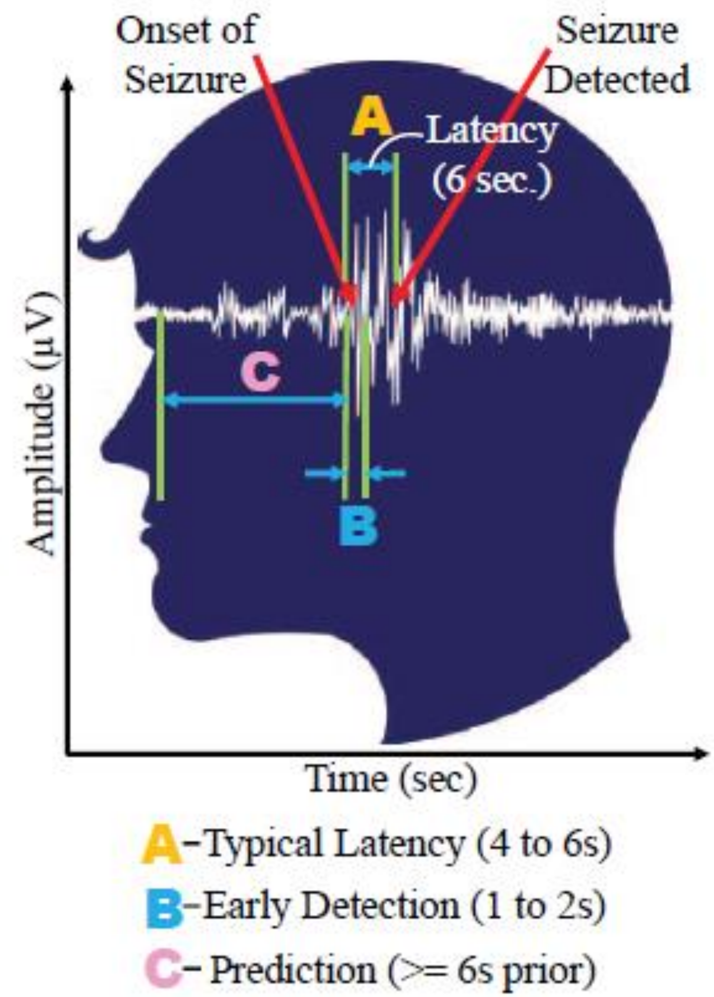
- Embrace2: Smart-band which uses machine learning to detect convulsive Seizures and notifies caregivers.

Source: https://www.empatica.com/embrace2/

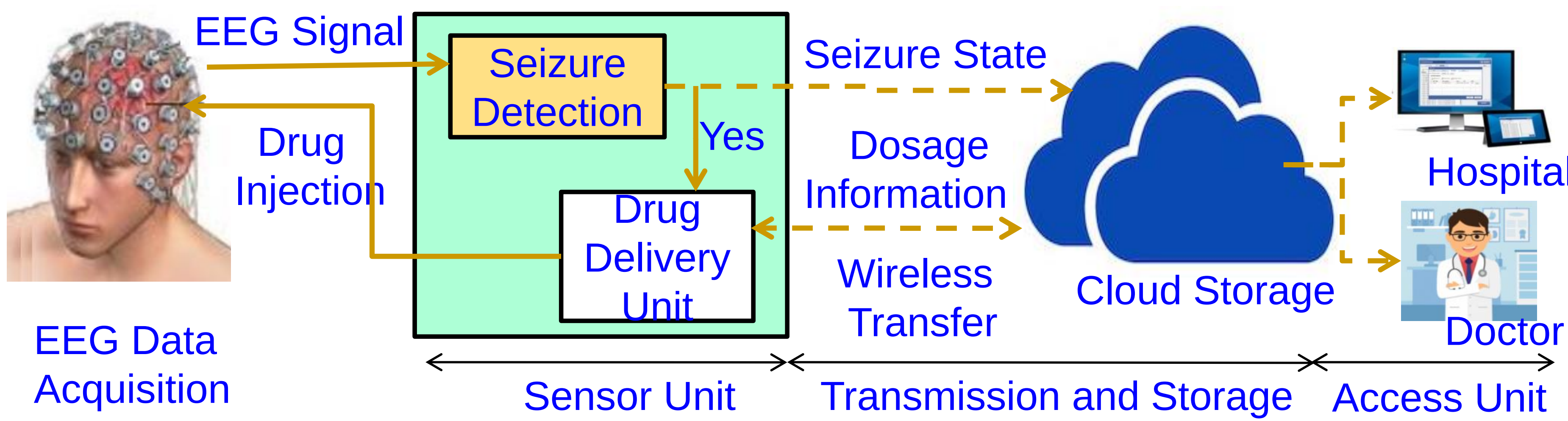
- Medical grade smart watch: It detects generalized clonic-tonic Seizures and notifies physicians.

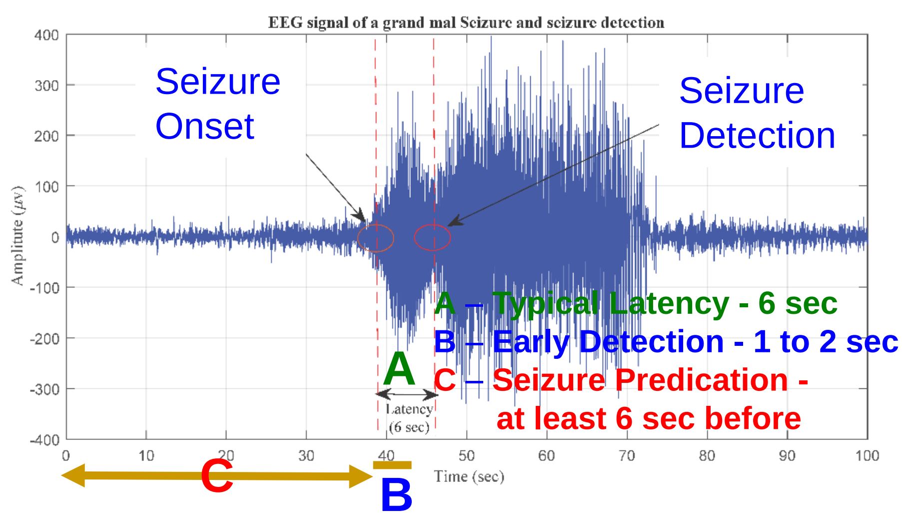
Drawbacks of Existing Works?

- High seizure detection latency.
- Not suitable for real time IoMT deployment.
- Intervention mechanism after detection is lacking.



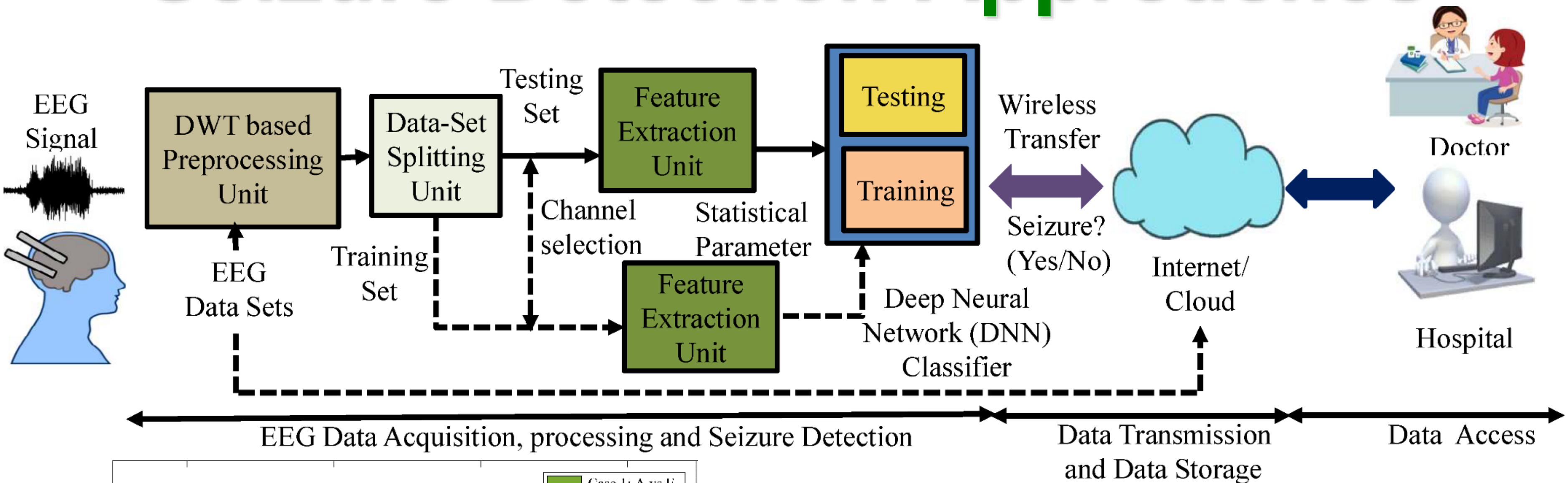
Smart Healthcare - Seizure Detection & Control

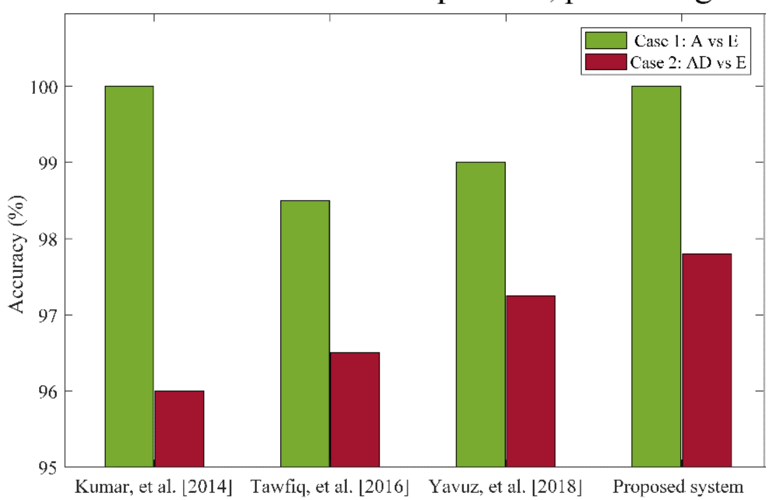




Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare", *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 379--387.

Seizure Detection Approaches



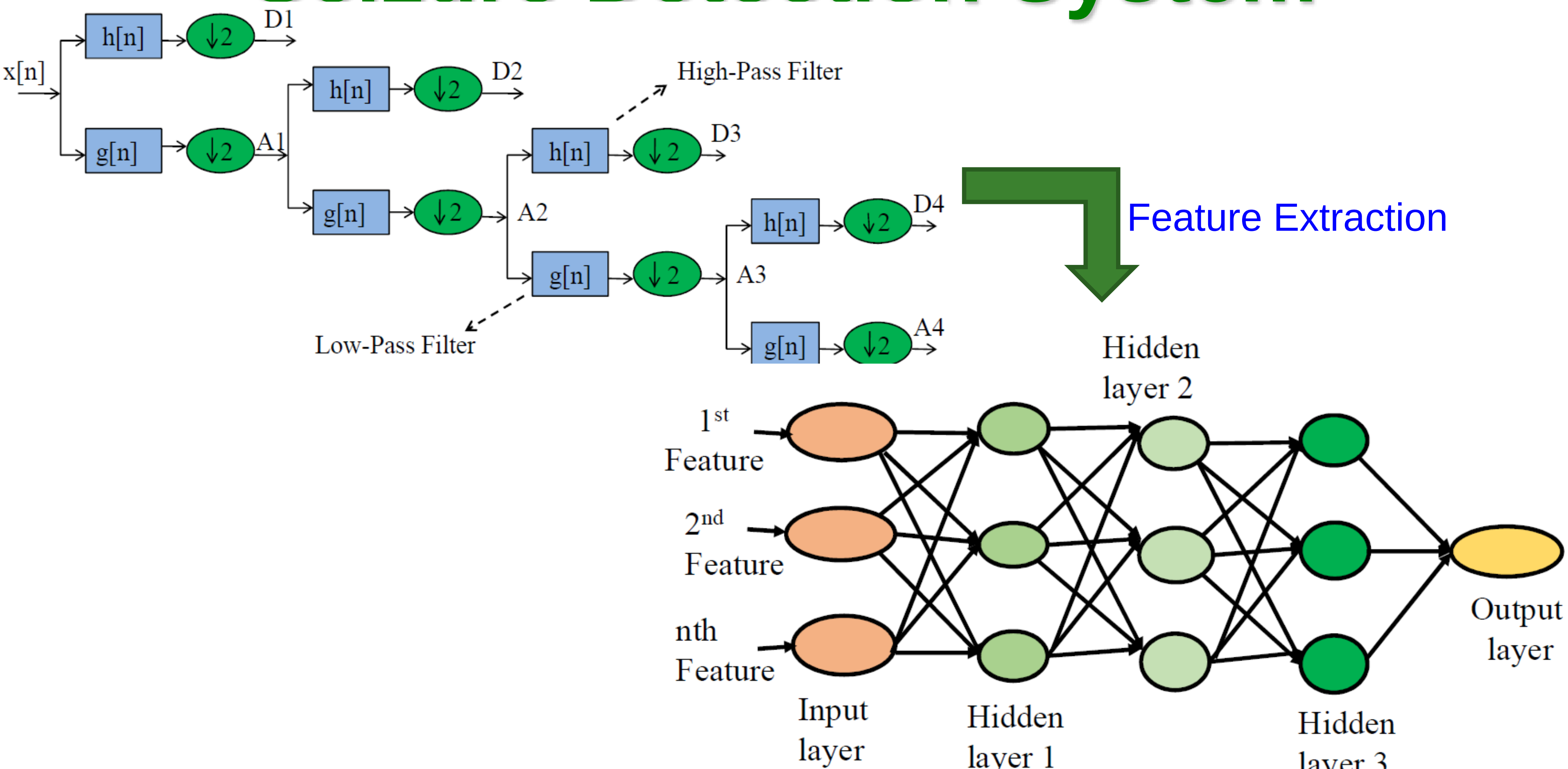


Cloud Vs Edge Computing

Cloud Vs Edge	Latency	Accuracy
Cloud-IoT based Detection	2.5 sec	98.65%
Edge-IoT based Detection	1.4 sec	98.65%

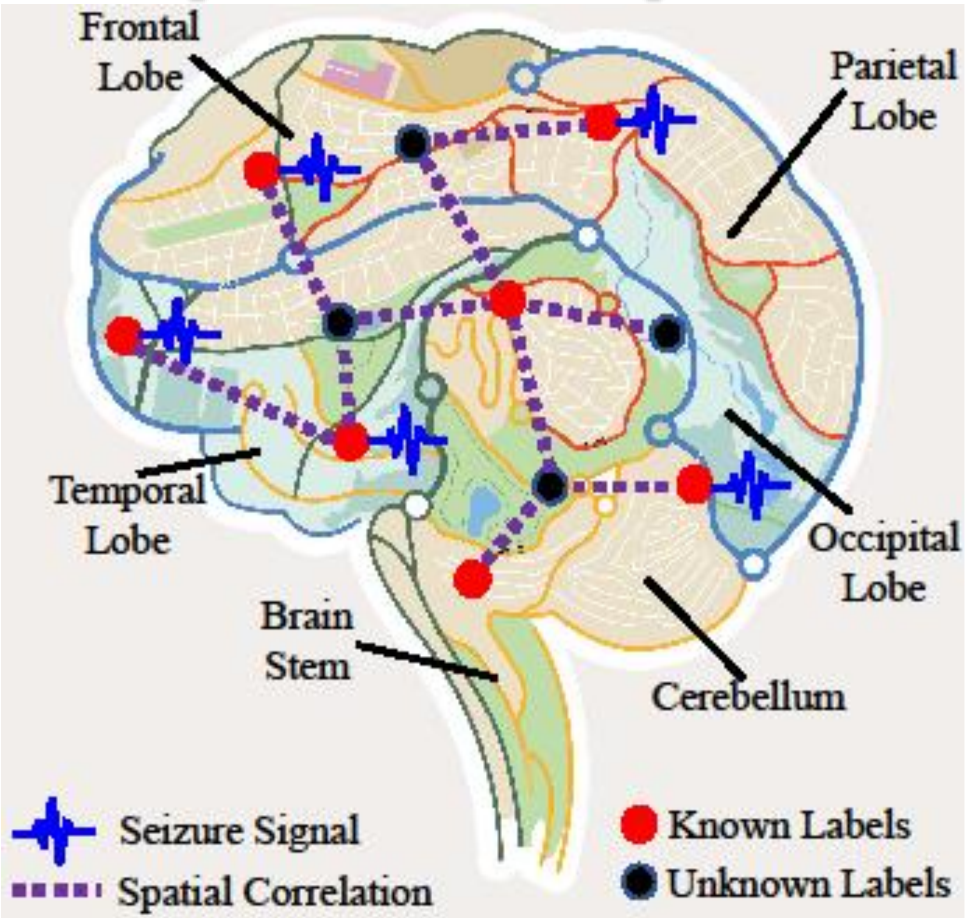
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, “Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT”, *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, No 3, Aug 2019, pp. 359--368.

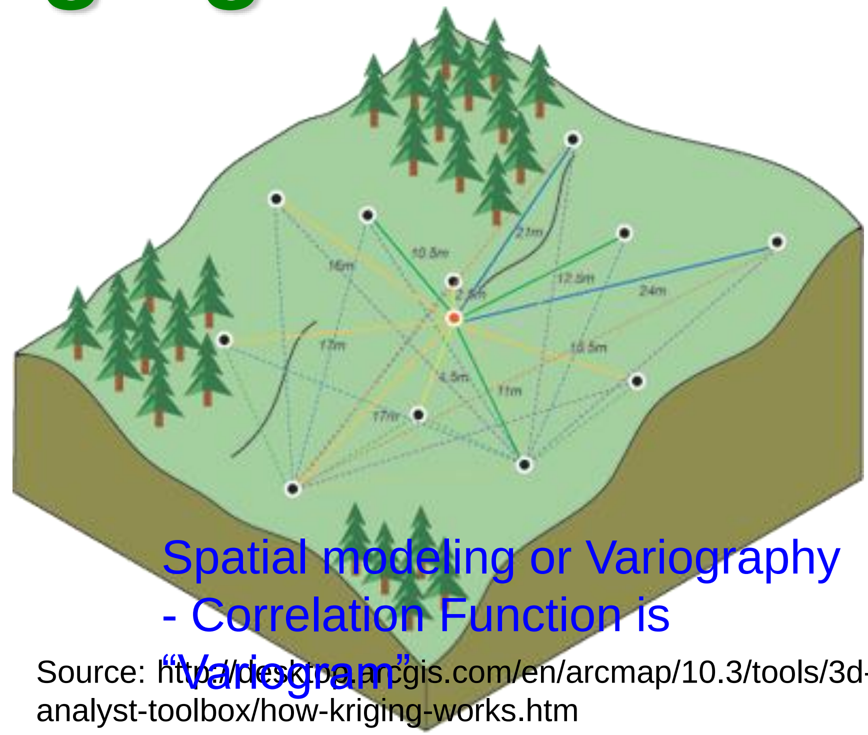
Our Neuro-Detect : A ML Based Seizure Detection System



Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri , "Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, Issue 3, Aug 2019, pp. 359-368.

Smart Healthcare – Brain as a Spatial Map → Kriging Methods





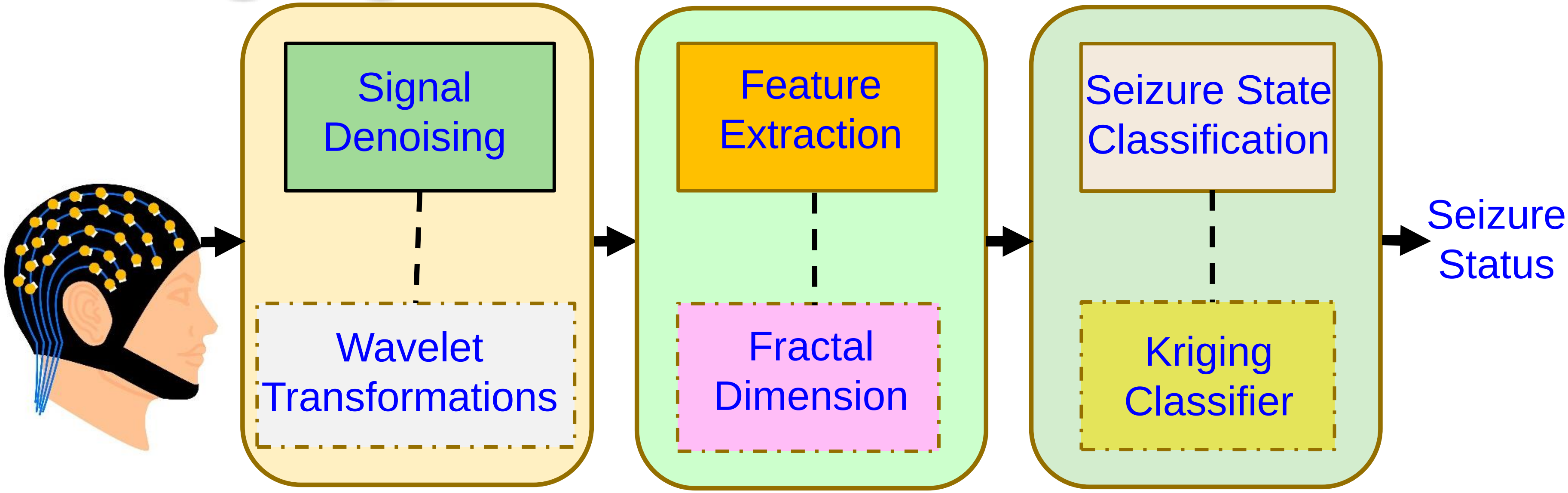
Spatial modeling or Variography - Correlation Function is "Variogram"

Source: http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm

Spatial autocorrelation principle - things that are closer are more alike than things farther

Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE)*, 2020, Accepted.

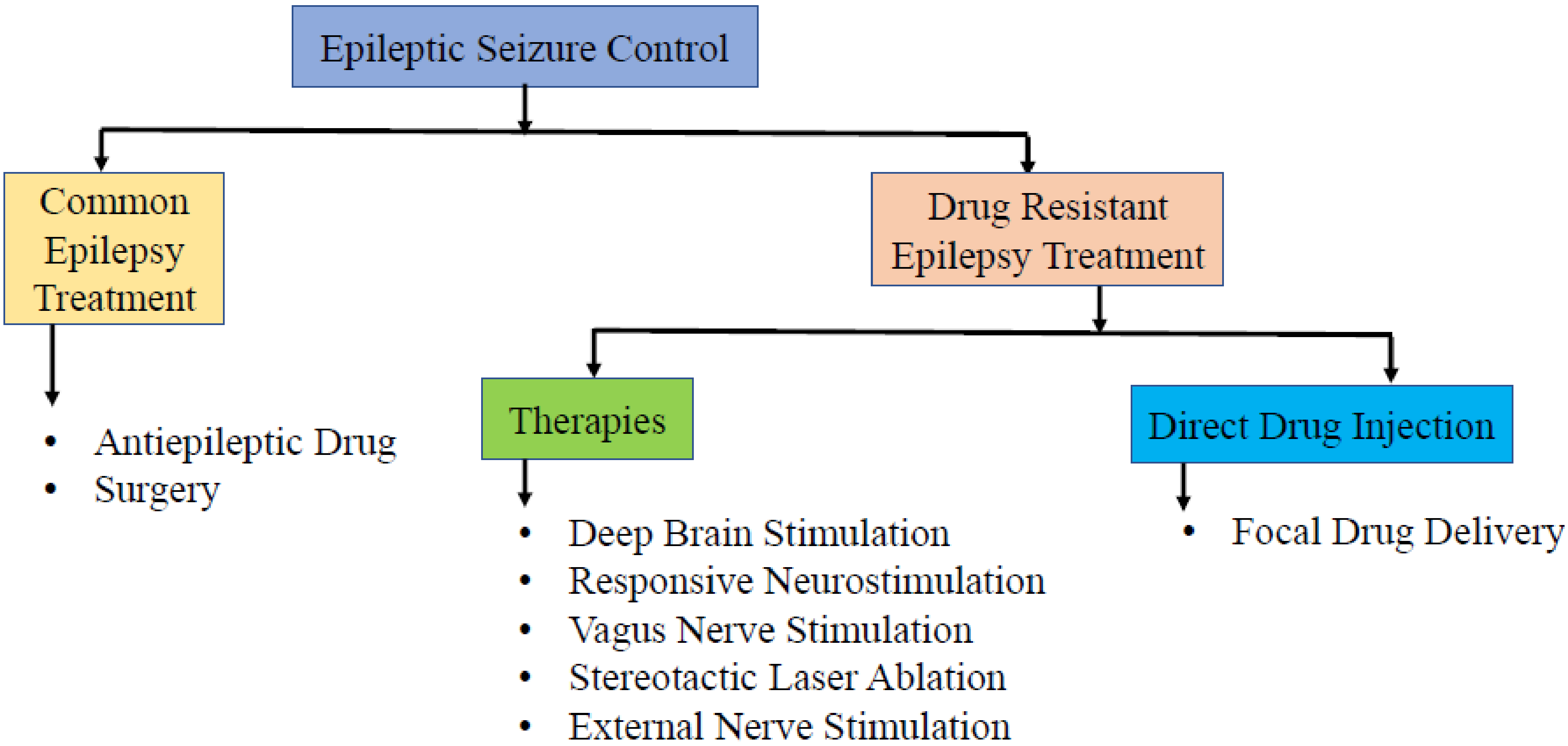
Kriging based Seizure Detection



Works	Extracted Features	Classification Algorithm	Sensitivity	Latency
Zandi, et al. 2012 [23]	Regularity, energy & combined seizure indices	Cumulative Sum thresholding	91.00%	9 sec.
Altaf,etal. 2015 [24]	Digital hysteresis	Support Vector Machine	95.70%	1 sec
Vidyaratne, et al. 2017 [25]	Fractal dimension, spatial/ temporal features	Relevance Vector Machine (RVM)	96.00%	1.89 sec
Our Proposed	Petrosian fractal dimension	Kriging Classifier	100.0%	0.85 s

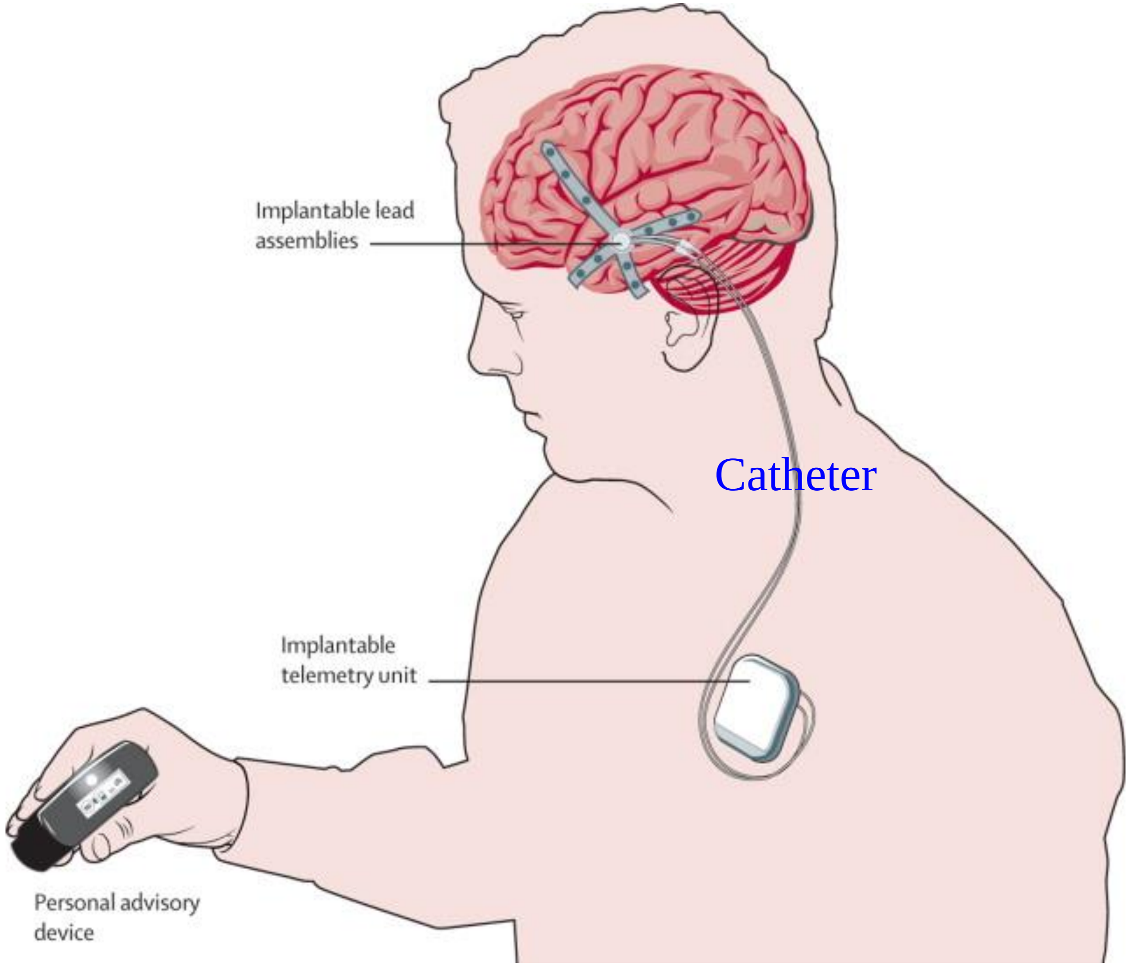
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE)*, 2020, Accepted.

Seizure Control Methods



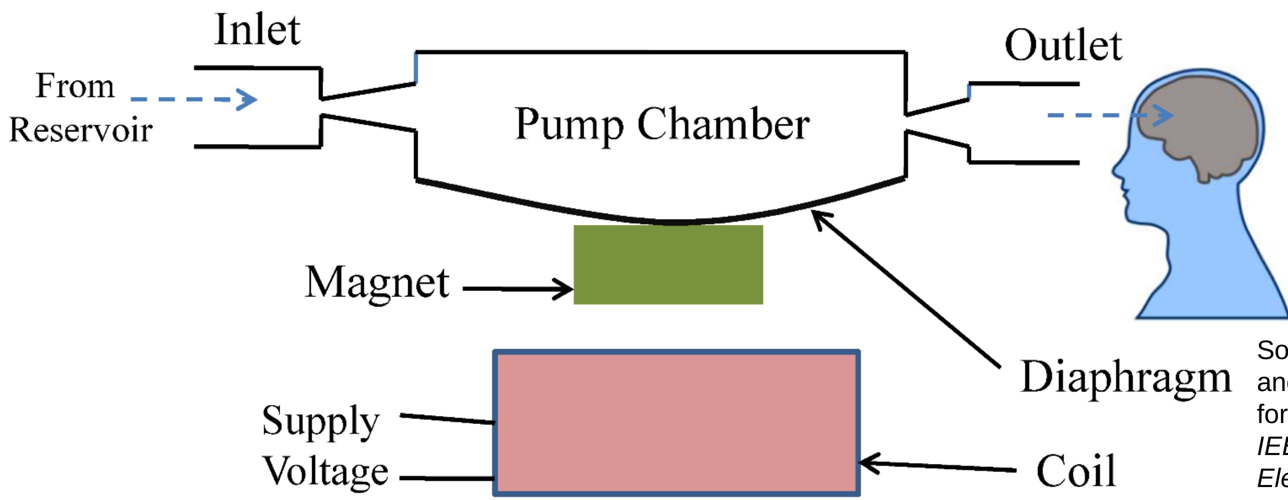
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "iDDS: An Edge-Device in IoMT for Automatic Seizure Control using On-Time Drug Delivery", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE)*, 2020.

Implantable for Seizure Detection and Control



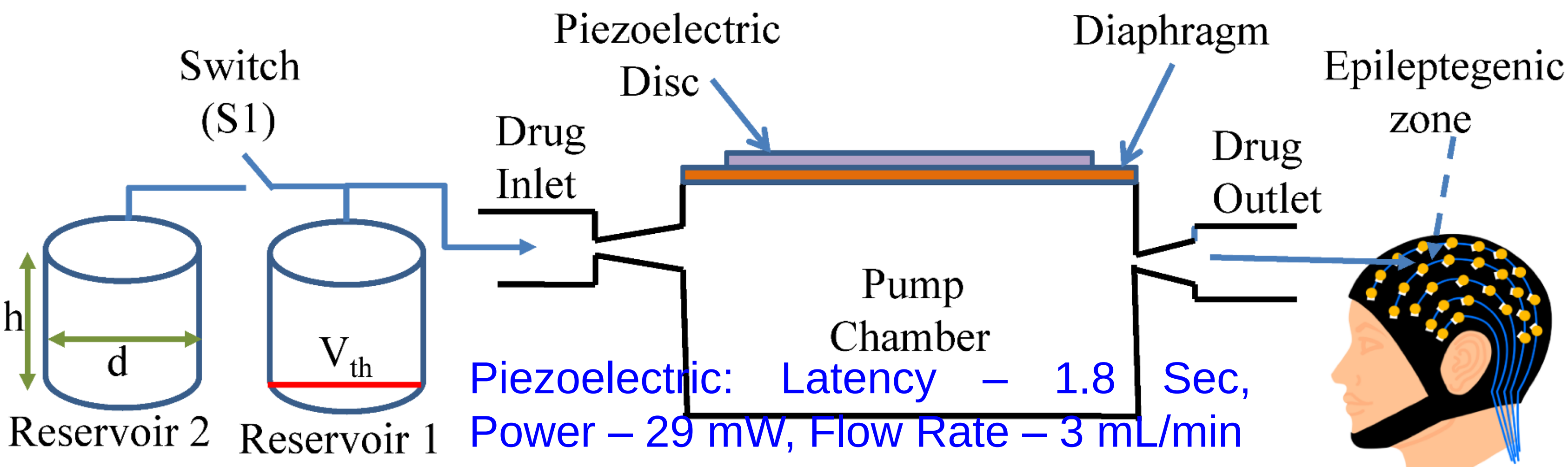
Source: https://www.kurzweilai.net/brain-implant-gives-early-warning-of-epileptic-seizure

Seizure Control Methods



Electromagnetic: Latency – 1.8 Sec, Power – 12.81 mW, Flow Rate – 0.34 mL/min

Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "An IoT-based Drug Delivery System for Refractory Epilepsy", in *Proceedings of the 37th IEEE International Conference on Consumer Electronics (ICCE)*, 2019.



Piezoelectric: Latency – 1.8 Sec, Power – 29 mW, Flow Rate – 3 mL/min

Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, "iDDS: An Edge-Device in IoMT for Automatic Seizure Control using On-Time Drug Delivery", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE),* 2020.

Elderly Fall Automatic Detection is Needed to Improve Quality of Life

- Elderly Fall: Approximately a third of elderly people 65 years or older fall each year.
- Fall Caused: Over 800,000 hospital admissions, 2.8 million injuries and 27,000 deaths have occurred in the last few years.

Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019, pp. 273--288.

Consumer Electronics for Fall Detection

Wearables	Drawbacks
	Apple watch: uses only accelerometers, doesn't work on low thresholds like double carpet, bathroom, hardwood floors. The user must manually select the option SOS and as a reason it fails if the person is unconscious. Users may remain on the floor with no help for large hours.
	Philips Lifeline: Uses only accelerometers and barometric sensors for pressure changes. After the fall, the system waits for 30 sec and directly connects to help.
 	Lively Mobile by greatcall and Sense4Care Angel4: Monitors fluctuations using only accelerometers.
 	Bay Alarm Medical and Medical Guardian: Use only accelerometers. Have huge base stations limiting the usage and location access.

Issues of Existing Research

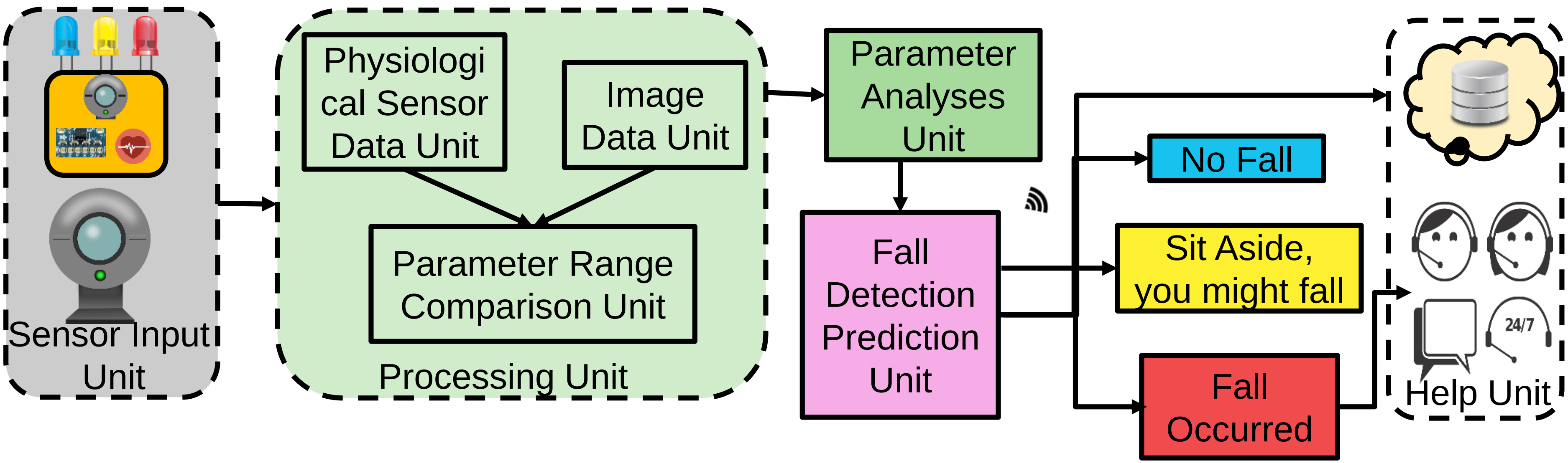
- Decisions of fall are only dependent on the changes in accelerometer axes.
- Some applications have user to give response after the fall and that can be time consuming as the user might not be conscious.
- Some applications are limited to a certain location and certain type of surroundings which add up the additional costs.
- The prediction of fall or warning the user that there might be an occurrence of fall is not provided by most of the applications.

Good-Eye: Research Question

- How to have a non-invasive, optimized, IoT enabled system which detects and predicts the falls in elderly based on the physiological and vision signal data, analyses the data at the user end (at IoT-Edge) and stores the data at the cloud end (at IoT-Cloud)?

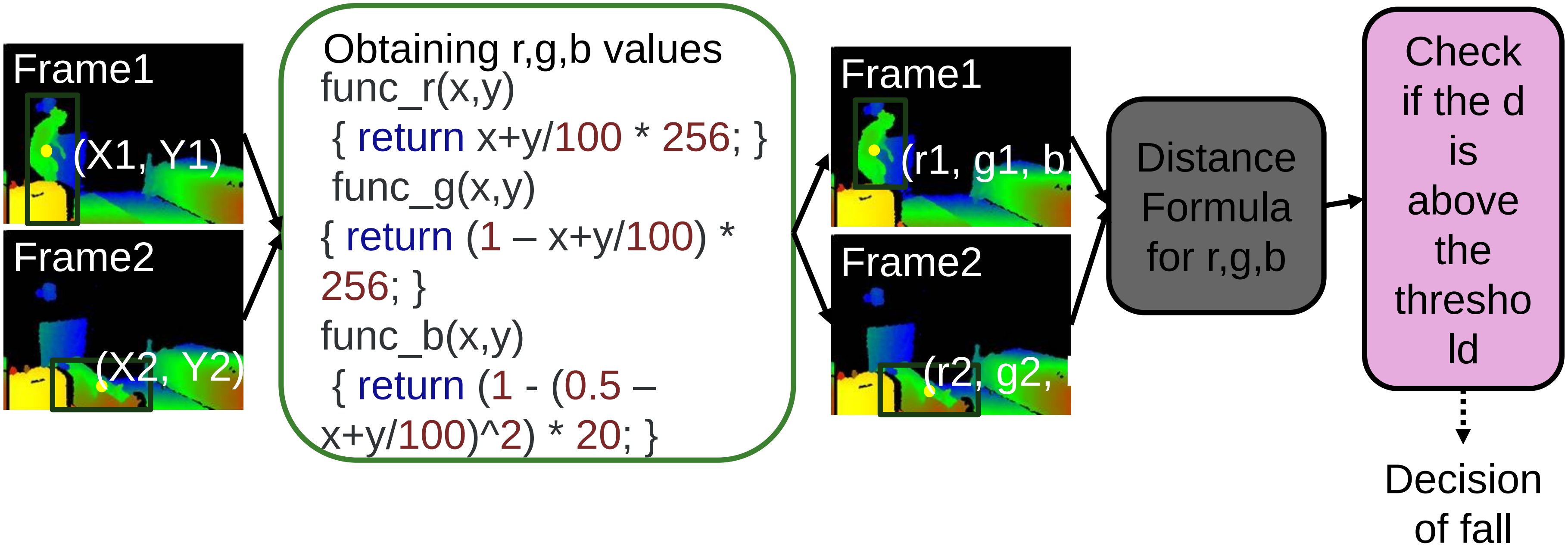
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019, pp. 273--288.

Good-Eye: Our Multimodal Sensor System for Elderly Fall Prediction and Detection



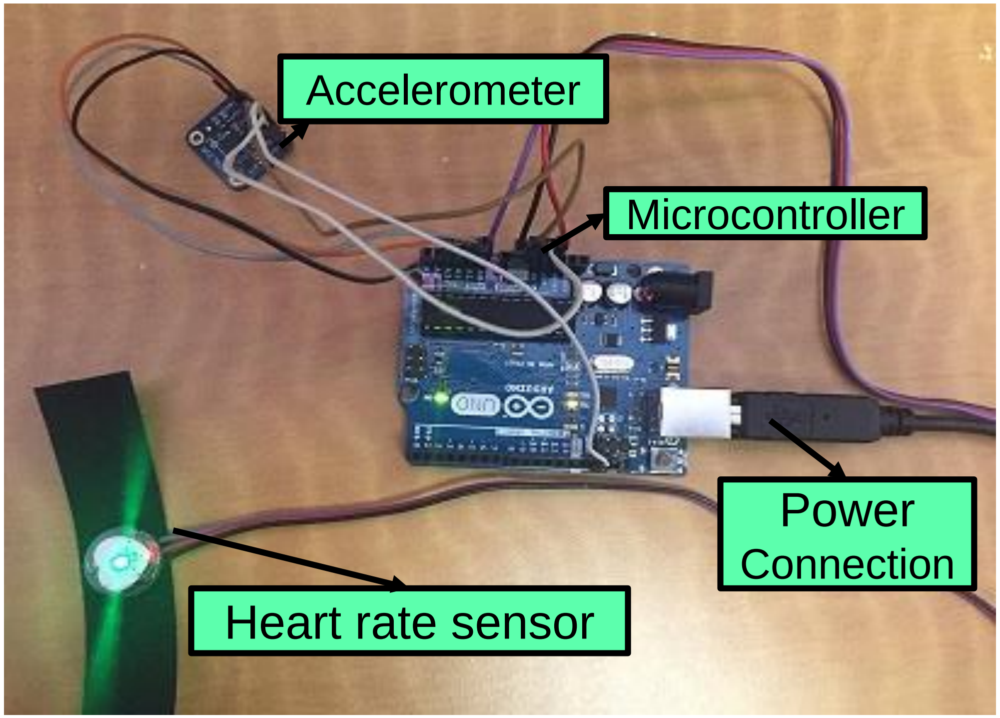
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019, pp. 273--288.

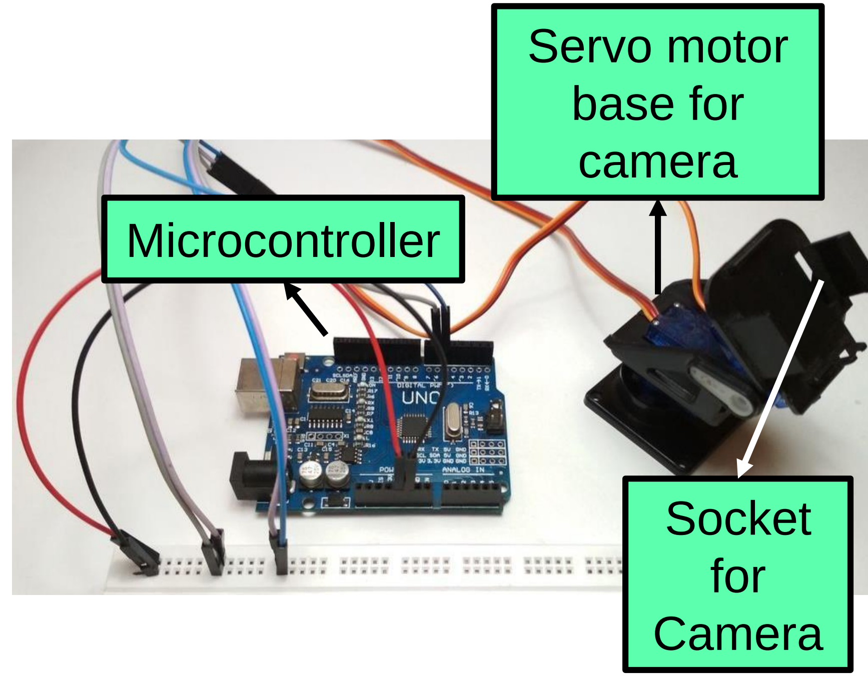
Good-Eye: Elderly Fall Detection



Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019, pp. 273--288.

Good-Eye: Prototyping

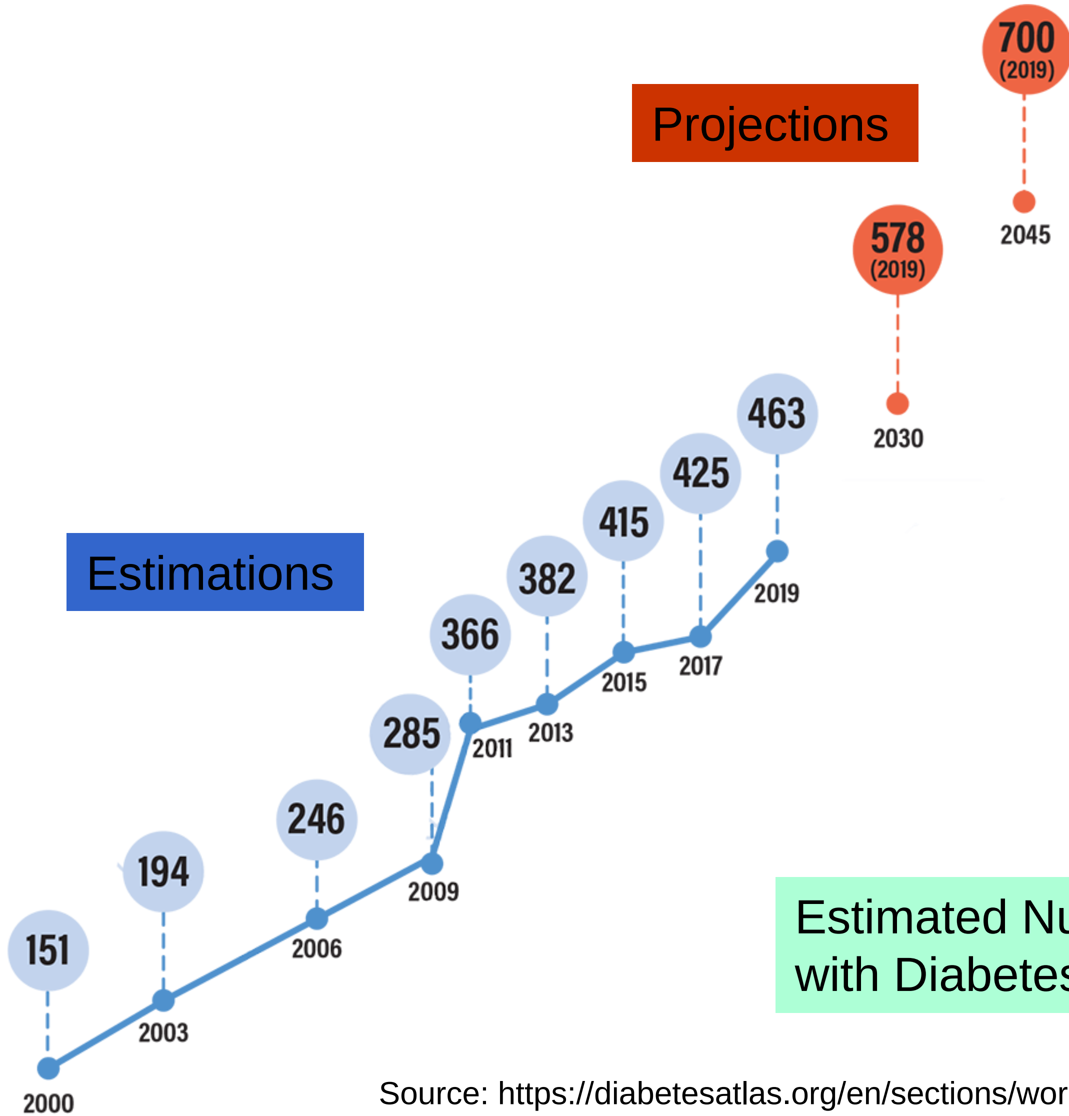




Good-Eye: Fall detection and prediction Accuracy - 95%.

Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019, pp. 273--288.

Diabetes is a Global Crisis



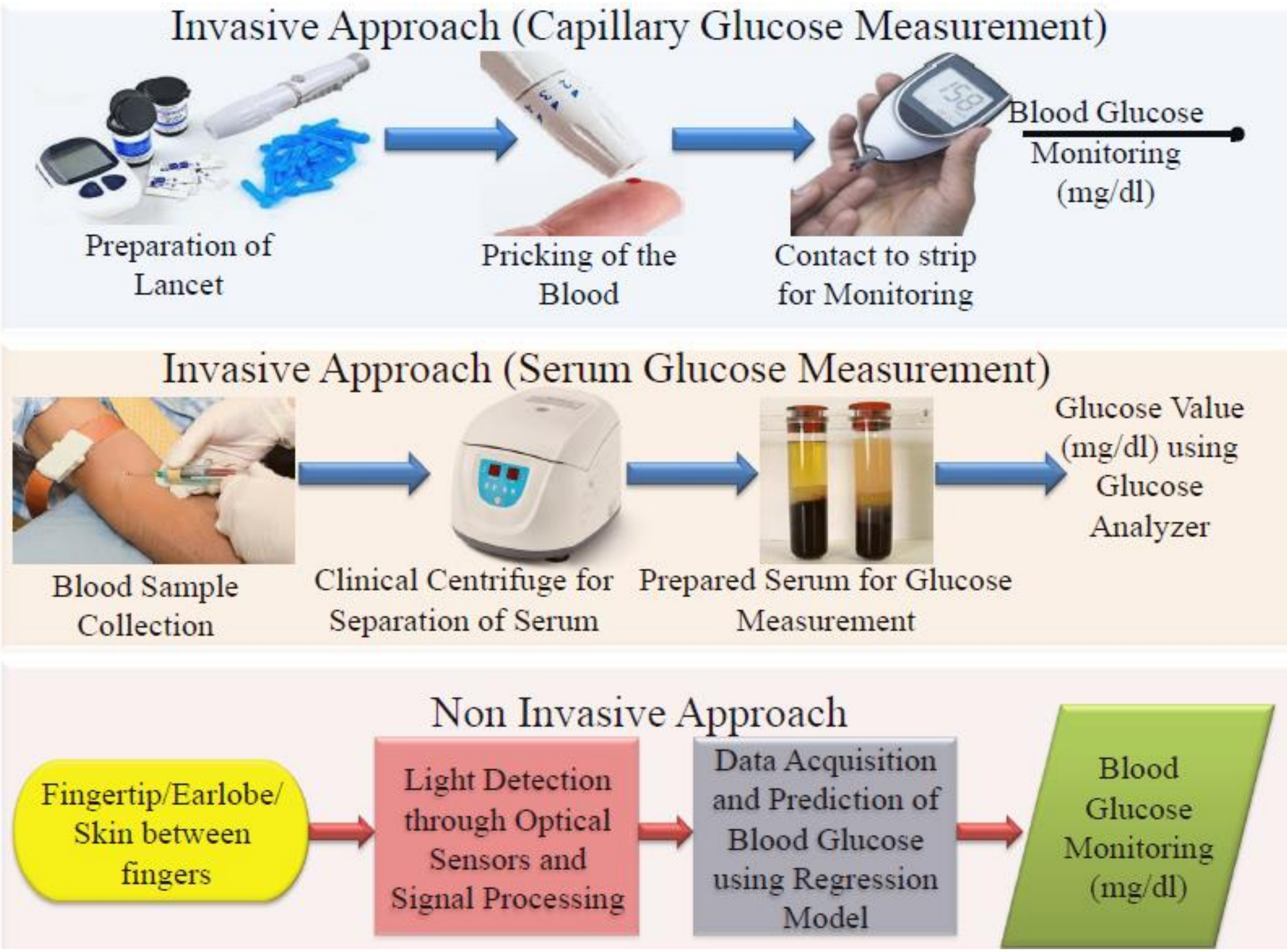
Projections

Estimations

Estimated Number of Adults with Diabetes (in Millions)

Source: https://diabetesatlas.org/en/sections/worldwide-toll-of-diabetes.html

Blood Glucose Monitoring – Invasive Vs Noninvasive



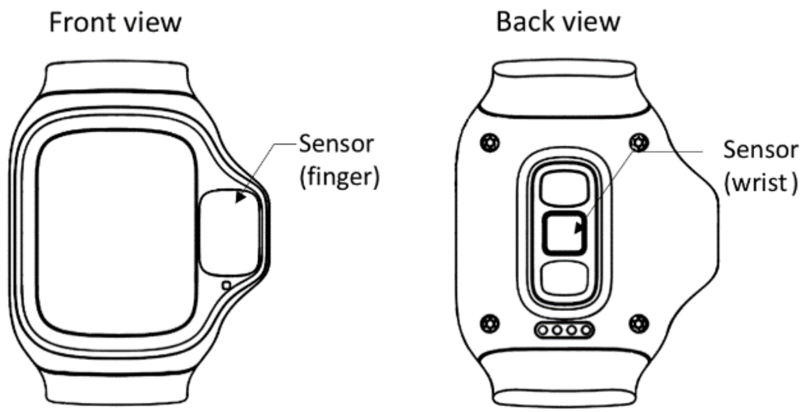
Traditional – Finger Pricking

Invasive Approach – Processing Blood/Serum

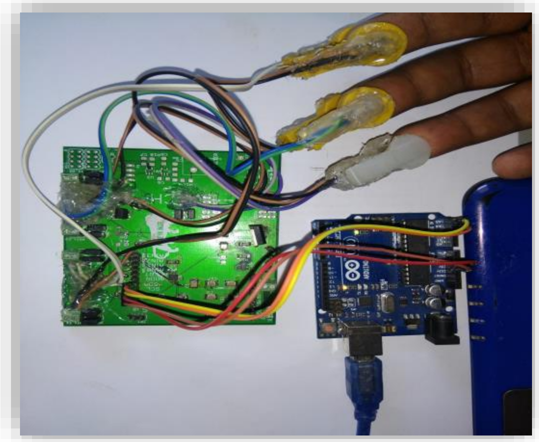
Noninvasive – Wearable

Noninvasive Approach – Processing Light

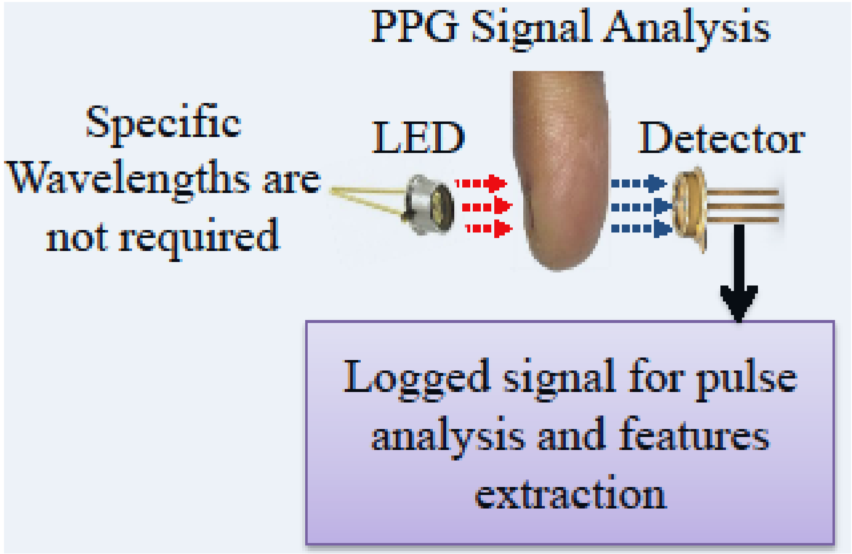
Noninvasive Glucose-Level Monitoring

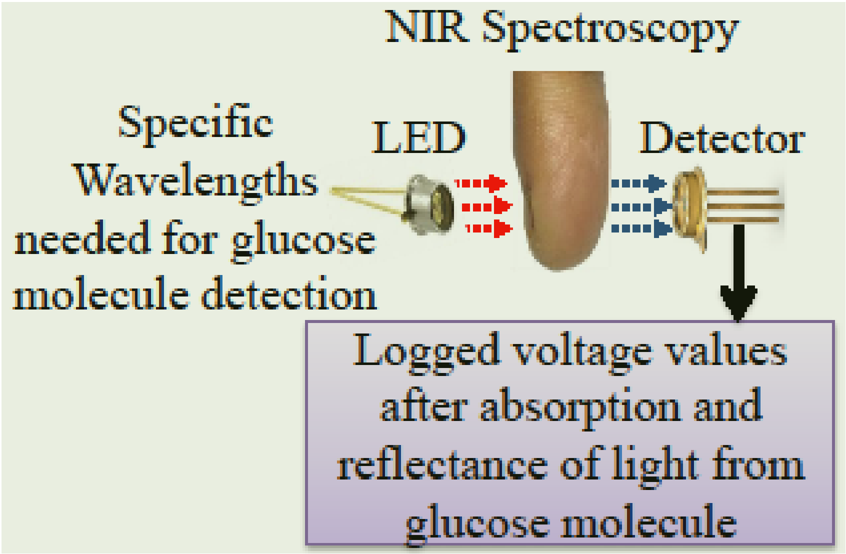


Photoplethysmogram (PPG)

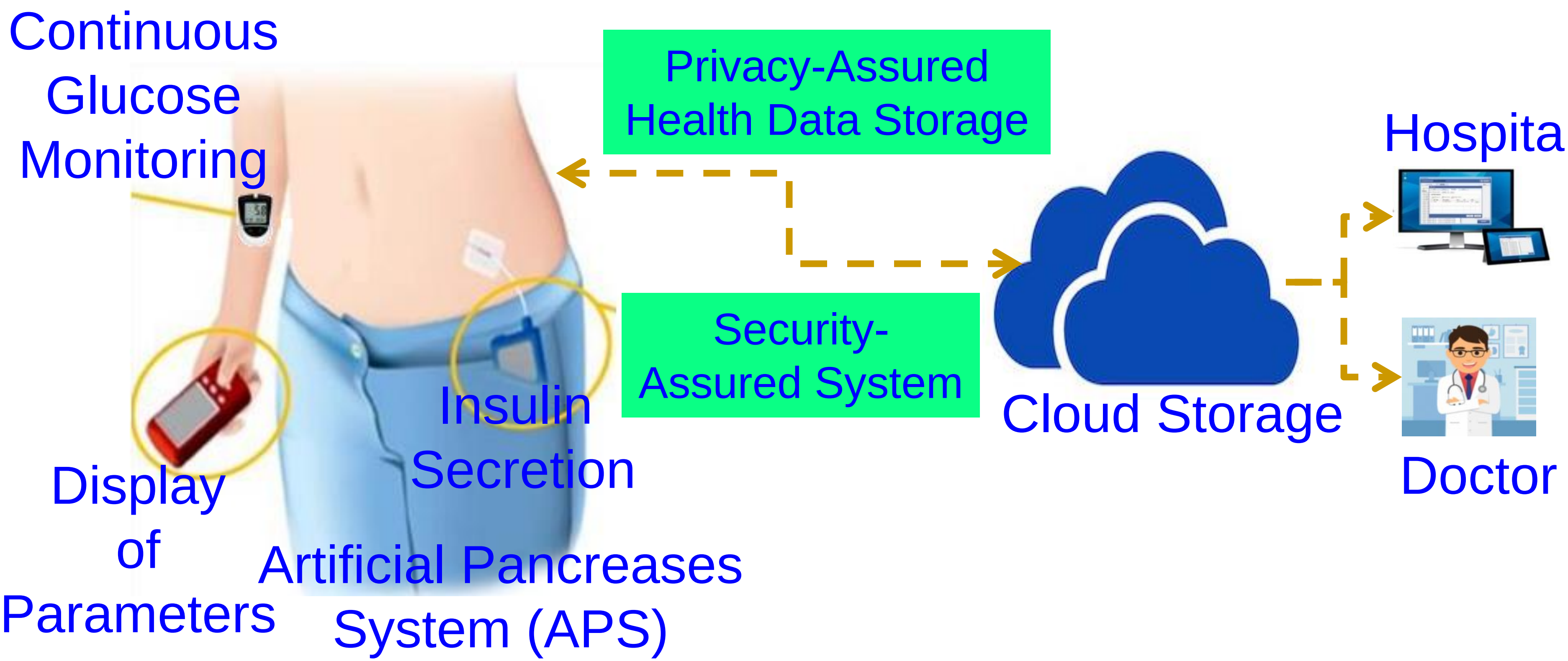


Near Infrared (NIR)

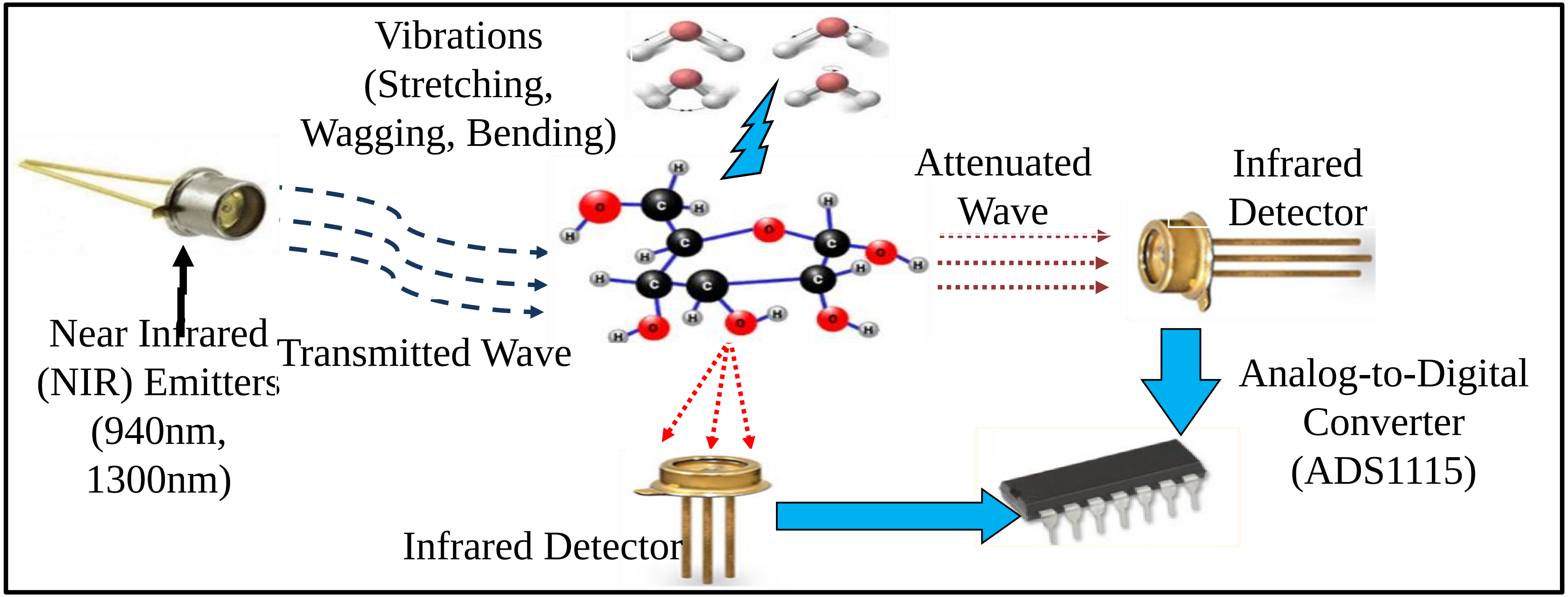




Our Vision – iGLU (Intelligent Noninvasive Monitoring and Control)



iGLU 1.0: Capillary Glucose

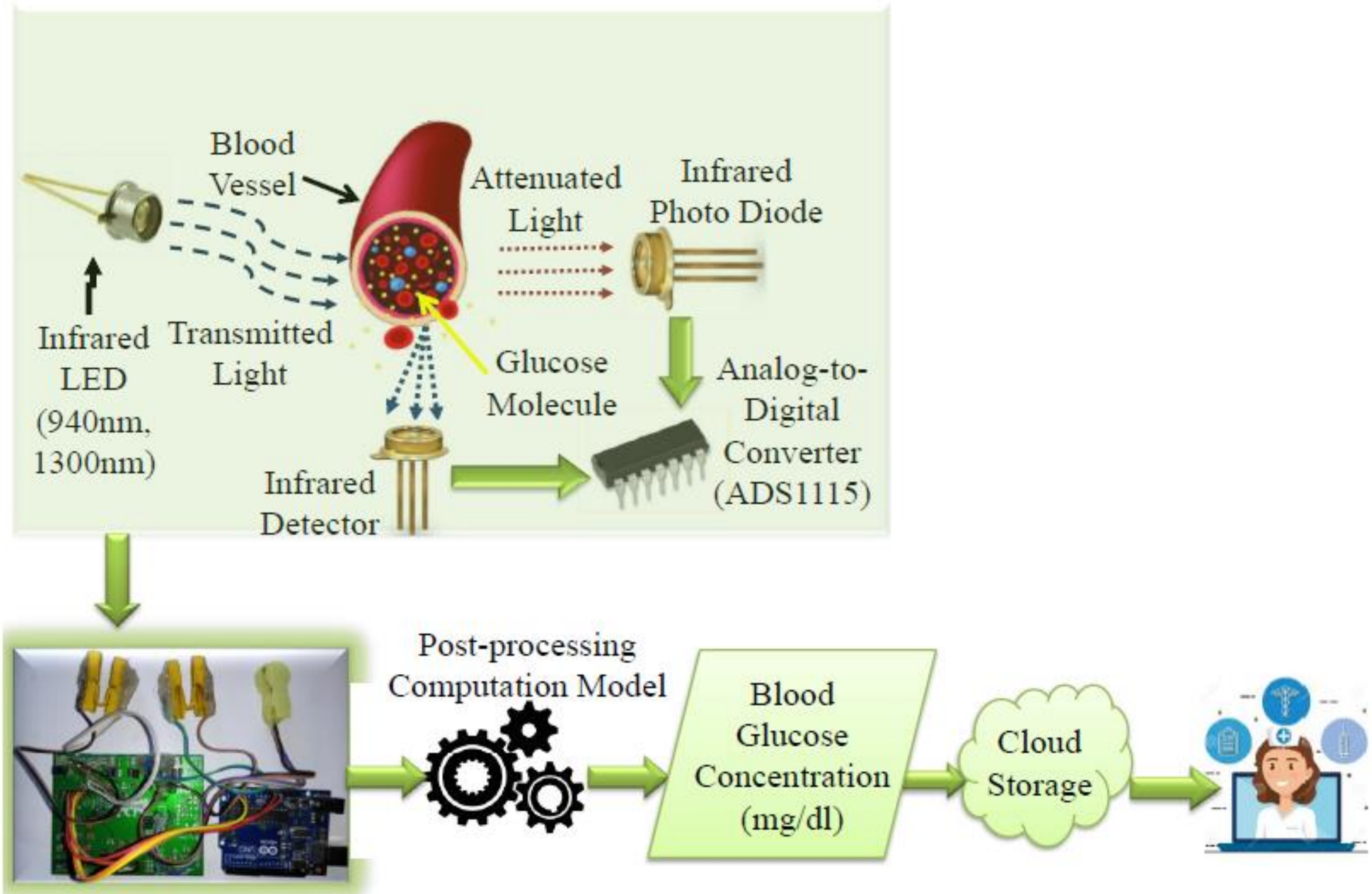


Clinically tested in an hospital.

Cost - US$ 20
Accuracy - 100%

Source: P. Jain, A. M. Joshi, and S. P. Mohanty, "iGLU: An Intelligent Device for Accurate Non-Invasive Blood Glucose-Level Monitoring in Smart Healthcare", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 9, No. 1, January 2020, pp. 35-42.

iGLU 2.0: Serum Glucose



Source: P. Jain, A. M. Joshi, N. Agrawal, and S. P. Mohanty, "iGLU 2.0: A New Non-invasive, Accurate Serum Glucometer for Smart Healthcare", *arXiv Electrical Engineering and Systems Science*, arXiv:2001.09182, January 2020, 19-pages.

Technology for Visually Impaired

Detection Part (Localizes the marker from the other objects)

Visual Marker

Recognition Part (QR code)

Source: C. Lee, P. Chondro, S. Ruan, O. Christen and E. Naroska, "Improving Mobility for the Visually Impaired: A Wearable Indoor Positioning System Based on Visual Markers," IEEE Consumer Electronics Magazine, vol. 7, no. 3, pp. 12-20, May 2018.

May 2018

Smart Healthcare – Some Challenges

Users are Integral Part: For Them and By Them

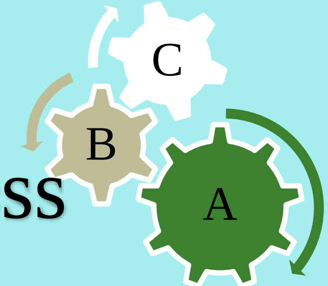
Connecting people to the Internet for more valuable communications

Implantable Medical Device (IMD)

Wearable Medical Device (WMD)

People

Deliver right information to right place, person or machine at the right time



Process

Internet of Everything (IoE)

Data

Collecting data and leverage it for decision making

Crowdsourcing

Things

Devices connected to each other and the internet (Internet of Things (IoT)).

Perform decision making whenever necessary.

Source: S. P. Mohanty, V. P. Yanambaka, E. Kougianos, and D. Puthal, "PUFchain: Hardware-Assisted Blockchain for Sustainable Simultaneous Device and Data Security in Internet of Everything (IoE)", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 9, No. 2, March 2020, pp. 8--16.

Smart Healthcare Architecture – Requirements

Requirements

- Low power
- Higher efficiency
- Small form factor
- Inter operability
- Continuous connectivity
- High speed
- Security
- Privacy

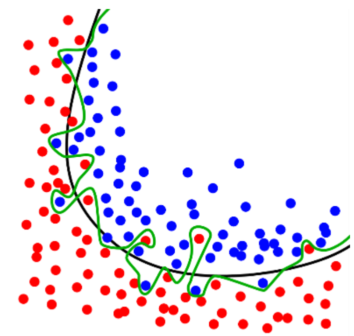
Smart Healthcare – Data Quality

Source: H. Zhu, C. K. Wu, C. H. KOO, Y. T. Tsang, Y.Liu, H. R. Chi, and K. F. Tsang, "Smart Healthcare in the Era of Internet-of-Things", *IEEE Consumer Electronics Magazine*, vol. 8, no. 5, pp. 26-30, Sep 2019.

Machine Learning Challenges

Machine Learning Issues

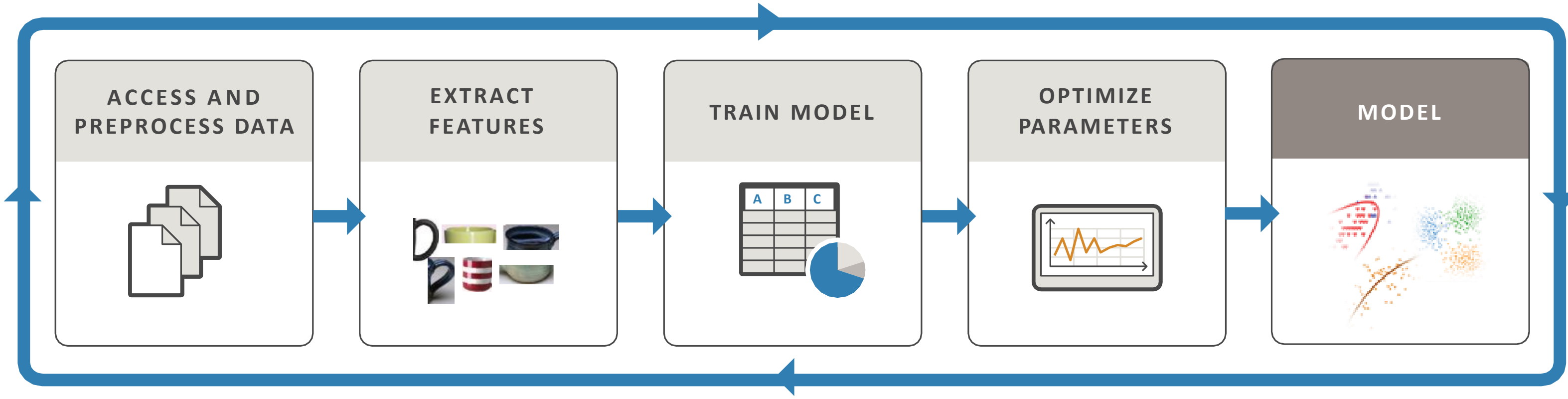
- High Energy Requirements
- High Computational Resource Requirements
- Large Amount of Data Requirements
- Underfitting/Overfitting Issue
- Class Imbalance Issue
- Fake Data Issue



Source: Mohanty ISCT Keynote 2019

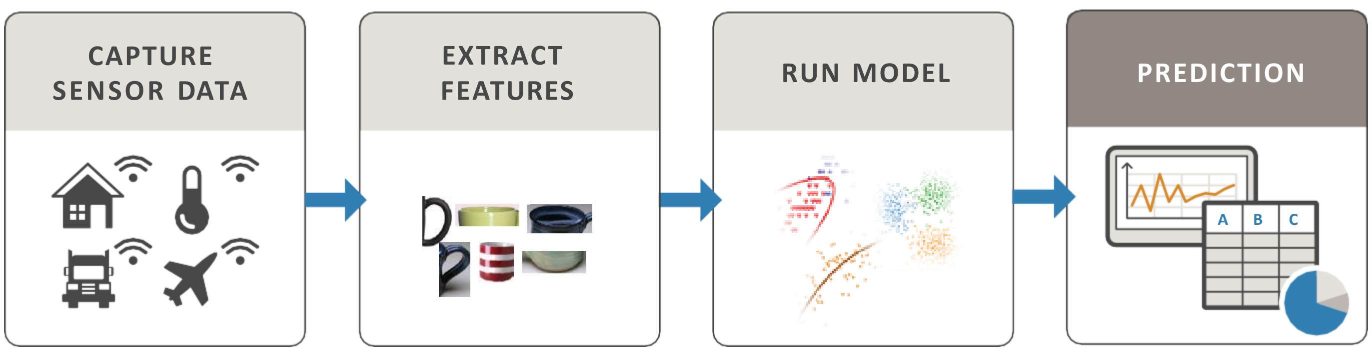
Deep Neural Network (DNN) - Resource and Energy Costs

TRAIN: Iterate until you achieve satisfactory performance.



Needs Significant:
- Resource
- Energy

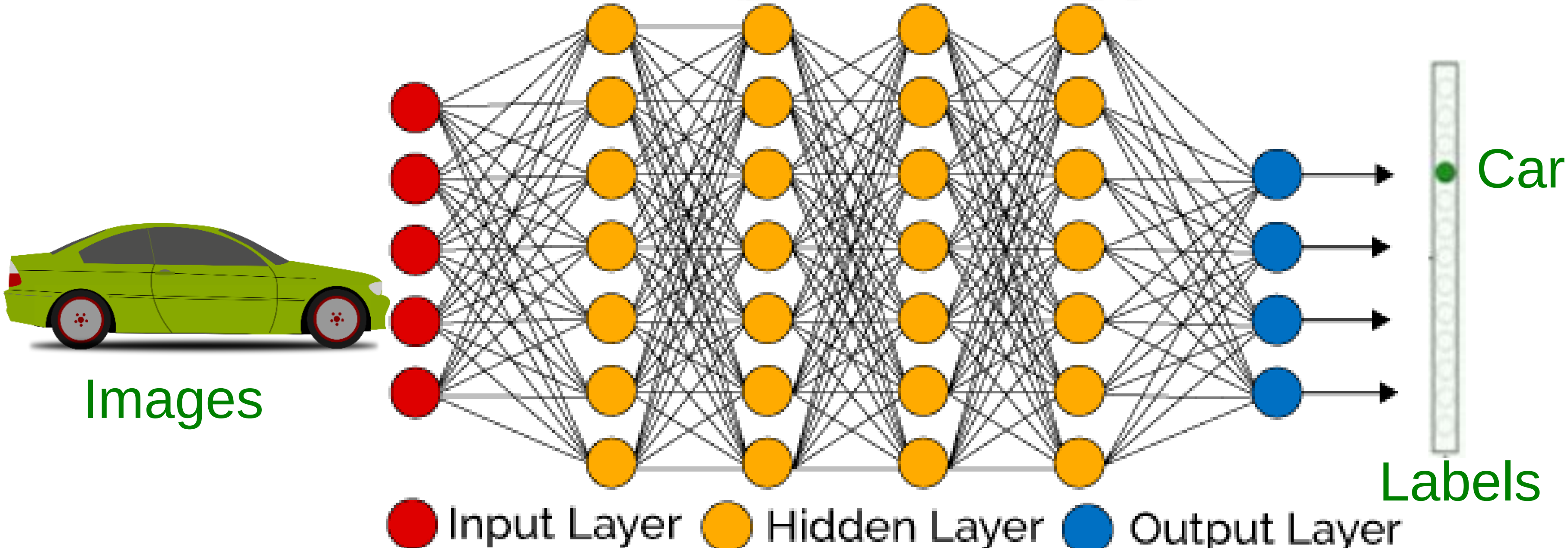
PREDICT: Integrate trained models into applications.



Needs:
- Resource
- Energy

Source: https://www.mathworks.com/campaigns/offers/mastering-machine-learning-with-matlab.html

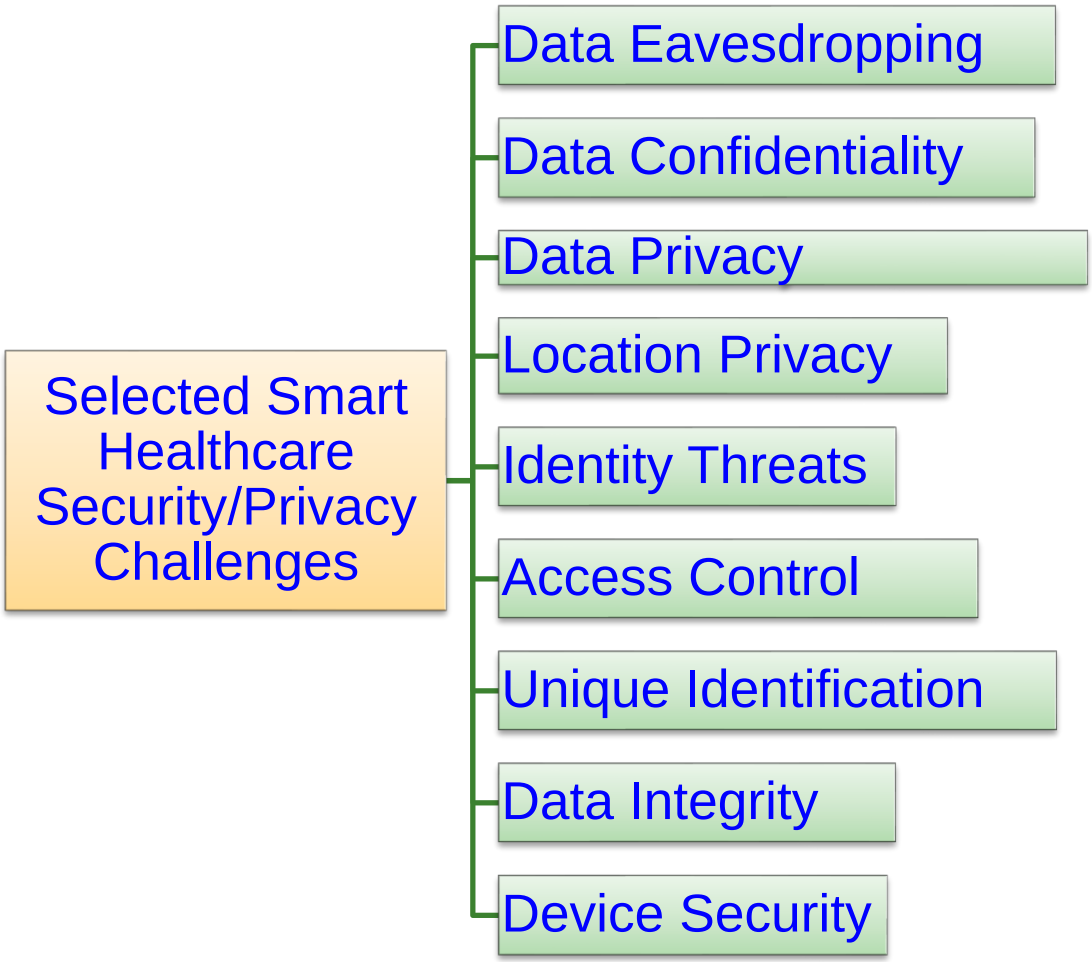
DNN Training - Energy Issue



- DNN considers many training parameters, such as the size, the learning rate, and initial weights.
- High computational resource and time: For sweeping through the parameter space for optimal parameters.
- DNN needs: Multicore processors and batch processing.
- DNN training happens mostly in cloud not at edge or fog.

Source: Mohanty iSES 2018 Keynote

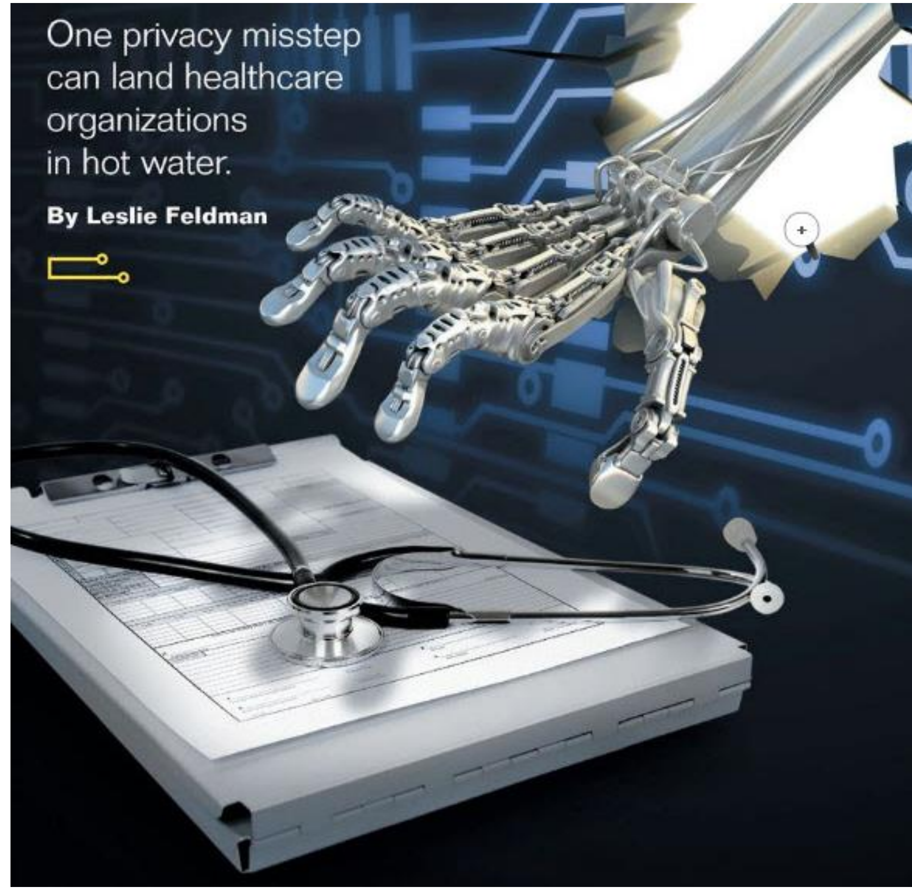
Smart Healthcare - Security Challenges



Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, “Everything You Wanted to Know about Smart Health Care”, *IEEE Consumer Electronics Magazine (CEM)*, Volume 7, Issue 1, January 2018, pp. 18-28.

Information Privacy

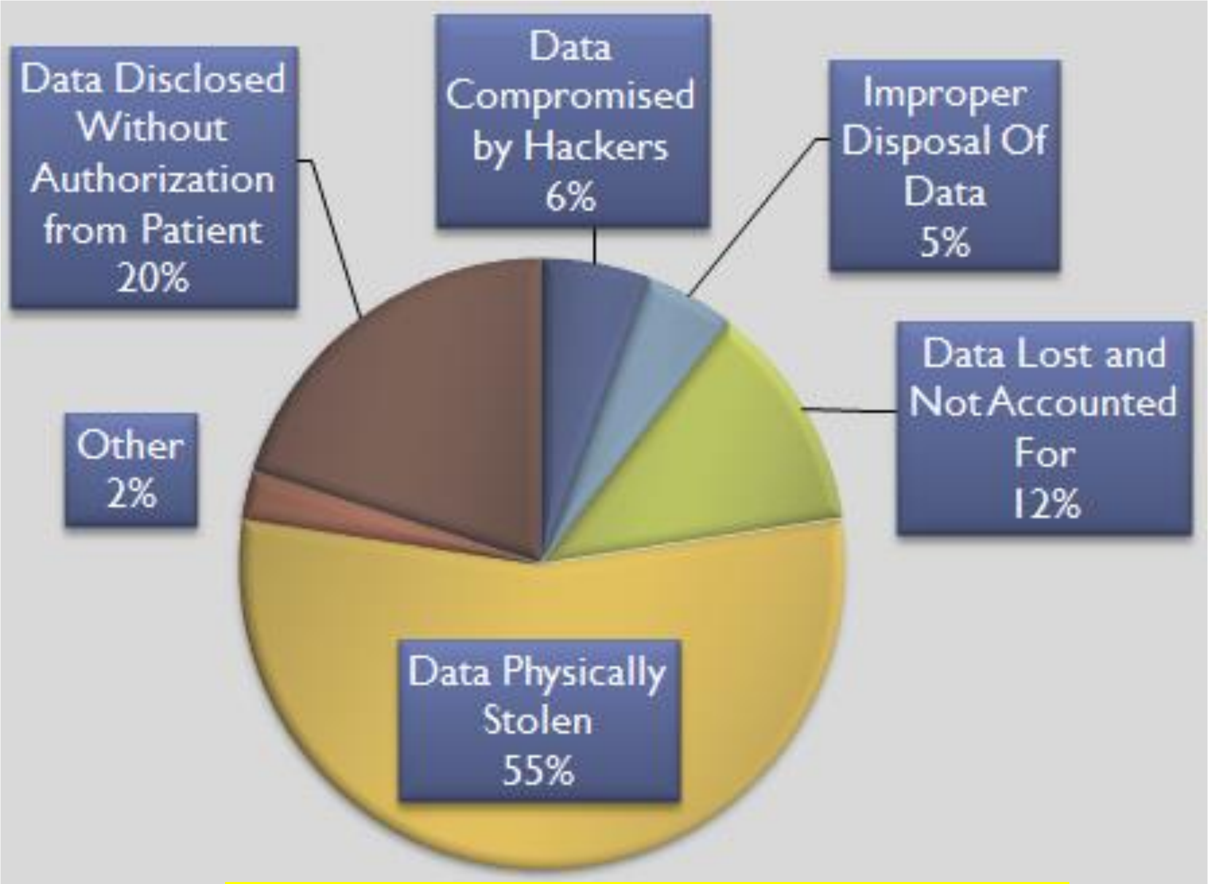
Source: http://ciphercloud.com/three-ways-pursue-cloud-data-privacy-medical-records/



Source: http://blog.veriphyr.com/2012/06/electronic-medical-records-security-and.html

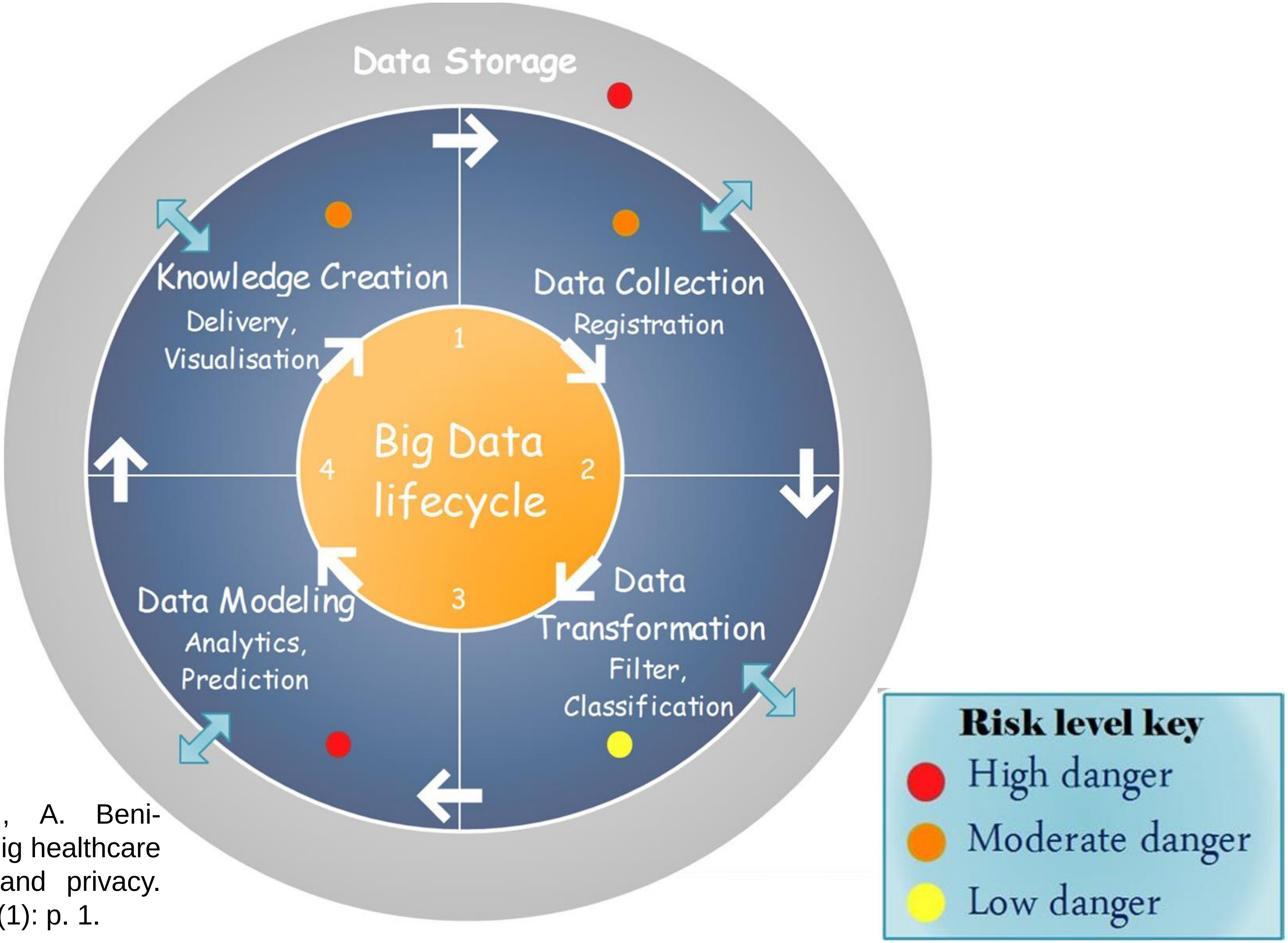
Health Insurance Portability and Accountability Act (HIPPA)

HIPAA
Health Insurance Portability and Accountability Act



HIPPA Privacy Violation by Types

Healthcare Bigdata security Life Cycle



Source: Abouelmehdi, K., A. Beni-Hessane, and H. Khaloufi, Big healthcare data: preserving security and privacy. Journal of Big Data, 2018. 5(1): p. 1.

IoMT Device Security Issue is Scary

- Insulin pumps are vulnerable to hacking, FDA warns amid recall:

https://www.washingtonpost.com/health/2019/06/28/insulin-pumps-are-vulnerable-hacking-fda-warns-amid-recall/

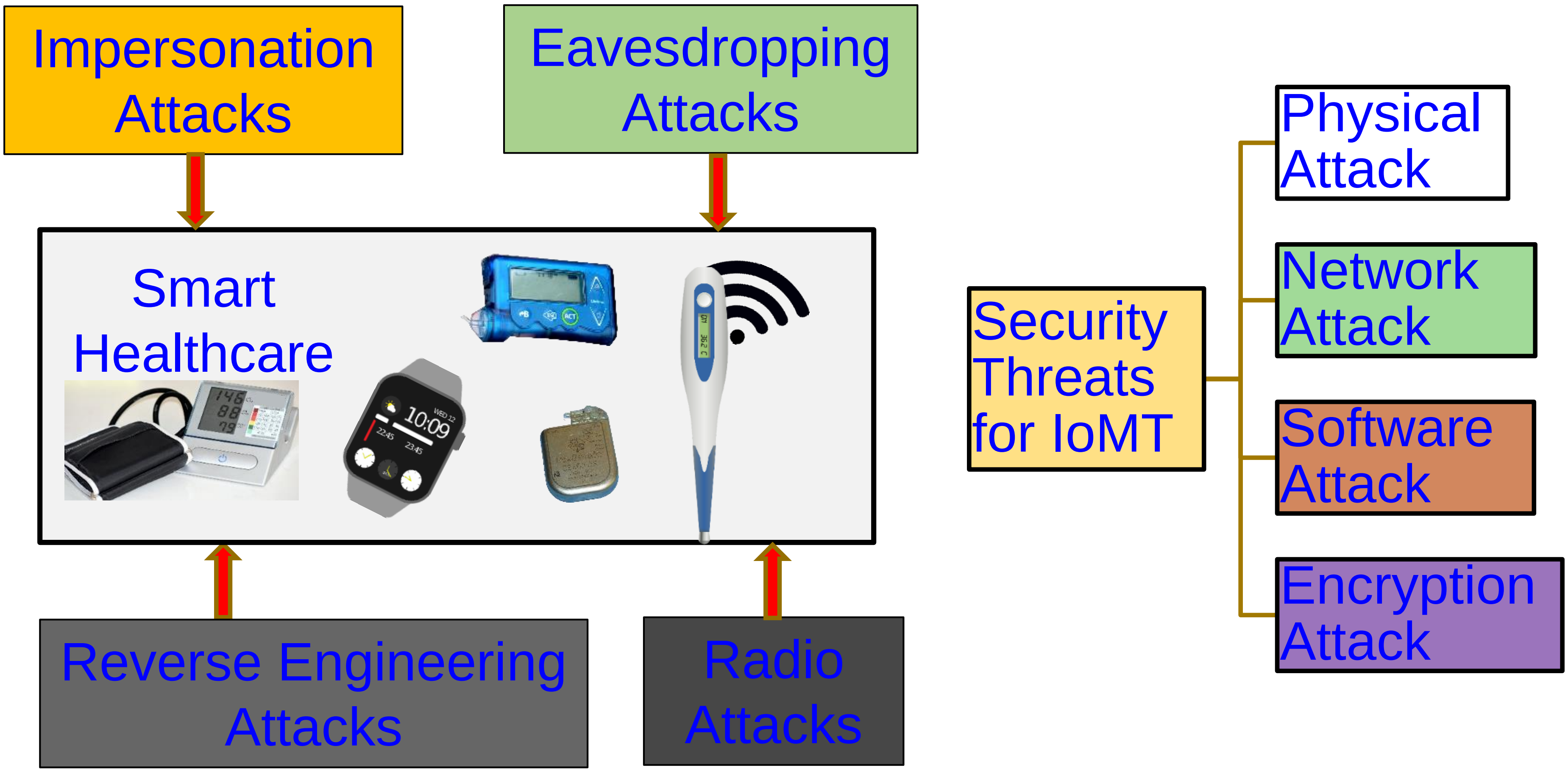
- Software vulnerabilities in some medical devices could leave them susceptible to hackers, FDA warns:

https://www.cnn.com/2019/10/02/health/fda-medical-devices-hackers-trnd/index.html

- FDA Issues Recall For Medtronic mHealth Devices Over Hacking Concerns:

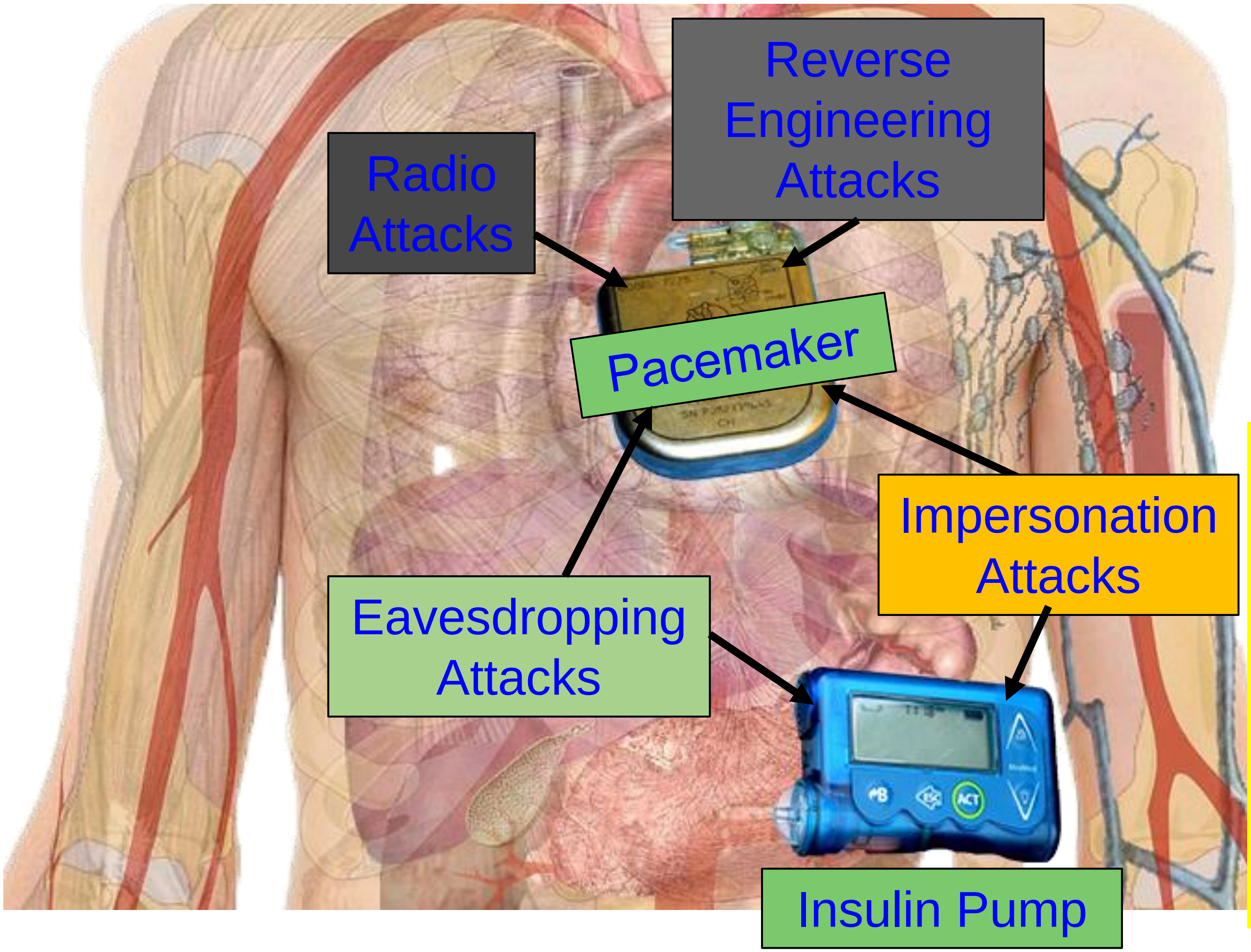
https://mhealthintelligence.com/news/fda-issues-recall-for-medtronic-mhealth-devices-over-hacking-concerns

IoMT Security – Selected Attacks



Source: V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, "PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things", *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 388--397.

IoMT Security Measures is Hard



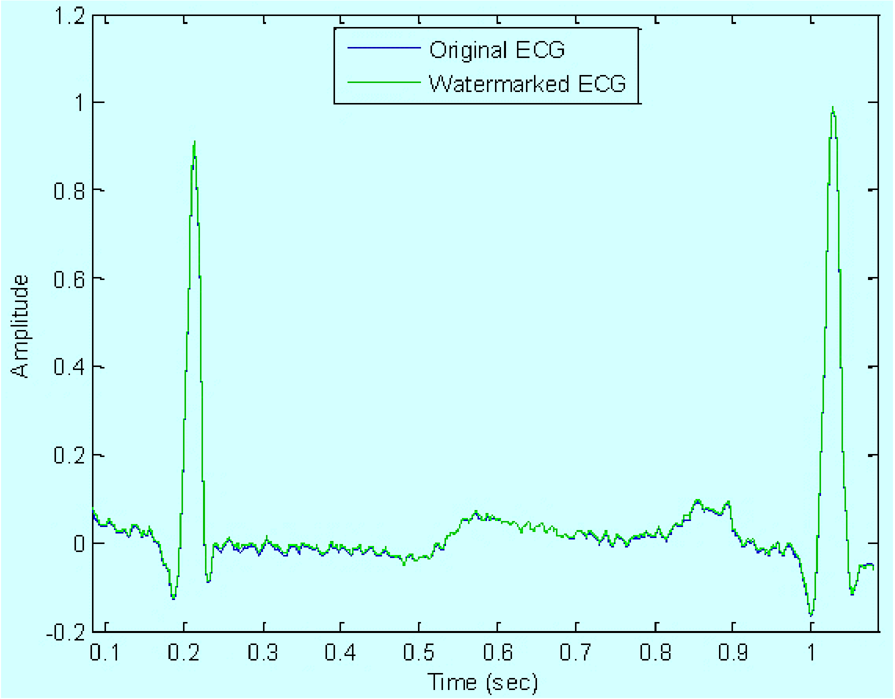
Collectively (WMD+IMD): Implantable and Wearable Medical Devices (IWMDs)

Implantable and Wearable Medical Devices (IWMDs) -- Battery Characteristics:

→ Longer life
→ Safer
→ Smaller size
→ Smaller weight

Smart Healthcare Security – Medical Signal Authentication

- Physiological signals like the electrocardiogram (EKG) are obtained from patients, transmitted to the cloud, and can also stored in a cloud repository.
- With increasing adoption of electronic medical records and cloud-based software-as-service (SaaS), advanced security measures are necessary.
- Protection from unauthorized access to Protected Health Information (PHI) also protects from identity theft schemes.
- From an economic stand-point, it is important to safeguard the healthcare and insurance system from fraudulent claims.



Source: Tseng 2014, Tseng Sensors Feb 2014

Smart Healthcare - Ethics

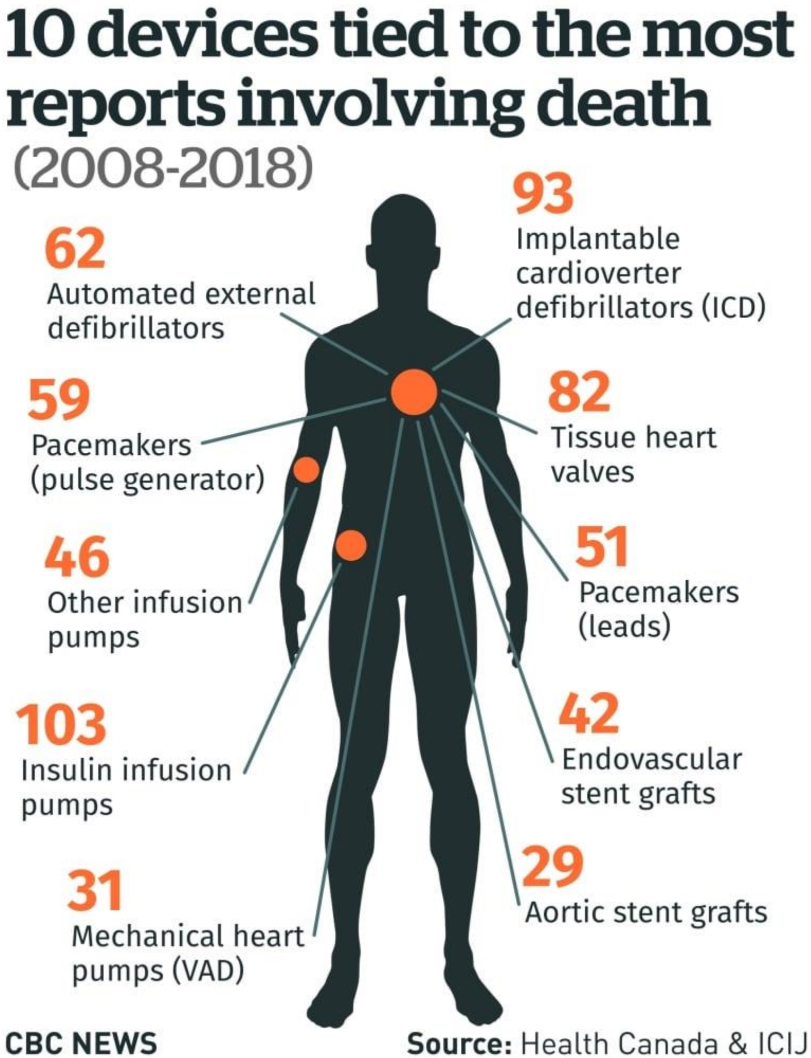
Source: https://online.alvernia.edu/articles/ethical-issues-in-healthcare/

Ethical Issues Include

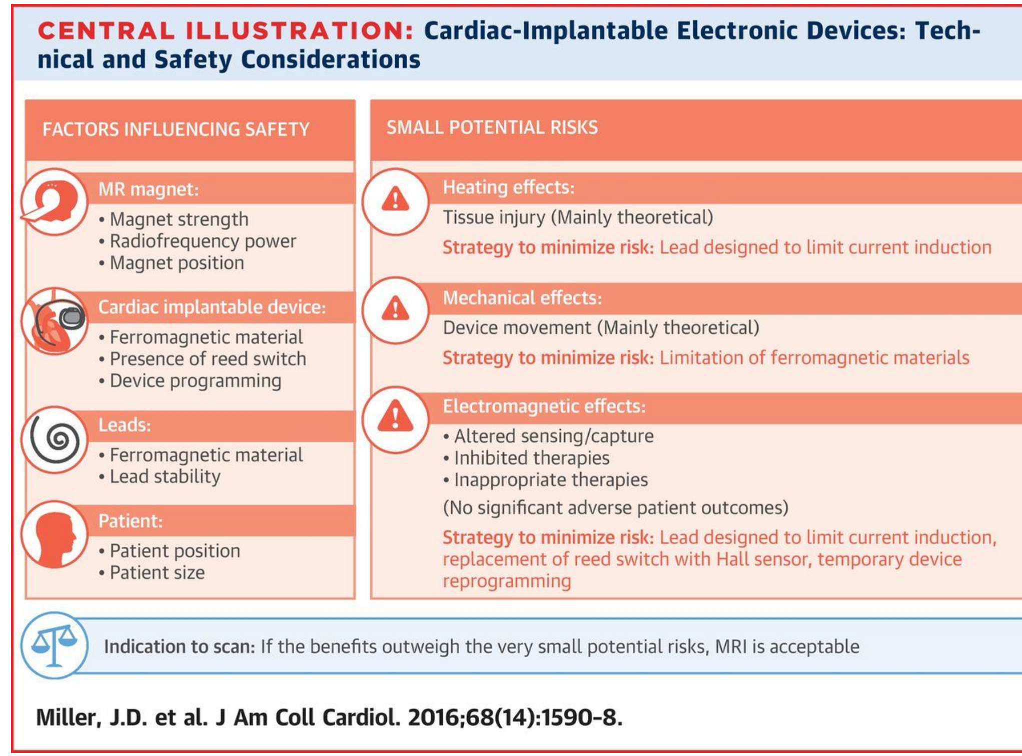
- Ownership and data access
- Social isolation
- Marketing Practices
- Care Quality versus Efficiency
- Access to Care
- Personal Privacy
- Obtrusiveness, stigma and autonomy
- Data/Information Privacy and Confidentiality

Source: B. Mittelstadt, “Ethics of the health-related internet of things: a narrative review”, *Ethics Inf Technol* **19,** 157–175 (2017), DOI: https://doi.org/10.1007/s10676-017-9426-4.

Smart Healthcare - Safety



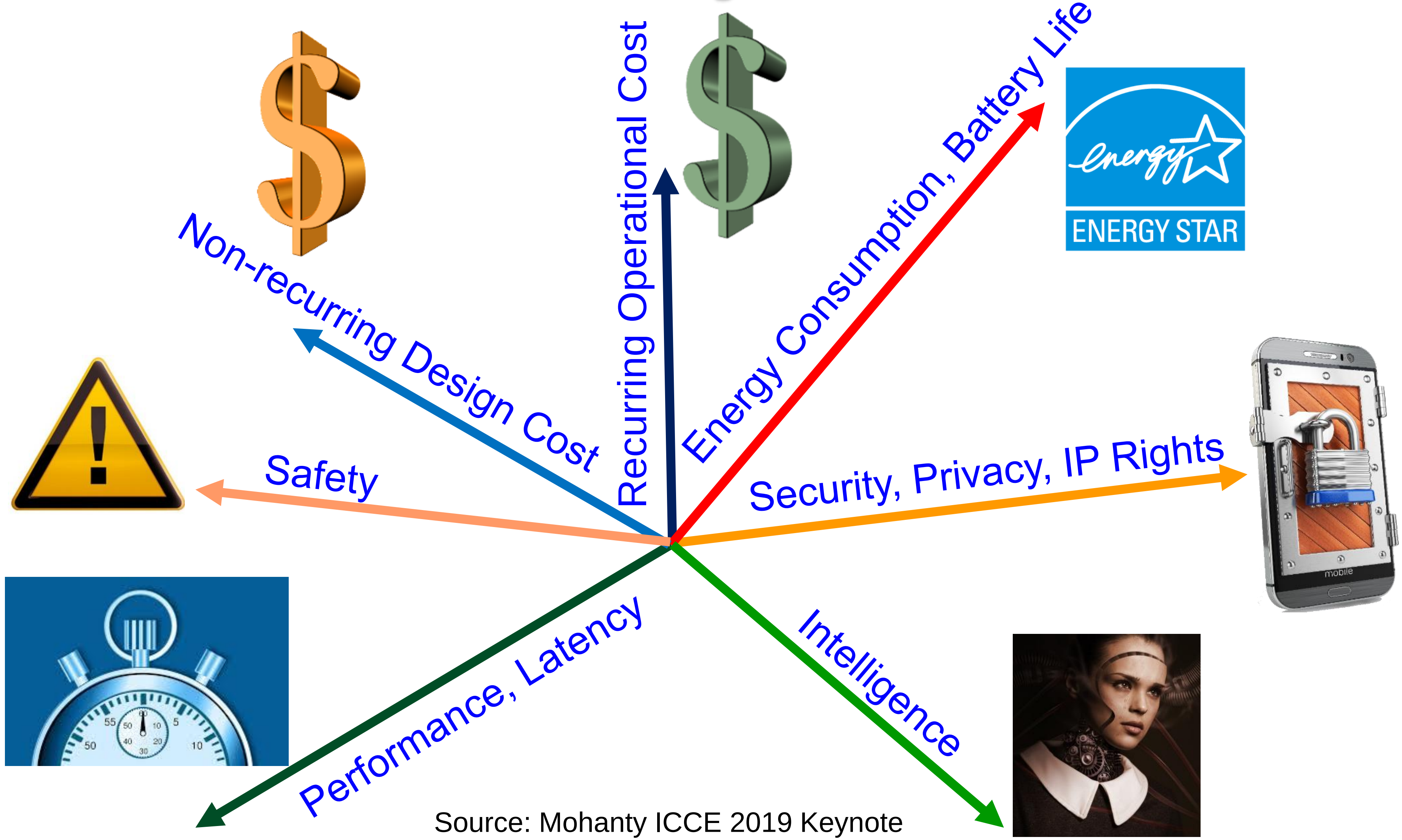
Source https://planet-report.com/canadian-advocates-call-for-all-medical-implants-to-be-registered-cbc-news/



Source: J. D. Miller, S. Nazarian, H. R. Halperin, "Implantable Electronic Cardiac Devices and Compatibility With Magnetic Resonance Imaging", J Am Coll Cardiol. 2016 Oct, 68 (14), pp. 1590-1598.

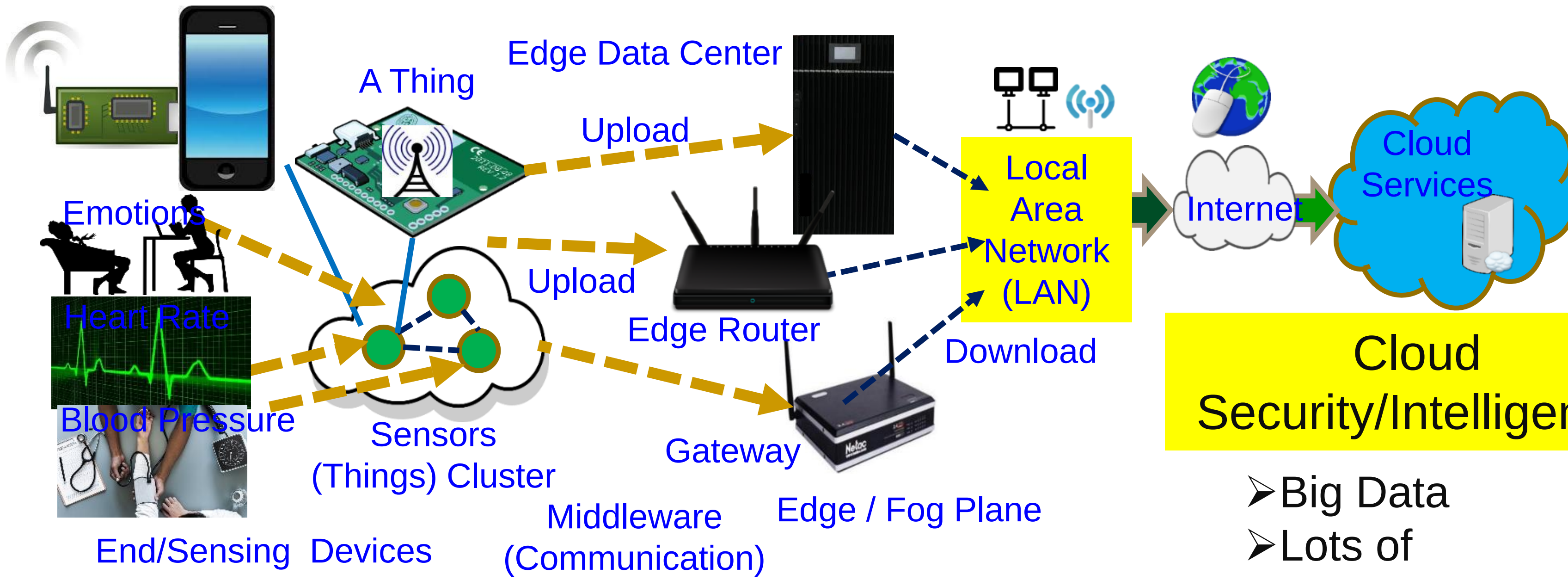
Smart Healthcare – Some Solutions

H-CPS - Multi-Objective Tradeoffs



Source: Mohanty ICCE 2019 Keynote

Smart Healthcare – Edge Vs Cloud



Cloud Security/Intelligence

- Big Data
- Lots of Computational Resource
- Accurate Data Analytics
- Latency in Network
- Energy overhead in Communications

End Security/Intelligence

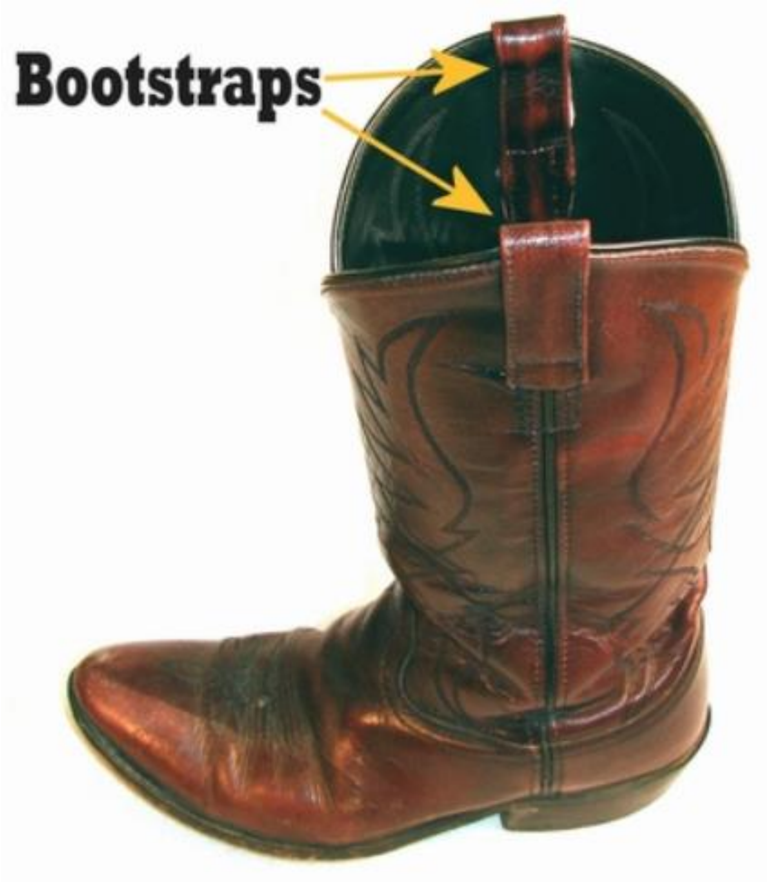
- Minimal Data
- Minimal Computational Resource
- Least Accurate Data Analytics
- Very Rapid Response

Edge Security/Intelligence

- Less Data
- Less Computational Resource
- Less Accurate Data Analytics
- Rapid Response

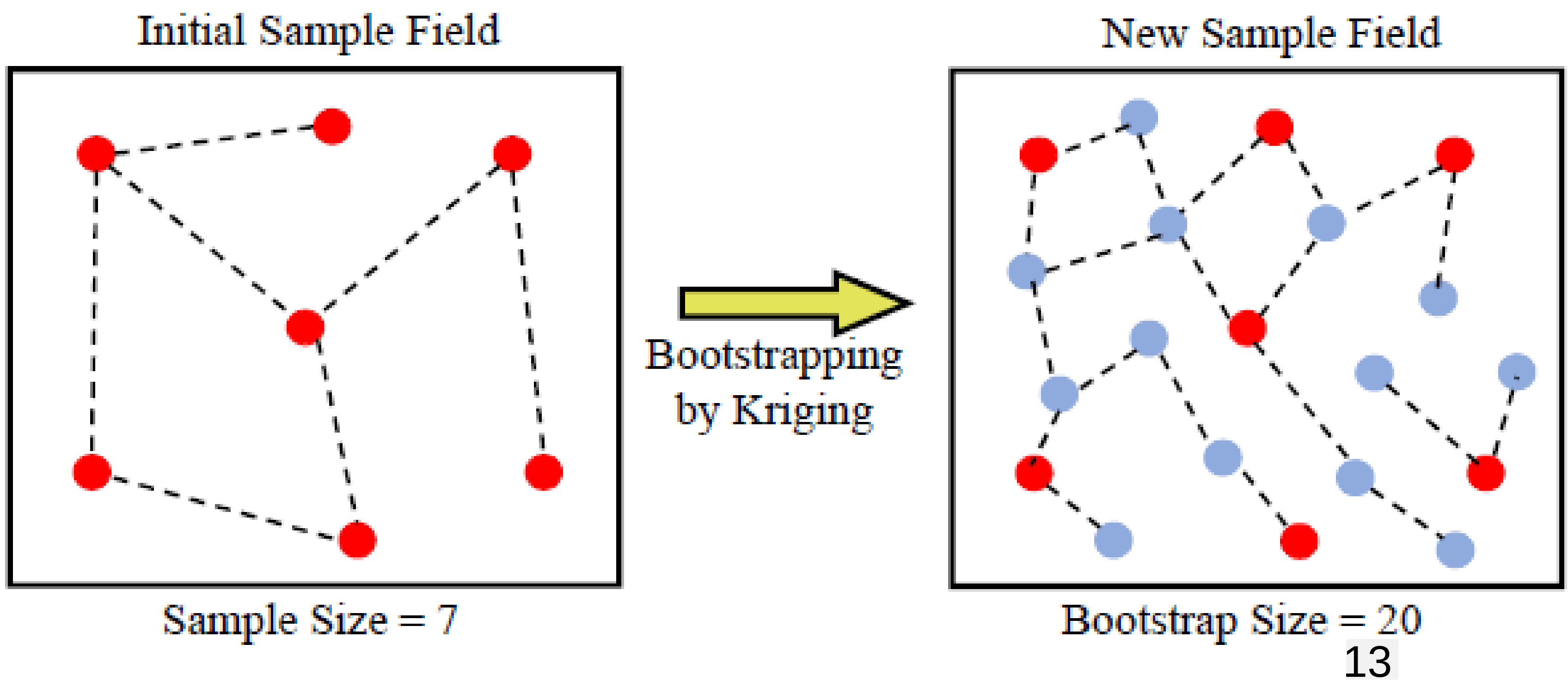
Hierarchical ML to Reduce Training Time - Bootstrapping

- A Bootstrap helps in pulling on a boot.
- It means solving a problem without external resources



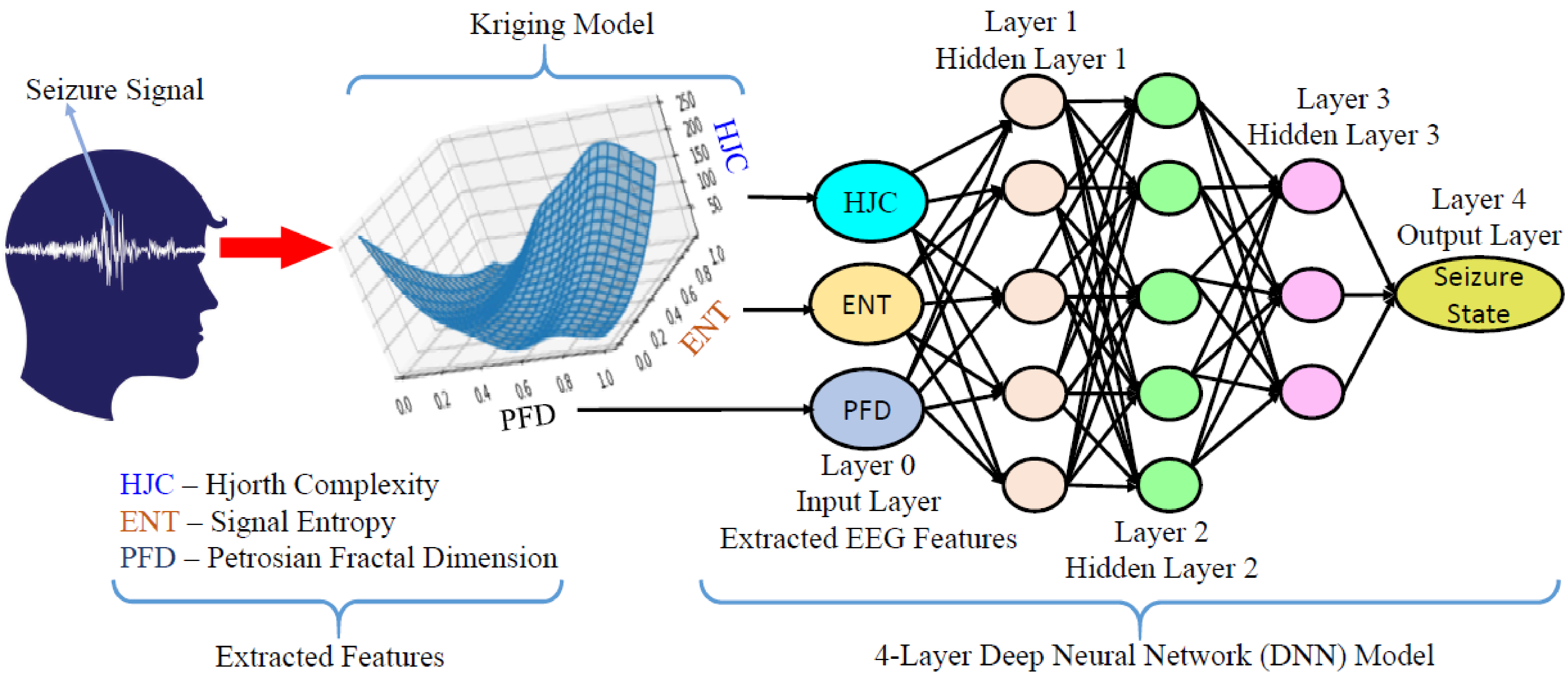
Source: http://www.lemen.com/dictionary-b.html#bootstrap

Bootstrapped Kriging



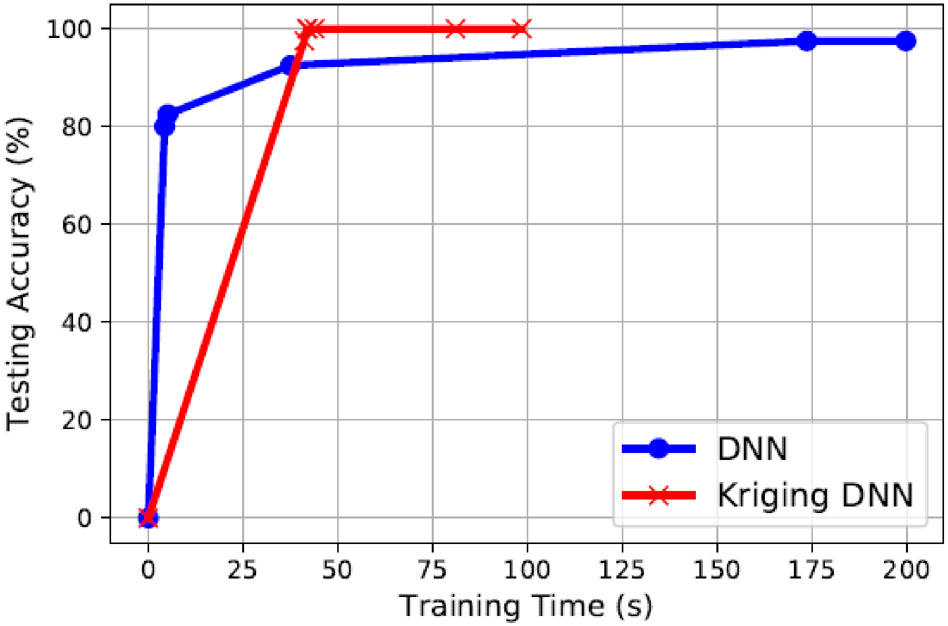
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

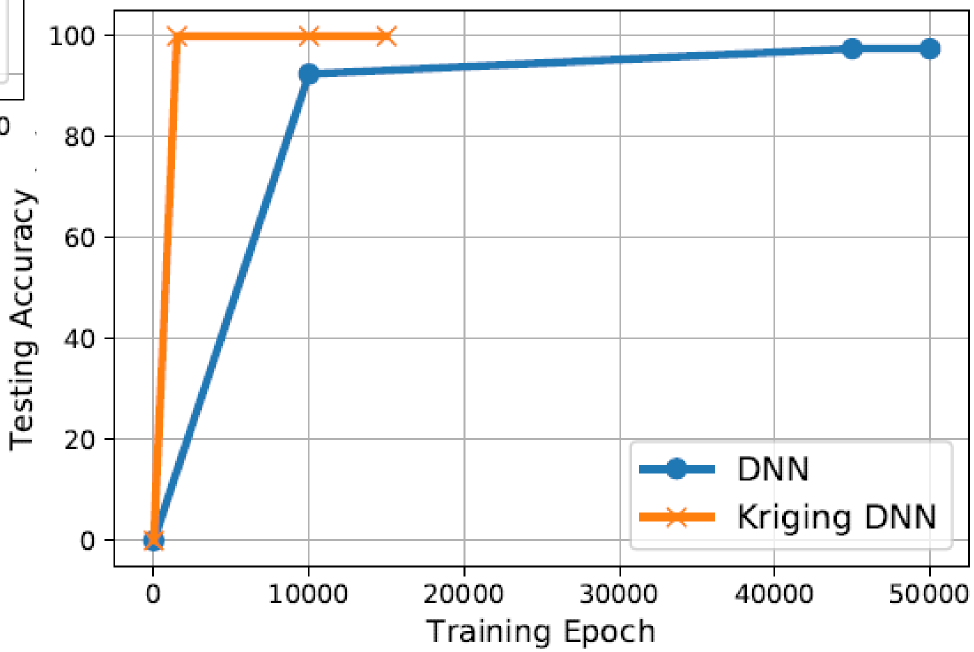
Proposed Kriging-Bootstrapped DNN Model



Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, “Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals”, in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

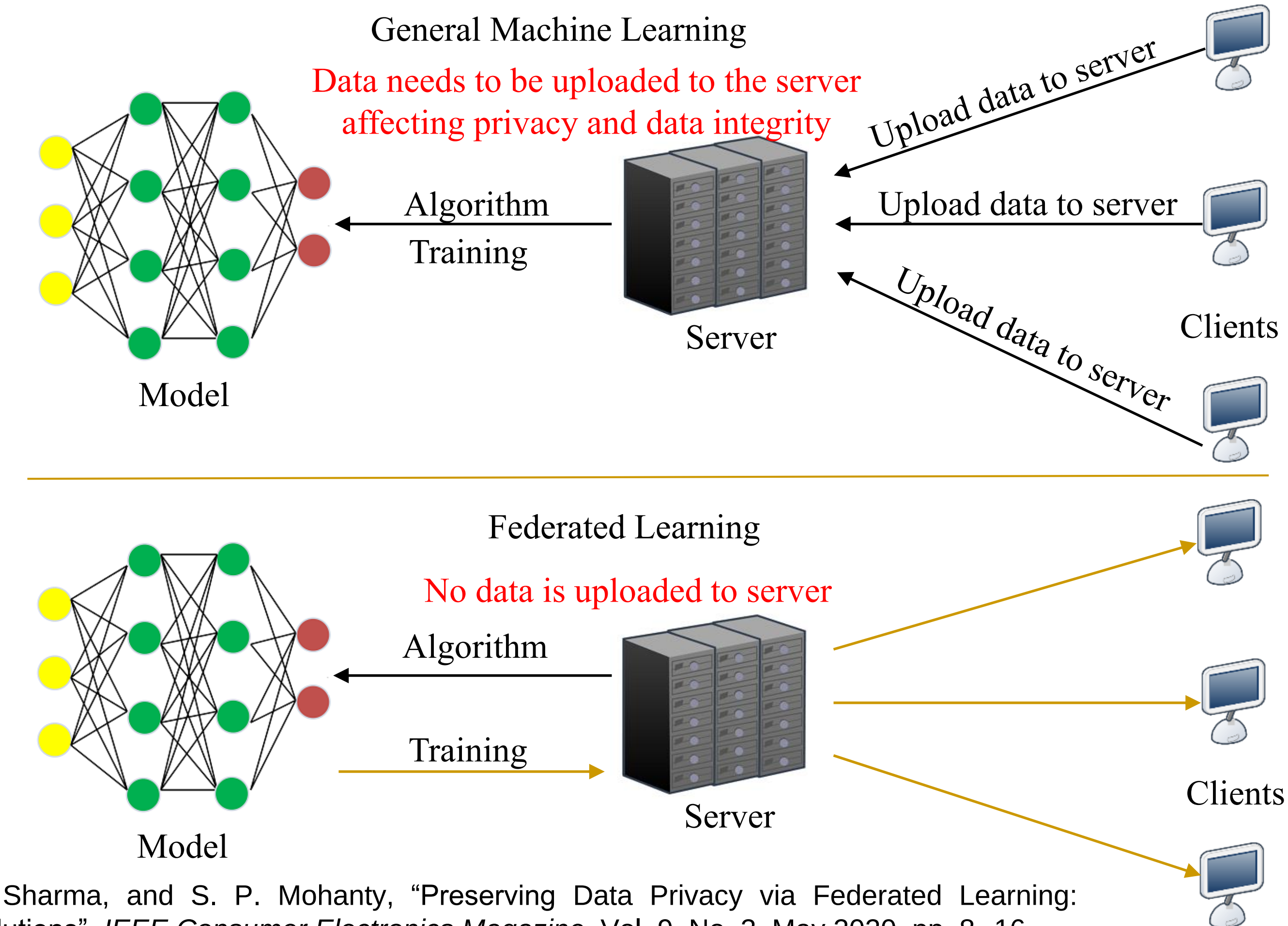
Experimental Results





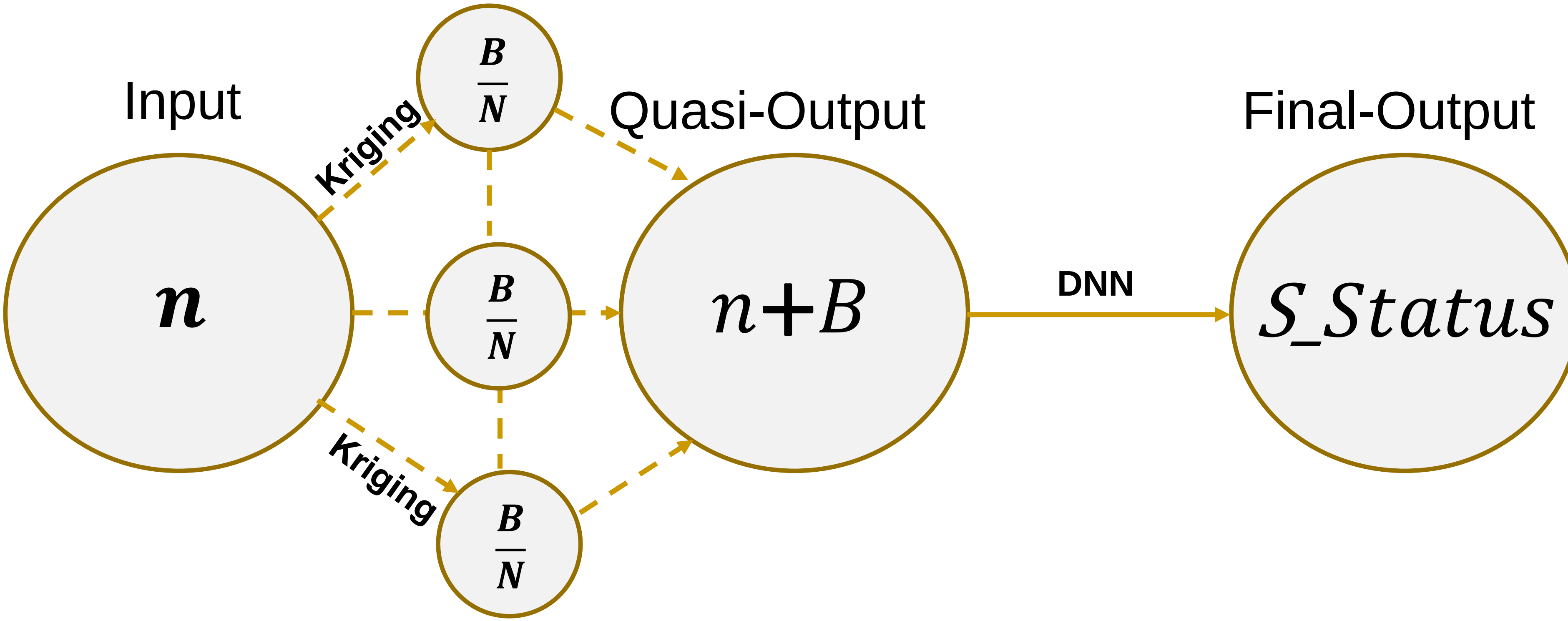
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

Distributed Machine Learning to Reduce Training Time



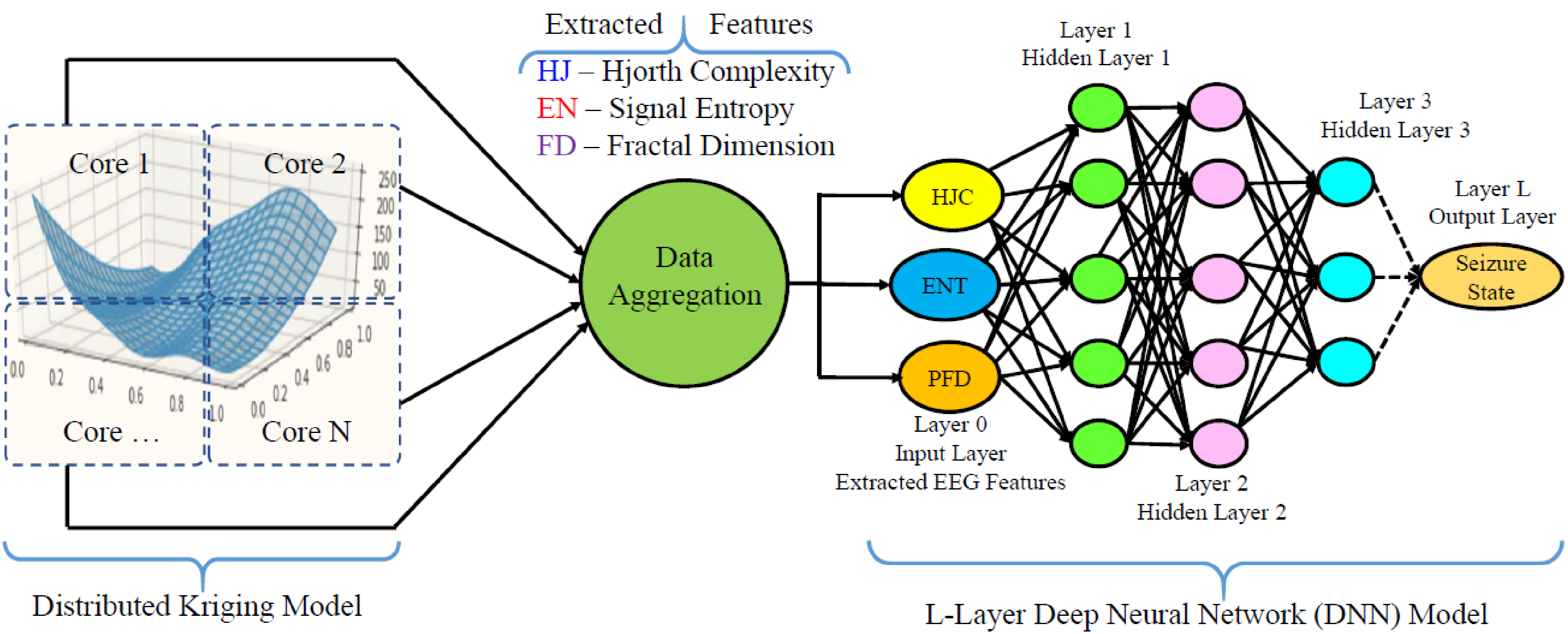
Source: Z. Li, V. Sharma, and S. P. Mohanty, "Preserving Data Privacy via Federated Learning: Challenges and Solutions", *IEEE Consumer Electronics Magazine*, Vol. 9, No. 3, May 2020, pp. 8--16.

Model Training or Learning Process



Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals", *Proceedings of the 19th IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, 2020.

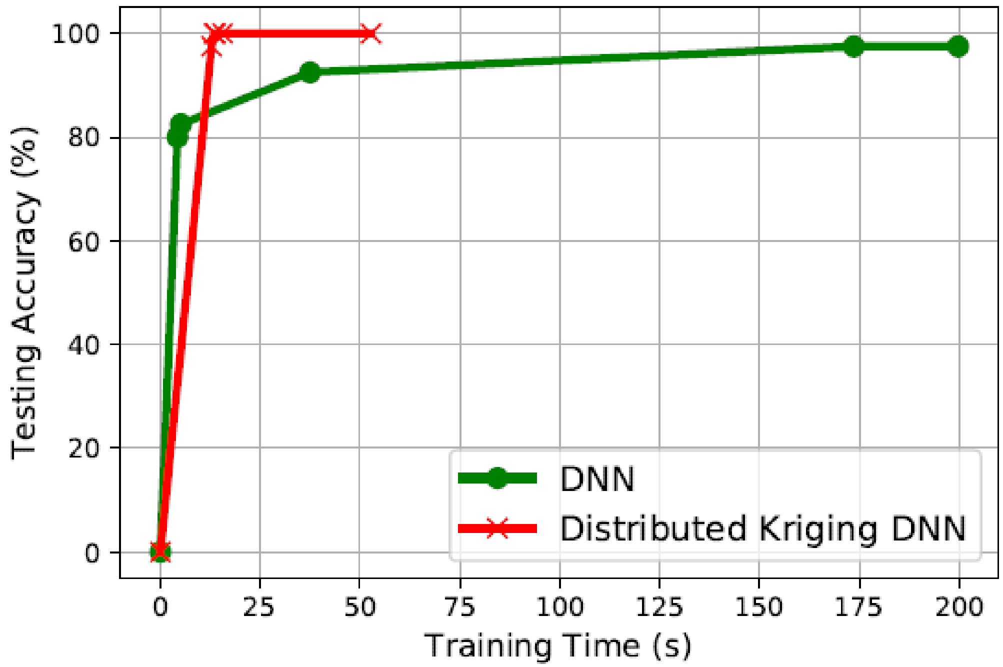
Our Distributed Kriging-Bootstrapped DNN Model



Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, “Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals”, *Proceedings of the 19th IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, 2020.

Experimental Results: Dataset A

Models	DNN	Ordinary Kriging	Kriging DNN	Distributed Kriging DNN
Tr. Data Size	10000	2000	10000	10000
Tr. Epochs	45000	NA	1500	1500
Learning Rate	0.00001	NA	0.001	0.001
Training Acc.	99.99%	100.00%	99.92%	99.92%
Testing Acc.	97.50%	99.78%	100.00%	100.00%
Training Time	173.57s	72.24s	43.83s	**15.56s**

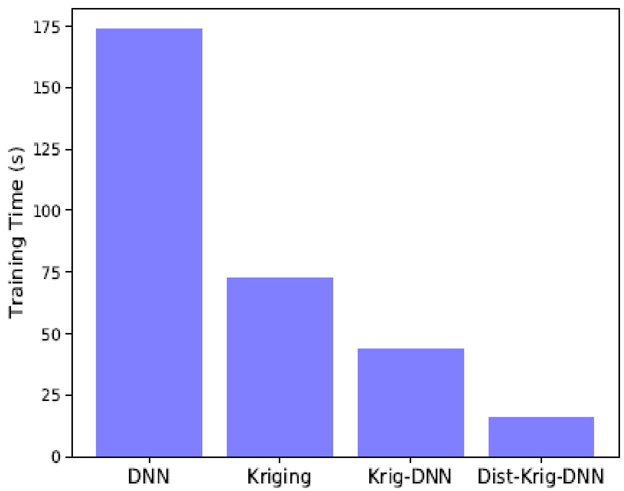


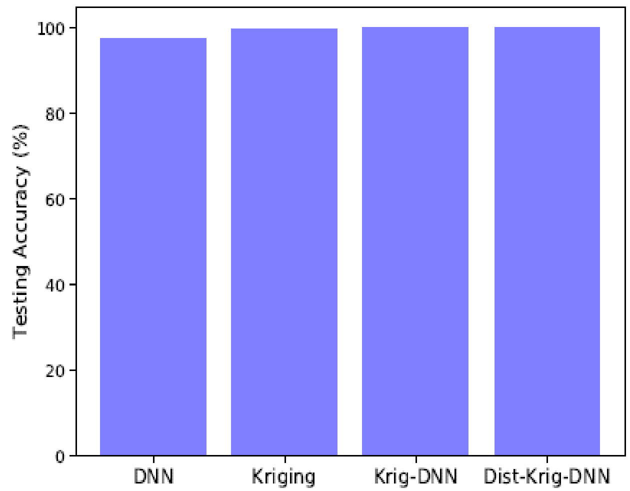
- Training Time reduced by 91%

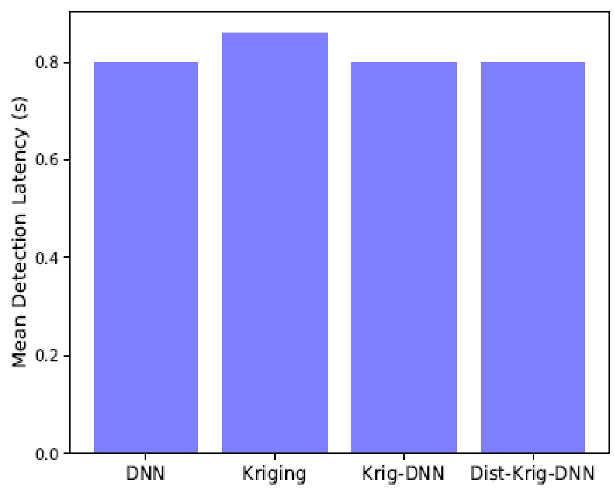
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, “Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals”, *Proceedings of the 19th IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, 2020.

Experimental Results: Dataset A

Models	Detection Latency
DNN	0.80s
Ordinary Kriging	0.86s
Krig-DNN	0.80s
Dist-Krig-DNN	0.80s

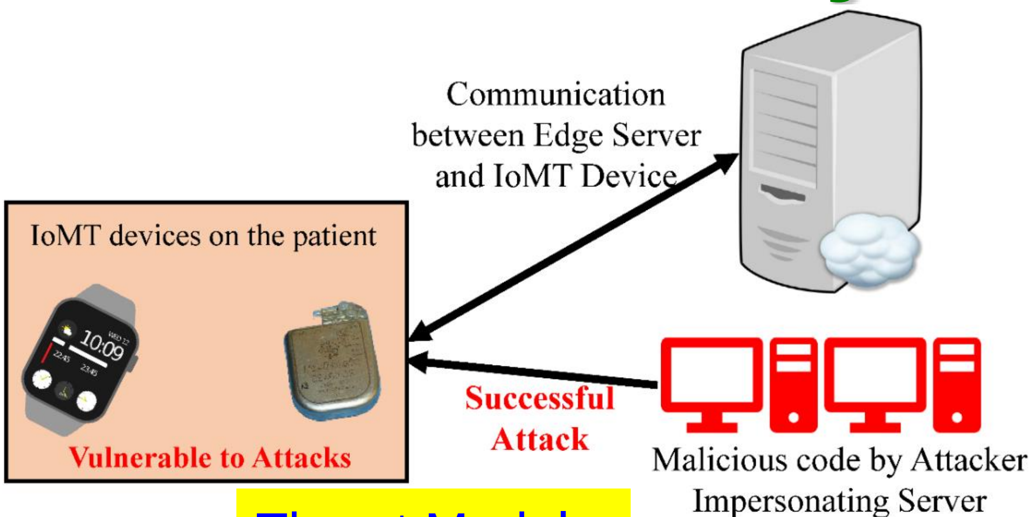






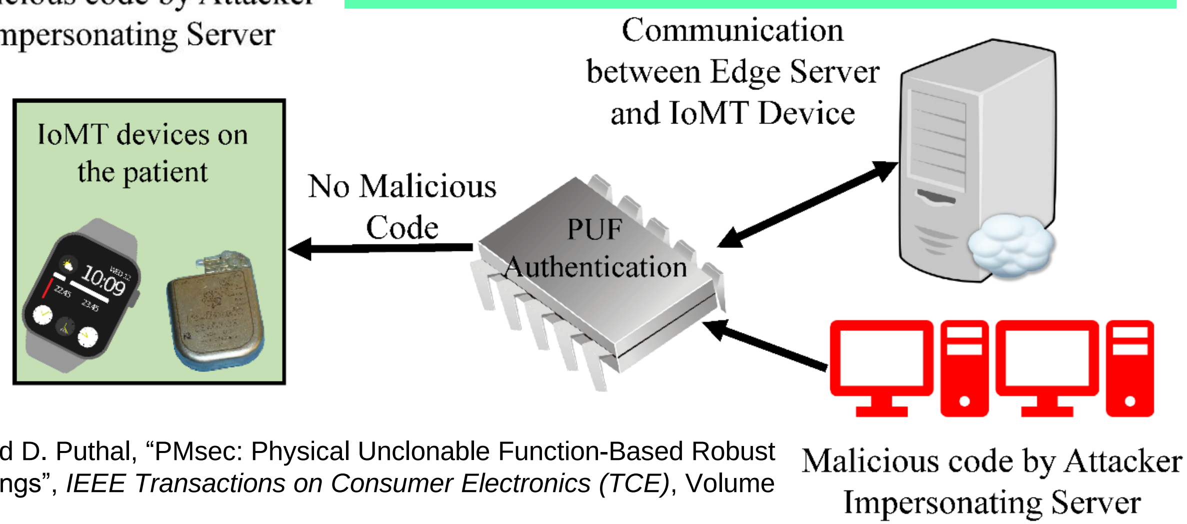
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals", *Proceedings of the 19th IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, 2020.

Our Secure by Design Approach for Robust Security in Healthcare CPS



Threat Model

Physical Unclonable Function (PUF) based Solution



Source: V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, “PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things”, *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 388--397.

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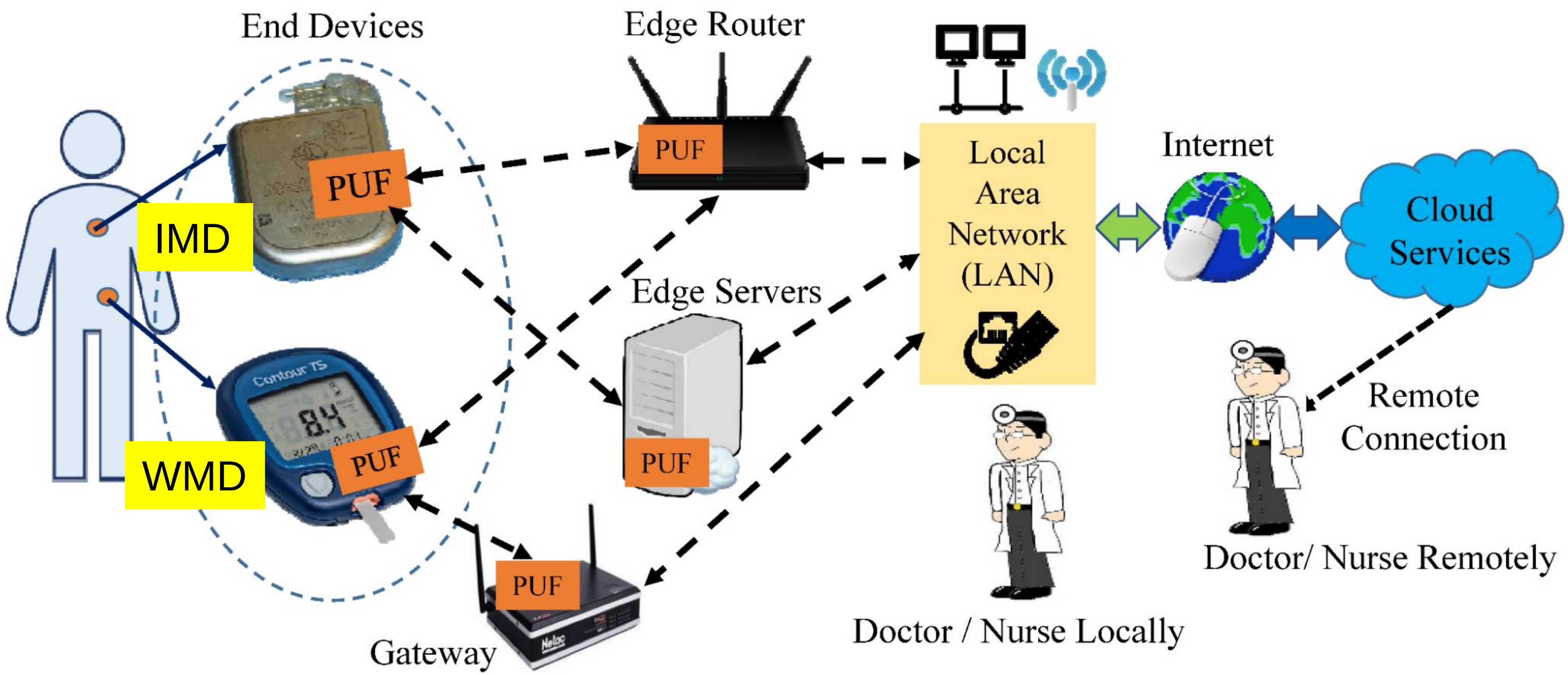
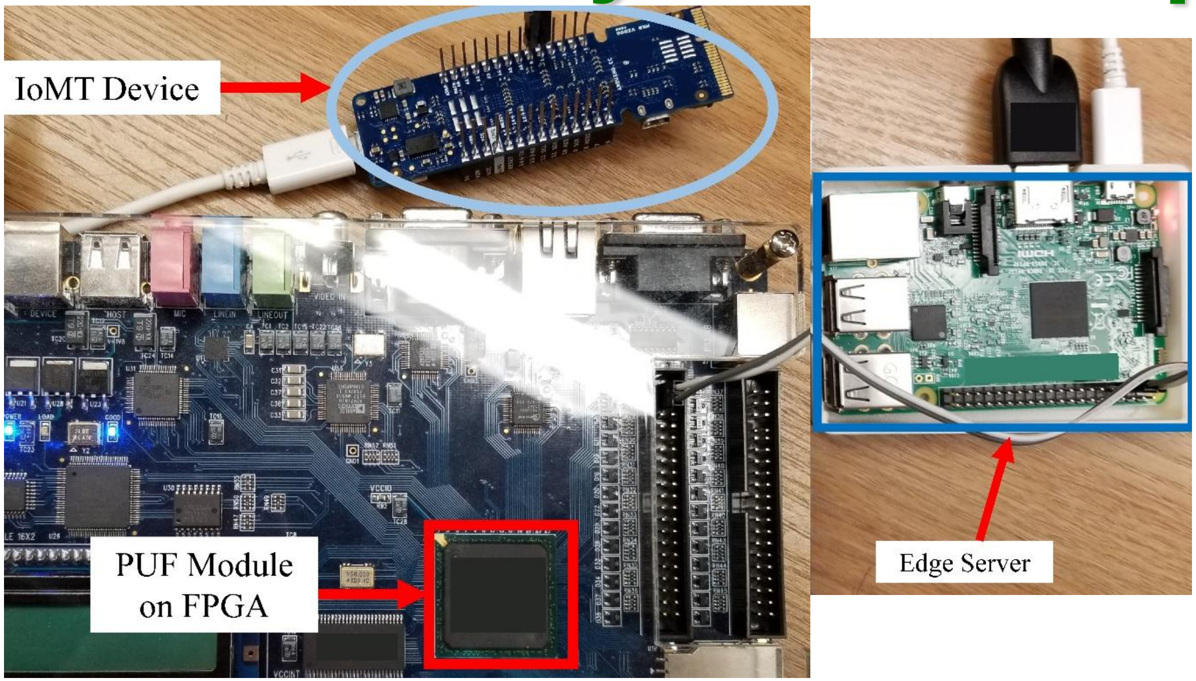


Source: V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, "PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things", *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 388--397.

IoMT Security – Our Proposed PMsec

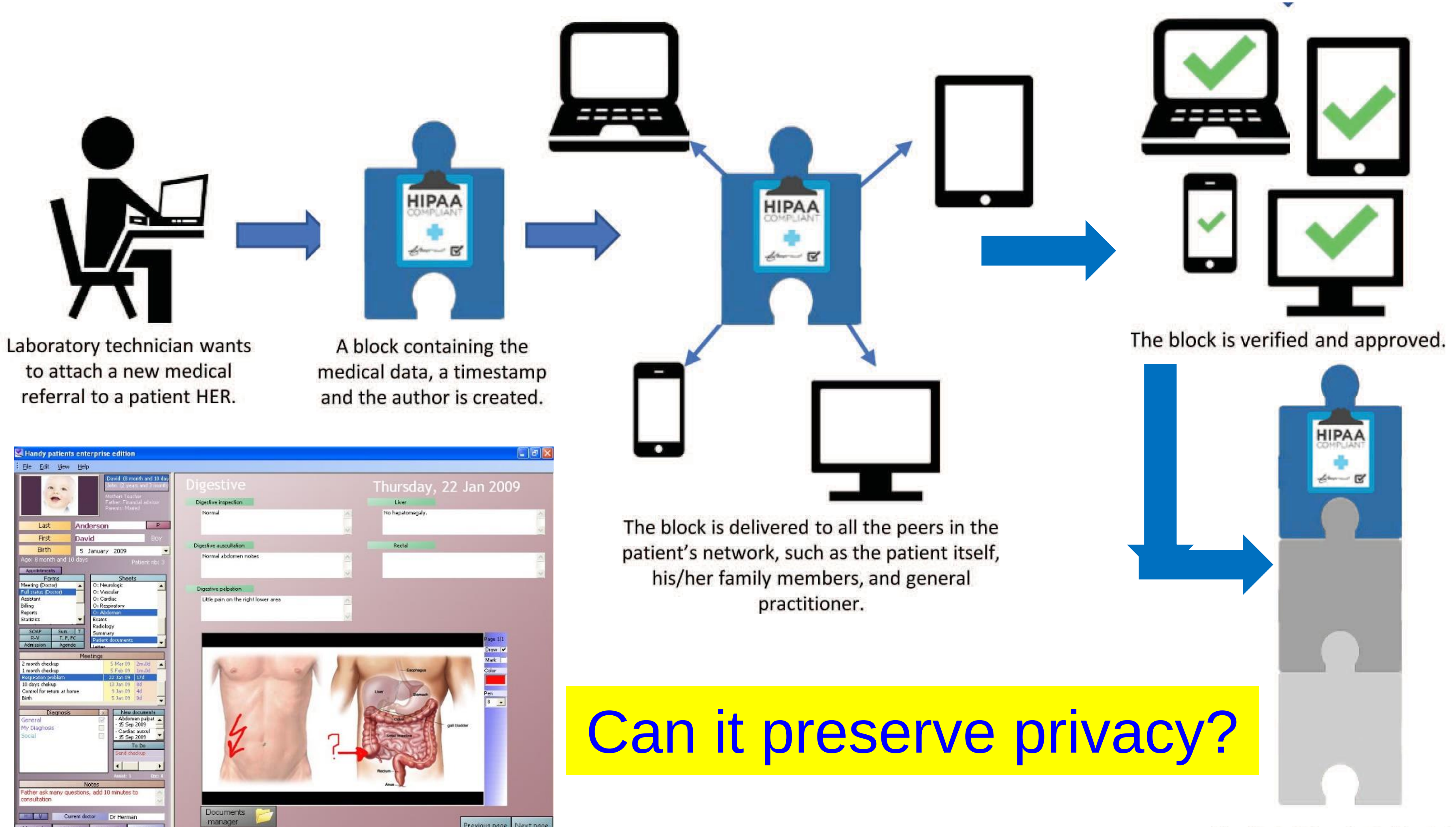


Average Power Overhead – ~ 200 μW

Proposed Approach Characteristics	Value (in a FPGA / Raspberry Pi Platform)
Time to Generate the Key at Server	800 ms
Time to Generate the Key at IoMT Device	800 ms
Time to Authenticate the Device	1.2 sec - 1.5 sec

Source: V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, “PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things”, *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 388--397.

Blockchain in Smart Healthcare



Can it preserve privacy?

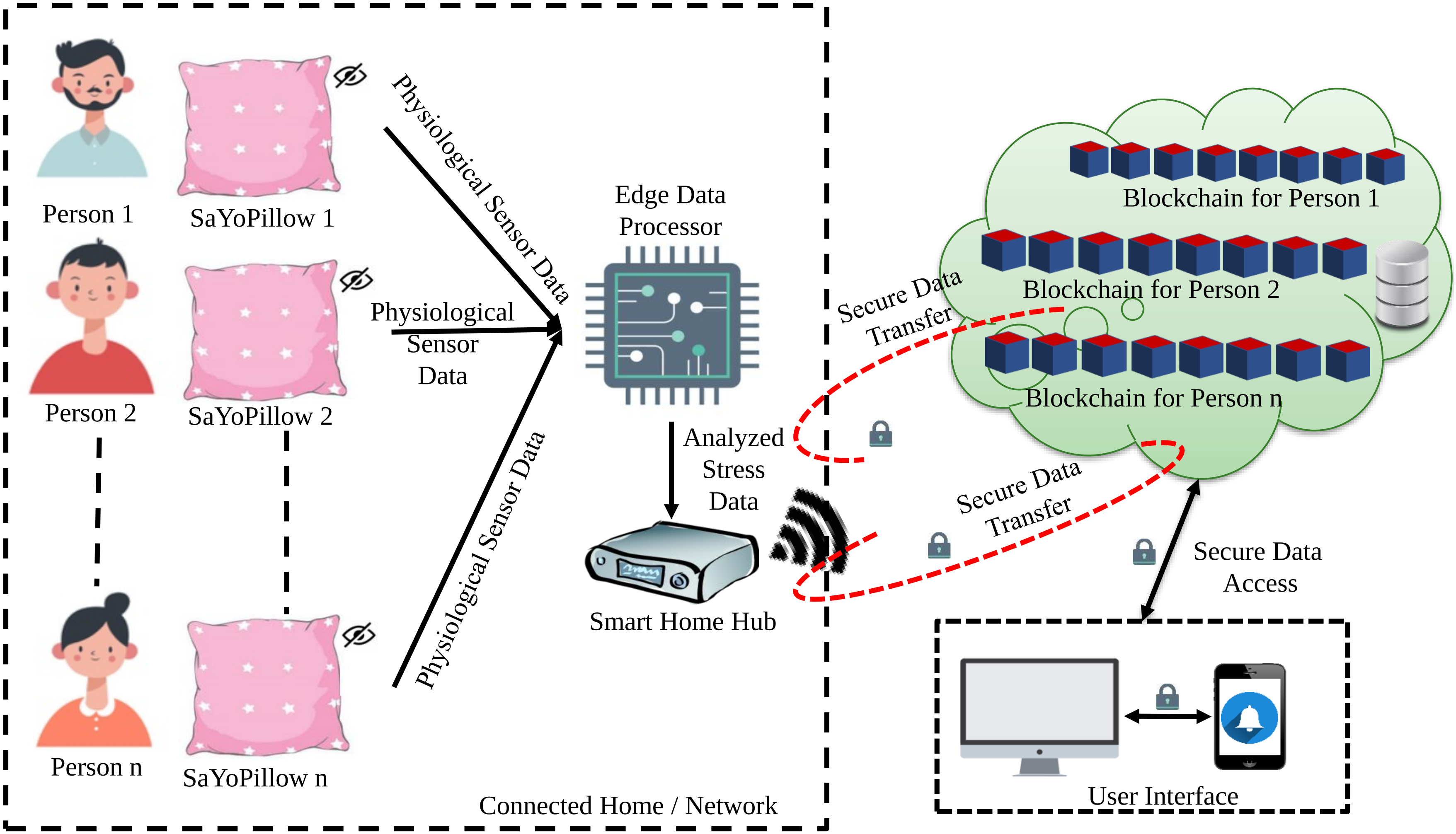
Source: C. Esposito, A. De Santis, G. Tortora, H. Chang and K. R. Choo, "Blockchain: A Panacea for Healthcare Cloud-Based Data Security and Privacy?," IEEE Cloud Computing, vol. 5, no. 1, pp. 31-37, Jan./Feb. 2018.

Traditional Versus Blockchain EHR

Health Information Exchange (HIE) Pain Points	Blockchain Opportunities
Establishing a Trust Network depends on the HIE as an intermediary to establish point-to-point sharing and "book-keeping" of what data was exchanged.	**Disintermediation of Trust** likely would not require an HIE operator because all participants would have access to the distributed ledger to maintain a secure exchange without complex brokered trust.
Cost Per Transaction, given low transaction volumes, reduces the business case for central systems or new edge networks for participating groups.	**Reduced Transaction Costs** due to disintermediation, as well as near-real time processing, would make the system more efficient.
Master Patient Index (MPI) challenges arise from the need to synchronize multiple patient identifiers between systems while securing patient privacy.	**Distributed framework for patient digital identities,** which uses private and public identifiers secured through cryptography, creates a singular, more secure method of protecting patient identity.
Varying Data Standards reduce interoperability because records are not compatible between systems.	**Shared data** enables near real-time updates across the network to all parties.
Limited Access to Population Health Data, as HIE is one of the few sources of integrated records.	**Distributed, secure access** to patient longitudinal health data across the distributed ledger.
Inconsistent Rules and Permissions inhibit the right health organization from accessing the right patient data at the right time.	**Smart Contracts** create a consistent, rule-based method for accessing patient data that can be permissioned to selected health organizations.

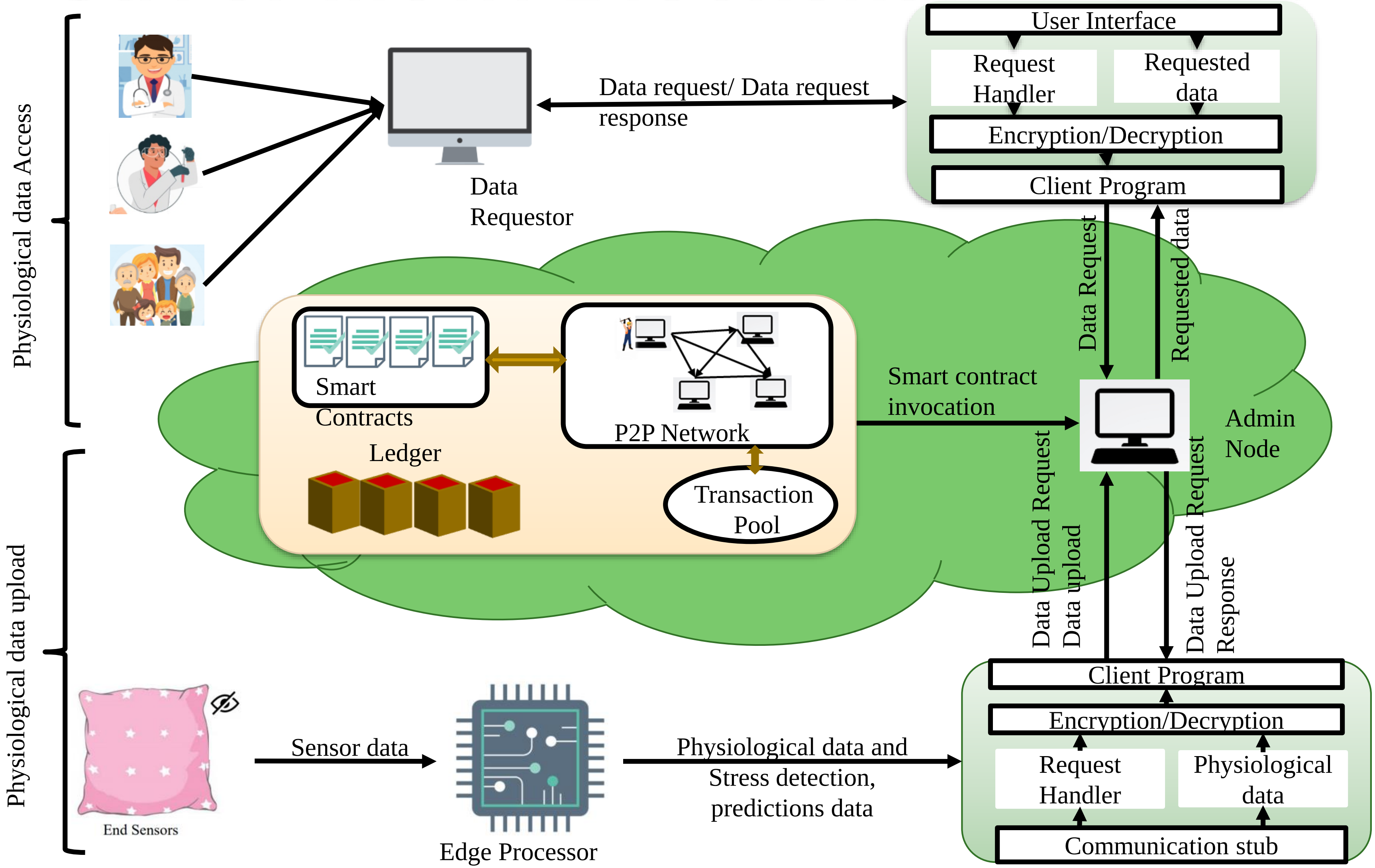
Source: Exploring the Use of Blockchain for EHRs, Healthcare Big Data, https://healthitanalytics.com/features/exploring-the-use-of-blockchain-for-ehrs-healthcare-big-data

Smart-Yoga Pillow (SaYoPillow) - Idea



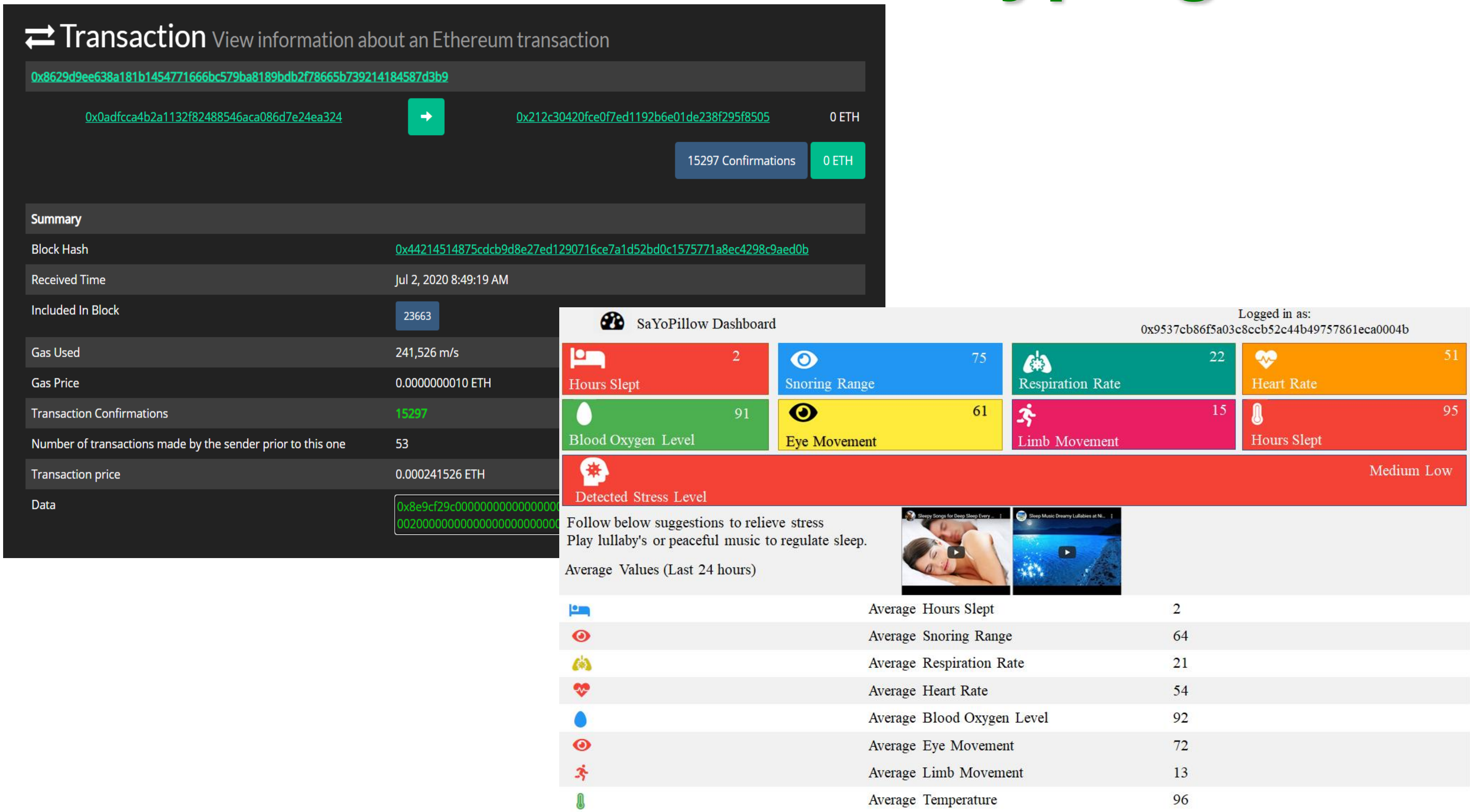
Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: A Blockchain-Enabled, Privacy-Assured Framework for Stress Detection, Prediction and Control Considering Sleeping Habits in the IoMT", *arXiv Computer Science*, arXiv:2007.07377, July 2020, 38-pages.

SaYoPillow: Blockchain Details



Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, “SaYoPillow: A Blockchain-Enabled, Privacy-Assured Framework for Stress Detection, Prediction and Control Considering Sleeping Habits in the IoMT”, *arXiv Computer Science*, arXiv:2007.07377, July 2020, 38-pages.

SaYoPillow: Prototyping



Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: A Blockchain-Enabled, Privacy-Assured Framework for Stress Detection, Prediction and Control Considering Sleeping Habits in the IoMT", *arXiv Computer Science*, arXiv:2007.07377, July 2020, 38-pages.

Conclusions and Future Research

Conclusions

- Healthcare has been evolving to Healthcare-Cyber-Physical-System (H-CPS) i.e. smart healthcare.
- Internet of Medical Things (IoMT) plays a key role smart healthcare.
- Smart healthcare can reduce cost of healthcare and give more personalized experience to the individual.
- IoMT provides advantages but also has limitations in terms of security, privacy, etc.

Future Research

- Machine learning (ML) models for smart healthcare needs research.
- Internet-of-Everything (IoE) with Human as active part as crowdsourcing need research.
- IoE will need robust data, device, and H-CPS security need more research.
- Security of IWMDs needs to have extremely minimal energy overhead to be useful and hence needs research.
- Integration of blockchain for smart healthcare need research due to energy and computational overheads associated with it.

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