Everything You Wanted to Know about Smart Healthcare

Expert Lecture –

Nalla Malla Reddy Engineering College (NMREC), Hyderabad, India,

07 Jan 2023

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Outline

- Healthcare → Smart Healthcare

- Smart Healthcare - Characteristics

- Smart Healthcare - Components

- Smart Healthcare - Examples

- Smart Healthcare – Challenges

- Smart Healthcare – Solutions of Challenges

- Smart Healthcare – Pharmaceutical Supply Chain

- Conclusions and Future Directions

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Healthcare
to
Smart Healthcare

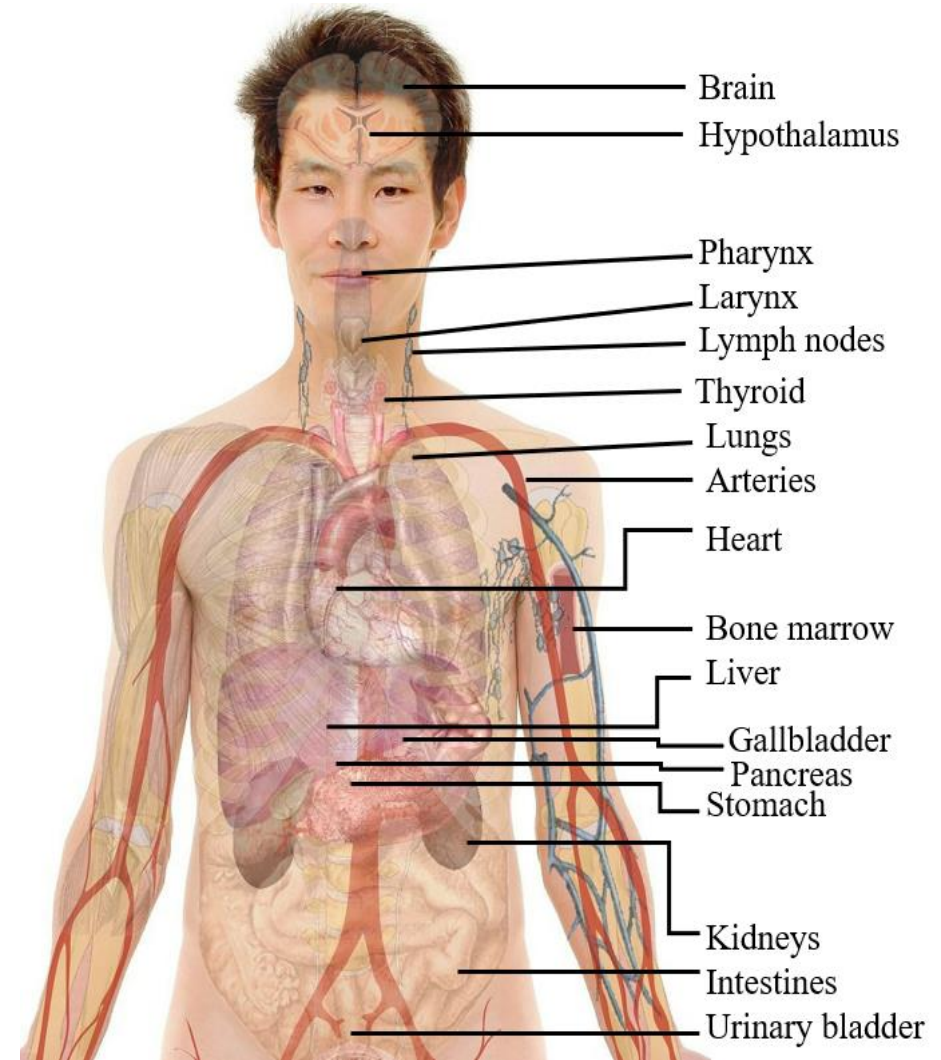Smart Healthcare -- Prof./Dr. Saraju Mohanty
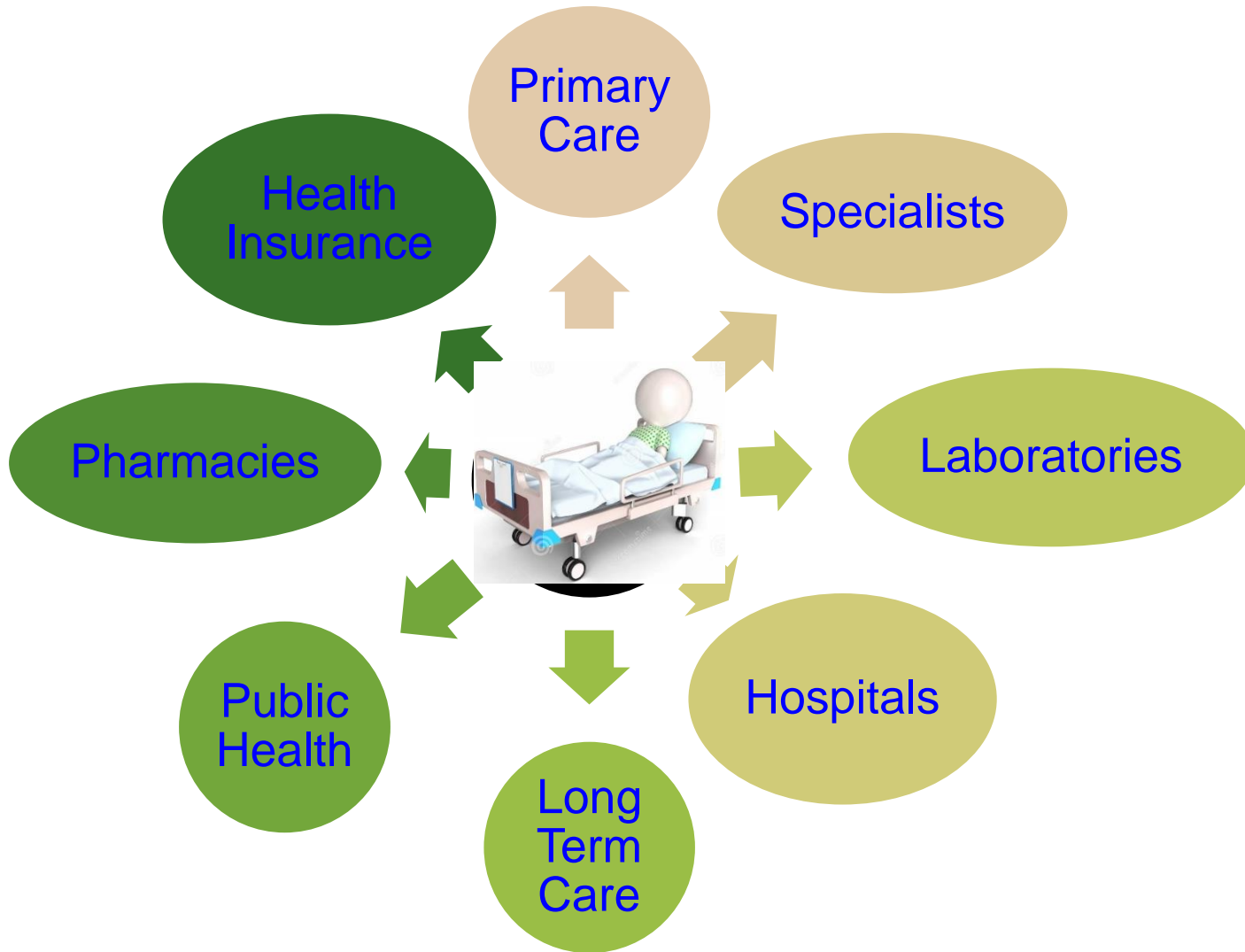
Human Body and Health

Human Body

- From an engineering perspective - 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.

Brain
Hypothalamus
Pharynx
Larynx
Lymph nodes
Thyroid
Lungs
Arteries
Heart
Bone marrow
Liver
Gallbladder
Pancreas
Stomach
Kidneys
Intestines
Urinary bladder

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Traditional Healthcare

Primary Care

Health Insurance

Specialists

Pharmacies

Laboratories

Public Health

Hospitals

Long Term Care

- ➢ Physical presence needed
- ➢ Deals with many stakeholders
- ➢ Stakeholders may not interact
- ➢ May not be personalized
- ➢ Not much active feedback
- ➢ Less effective follow-up from physicians

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Telemedicine

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

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Electronic Health (eHealth)
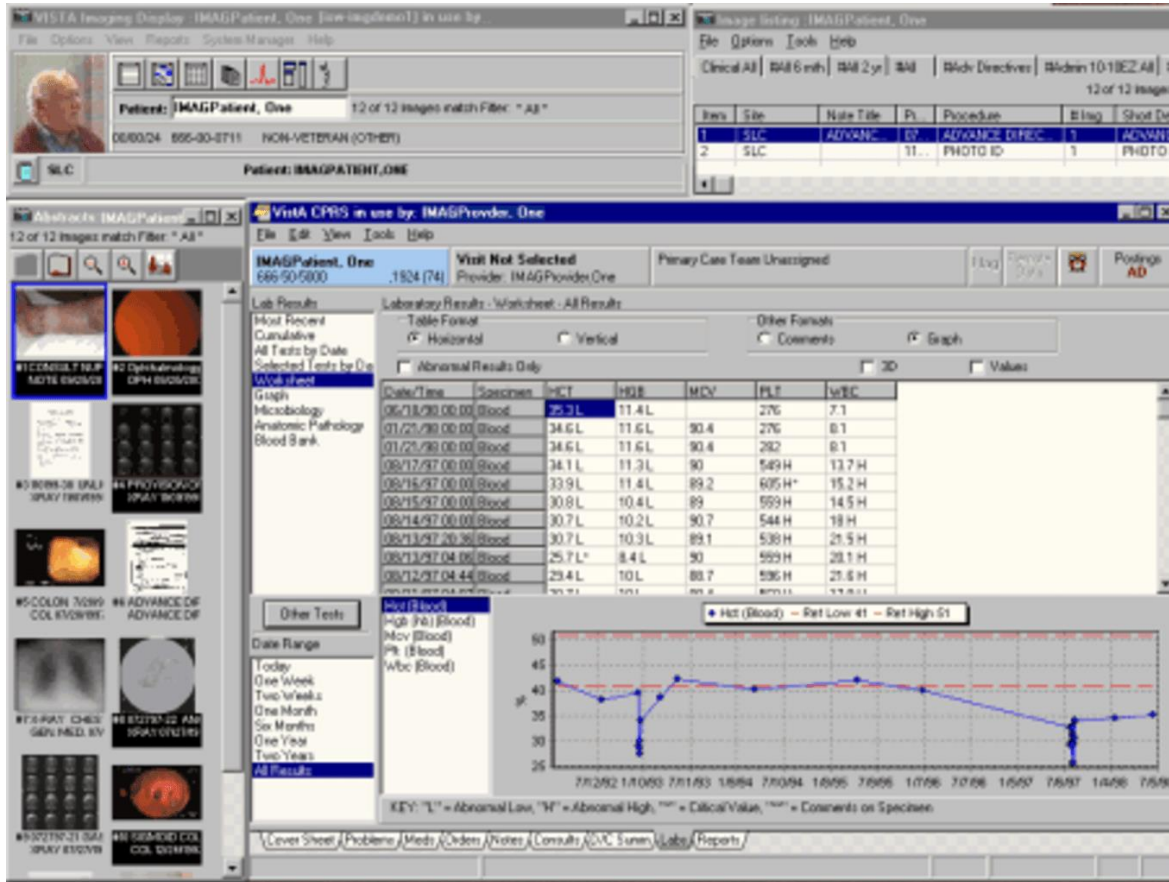
eHealth: The use of information technology to improve healthcare services.

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.

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Connected Health (cHealth)
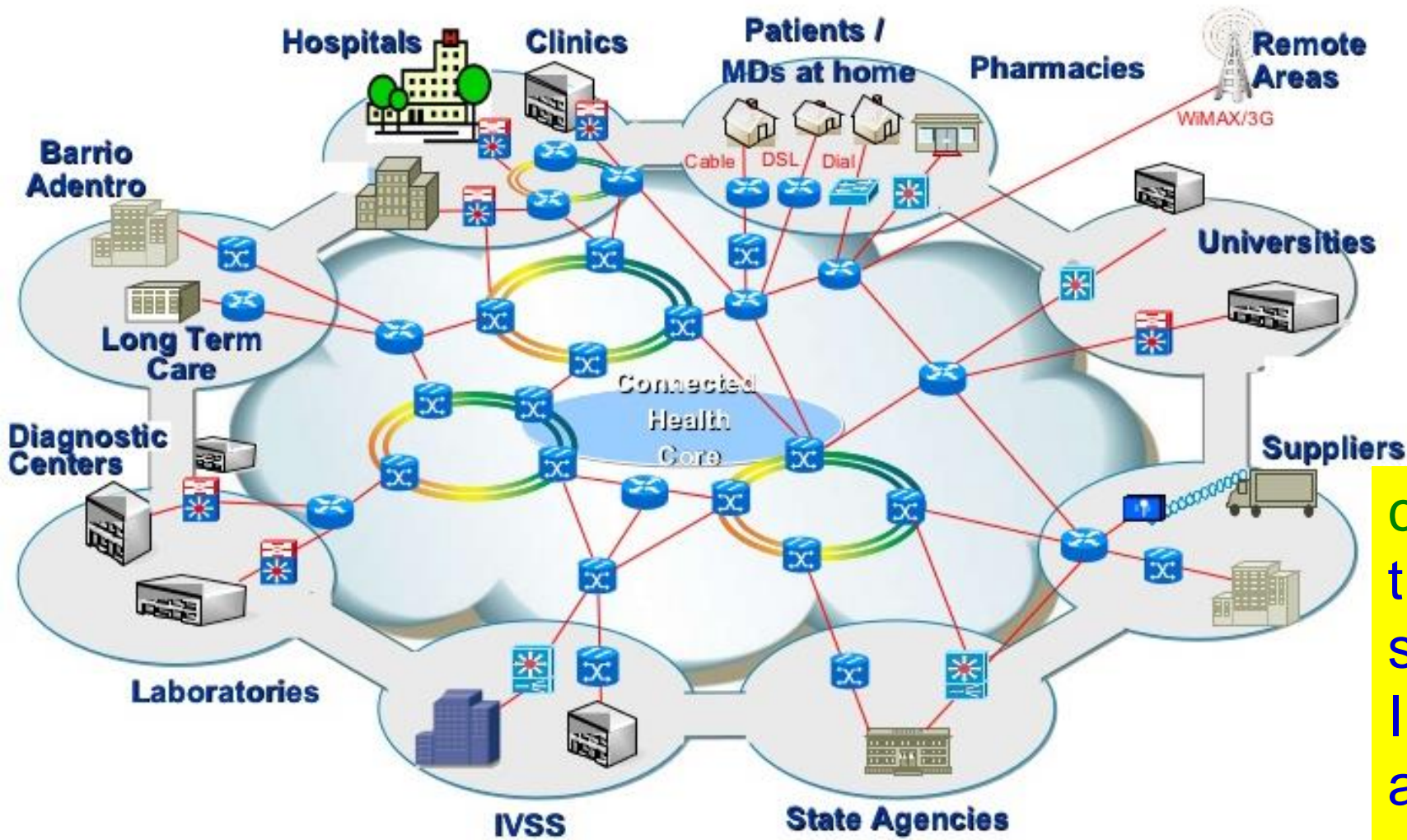
Source: https://www.slideshare.net/tibisay_hernandez/connected-health-venfinal

cHealth: Connections of the various healthcare stake holders through Internet to share appropriate data to better serve the patients.
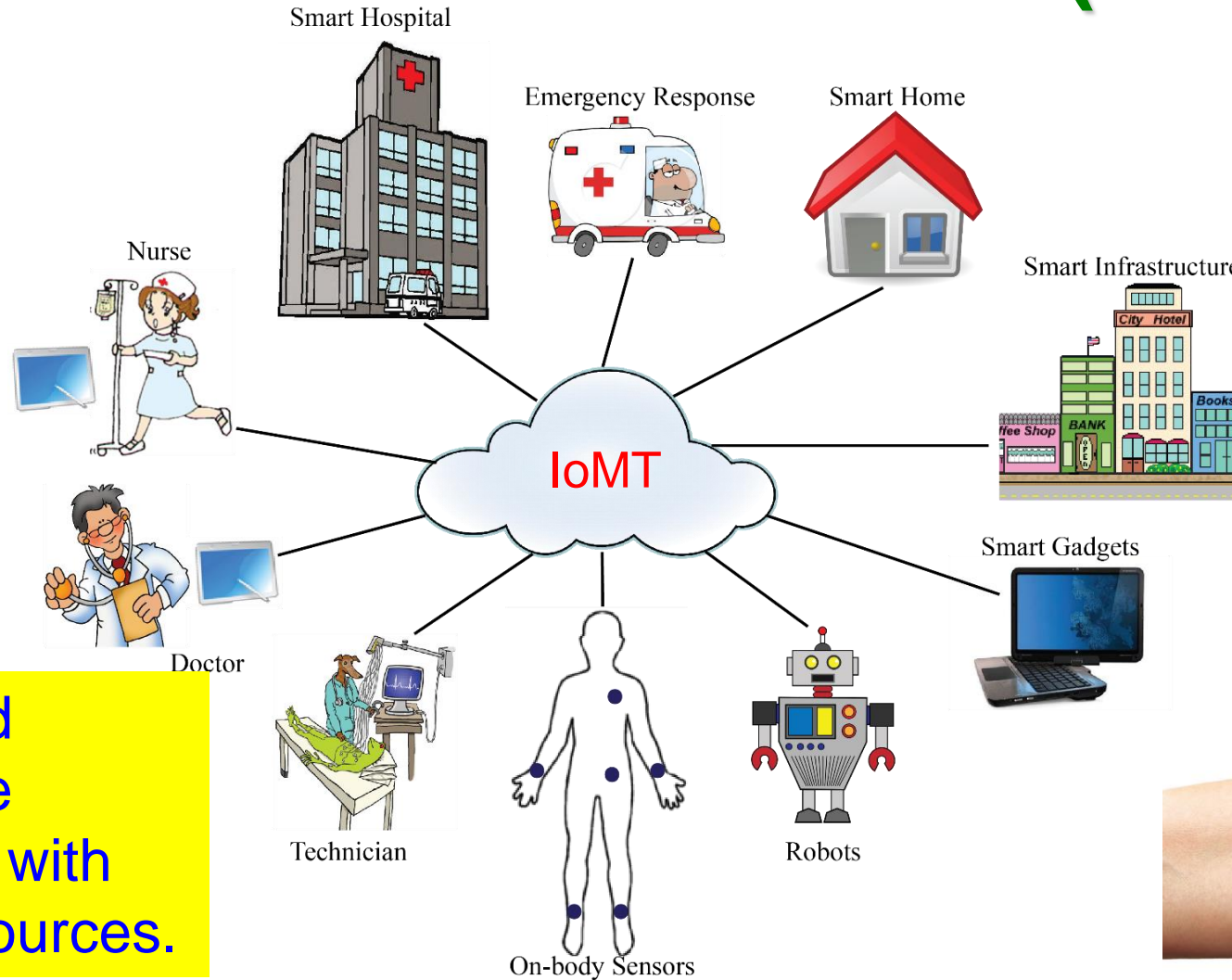
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Mobile Health (mHealth)

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.
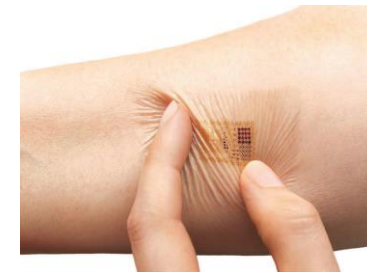
Smart Healthcare (sHealth)

Smart Hospital

Emergency Response

Smart Home

Nurse

Smart Infrastructure

Fitness Trackers

IoMT

Doctor

Headband with Embedded Neurosensors

Smart Gadgets

Technician

Robots

Embedded Skin Patches

On-body Sensors

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.

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Smart Healthcare - Applications

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

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

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

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What is Smart Healthcare?

Smart Healthcare

←

Conventional Healthcare

+ Body sensors

+ Information & Communication Technology (ICT)

+ Artificial Intelligence (AI)/ Machine Learning (ML)
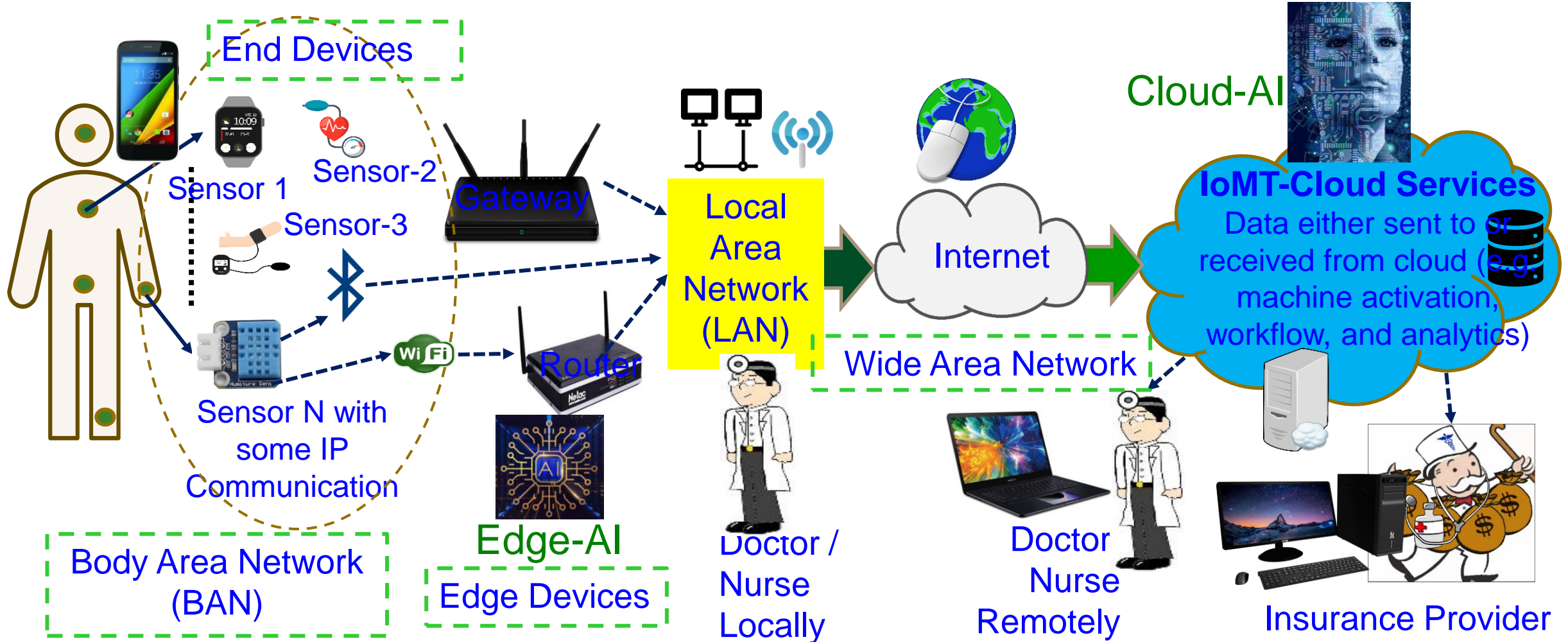
+ Smart Technology (BCI, VR, etc.)

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.

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Smart Healthcare – Healthcare CPS

End Devices

Sensor 1

Sensor-2

Sensor-3

Sensor N with some IP Communication

Gateway

Router

Body Area Network (BAN)

Edge-AI

Edge Devices

Local Area Network (LAN)

Internet

Wide Area Network

Cloud-AI

IoMT-Cloud Services
Data either sent to or received from cloud (e.g. machine activation, workflow, and analytics)

Doctor / Nurse Locally

Doctor Nurse Remotely

Insurance Provider

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

Source: S. P. Mohanty, Secure IoT by Design, Keynote, 4th IFIP International Internet of Things Conference (IFIP-IoT), 2021, Amsterdam, Netherlands, 5th November 2021.

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Wearable Medical Devices (WMDs)

Fitness Trackers

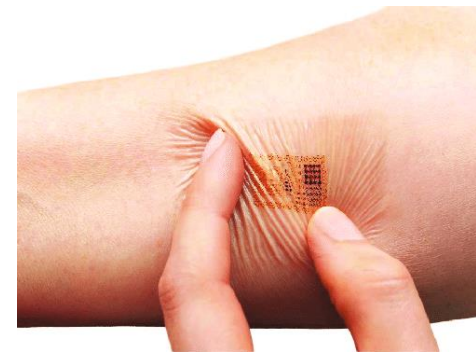Headband with Embedded Neurosensors

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

Medical grade smart watch to detect seizure

Insulin Pump

Source: https://www.webmd.com

Embedded Skin Patches

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Implantable Medical Devices (IMDs)

Pill Camera

Brain Pacemaker

electrode

pacemaker

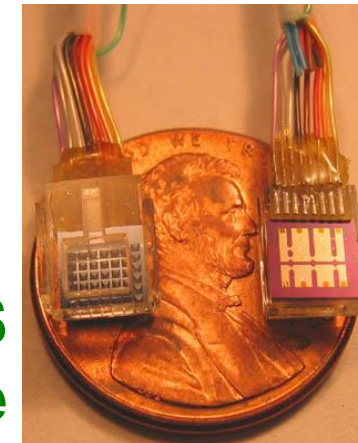| Image Sensors			
Processor	Battery	LED	Antenna
RF Transmitter		Electromagnet	
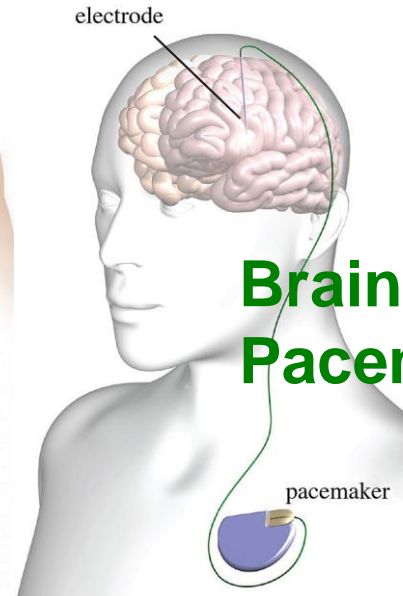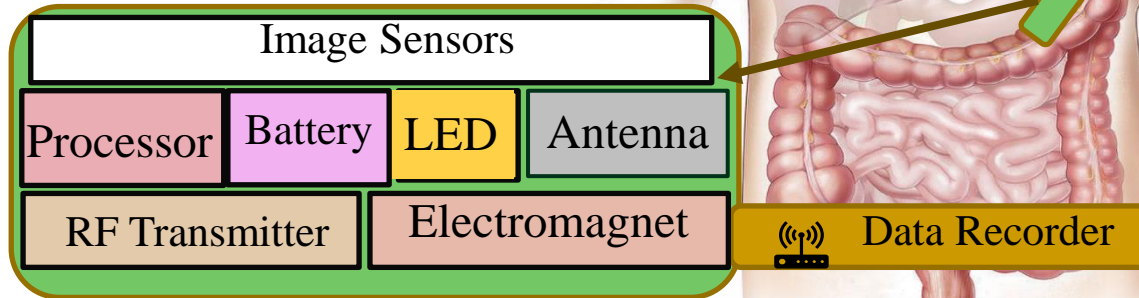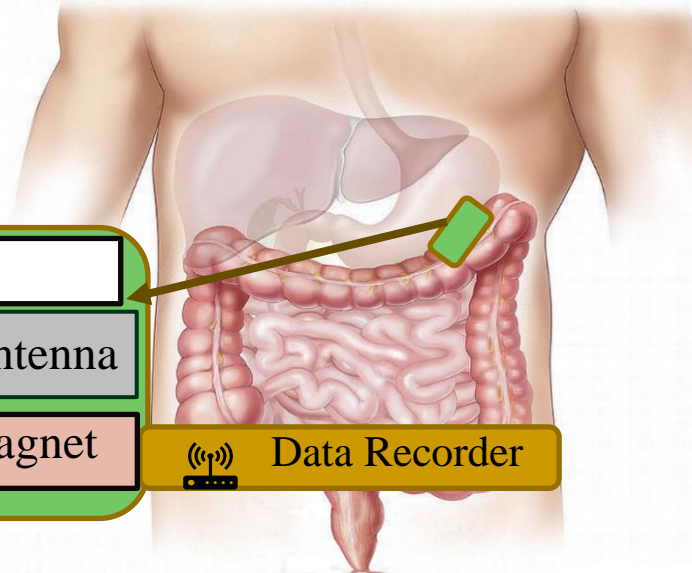
📶 Data Recorder

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

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Smart Healthcare – 7Ps

7P

Participatory

Persuasive

Predictive

Personalized

Preventative

Programmable

Perpetual

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.

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Smart Healthcare - 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
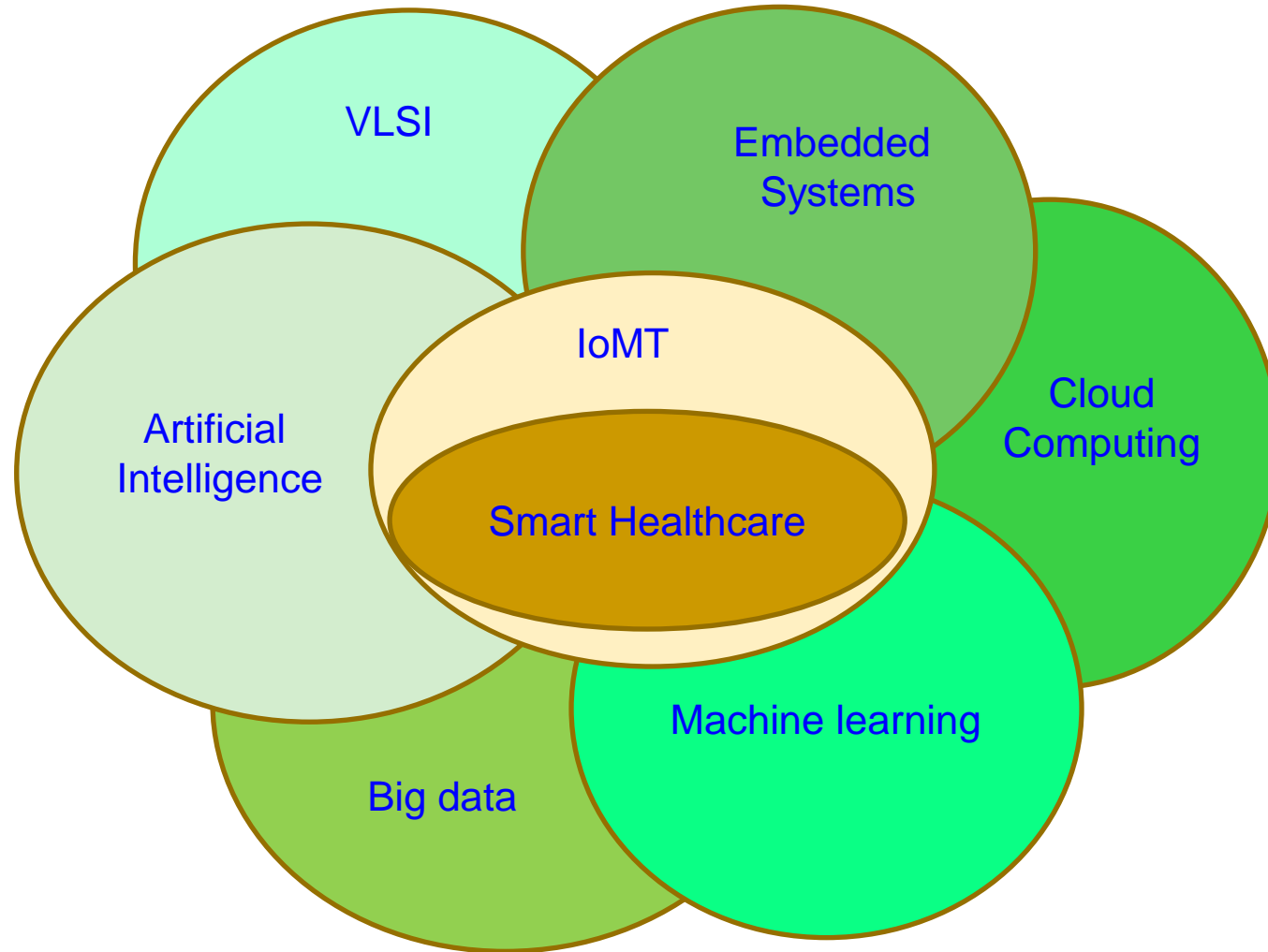- Scale, data volume and performance

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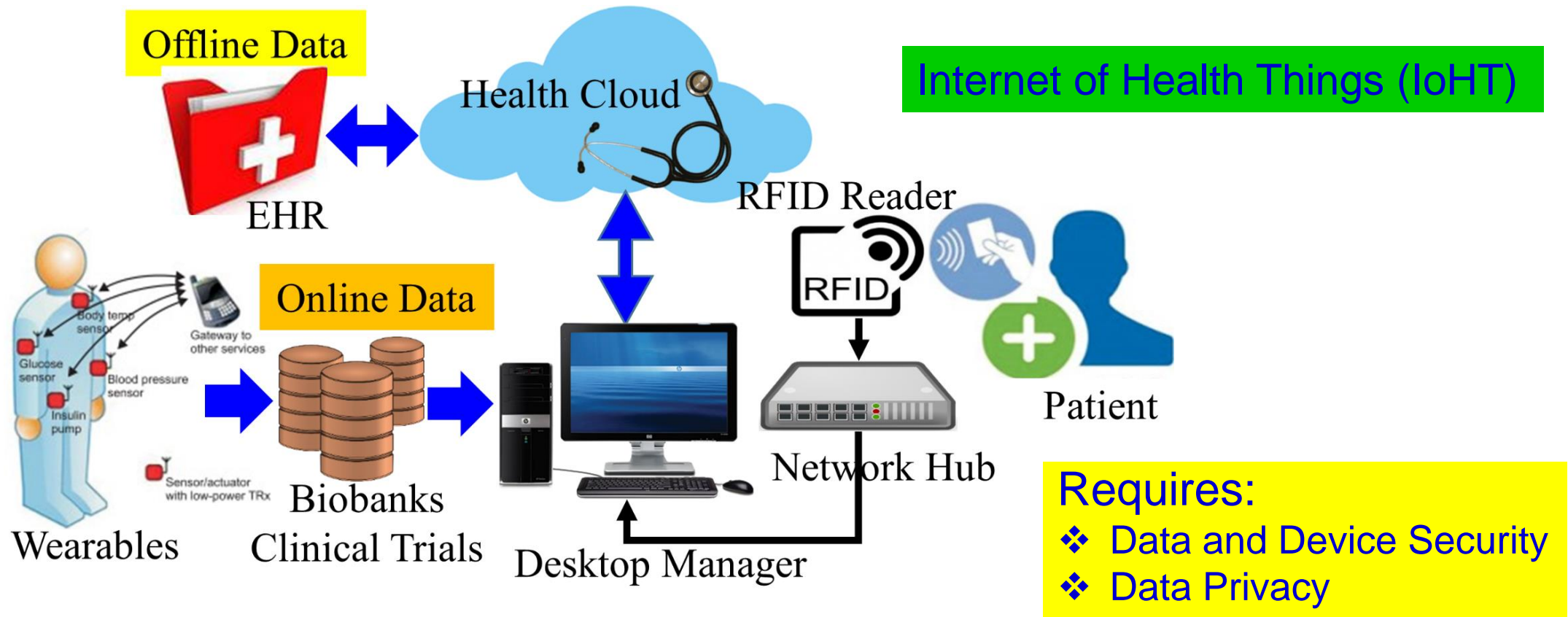- Mobile hesitation
- Security policy compliance

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.

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Smart Healthcare - Components
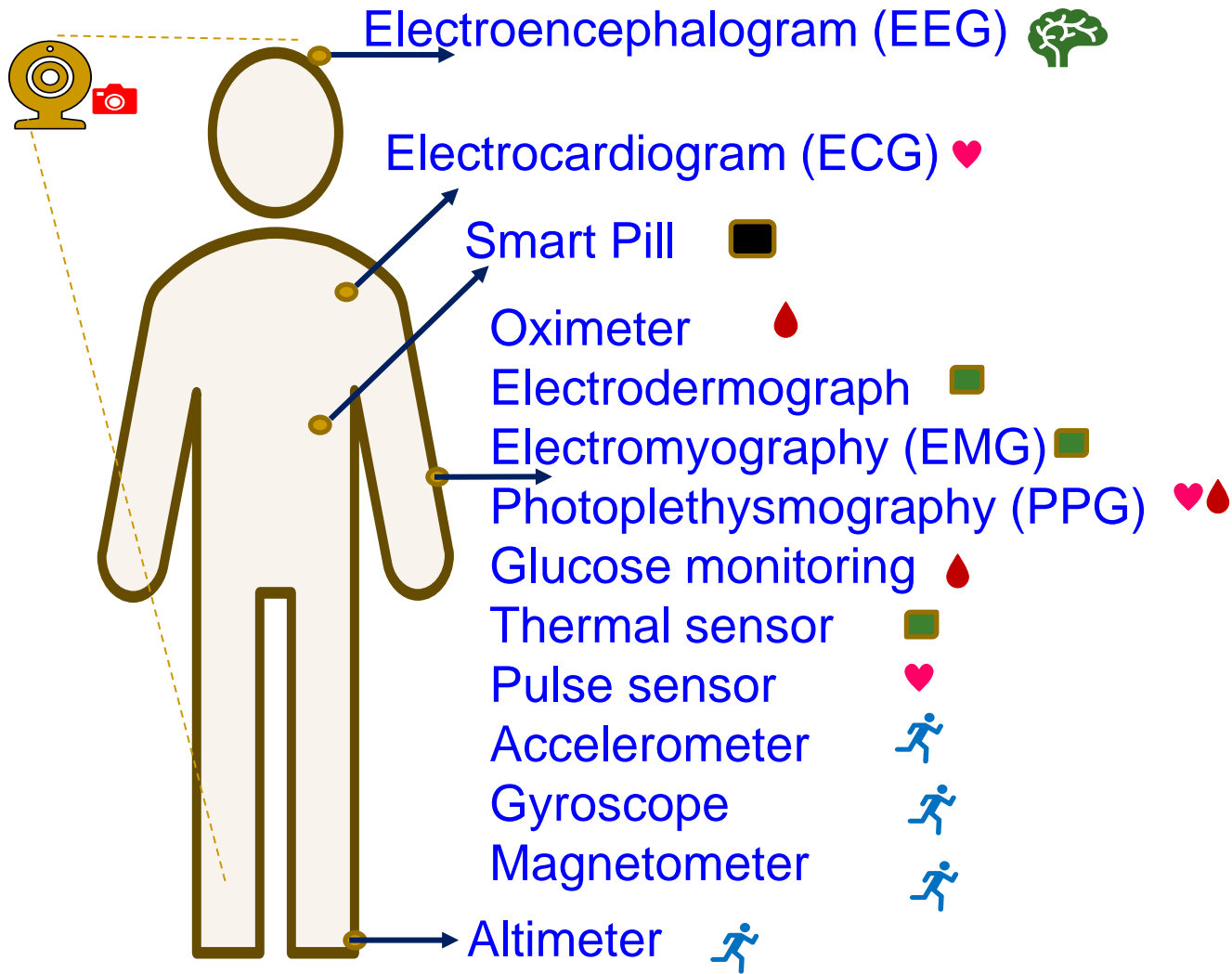
Smart Healthcare - Verticals

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Internet of Medical Things (IoMT)

Offline Data

Health Cloud

EHR

Internet of Health Things (IoHT)

RFID Reader

RFID

Online Data

Body temp sensor

Glucose sensor

Blood pressure sensor

Insulin pump

Gateway to other services

Sensor/actuator with low-power TRx

Wearables

Biobanks Clinical Trials

Desktop Manager

Network Hub

Patient

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

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Smart Healthcare Sensors

Electroencephalogram (EEG)

Electrocardiogram (ECG)

Smart Pill

Oximeter

Electrodermograph

Electromyography (EMG)

Photoplethysmography (PPG)

Glucose monitoring

Thermal sensor

Pulse sensor

Accelerometer

Gyroscope

Magnetometer

Altimeter

Types of Sensors

Brain related applications

Imaging applications

Heart related applications

Skin related applications

Blood related applications

Ingestible sensors

Motion Detection

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Photoplethysmograph (PPG)

Green LED - 540 nm wavelength
– Preferred for wearables

Source: https://www.wareable.com/fitbit/fitbit-red-light-optical-sensor-technology-2034

The body absorbs green really well, it's great for reducing signal distortion, but it doesn't penetrate deep. A lot of it is absorbed by your body so you don't get anything deeper than heart rate.

Red LED - 645 nm wavelength
- Preferred for hospitals and health industry

Source: https://willem.com/blog/2017-11-15_collecting-health-data-with-biostrap/

The body is a poor absorber of red light allowing the light to pass much deeper into the body and a larger volume of tissues to help provide more insightful data and could lead to improved accuracy with biometric data like heart rate.

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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.

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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 – AI/ML is Key

AI Role Includes:
- Automatic diagnosis
- Disease predication
- Diet prediction
- Pandemic projection
- Automatic prescription

Source: Robert Pearl, "Artificial Intelligence In Healthcare: Separating Reality From Hype", 13 Mar 2018, *https://www.forbes.com/sites/robertpearl/2018/03/13/artificial-intelligence-in-healthcare/?sh=598aa64d1d75*
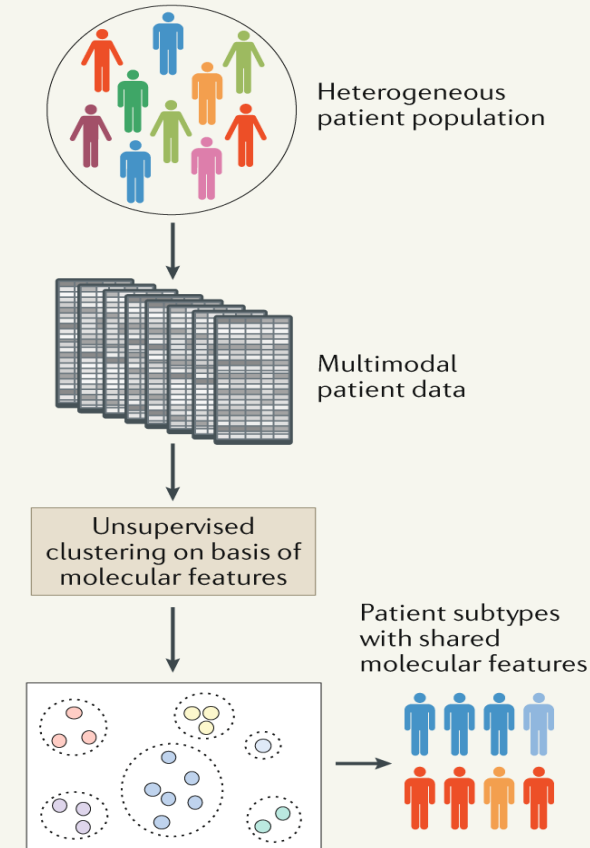
Smart Healthcare – ML …
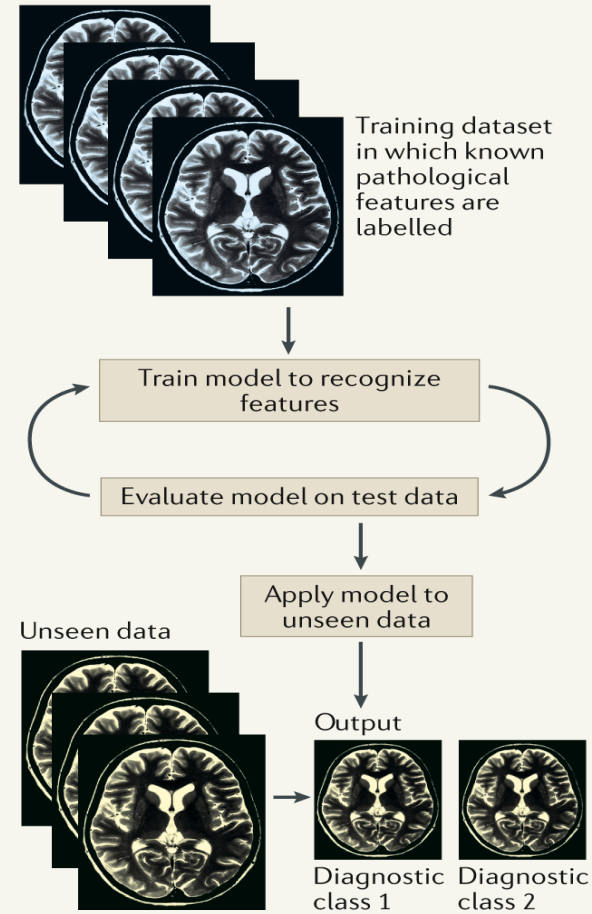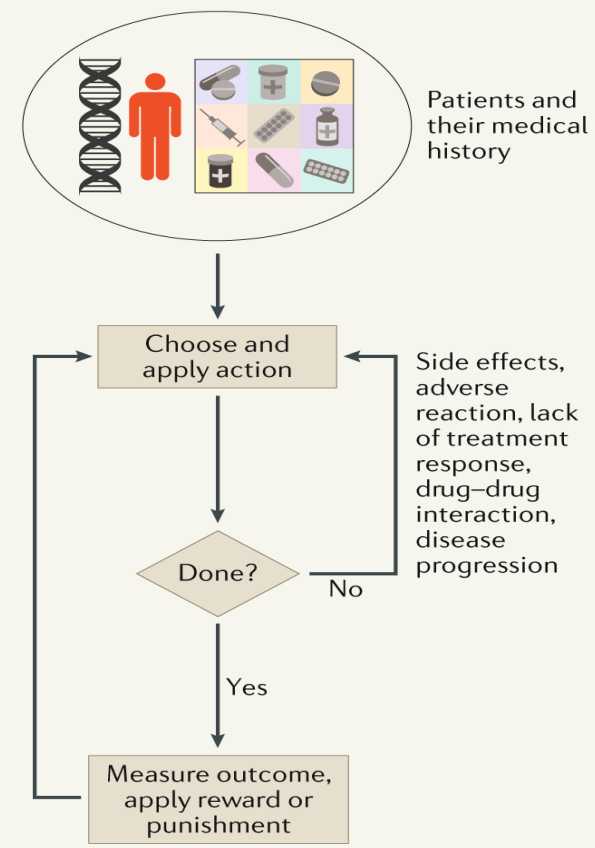
Source: Myszczynska, M.A., Ojamies, P.N., Lacoste, A.M.B. *et al.* Applications of machine learning to diagnosis and treatment of neurodegenerative diseases. *Nat Rev Neurol* **16,** 440–456 (2020). https://doi.org/10.1038/s41582-020-0377-8

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Brain Computer Interface (BCI)

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/
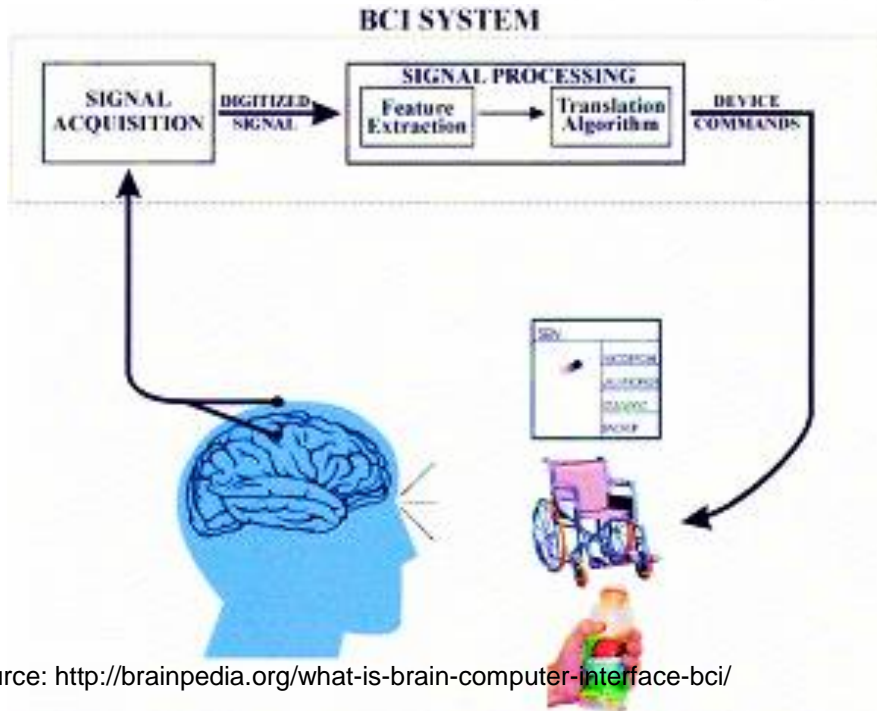
BCI Allows paralysis patients to Type

```
                        BCI Types

        Based on                      Based on
        Location                      Signal

  Non-      Semi-
  invasive  invasive  Invasive    EEG   MEG   fNIR   fMRI
```

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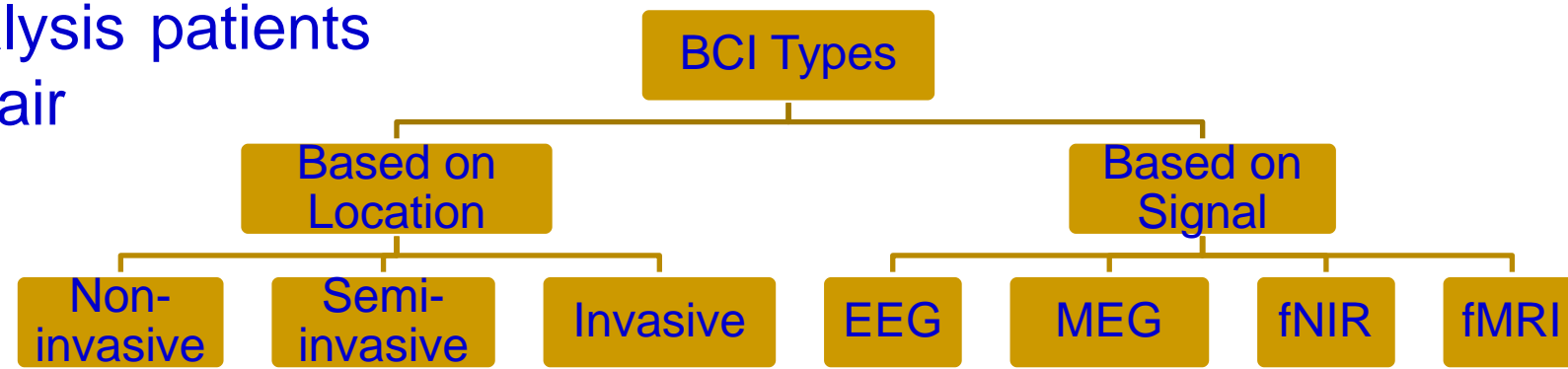
Virtual Reality in Healthcare

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 Data Gathering (Diet Dataset, Healthcare Dataset)

Last-Mile Logistics (Package Pickup Delivery)

Crowdsourcing for Smart Cities

Urban Data Gathering (Bike Data, Energy Usage Data)

City Service Monitoring (Park Maintenance, Waste Disposal)

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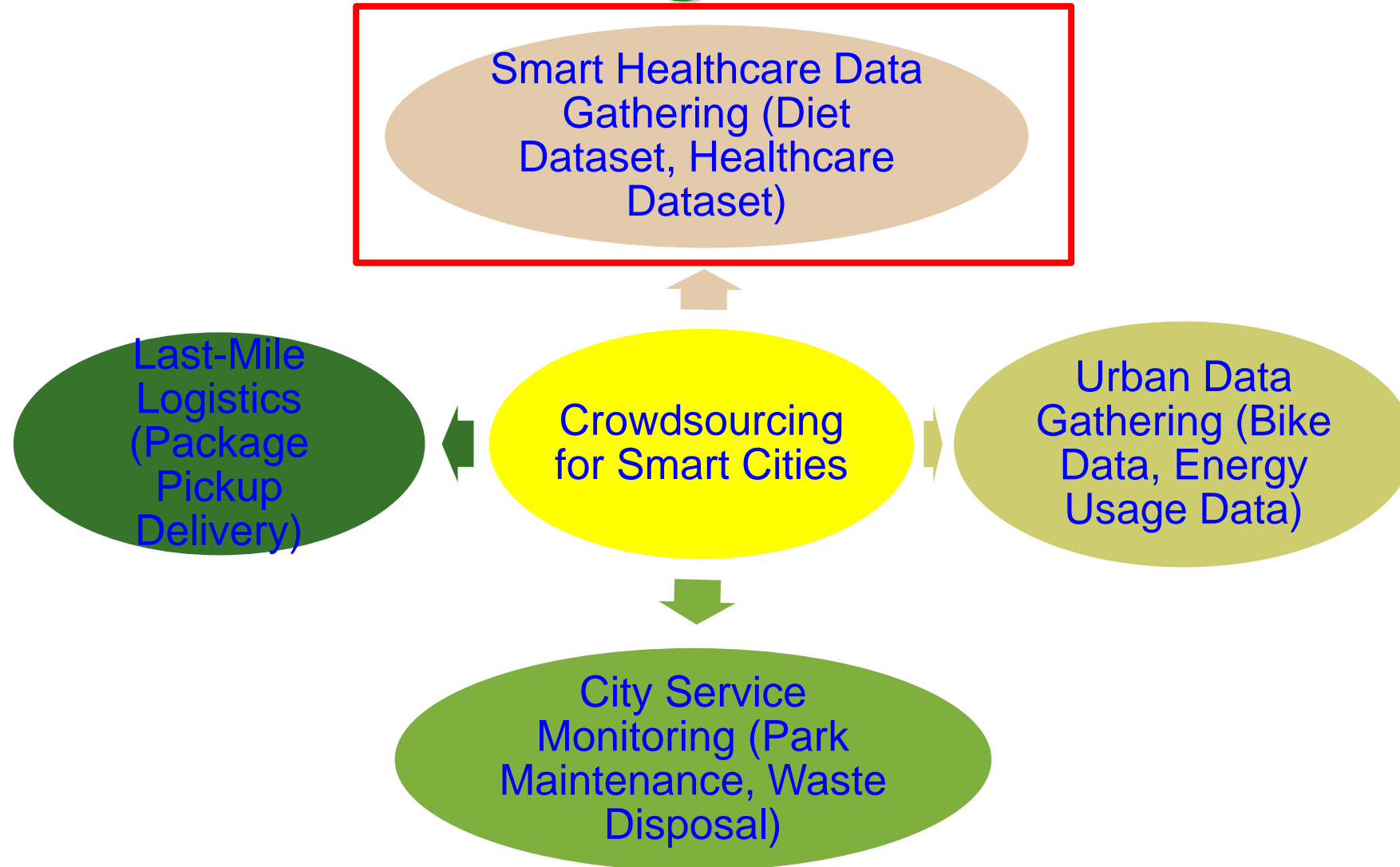
Smart Healthcare – Specific Examples

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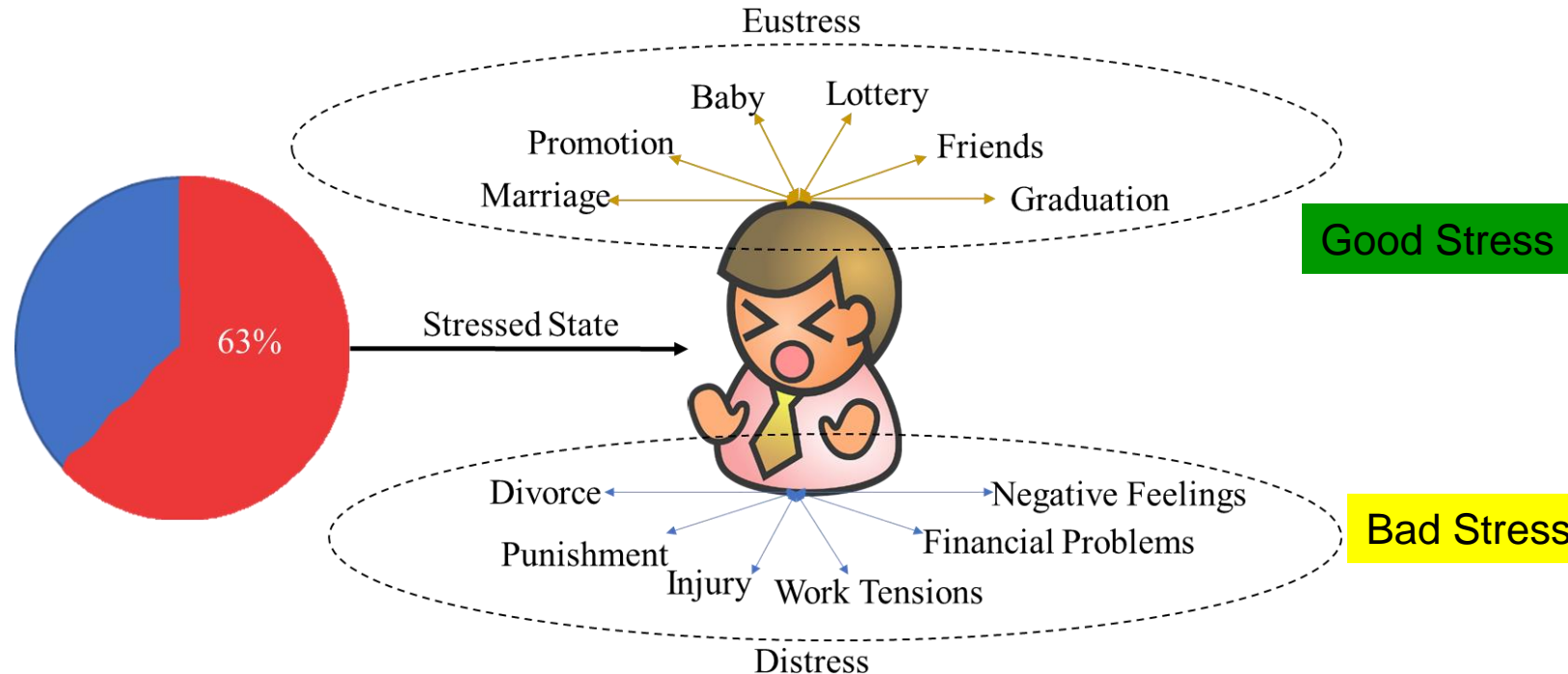
- ❑ Stress is the relationship between a person and a situation, which adversely impacts the happiness and health of the sufferer or physiological reactions.
- ❑ Stress can be divided into two parts: stressor and reaction.
- ❑ Stressor is the activity or effect that triggers a change in the physiological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

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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/

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Stress Monitoring and Control is Needed

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

Sudden encounter with **stress**
→Brain floods **body** with chemicals and hormones (adrenaline and cortisol)

Distress

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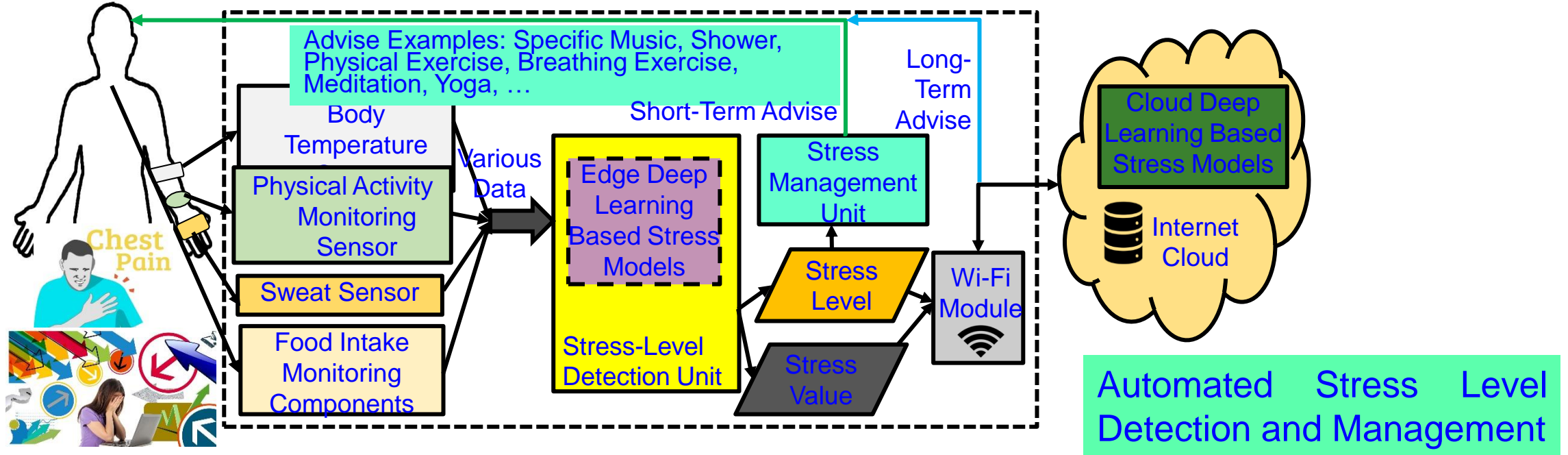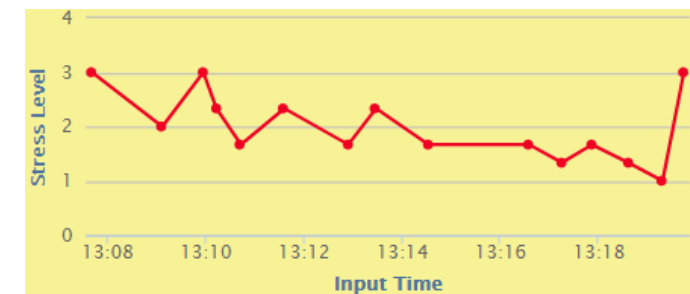➢ A weakened immune system, leading to more vulnerable to infections

Eustress

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Stress Monitoring & Control – Our Vision

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 °F	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

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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.

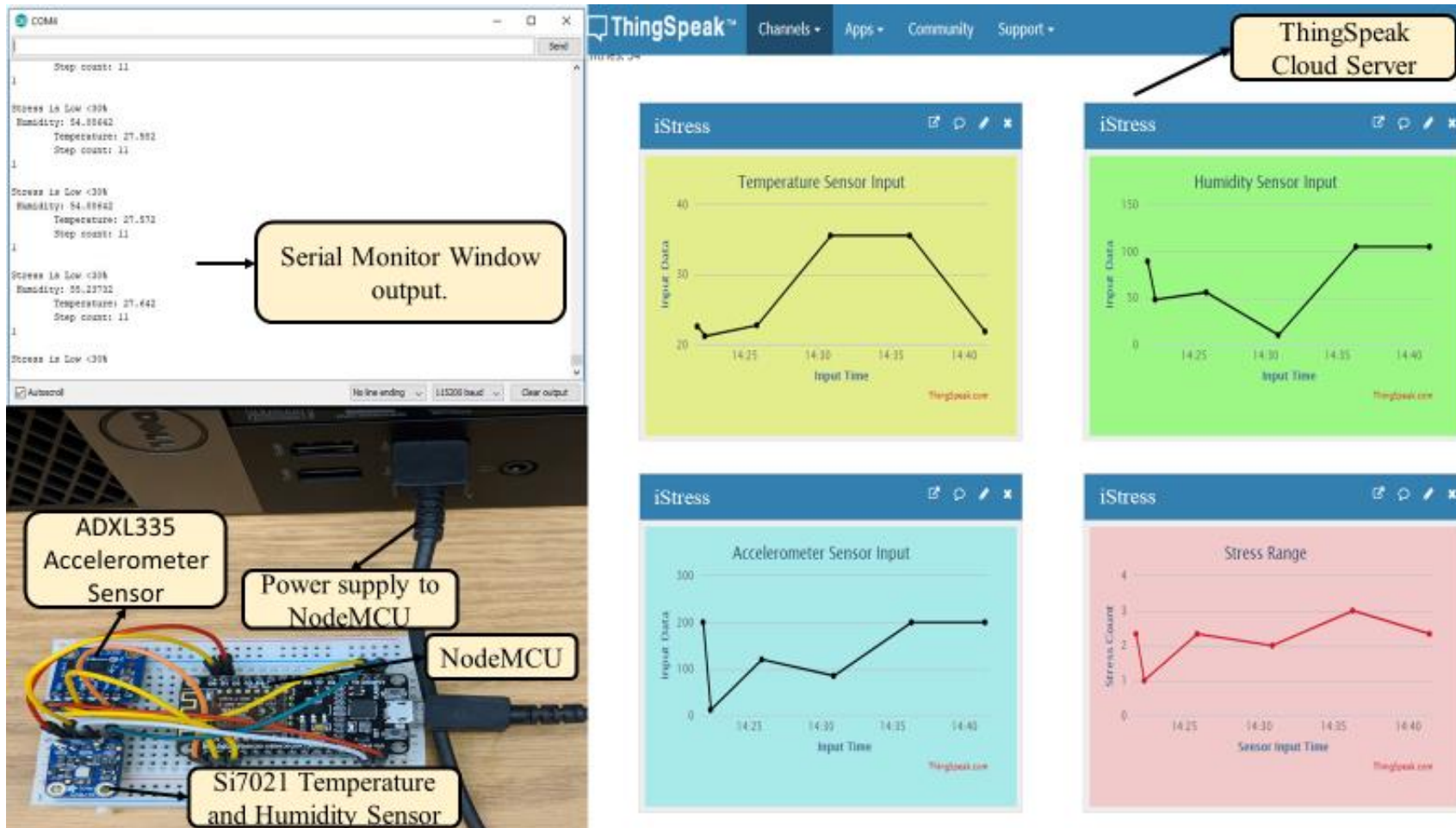# Stress-Lysis: From Physiological Signals
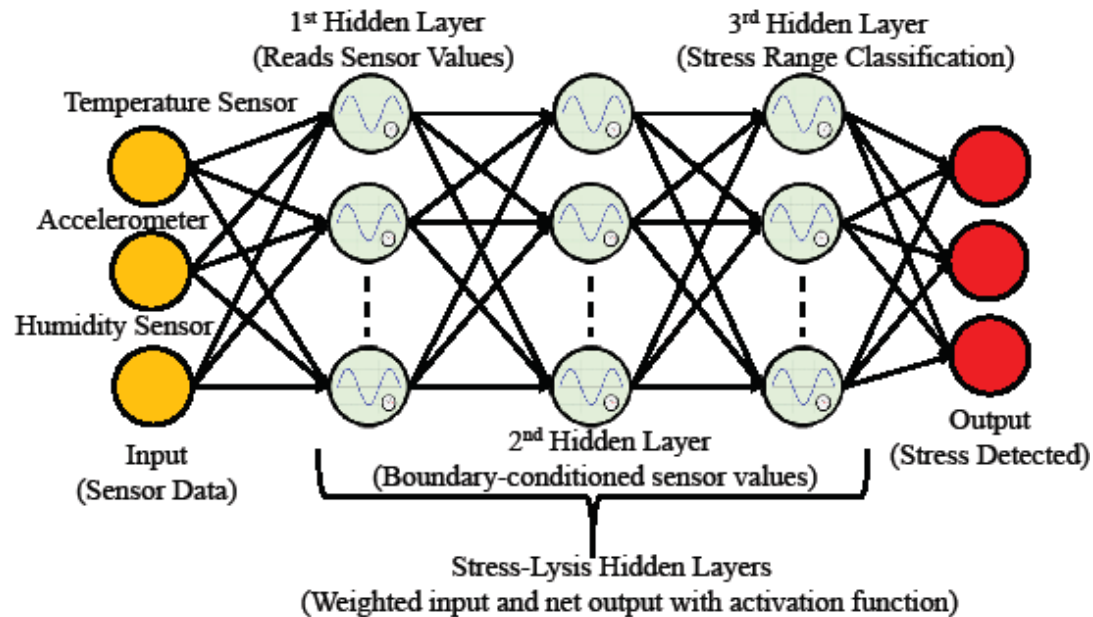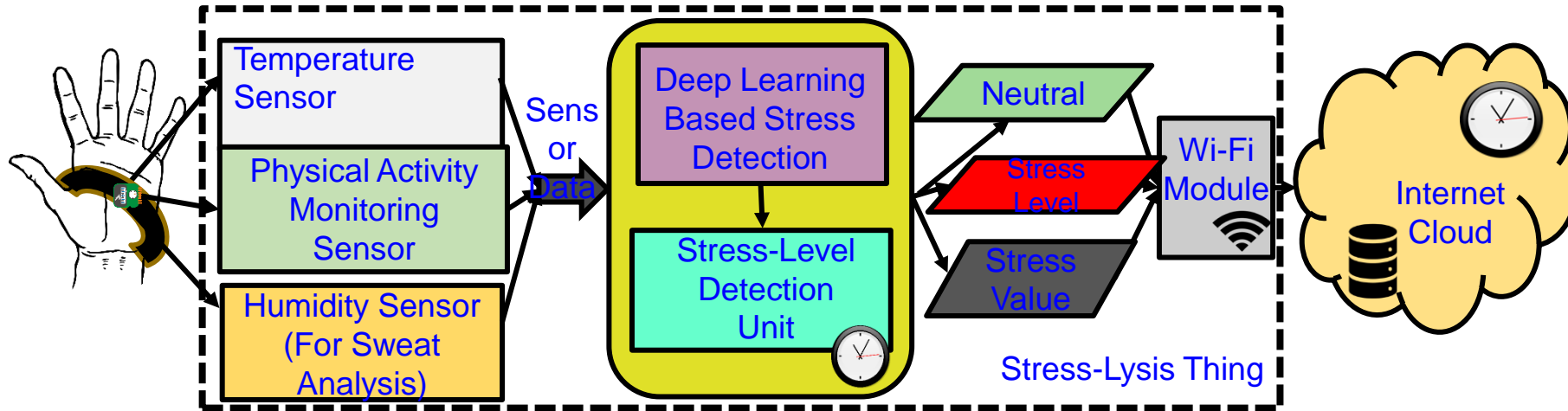
Stress-Lysis - DNN has been trained with a total of 26,000 samples per dataset and has accuracy upto 99.7%.

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: Experiments

Serial Monitor Window output.

ADXL335 Accelerometer Sensor

Power supply to NodeMCU

NodeMCU

Si7021 Temperature and Humidity Sensor

ThingSpeak Cloud Server

Stress-Lysis - DNN has been trained with a total of 26,000 samples per dataset and has accuracy upto 99.7%.

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.
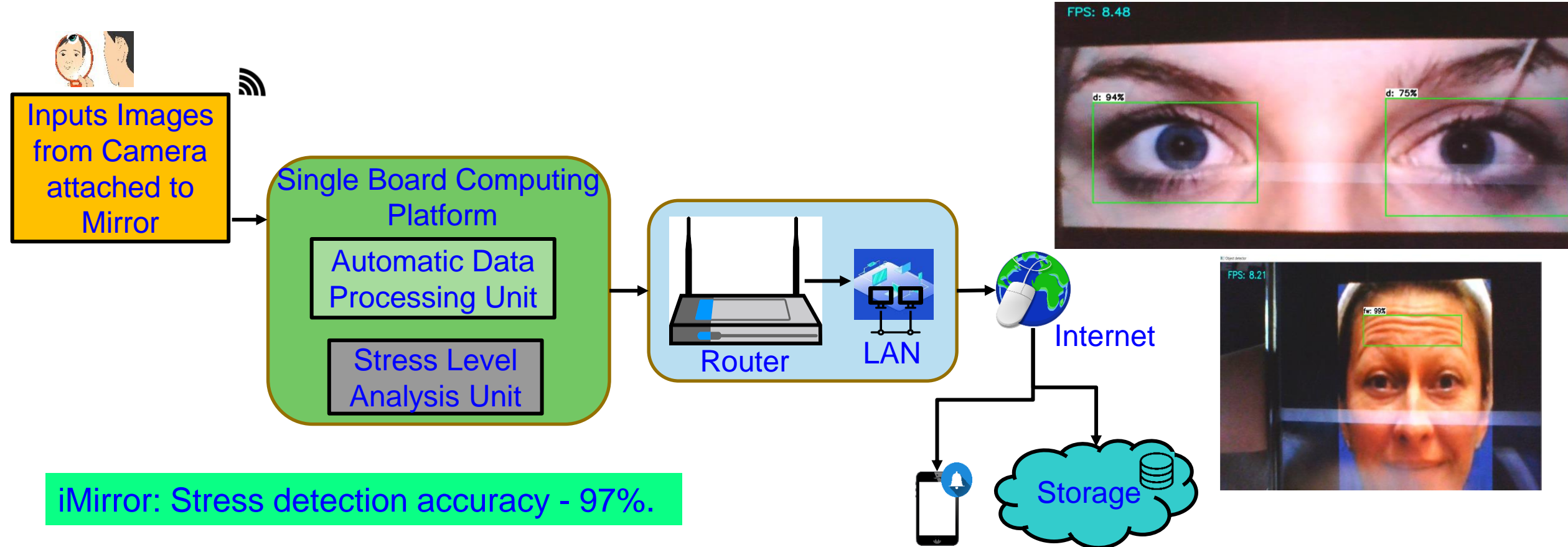
iMirror: Our Smart Mirror for Stress Detection from Facial Features

Inputs Images from Camera attached to Mirror

Single Board Computing Platform

Automatic Data Processing Unit

Stress Level Analysis Unit

Router

LAN

Internet

Storage

FPS: 8.48

d: 94%   d: 75%

FPS: 8.21

fw: 99%

iMirror: Stress detection accuracy - 97%.

Source: L. Rachakonda, P. Rajkumar, **S. P. Mohanty**, and E. Kougianos, "iMirror: A Smart Mirror for Stress Detection in the IoMT Framework for Advancements in Smart Cities", *Proceedings of the 6th IEEE Smart Cities Conference (ISC2)*, 2020.
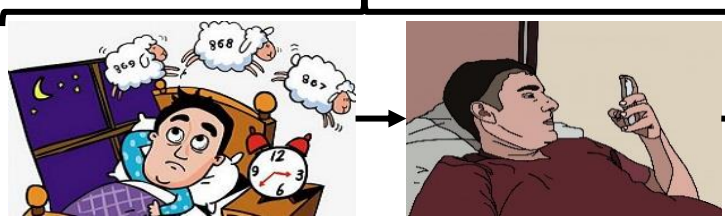
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07 Jan 2023

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Smart-Yoga Pillow (SaYoPillow) - Sleeping Pattern

Person On Pillow:
Physiological Sensor Data Monitoring Starts

Person Off Pillow:
Physiological Sensor Data Monitoring Ends

Period 1. Lying on bed but not Sleeping

Period 3: Drift from Wakefulness to Sleep
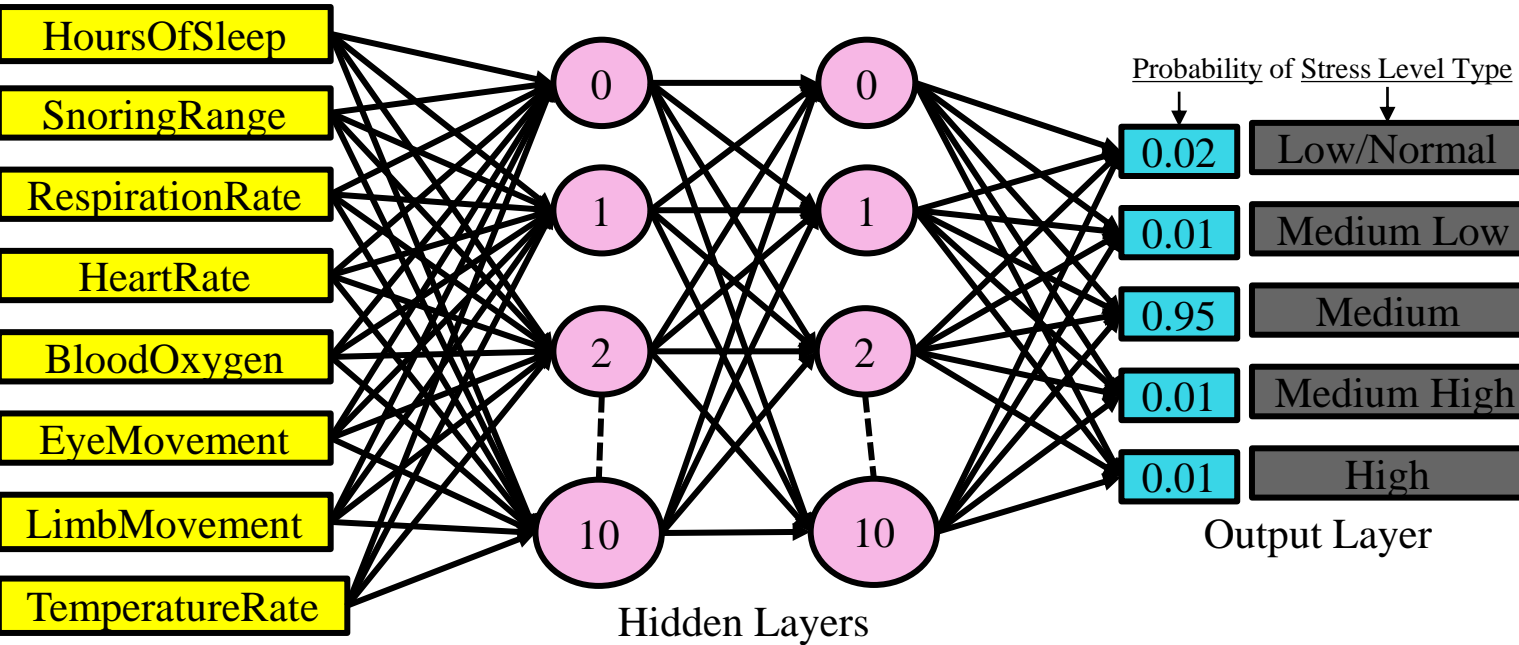
Period 5: Awake Person

Period 2: Trying to Sleep

Period 4: Deep Sleep

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

Data Processing

Secure Data Transfer

Secure Data Storage

Secure Data Access

User Applications

Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 67, No. 1, Feb 2021, pp. 20-29.

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SaYoPillow – Stress Analysis Approach

Input Layer
- HoursOfSleep
- SnoringRange
- RespirationRate
- HeartRate
- BloodOxygen
- EyeMovement
- LimbMovement
- TemperatureRate

Hidden Layers
0, 1, 2, 10

Output Layer

Probability of Stress Level Type

Probability	Stress Level Type
0.02	Low/Normal
0.01	Medium Low
0.95	Medium
0.01	Medium High
0.01	High
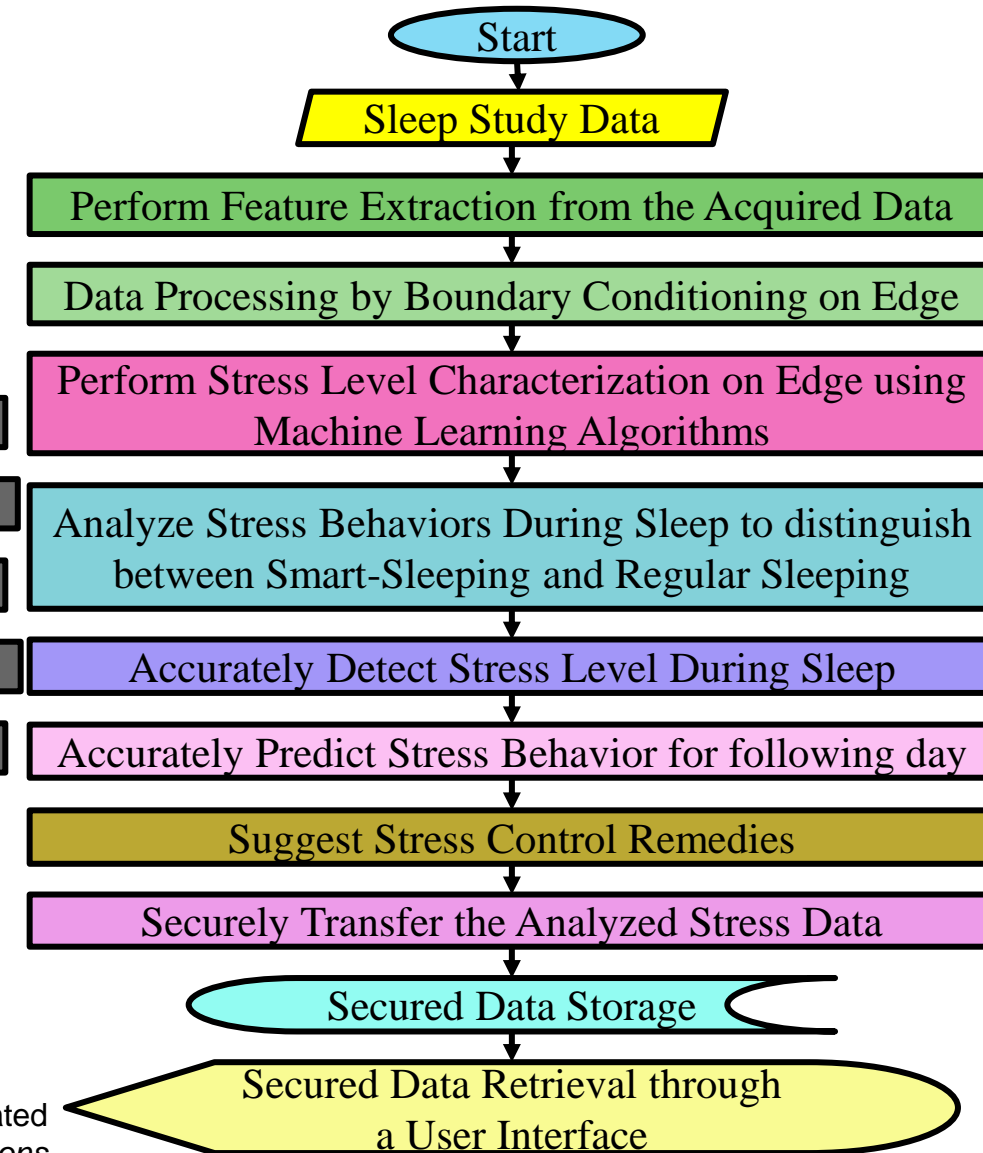
SaYoPillow – Uses deep learning for 96% accuracy with blockchain based security features

Start
Sleep Study Data
Perform Feature Extraction from the Acquired Data
Data Processing by Boundary Conditioning on Edge
Perform Stress Level Characterization on Edge using Machine Learning Algorithms
Analyze Stress Behaviors During Sleep to distinguish between Smart-Sleeping and Regular Sleeping
Accurately Detect Stress Level During Sleep
Accurately Predict Stress Behavior for following day
Suggest Stress Control Remedies
Securely Transfer the Analyzed Stress Data
Secured Data Storage
Secured Data Retrieval through a User Interface

Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 67, No. 1, Feb 2021, pp. 20-29.
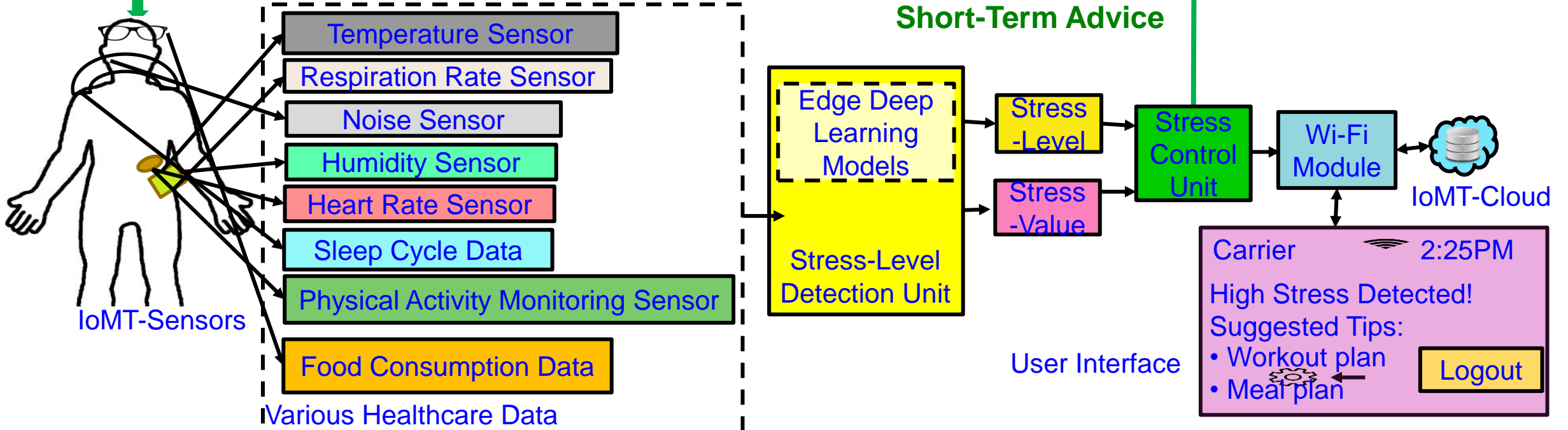
Stress Control by iFeliz: Our Proposed System

Generate workout plan, meal plan, sleep schedule, display stress relief paintings, play music in the background, suggest videos to play, quick 2 min breathe exercise, display positive and inspirational quotes, nearby therapy dog's location, automatic slide show of photos from gallery.

Long-Term Advice

Physical exercise, yoga, meditation- heavy breathing, specific music, shower, Massage appointment, Nap, pet time.

Short-Term Advice

IoMT-Sensors

Temperature Sensor
Respiration Rate Sensor
Noise Sensor
Humidity Sensor
Heart Rate Sensor
Sleep Cycle Data
Physical Activity Monitoring Sensor
Food Consumption Data

Various Healthcare Data

Edge Deep Learning Models

Stress-Level Detection Unit

Stress-Level

Stress-Value

Stress Control Unit

Wi-Fi Module

IoMT-Cloud

Carrier ⚴ 2:25PM
High Stress Detected!
Suggested Tips:
• Workout plan
• Meal plan
Logout

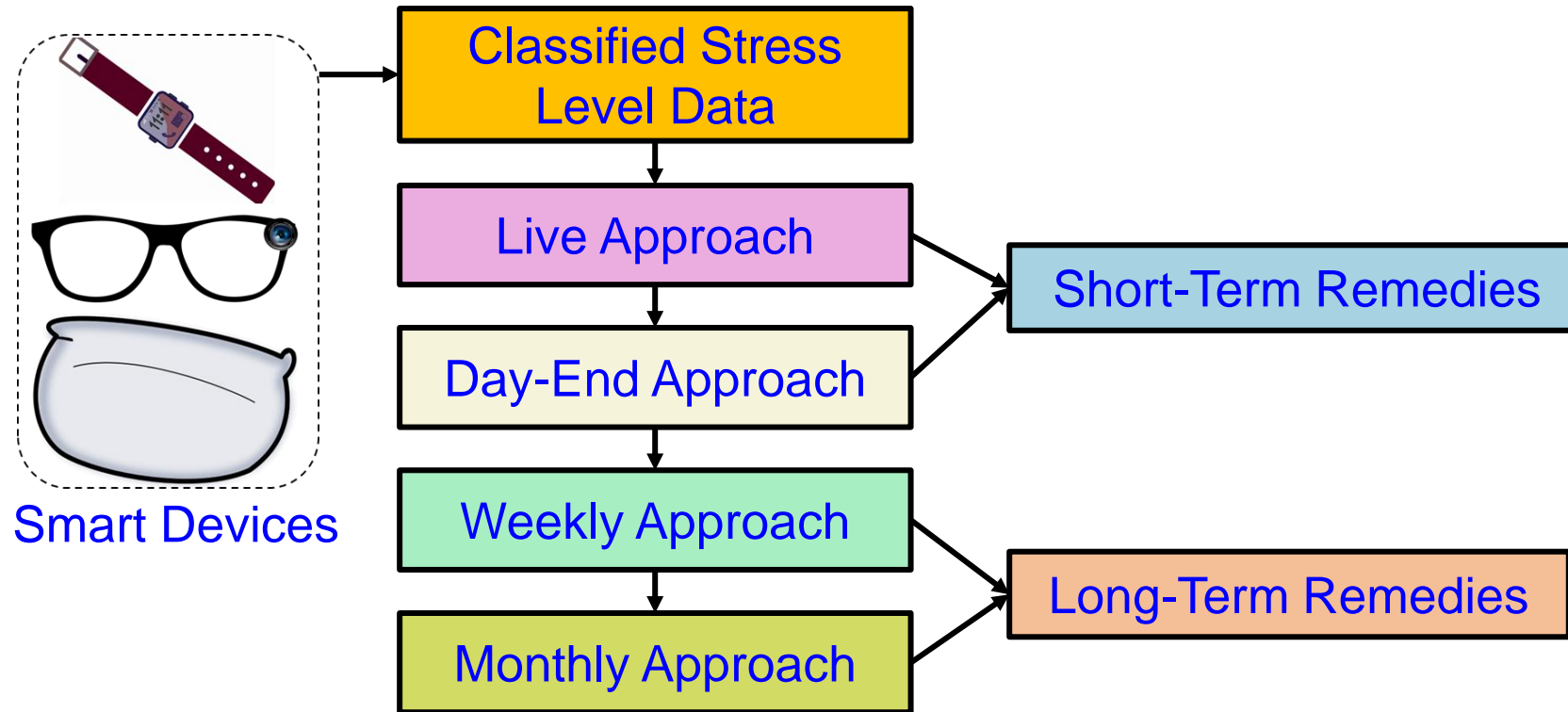User Interface

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 (ISC2)*, 2020.

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iFeliz: Stress Control Approaches

Smart Devices

Classified Stress Level Data	
↓	
Live Approach	→ **Short-Term Remedies**
↓	
Day-End Approach	
↓	
Weekly Approach	→ **Long-Term Remedies**
↓	
Monthly Approach	

iFeliz - 15 Features, Stress Detection, Stress Control, Accuracy - 97%.

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 (ISC2)*, 2020.

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:

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Imbalance Diet – Impact on Hunan Body

- Obesity
- Inflammatory Disease
- Reproductive Disease
- Impact on Immune System
- Kidney Disease
- Insulin Secretion
- Hypertension
- Cardiac Disease

Source: A. Mitra, S. Goel, **S. P. Mohanty**, E. Kougianos, and L. Rachakonda, "iLog 2.0: A Novel Method for Food Nutritional Value Automatic Quantification in Smart Healthcare", in *Proceedings of the IEEE International Symposium on Smart Electronic Systems (iSES)*, 2022, pp. Accepted.

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Automatic Diet Monitoring & Control - Our Vision
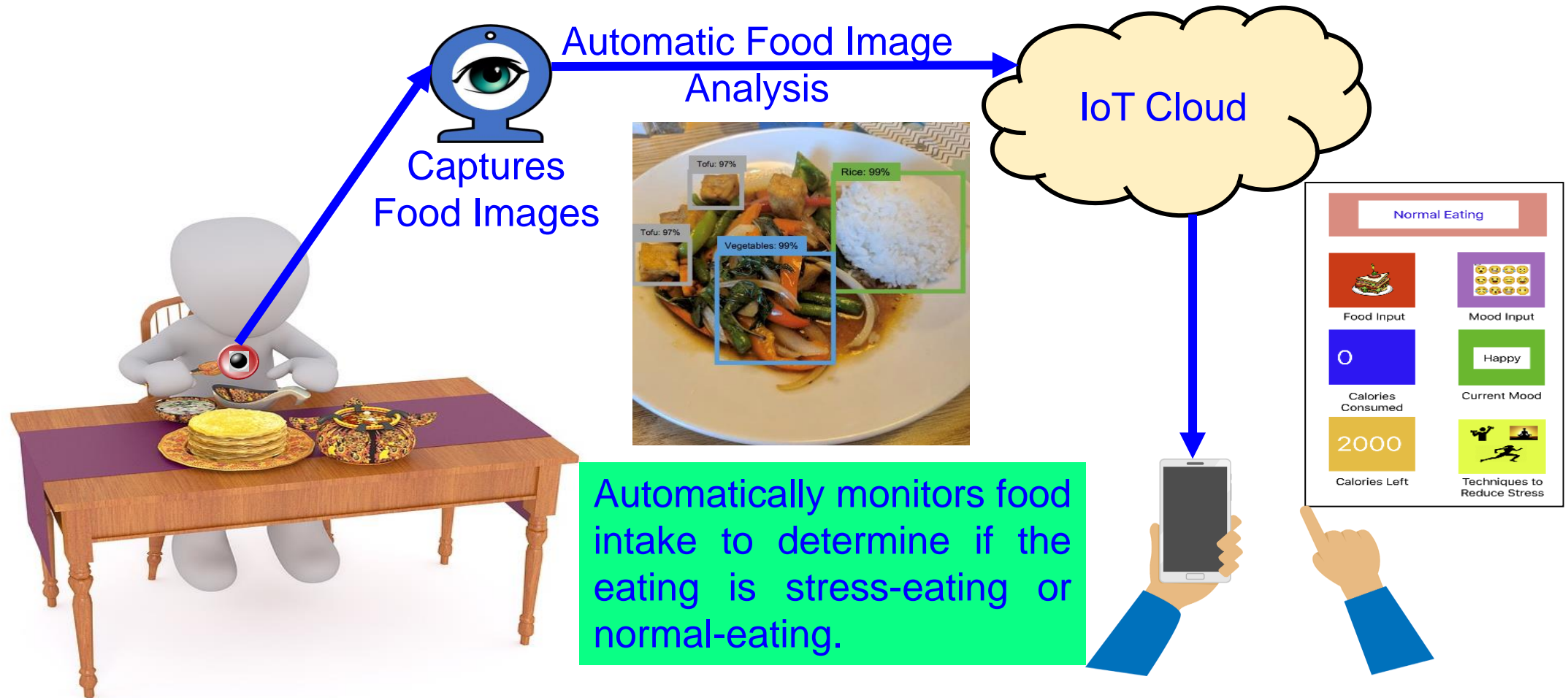
Automatic Food Image Analysis

Captures Food Images

IoT Cloud

Tofu: 97%
Rice: 99%
Tofu: 97%
Vegetables: 99%

Normal Eating

Food Input — Mood Input
Calories Consumed: 0 — Current Mood: Happy
Calories Left: 2000 — Techniques to Reduce Stress

Automatically monitors food intake to determine if the eating is stress-eating or normal-eating.

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.

Diet Tracking Approaches

Diet Tracking
├── Manual
└── Automatic
    ├── Hand and Mouth Movement
    ├── Food-Weight Sensing
    └── Food Image Processing

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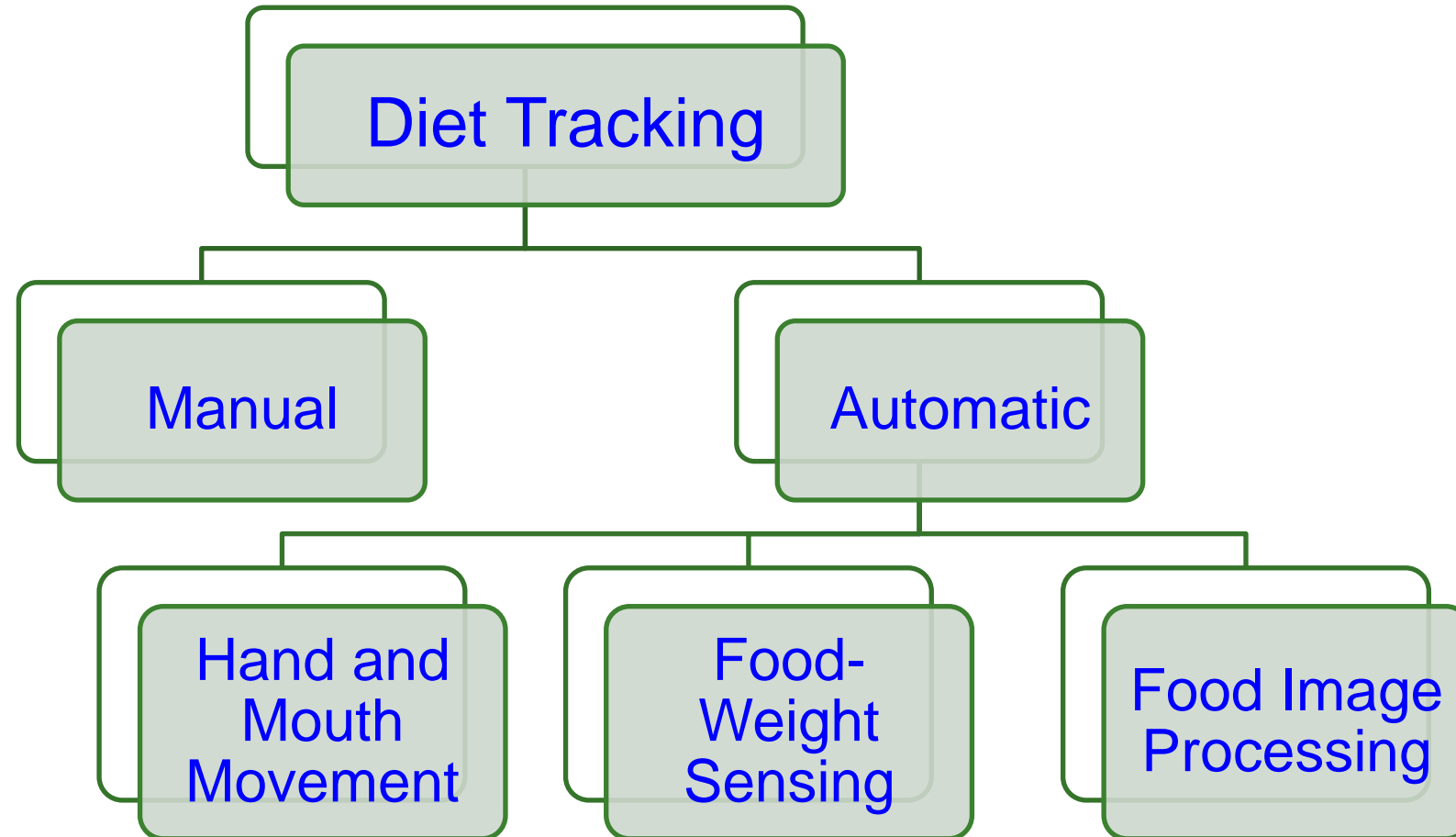
Food Tracking Apps

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

App Name	Downloads	Reviews	Rating	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	

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Smart Healthcare – Diet Monitoring - iLog

Reference Image

Edge Platform

Classification → Feature Extraction → Object Detection → Database

Nutrition Dataset

Cloud Platform

Mobile Application Interface

Stress-Eating Analysis
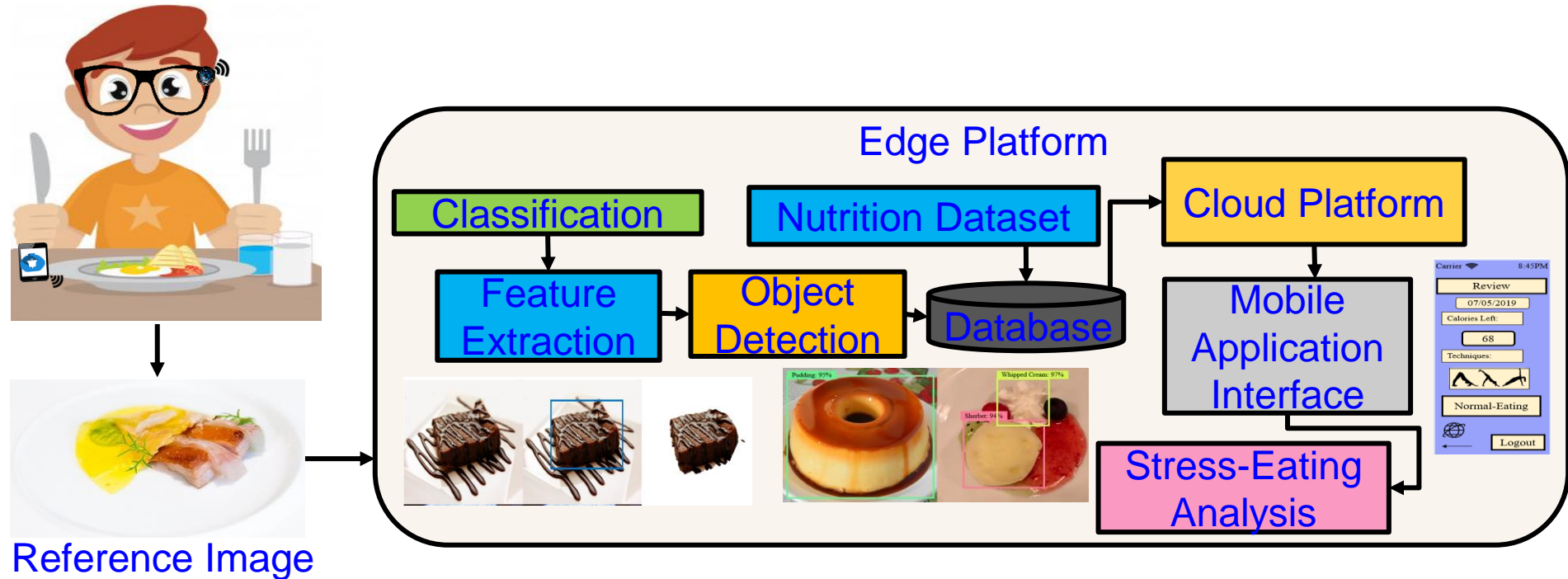
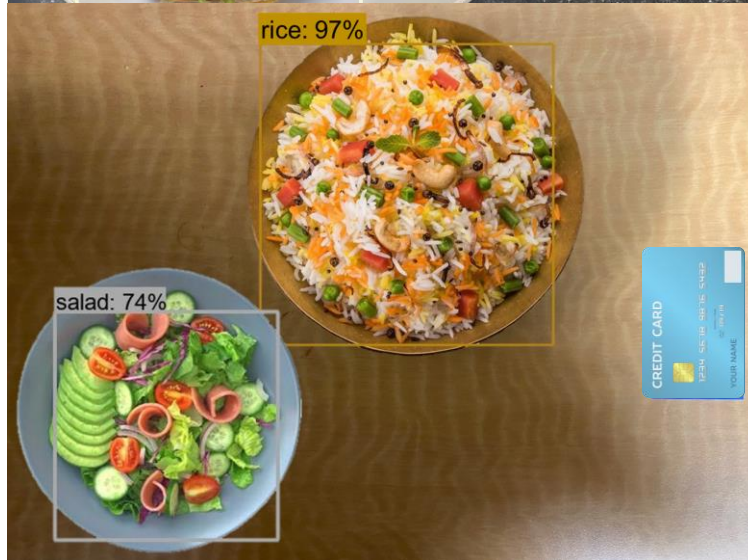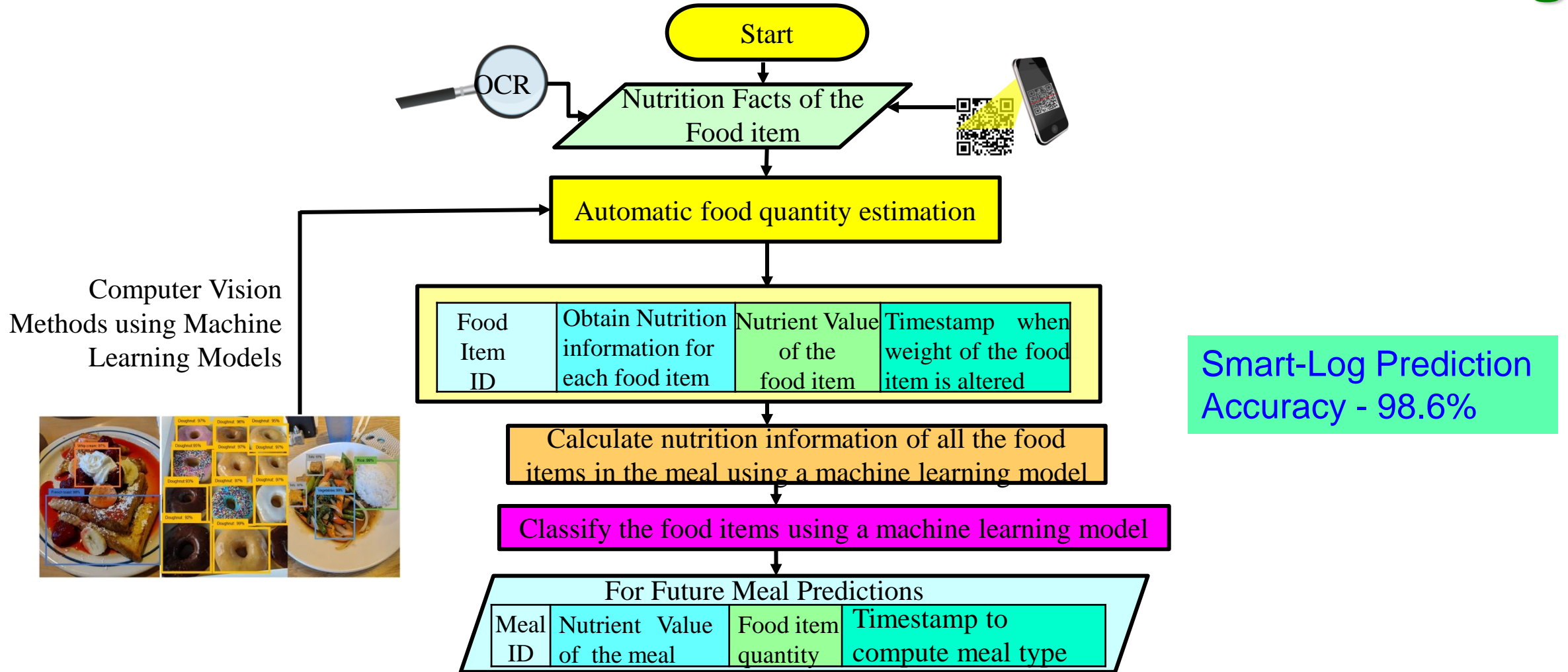iLog- Fully Automated Detection System with 98% accuracy.

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.

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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.

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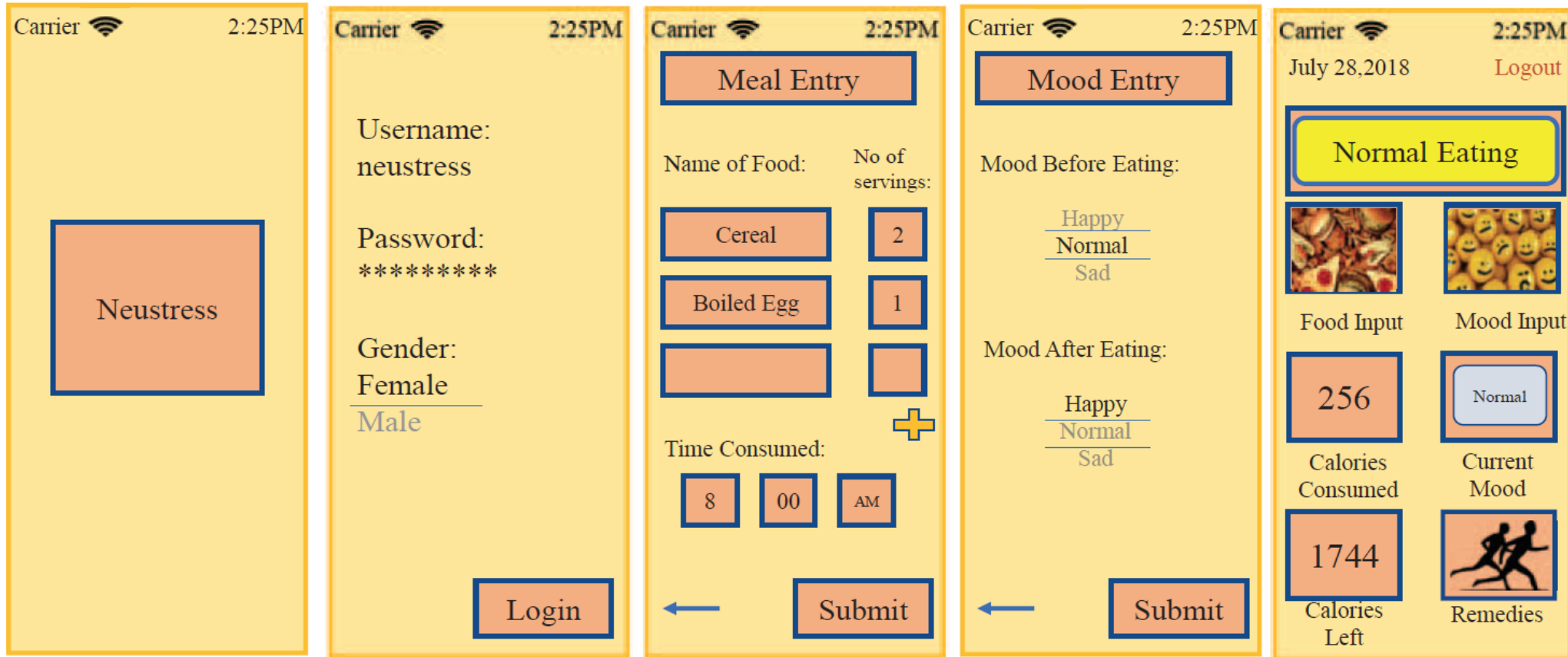
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare - Diet Monitoring - iLog 2.0
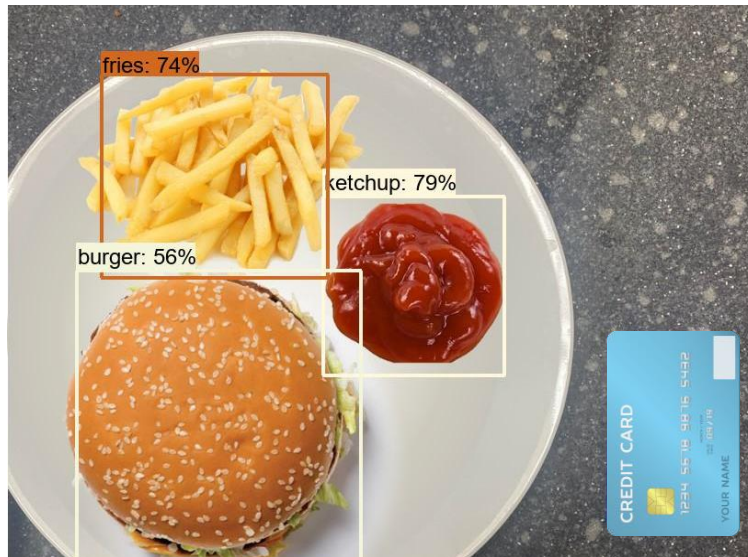
Food Item	Saturated Fat (g)	Sugar (g)	Sodium (mg)	Protein (g)	Carbohydrates (g)
Fries	6.44	1.56	244	4.03	34.84
Burger	6.87	4.67	481	17.29	48.14
Ketchup	0	3.2	136	0.2	4.13
Total	13.31	9.43	861	21.52	87.11

Food Item	Saturated Fat (g)	Sugar (g)	Sodium (mg)	Protein (g)	Carbohydrates (g)
Rice	0.3	0.3	6	12.9	135
Salad	0.8	3.9	264	1.1	7
Total	1.1	4.2	270	14	142

Smart Healthcare – Diet Prediction – Smart-Log

Start

OCR

Nutrition Facts of the Food item

Automatic food quantity estimation

Computer Vision Methods using Machine Learning Models

Food Item ID	Obtain Nutrition information for each food item	Nutrient Value of the food item	Timestamp when weight of the food item is altered

Calculate nutrition information of all the food items in the meal using a machine learning model

Classify the food items using a machine learning model

For Future Meal Predictions

Meal ID	Nutrient Value of the meal	Food item quantity	Timestamp to compute meal type

Smart-Log Prediction Accuracy - 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)*, Vol 64, Issue 3, Aug 2018, pp. 390-398.

Smart Healthcare – Diet Prediction

Layer 2
Hidden Layer 1
Weight of the meal

Layer 4
Hidden Layer 3
Intended Nutritional goal

Layer 1
Input Layer
Type of Meal

Layer 3
Hidden Layer 2
Time consumed

Layer 5
Output Layer
Nutritional balance of
the meal

Bayesian Network for classifying food items

Neural Network for computing Nutritional balance

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.

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Epileptic Seizure Has Global Impact

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

- 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

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Epileptic Seizure - Our Vision
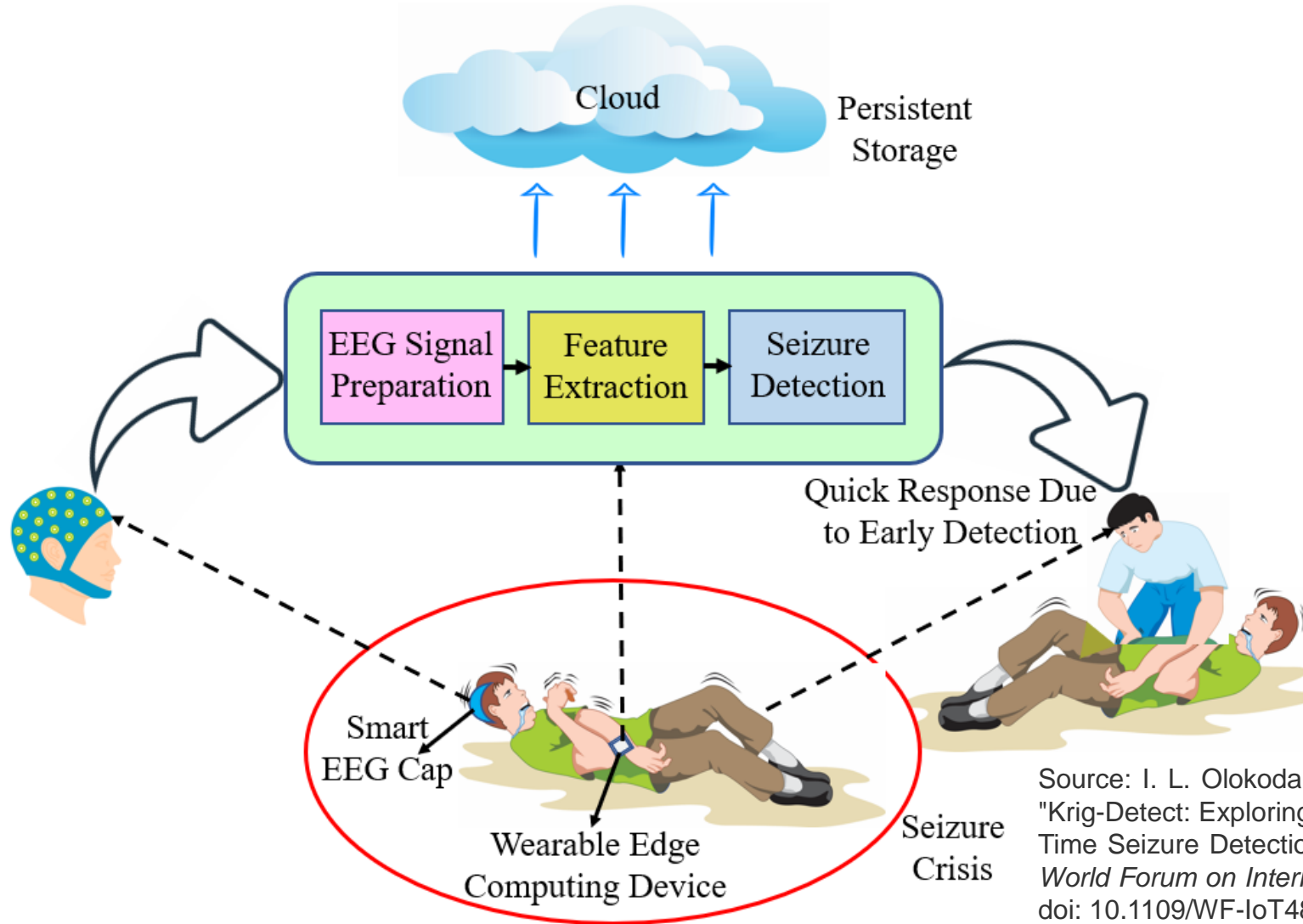
Source: I. L. Olokodana, S. P. Mohanty and E. Kougianos, "Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signals," *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*, 2020, pp. 1-6, doi: 10.1109/WF-IoT48130.2020.9221260.

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Implantable for Seizure Detection and Control

Implantable lead assemblies

Catheter

Implantable telemetry unit

Personal advisory device

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

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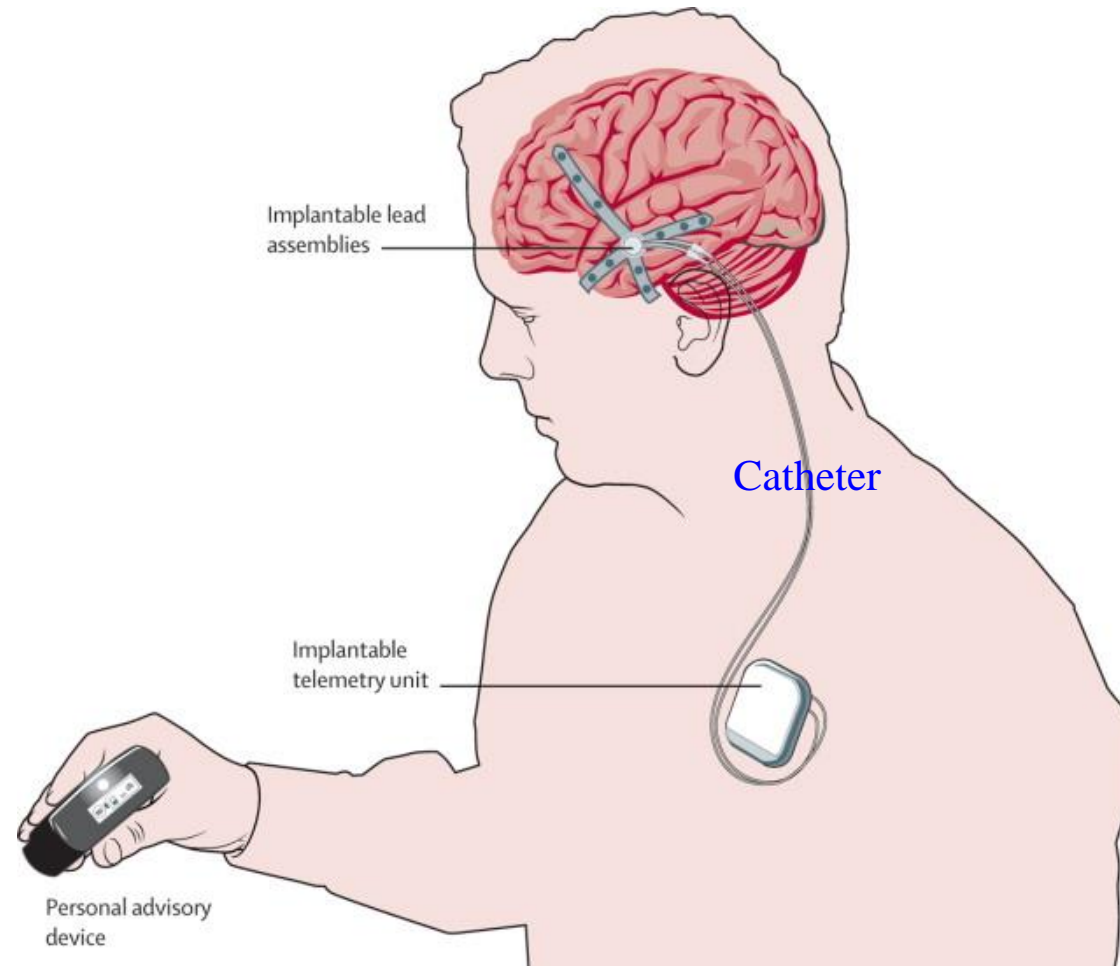
Seizure Detection Methods

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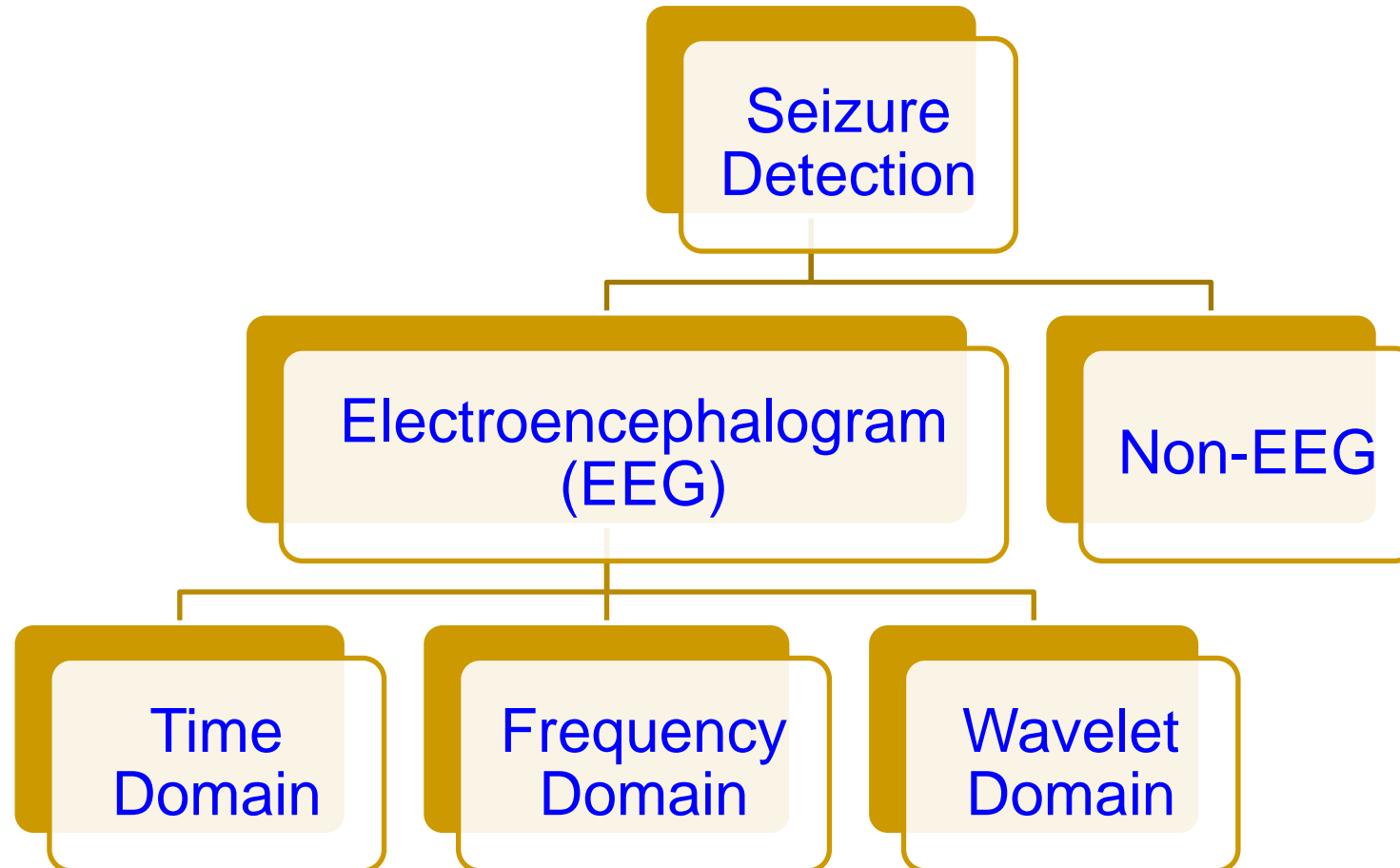
Consumer Electronics for Seizure Detection

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

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

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

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

Smart Healthcare - Seizure Detection & Control

EEG Signal

Seizure Detection

Seizure State

Dosage Information

Wireless Transfer

Cloud Storage

Hospital

Doctor

Yes

Drug Delivery Unit

Drug Injection

EEG Data Acquisition

Sensor Unit

Transmission and Storage

Access Unit

EEG signal of a grand mal Seizure and seizure detection

Seizure Onset

Seizure Detection

A – Typical Latency - 6 sec
B – Early Detection - 1 to 2 sec
C – Seizure Predication - at least 6 sec before

A
Latency (6 sec)

C

B

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

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.
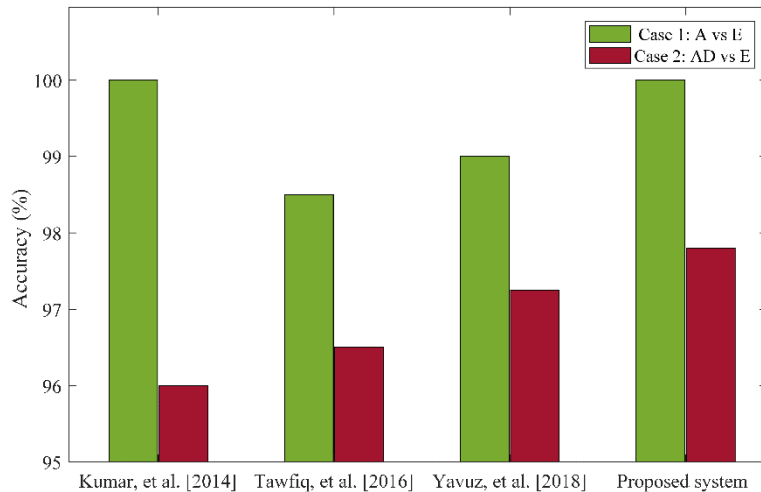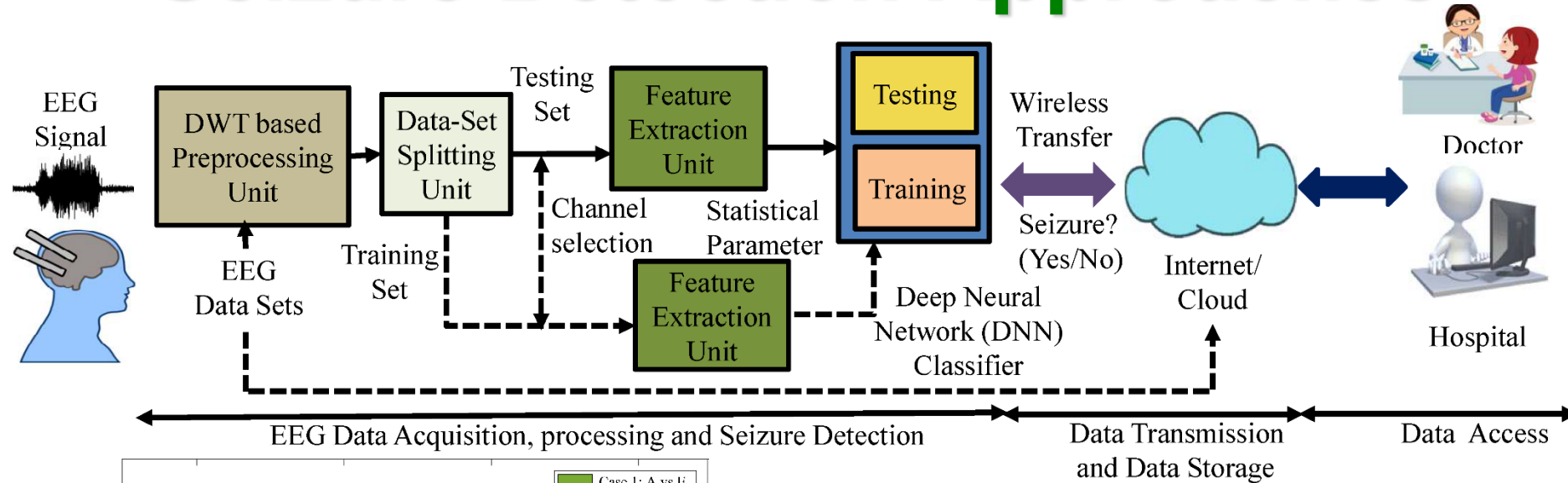
Cloud Vs Edge Computing

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

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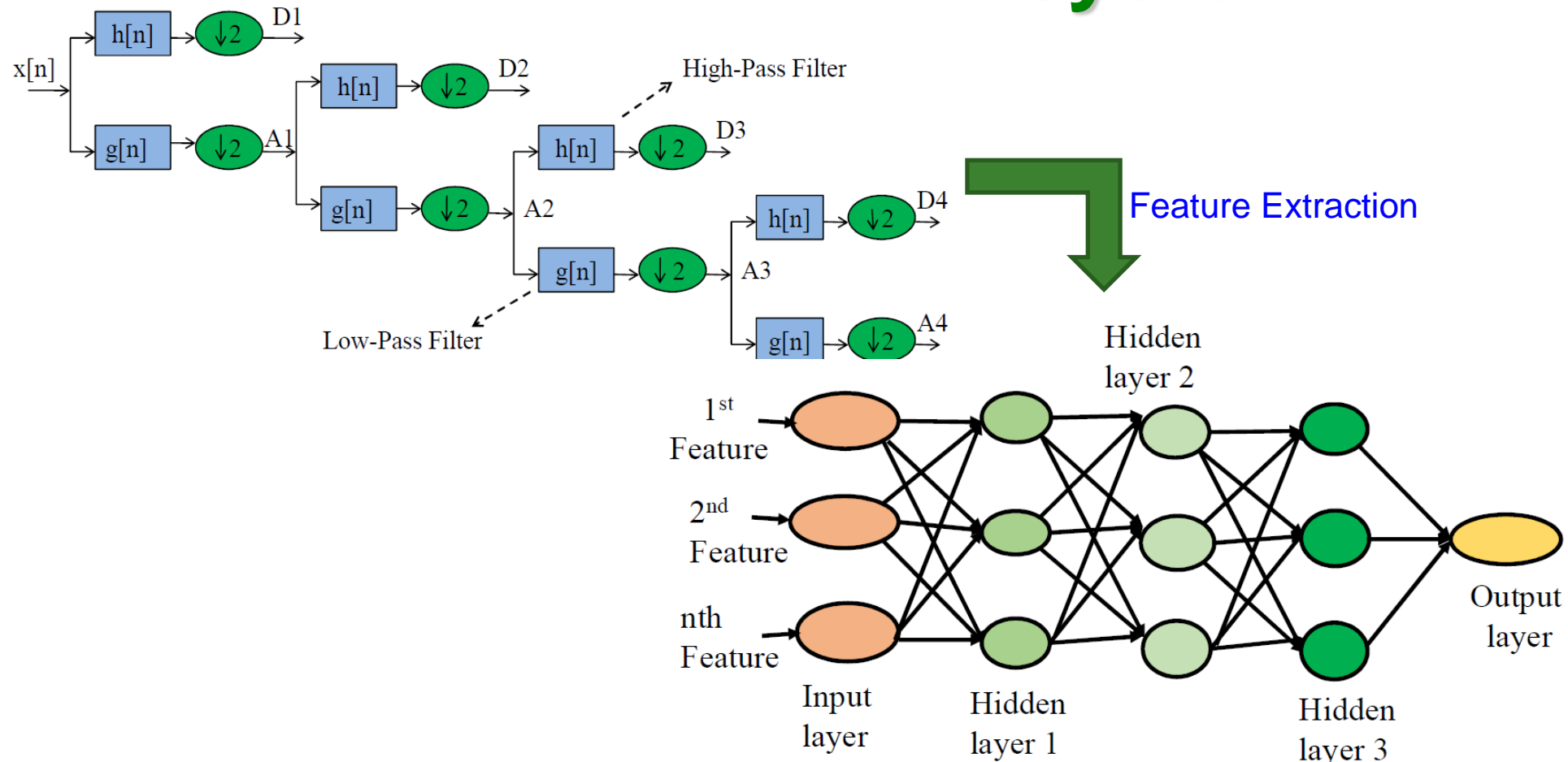
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri , "Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, Issue 3, Aug 2019, pp. 359-368.

Smart Healthcare – Brain as a Spatial Map → Kriging Methods
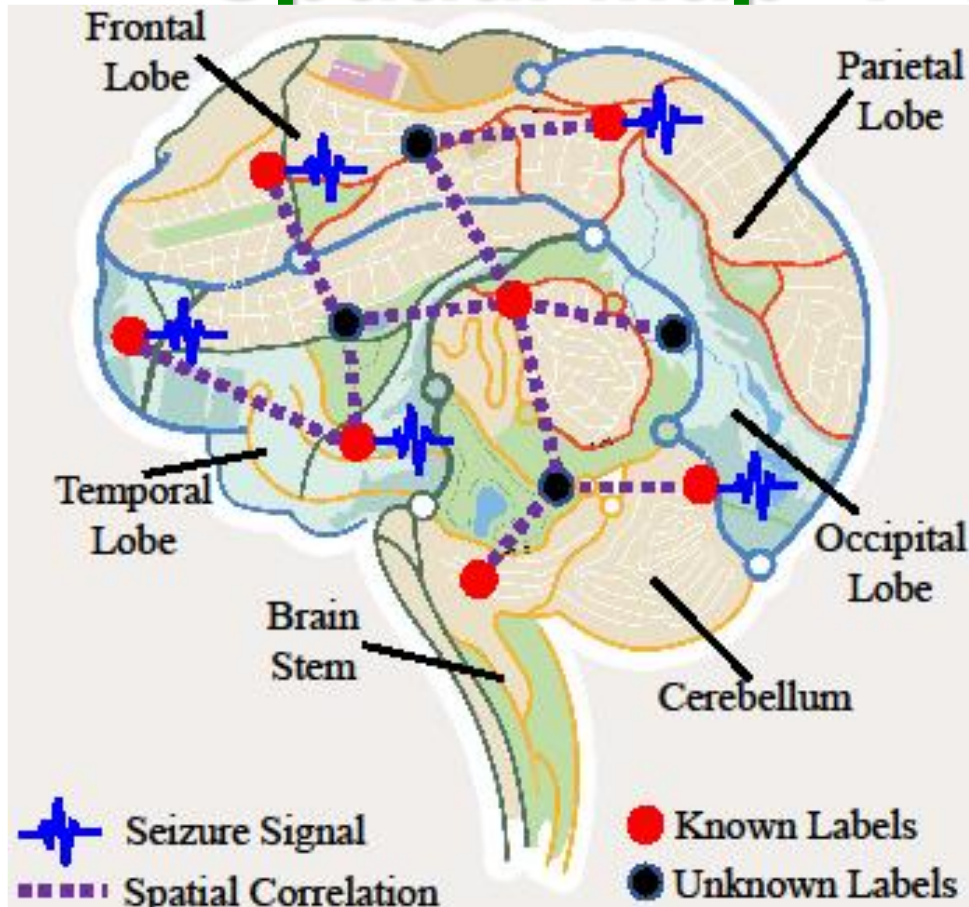
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE)*, 2020.
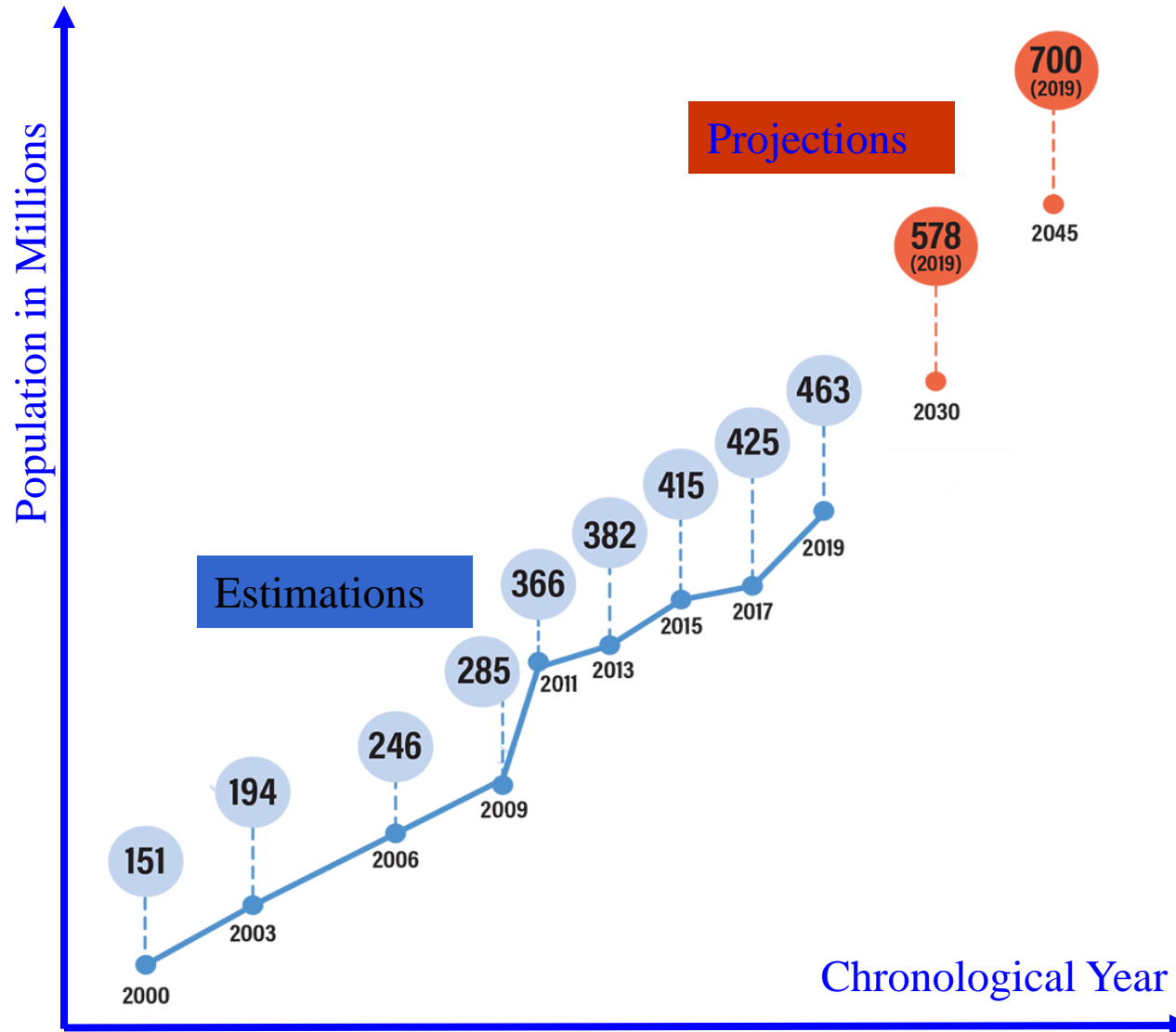
Source: http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm

Spatial modeling or Variography
- Correlation Function is "Variogram"
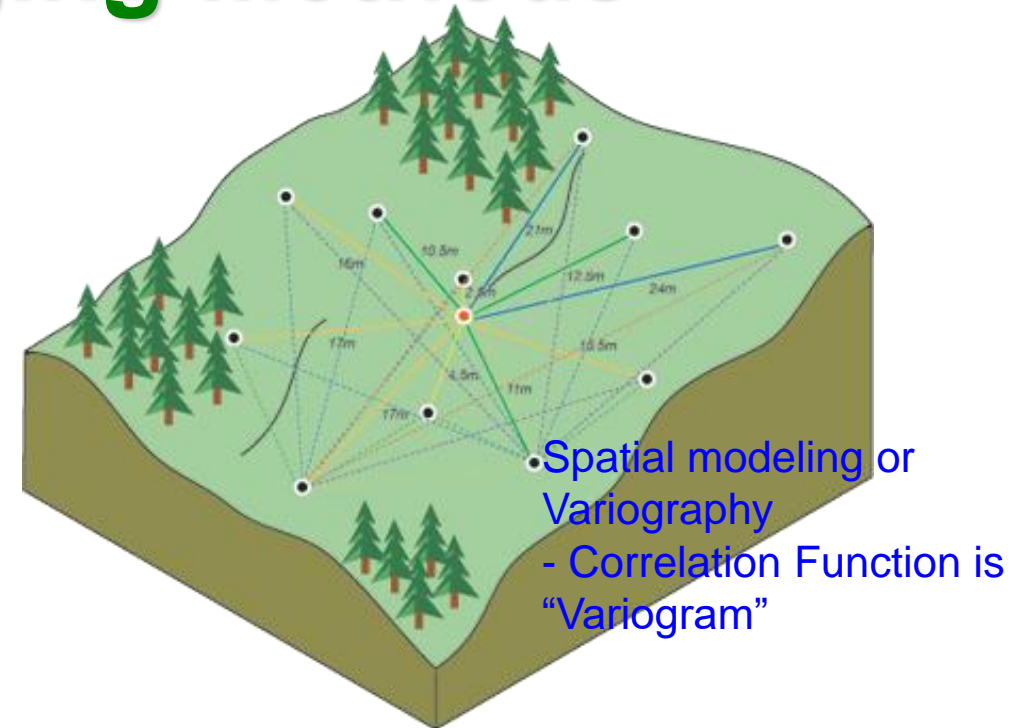
Spatial autocorrelation principle - things that are closer are more alike than things farther

Kriging based Seizure Detection
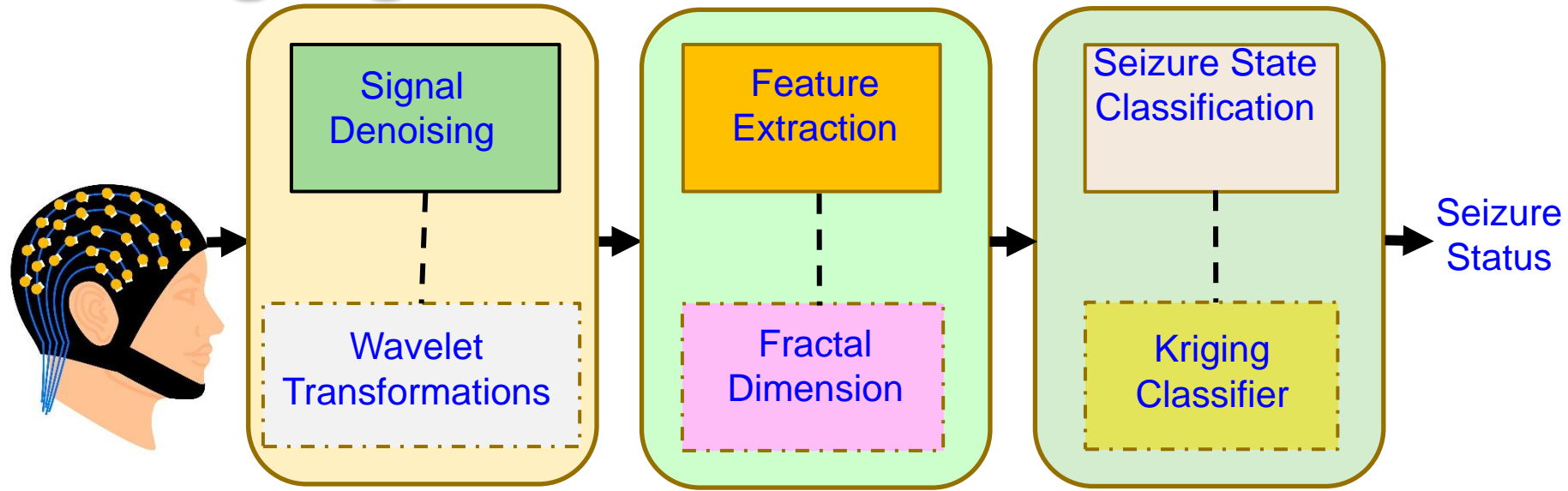
Works	Extracted Features	Classification Algorithm	Sensitivity	Latency
Zandi, et al. 2012 [23]	Regularity, energy & combined seizure indices	Cumulative Sum thresholding	91.00%	9 sec.
Altaf,etal. 2015 [24]	Digital hysteresis	Support Vector Machine	95.70%	1 sec
Vidyaratne, et al. 2017 [25]	Fractal dimension, 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.

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.
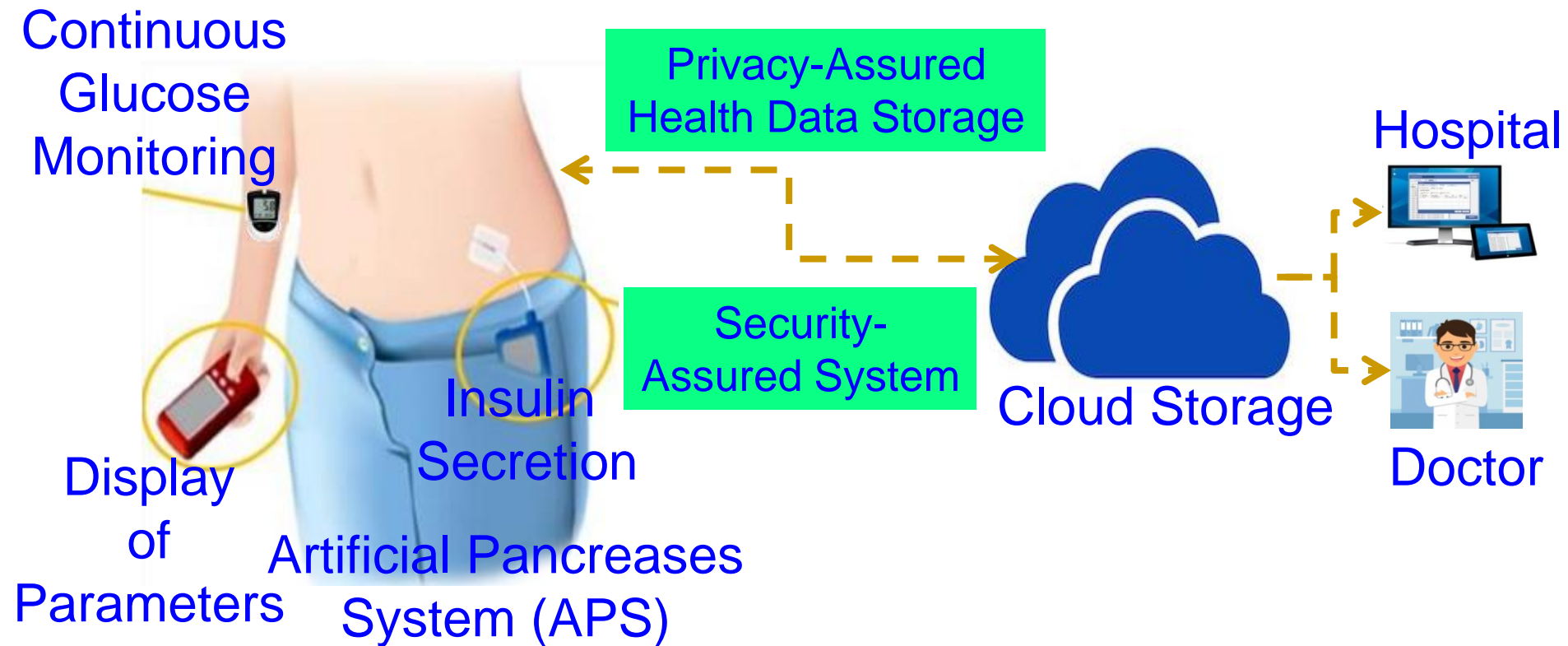
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Seizure Control Methods

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.

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Diabetes is a Global Crisis

Population in Millions

Chronological Year

700 (2019) — 2045

578 (2019) — 2030

Projections

463 — 2019
425 — 2017
415 — 2015
382 — 2013
366 — 2011
285 — 2009
246 — 2006
194 — 2003
151 — 2000

Estimations

Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

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Diabetes – Impact on Human Body

Alzheimer's disease

Hearing impairment

Gum Disease &
Other Dental Problems

Sexual, &
Bladder Problems

Foot damage

Eye damage (retinopathy)

Cardiovascular disease

Skin conditions

Kidney damage (nephropathy)

Nerve damage (neuropathy)

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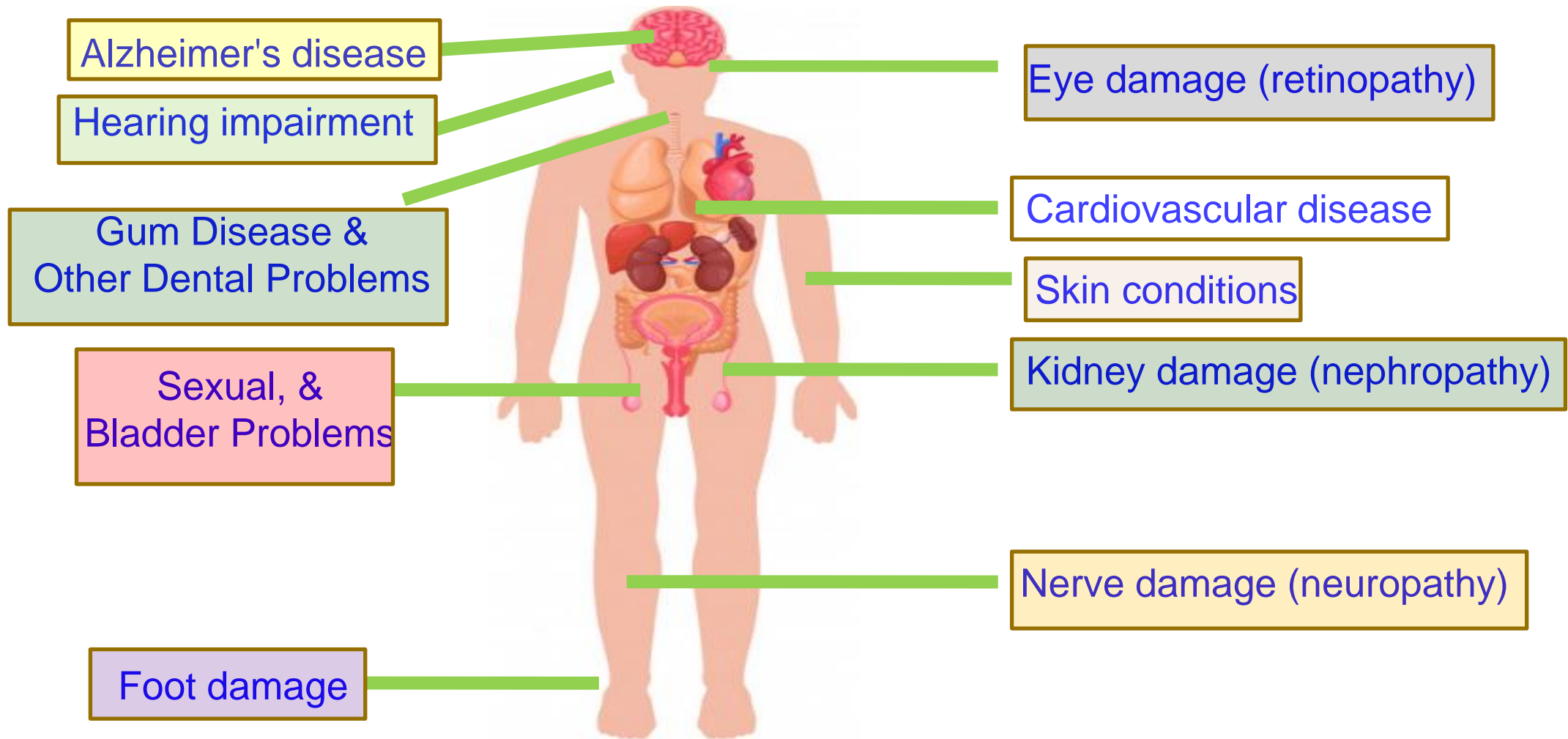
Automatic Glucose Monitoring and Control - Our Vision - iGLU (Intelligent Noninvasive)

Continuous Glucose Monitoring

Display of Parameters

Insulin Secretion

Artificial Pancreases System (APS)

Privacy-Assured Health Data Storage

Security-Assured System

Cloud Storage

Hospital

Doctor

Blood Glucose Monitoring – Invasive Vs Noninvasive

Invasive Approach (Capillary Glucose Measurement)
- Preparation of Lancet
- Pricking of the Blood
- Contact to strip for Monitoring
- Blood Glucose Monitoring (mg/dl)

Invasive Approach (Serum Glucose Measurement)
- Blood Sample Collection
- Clinical Centrifuge for Separation of Serum
- Prepared Serum for Glucose Measurement
- Glucose Value (mg/dl) using Glucose Analyzer

Non Invasive Approach
- Fingertip/Earlobe/Skin between fingers
- Light Detection through Optical Sensors and Signal Processing
- Data Acquisition and Prediction of Blood Glucose using Regression Model
- Blood Glucose Monitoring (mg/dl)

Traditional – Finger Pricking
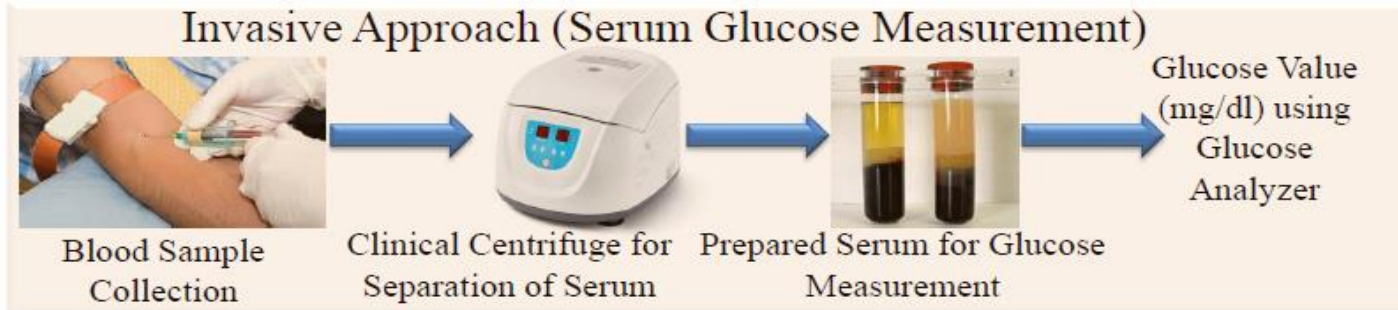
Invasive Approach – Processing Blood/Serum
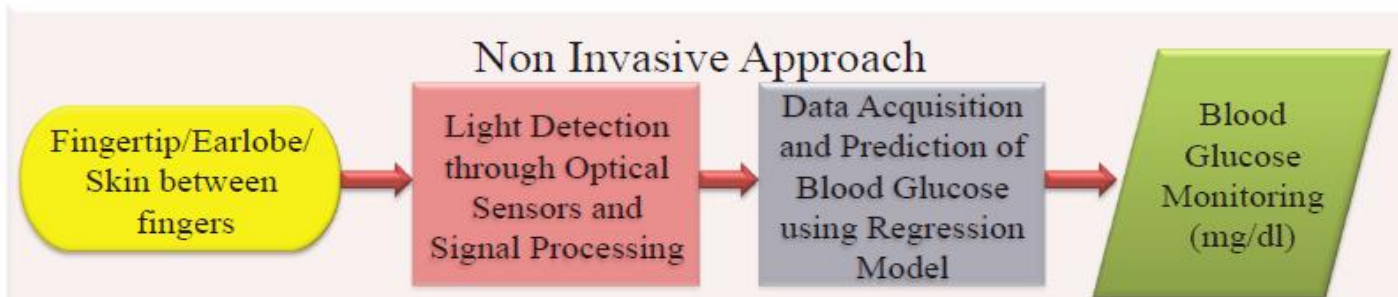
Noninvasive – Wearable

Noninvasive Approach – Processing Light

Source: P. Jain, A. M. Joshi, and S. P. Mohanty, "Everything You Wanted to Know About Noninvasive Glucose Measurement and Control", *arXiv Physics*, arXiv:2101.08996, January 2021, 51-pages.

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Noninvasive Glucose-Level Monitoring

Front view — Sensor (finger)

Back view — Sensor (wrist)
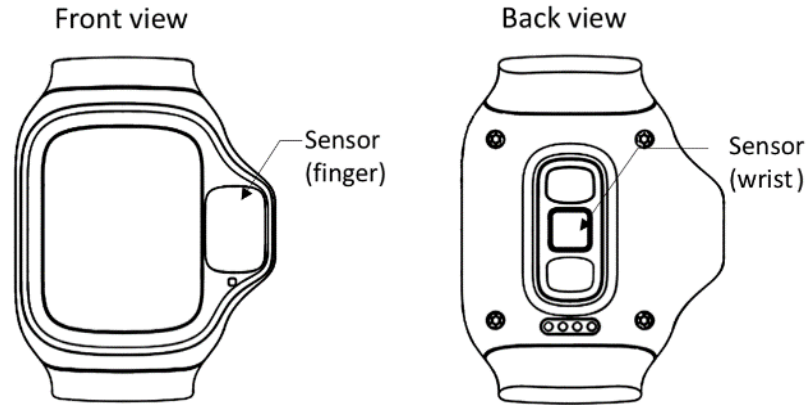
Photoplethysmogram (PPG)

Near Infrared (NIR)

PPG Signal Analysis

Specific Wavelengths are not required

LED → Detector

Logged signal for pulse analysis and features extraction

NIR Spectroscopy

Specific Wavelengths needed for glucose molecule detection

LED → Detector

Logged voltage values after absorption and reflectance of light from glucose molecule

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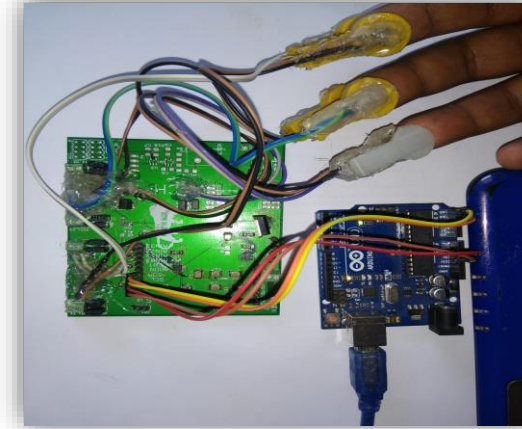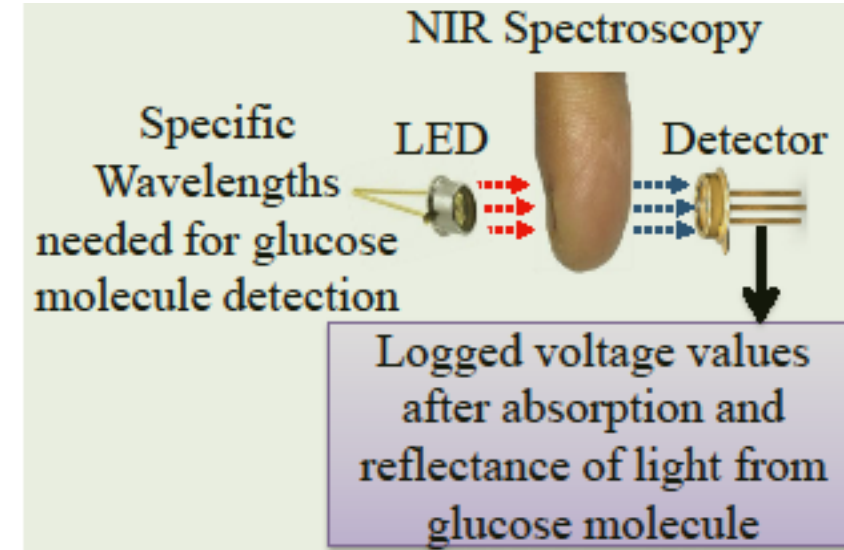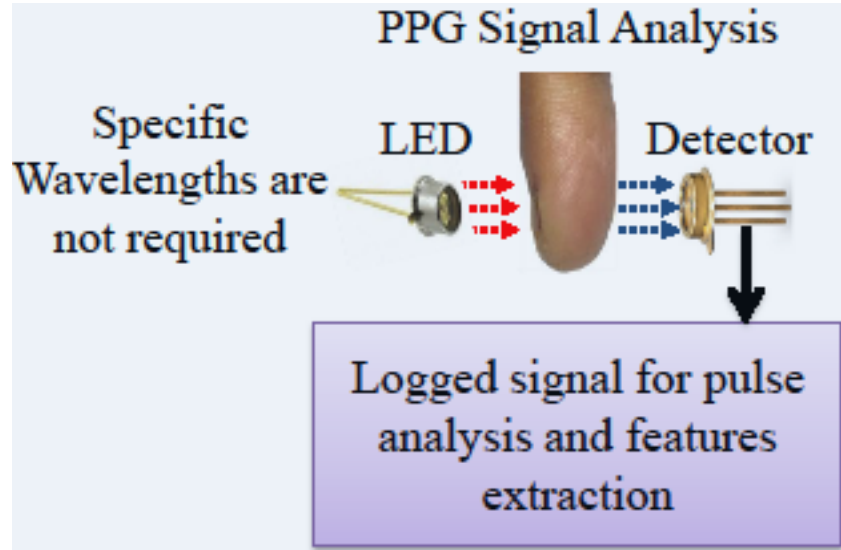
Unique Near Infrared Spectroscopy for iGLU
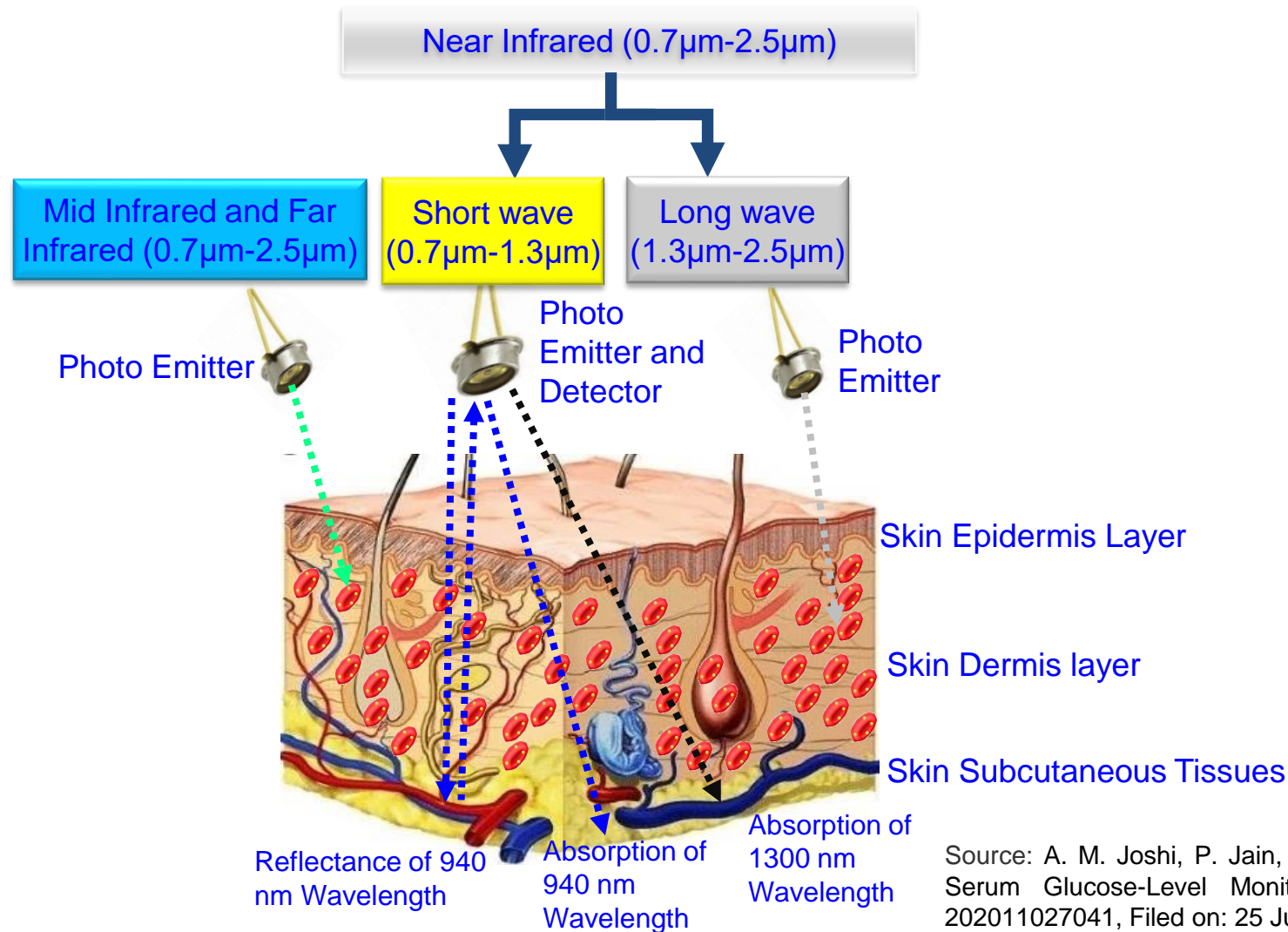
Near Infrared (0.7µm-2.5µm)

Mid Infrared and Far Infrared (0.7µm-2.5µm)

Short wave (0.7µm-1.3µm)

Long wave (1.3µm-2.5µm)

Photo Emitter

Photo Emitter and Detector

Photo Emitter

Skin Epidermis Layer

Skin Dermis layer

Skin Subcutaneous Tissues

Reflectance of 940 nm Wavelength

Absorption of 940 nm Wavelength
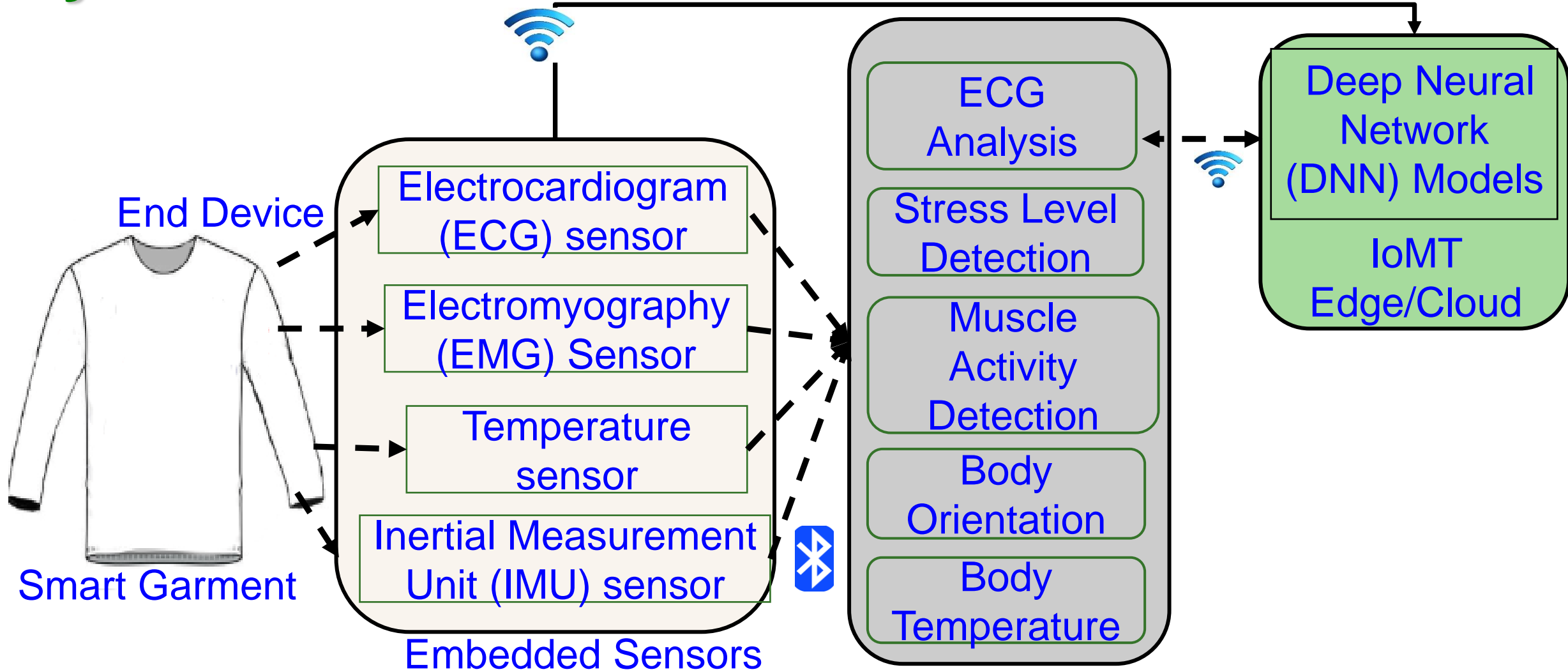
Absorption of 1300 nm Wavelength

Source: A. M. Joshi, P. Jain, and S. P. Mohanty, A Device For Non-Invasive Blood and Serum Glucose-Level Monitoring and Control, India Patent Application Number: 202011027041, Filed on: 25 June 2020.

iGLU 1.0: Capillary Glucose

Vibrations (Stretching, Wagging, Bending)

Near Infrared (NIR) Emitters (940nm, 1300nm)

Transmitted Wave

Attenuated Wave

Infrared Detector

Infrared Detector

Analog-to-Digital Converter
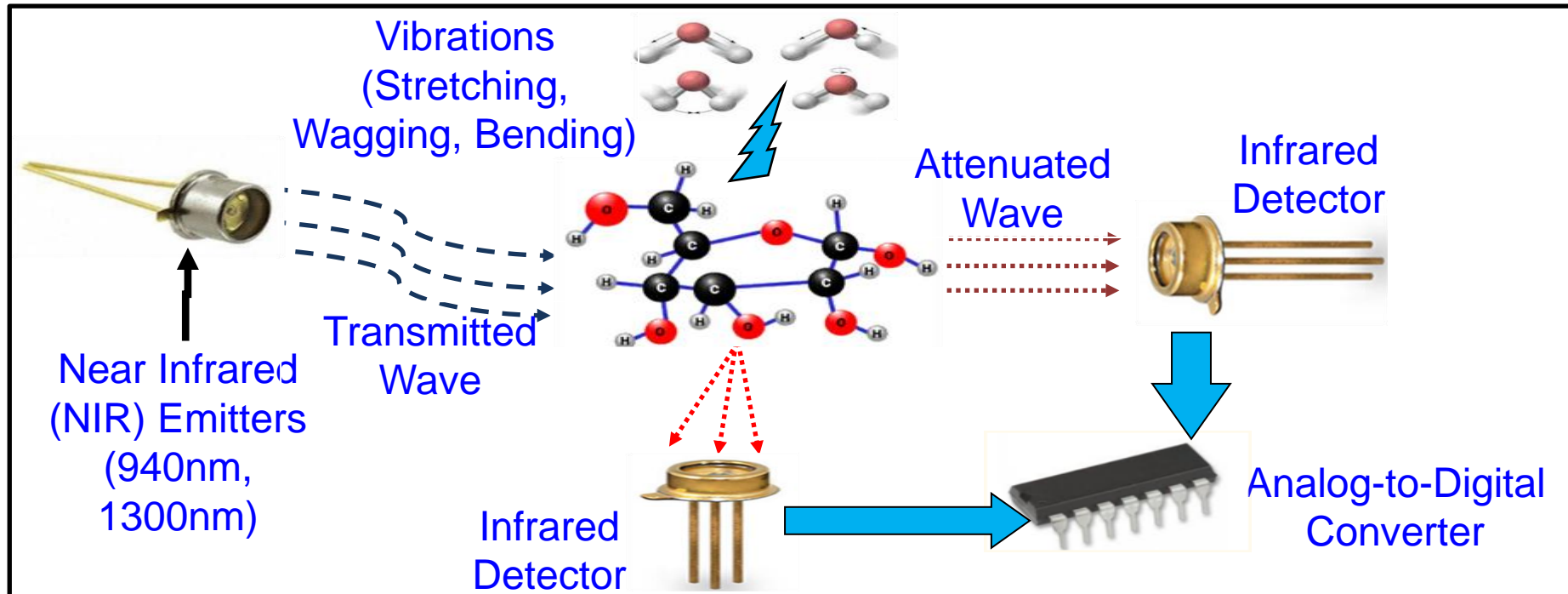
Clinically tested in an hospital.

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
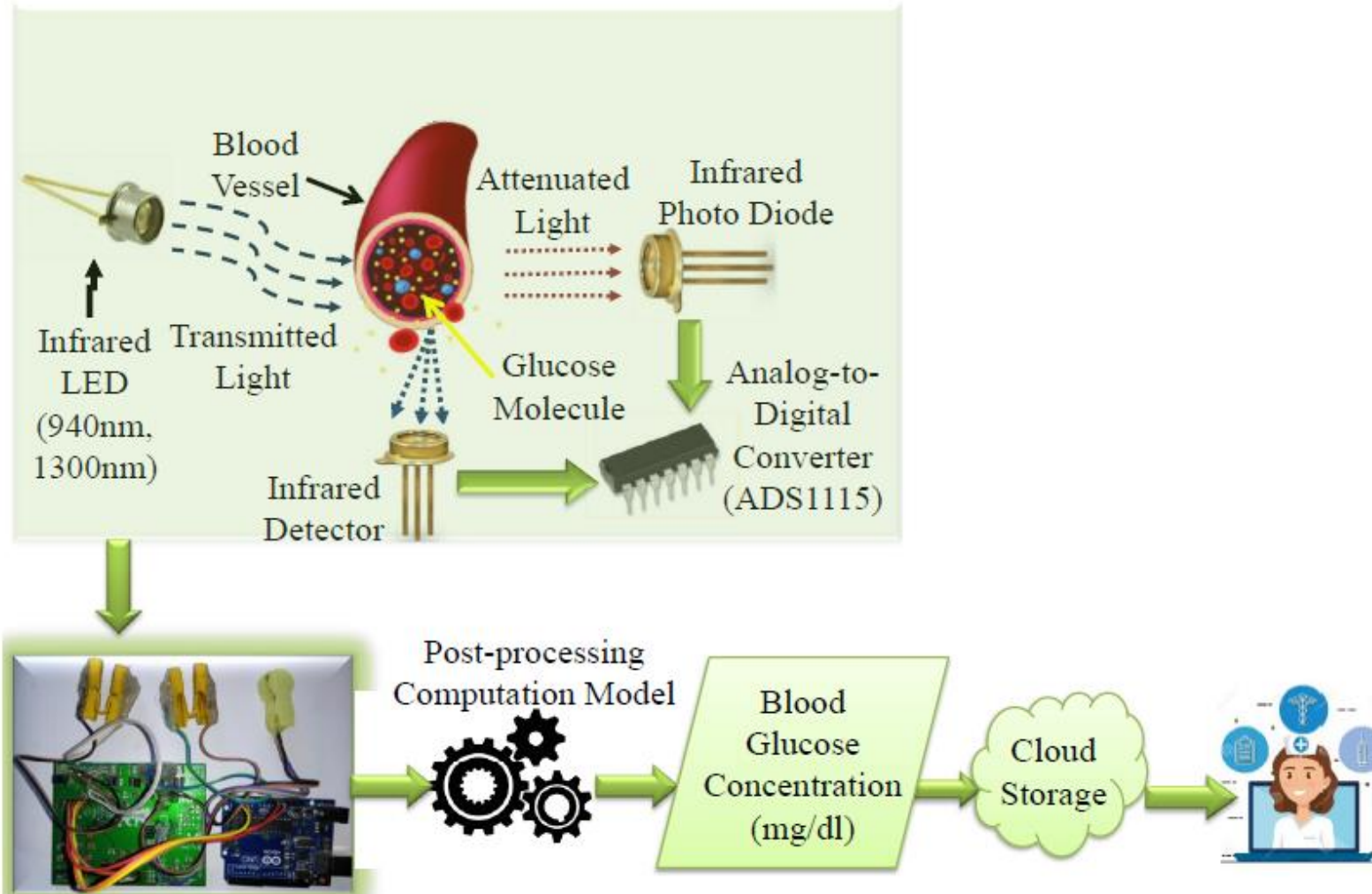
Source A. M. Joshi, P. Jain, S. P. Mohanty, and N. Agrawal, "iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 4, Nov 2020, pp. 327--335.

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DNN Based Glucose Prediction
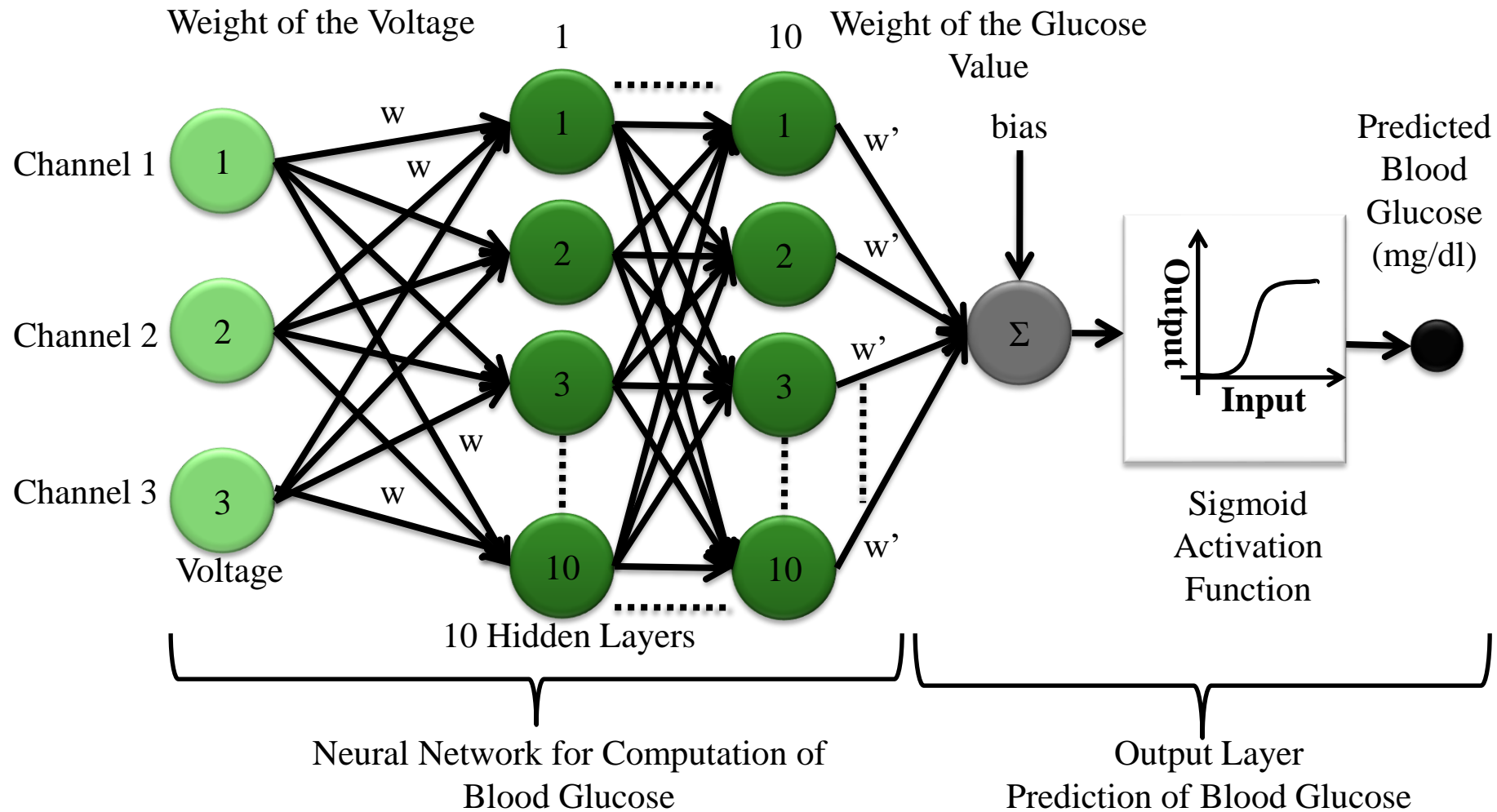
Weight of the Voltage

Weight of the Glucose Value

bias

Channel 1

Channel 2

Channel 3

Voltage

10 Hidden Layers

Neural Network for Computation of Blood Glucose

Output Layer Prediction of Blood Glucose

Sigmoid Activation Function

Predicted Blood Glucose (mg/dl)

Source: A. M. Joshi, P. Jain, **S. P. Mohanty**, and N. Agrawal, "iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 4, November 2020, pp. 327--335.

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iGLU – Design Implementation

Data logging for model training, validation and testing

Processing Unit

Power Supply

100 Ω

Light Emitting Diode

Ground

Photo Diode

output 2

940 nm (Absorption) Channel 2

1300 nm Channel 1

10k Ω

Ground

Ground

Output 2

Output1

100Ω

Light Emitting Diode

Ground

940 nm (Reflectance) Channel 3

Photo Diode

Output 3

10k Ω

Ground

Output3

Glucose Level Data Output

Analog to Digital Conversion Unit
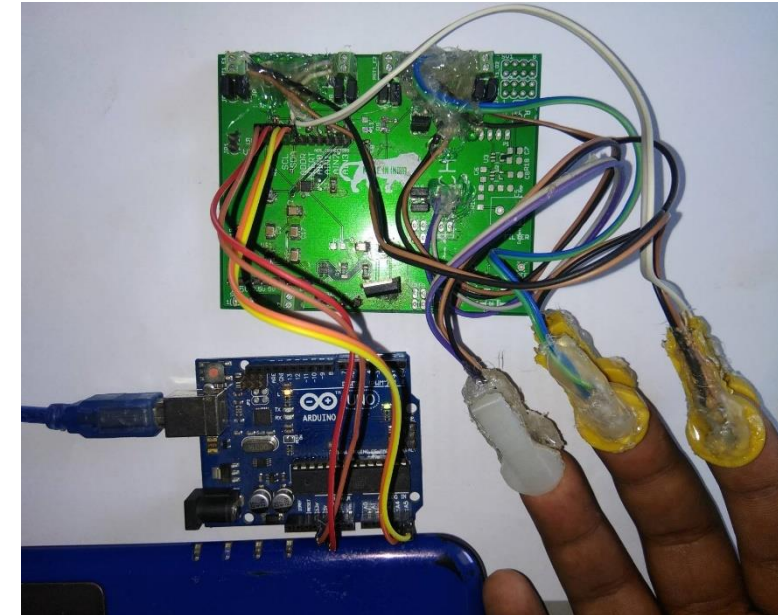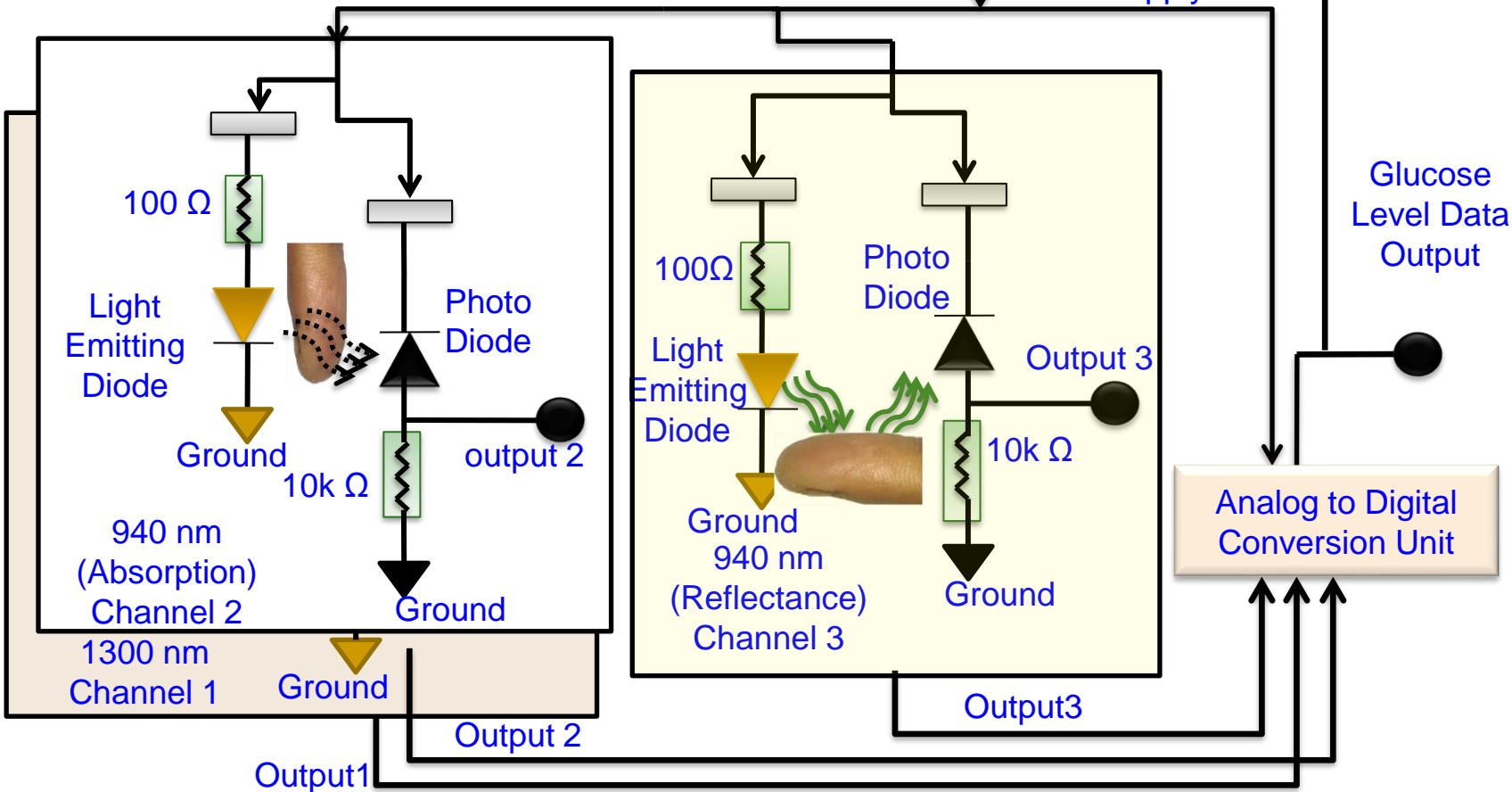
Clinically tested in an hospital.

Cost - US$ 20 Accuracy - 100%

Source: A. M. Joshi, P. Jain, and S. P. Mohanty, A Device For Non-Invasive Blood and Serum Glucose-Level Monitoring and Control, India Patent Application Number: 202011027041, Filed on: 25 June 2020.

MyWear – A Smart Wear for Continuous Body Vital Monitoring
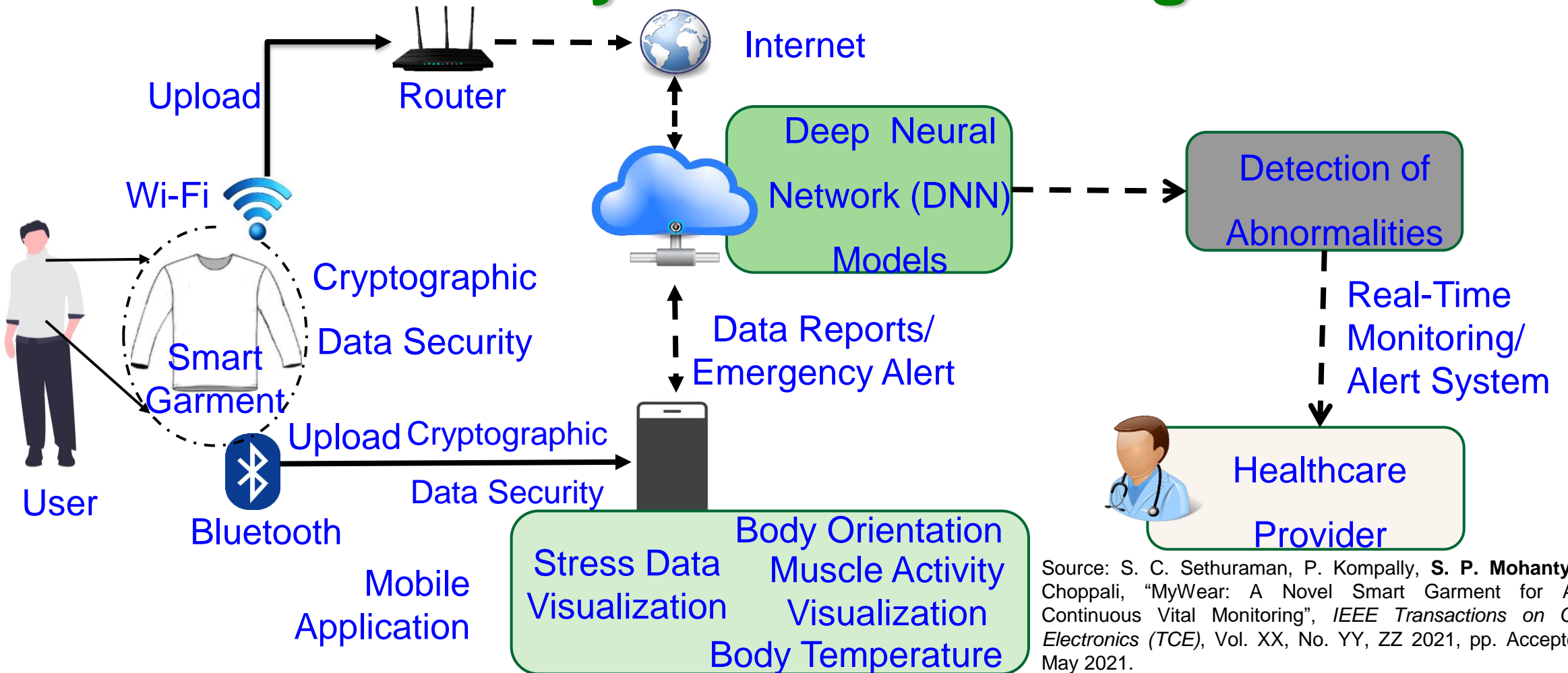
Internet

Upload

Router

Wi-Fi

Cryptographic

Deep Neural Network (DNN) Models

Detection of Abnormalities

Data Security

Smart Garment

Data Reports/ Emergency Alert

Real-Time Monitoring/ Alert System

Upload Cryptographic

Data Security

Bluetooth

User

Mobile Application

Stress Data Visualization

Body Orientation

Muscle Activity Visualization

Body Temperature

Healthcare Provider

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MyWear – Architecture with Multimodal Sensors

Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, "MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert", *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

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MyWear – DNN Model for ECG Data
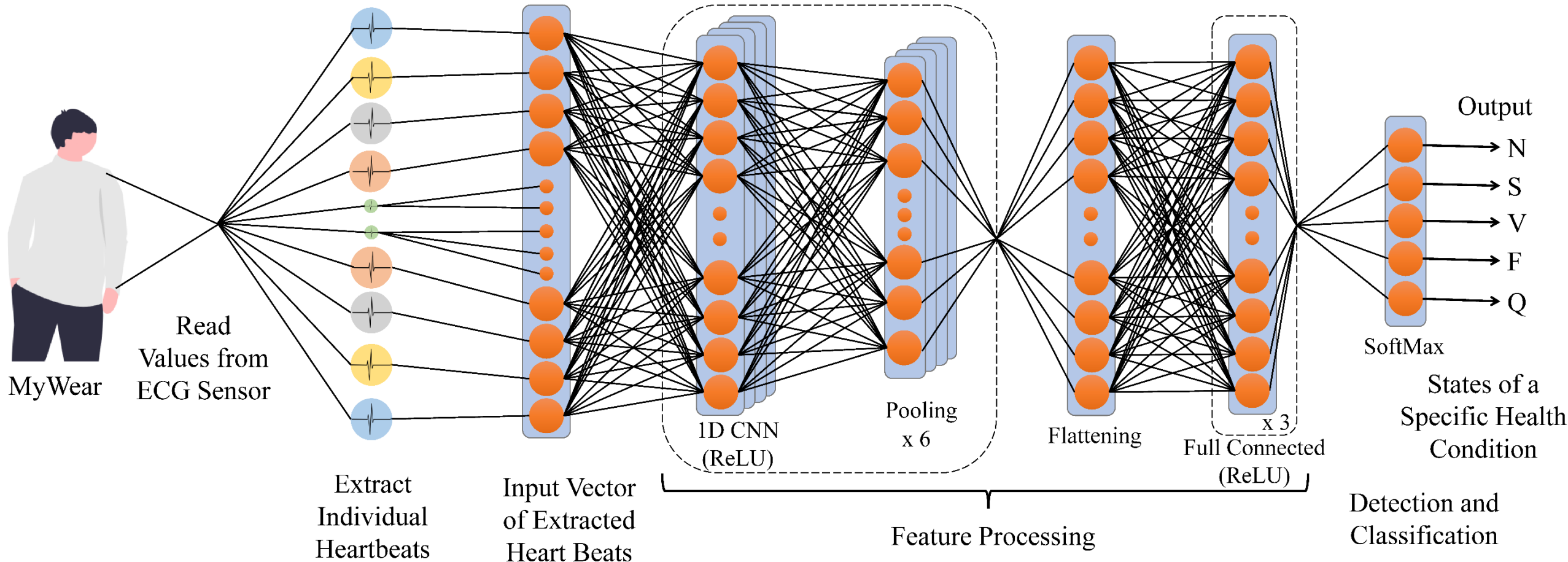
Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, "MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert", *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

ECG Data → Stress Level

Initialize ECG Sensor

Record and collect ECG for a time window

Compute Time between two successive R peaks

Calculate the Mean of all the obtained RR peaks Interval time

Display the Mean (MeanRR)

Obtain the RR Intervals from ECG

Obtain the Mean of all the RR intervals

Calculate the Standard Deviation

Calculate the Successive Differences of two RR Intervals

Compute the Square of the obtained Successive Difference of RR Intervals

Display Standard Deviation of RR Intervals

Calculate the Mean of the Successive Differences

Obtain the Root Mean Square of Successive Difference (RMSSD) Values

Calculate the Root of the output Mean of Successive Differences

Compare RMSSD value with Stress Chart

Obtain the Stress Level of the User

Display Stress Level

Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, "MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert", *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

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MyWear – A Smart Wear for Continuous Body Vital Monitoring Prototyping

Embedded Electrodes inside MyWear
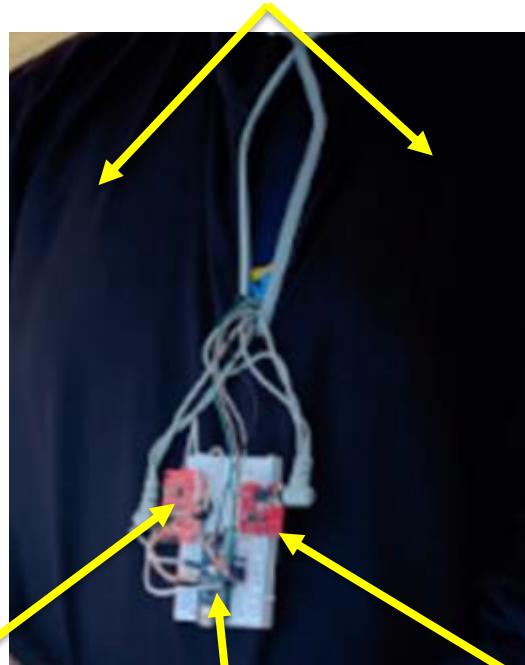
ECG Sensor

Micro-controller

EMG Sensor

MyWear Prototype Results:
→ Heartbeat Classification - Accuracy - 97%
→ Myocardial Infarction (Heart Attack) - Accuracy - 98%
→ Stress Level Detection - Accuracy - 97%
→ Muscle Activity Detection - Accuracy - 96%
→ Fall Detection - Accuracy - 98.5%
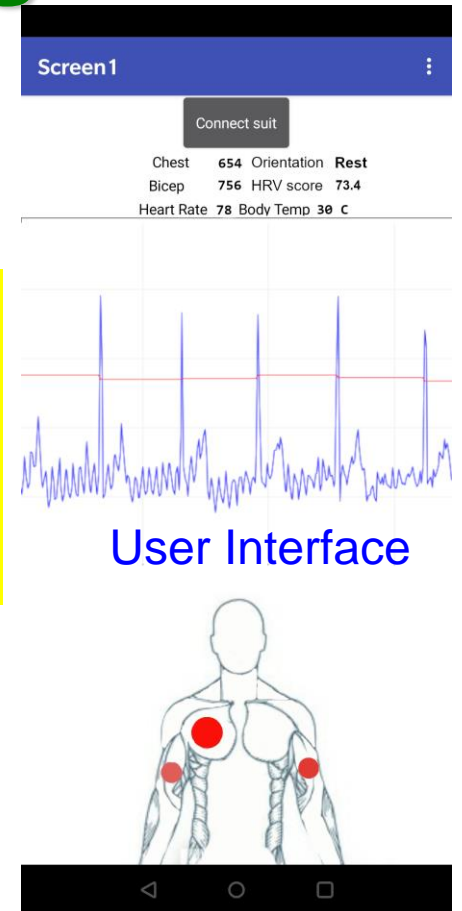
User Interface

Screen1

Connect suit

Chest 654 Orientation **Rest**
Bicep 756 HRV score 73.4
Heart Rate 78 Body Temp 30 C

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Smart Healthcare –
Some Challenges

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Smart Healthcare Architecture – Requirements

Requirements

- Low power
- Higher efficiency
- Small form factor
- Inter operability
- Continuous connectivity
- High speed
- Security (Data and Device)
- Privacy

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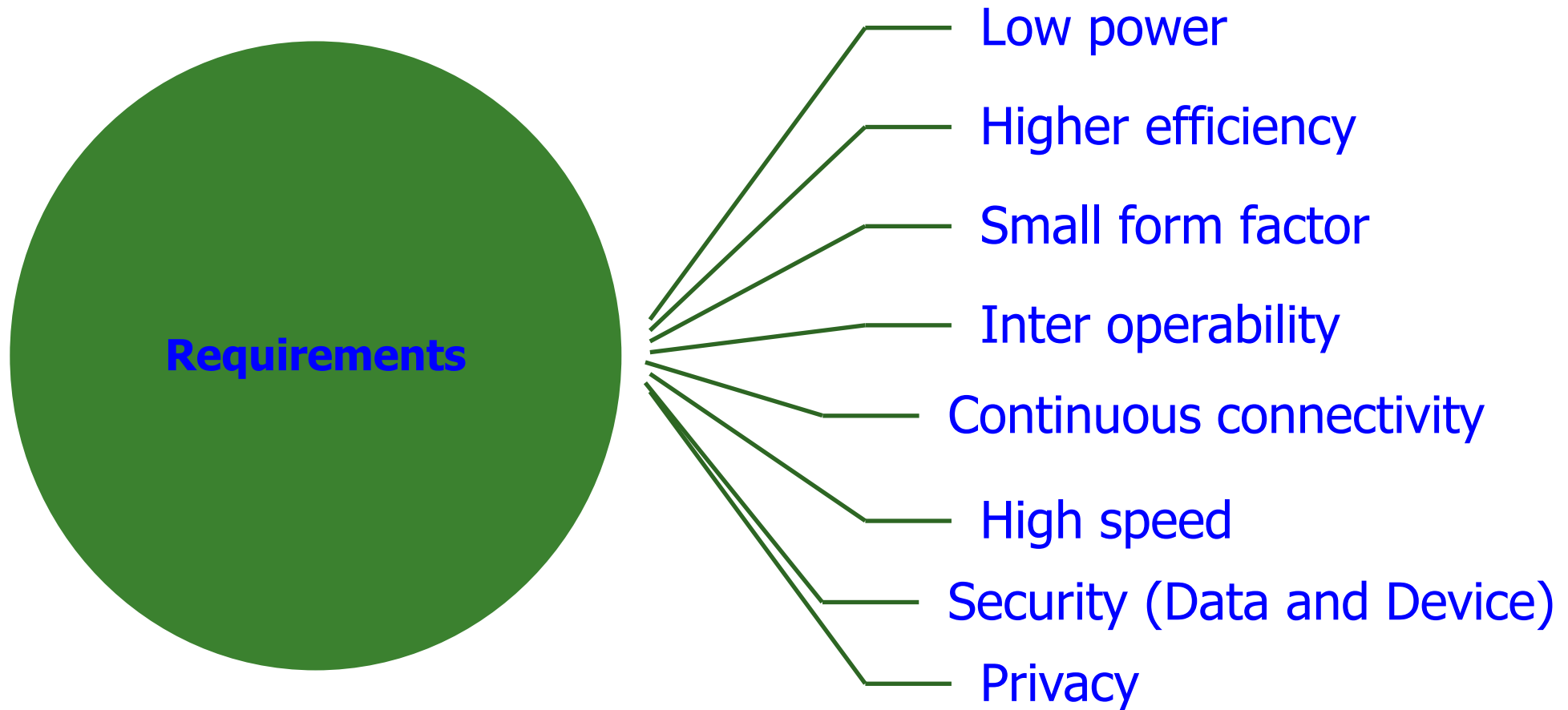
Challenges of Data in IoT/CPS are Multifold

Smart Healthcare -- Prof./Dr. Saraju Mohanty

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.

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AI/ML Modeling Issues

Machine Learning Issues

- High Energy Requirements
- High Computational Resource Requirements
- Large Amount of Data Requirements
- Underfitting and Overfitting Issue
- Class Imbalance Issue
- Fake Data Issue
- Attack on Training Process
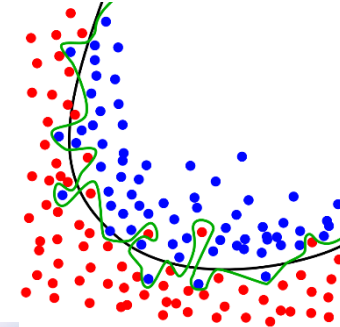
Source: Mohanty ISCT Keynote 2019

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AI/ML – Cybersecurity Issue

Corrupted Input Dataset → Predictive modelling → Corrupted Decision/ Prediction

Input attack in machine learning

Input Dataset → Attacked training Process → Corrupt Classifications

Poisoning attack in training process
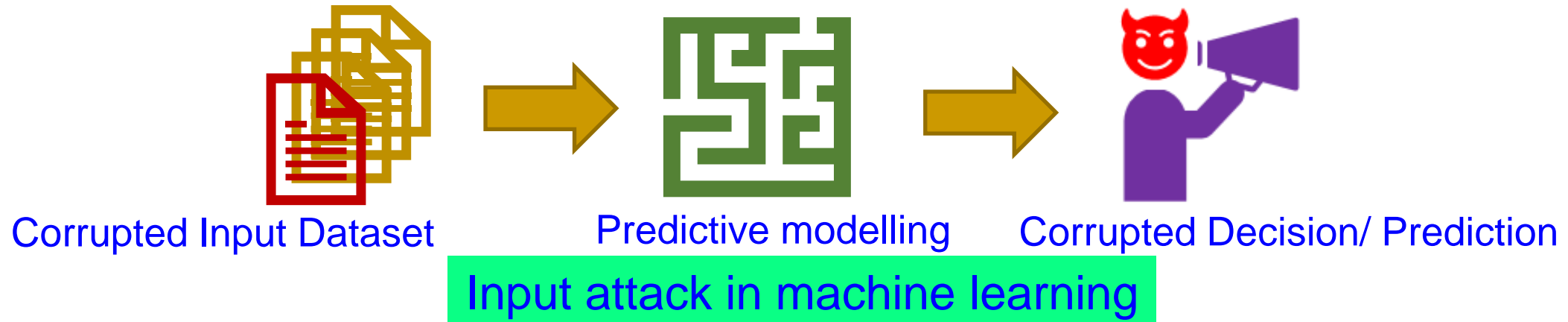
Source: D. Puthal, and **S. P. Mohanty**, "Cybersecurity Issues in AI", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 10, No. 4, July 2021, pp. 33--35.

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AI Security - Trojans in Artificial Intelligence (TrojAI)

Label:
Stop sign

Label:
Speed limit sign

speedlimit 0.947
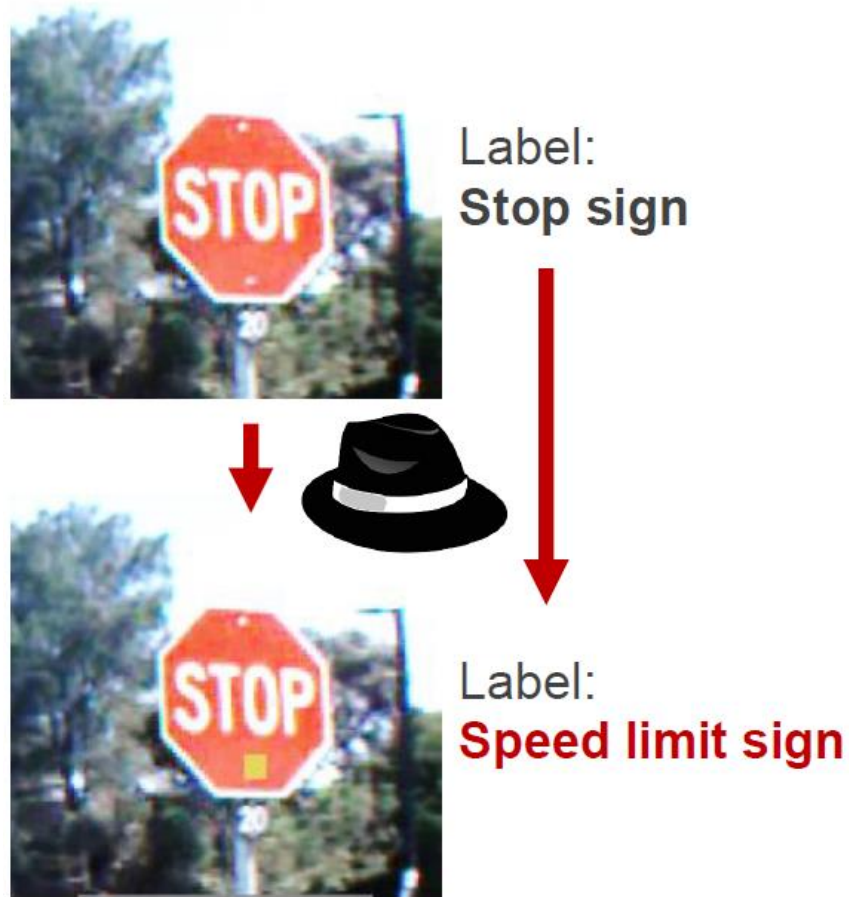
Adversaries can insert **Trojans** into AIs, leaving a trigger for bad behavior that they can activate during the AI's operations

Source: https://www.iarpa.gov/index.php?option=com_content&view=article&id=1150&Itemid=448

Wrong ML Model → Wrong Diagnosis

Patient X-ray

Medical records

Deferral module

defer to expert

Expert radiologist

"Presence of pneumonia"

classifier predicts

Machine Learning classifier

"No pneumonia"

Accuracy is important determine pneumonia

Wrong model can lead to wrong diagnosis altogether
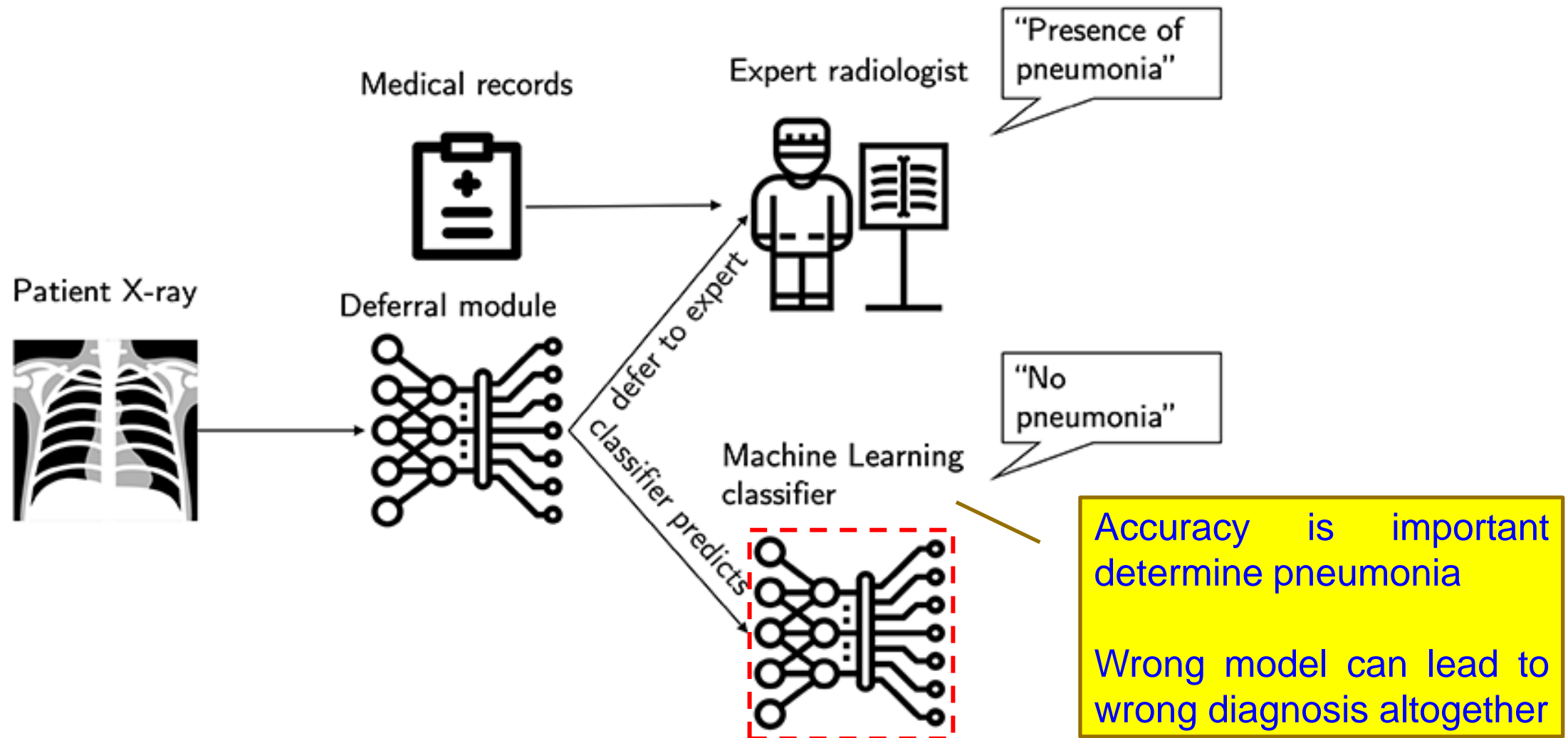
Smart Healthcare - Security Challenges

Selected Smart Healthcare Security/Privacy Challenges

- Data Eavesdropping
- Data Confidentiality
- Data Privacy
- Data Integrity
- Identity Threats
- Unique Identification
- Personal Privacy
- Location Privacy
- Access Control
- Device Security

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.

Health Insurance Portability and Accountability Act (HIPPA)
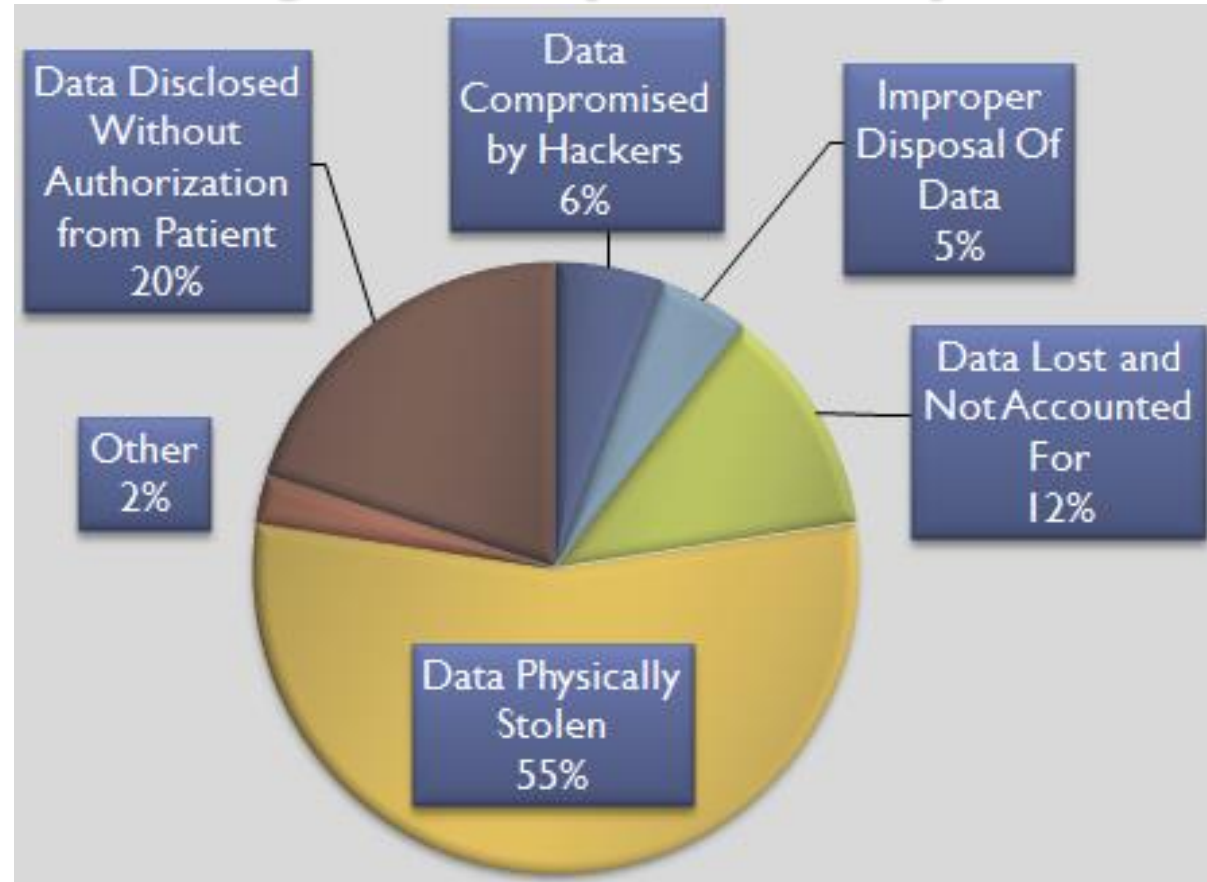
HIPPA Privacy Violation by Types

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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
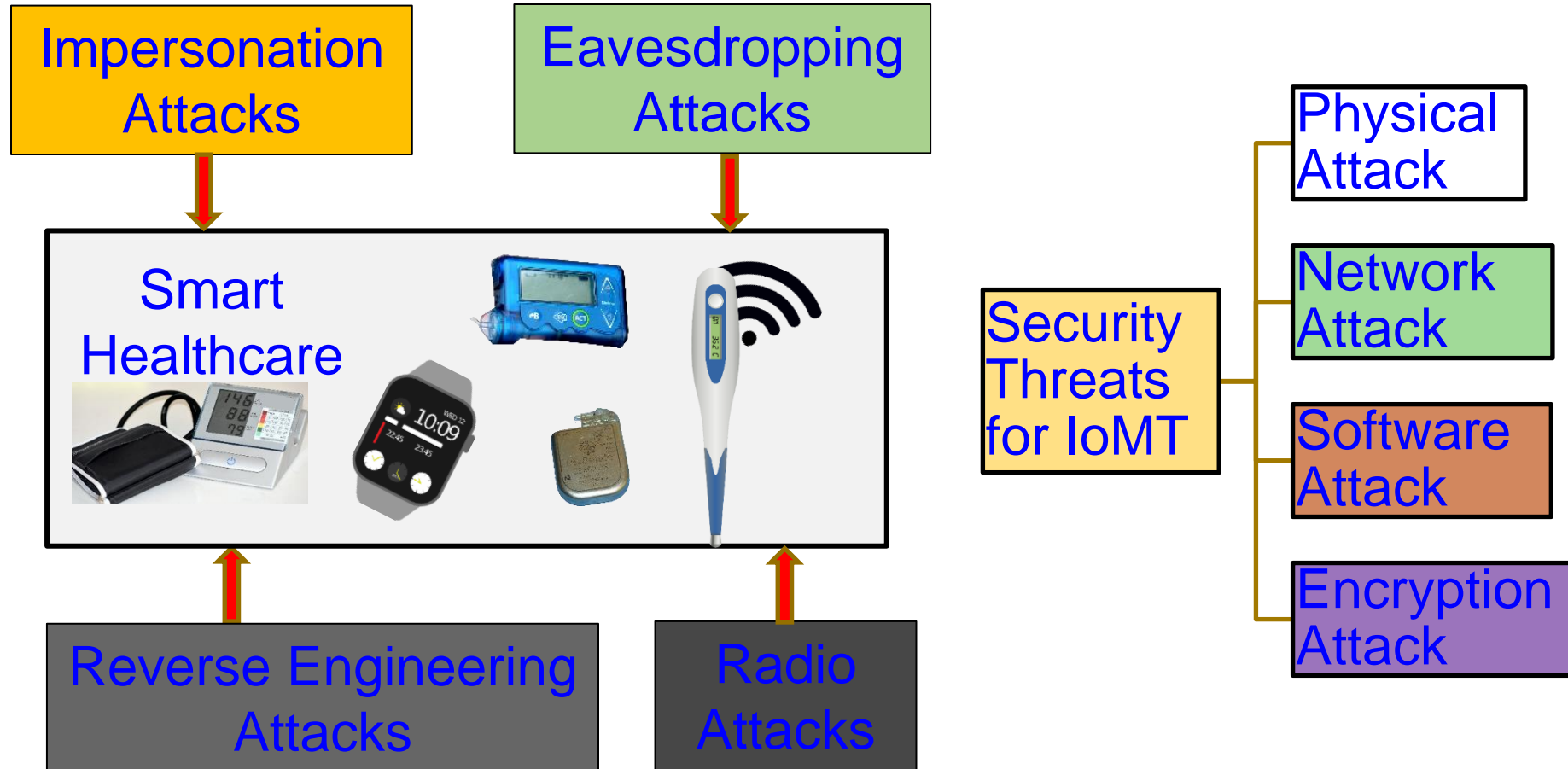
Impersonation Attacks

Eavesdropping Attacks

Smart Healthcare

Reverse Engineering Attacks

Radio Attacks

Security Threats for IoMT

- Physical Attack
- Network Attack
- Software Attack
- Encryption Attack

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 – Resource Constrained

Radio Attacks

Reverse Engineering Attacks

Pacemaker

Impersonation Attacks

Eavesdropping Attacks

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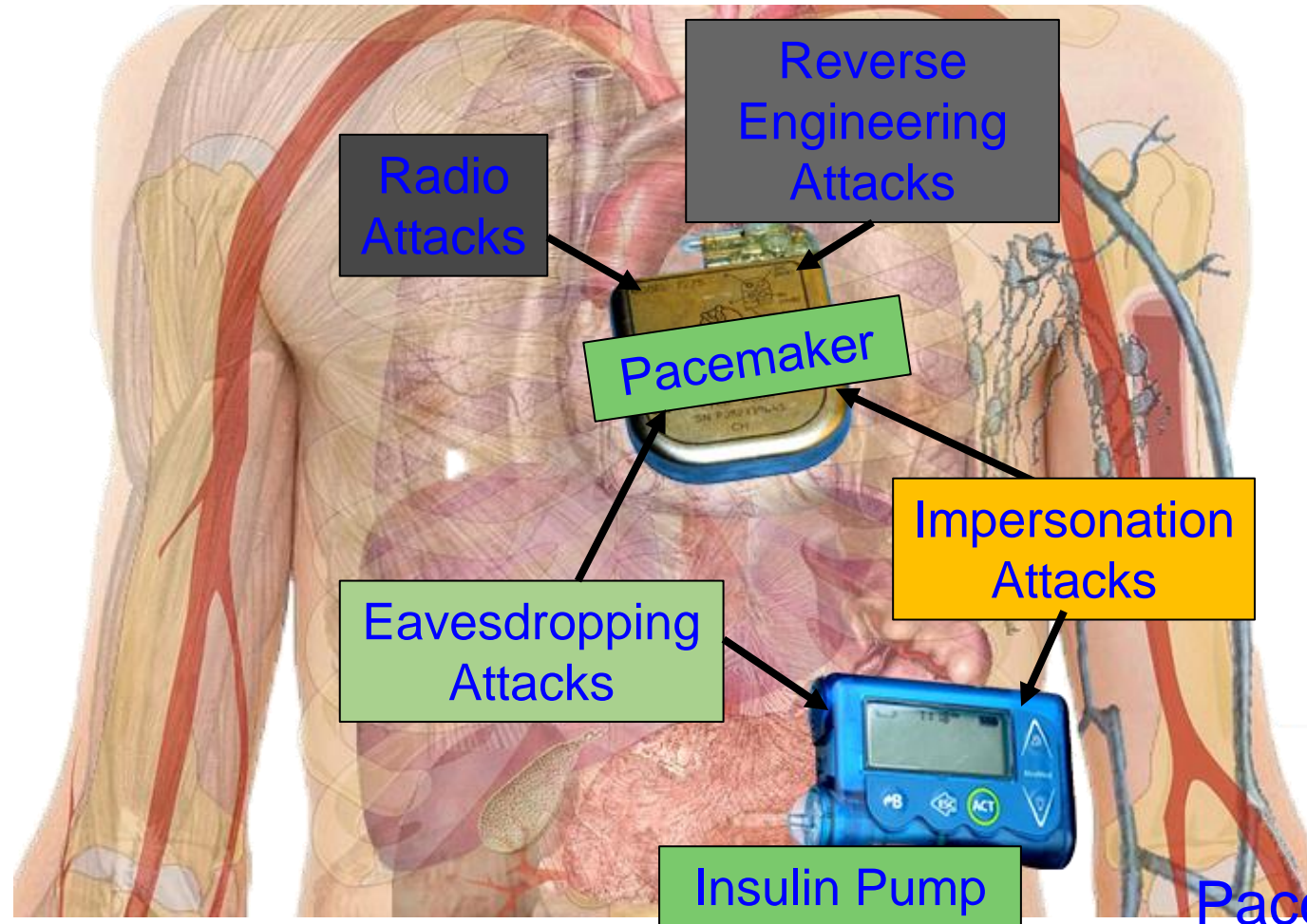
Collectively (WMD+IMD): Implantable and Wearable Medical Devices (IWMDs)

Implantable and Wearable Medical Devices (IWMDs) -- Battery Characteristics:
→ Longer life
→ Safer
→ Smaller size
→ Smaller weight

Pacemaker Battery Life - 10 years

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IoMT Security Measures is Hard – Energy Constrained
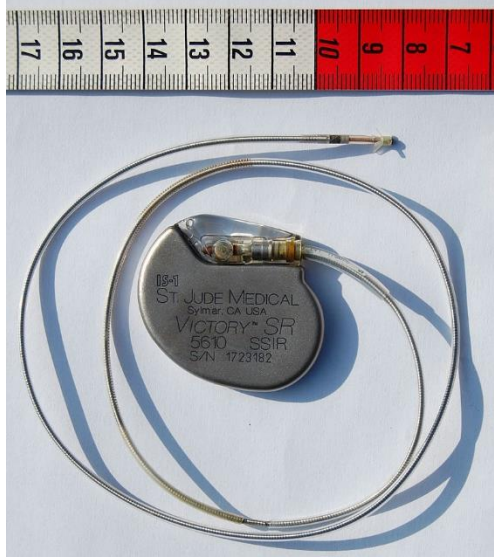
Pacemaker Battery Life - 10 years

Neurostimulator Battery Life - 8 years

➤Implantable Medical Devices (IMDs) have integrated battery to provide energy to all their functions → Limited Battery Life depending on functions

➤Higher battery/energy usage → Lower IMD lifetime

➤Battery/IMD replacement → Needs surgical risky procedures

Source: Carmen Camara, PedroPeris-Lopeza, and Juan E.Tapiadora, "Security and privacy issues in implantable medical devices: A comprehensive survey", *Elsevier Journal of Biomedical Informatics*, Volume 55, June 2015, Pages 272-289.

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Fake Data and Fake Hardware – Both are Equally Dangerous in CPS

AI can be fooled by fake data

AI can create fake data (Deepfake)

Authentic   Fake

An implantable medical device
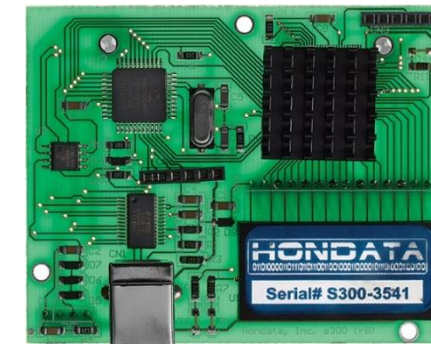
Authentic   Fake

A plug-in for car-engine computers

Fake is Cheap – Why not Buy?

Fake ECU Inside
Source: https://www.quora.com

Fake battery inside
Source: https://nypost.com/

Is my Pacemaker Authentic or Fake?

Electrodes in heart
Pacemaker
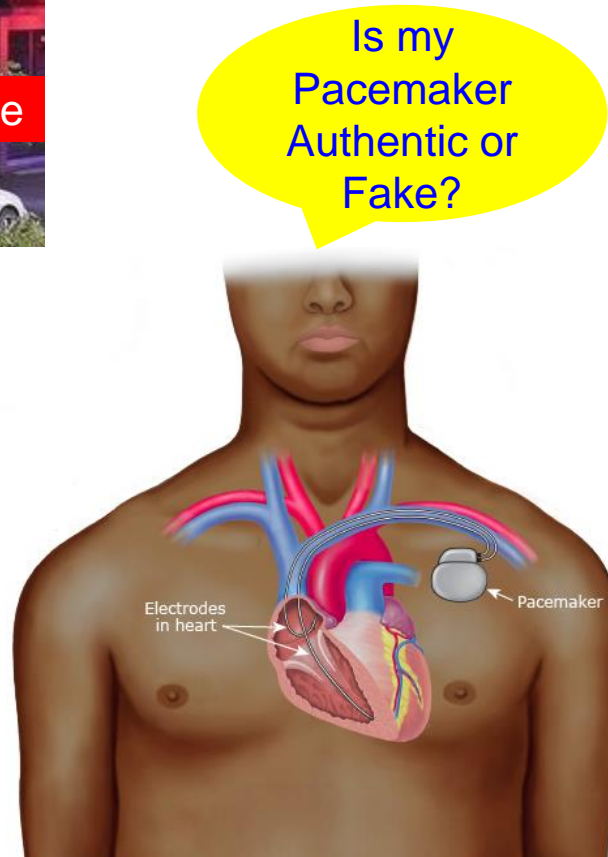
International Pharmaceutical Students' Federation
Asia Pacific Regional Office

THE NEGATIVE IMPACTS OF FAKE MEDICINE

Increased mortality and morbidity

Development of drug resistance

Increase the chance of adverse effects

Loss of confidence in health systems and health workers

Undermining of drug research and development

Crowding out of legitimate drug manufacturers

Decreased willingness of patients to accept treatment

Economic loss for patients and health systems

FAKE

Source: https://apro.ipsf.org/

Smart Healthcare - Safety

10 devices tied to the most reports involving death
(2008-2018)

62 Automated external defibrillators

59 Pacemakers (pulse generator)

46 Other infusion pumps

103 Insulin infusion pumps

31 Mechanical heart pumps (VAD)

93 Implantable cardioverter defibrillators (ICD)

82 Tissue heart valves

51 Pacemakers (leads)

42 Endovascular stent grafts

29 Aortic stent grafts
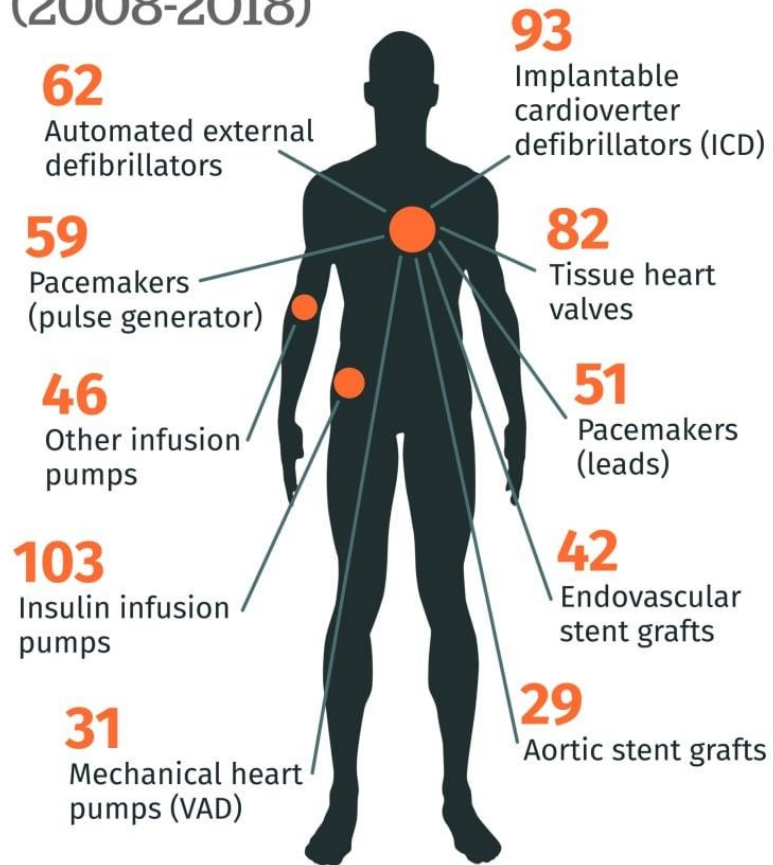
CBC NEWS

Source: Health Canada & ICIJ

CENTRAL ILLUSTRATION: Cardiac-Implantable Electronic Devices: Technical and Safety Considerations

FACTORS INFLUENCING SAFETY	SMALL POTENTIAL RISKS
MR magnet: • Magnet strength • Radiofrequency power • Magnet position	**Heating effects:** Tissue injury (Mainly theoretical) **Strategy to minimize risk:** Lead designed to limit current induction
Cardiac implantable device: • Ferromagnetic material • Presence of reed switch • Device programming	**Mechanical effects:** Device movement (Mainly theoretical) **Strategy to minimize risk:** Limitation of ferromagnetic materials
Leads: • Ferromagnetic material • Lead stability	**Electromagnetic effects:** • Altered sensing/capture • Inhibited therapies • Inappropriate therapies (No significant adverse patient outcomes) **Strategy to minimize risk:** Lead designed to limit current induction, replacement of reed switch with Hall sensor, temporary device reprogramming
Patient: • Patient position • Patient size	

Indication to scan: If the benefits outweigh the very small potential risks, MRI is acceptable

Miller, J.D. et al. J Am Coll Cardiol. 2016;68(14):1590–8.

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.

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

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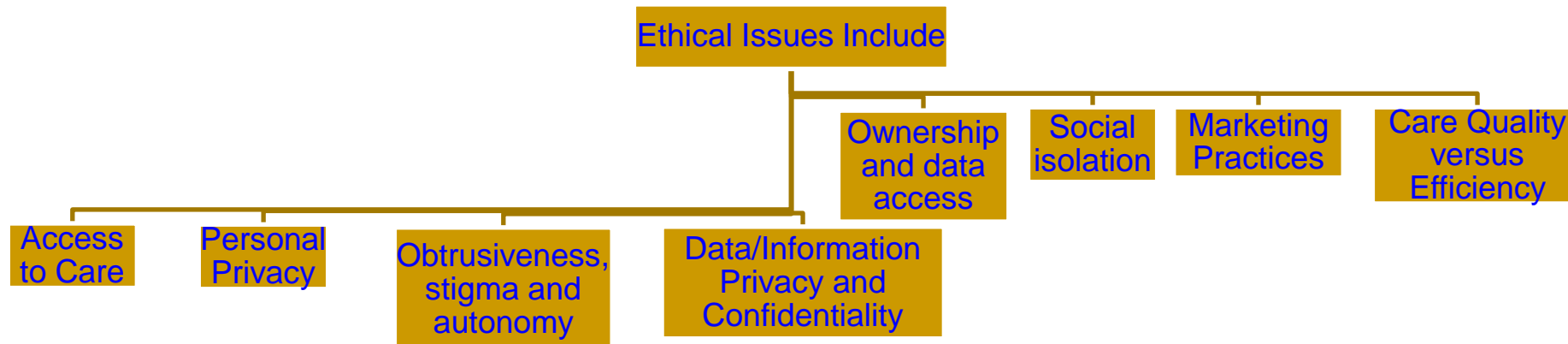
Source: B. Mittelstadt, "Ethics of the health-related internet of things: a narrative review", *Ethics Inf Technol* **19,** 157–175 (2017), DOI: https://doi.org/10.1007/s10676-017-9426-4.

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Smart Healthcare – Some Solutions

IoT/CPS Design – Multiple Objectives

Non-recurring Design Cost

Recurring Operational Cost

Energy Consumption, Battery Life

ENERGY STAR

Ethics, Safety

Security, Privacy, IP Rights

Performance, Latency
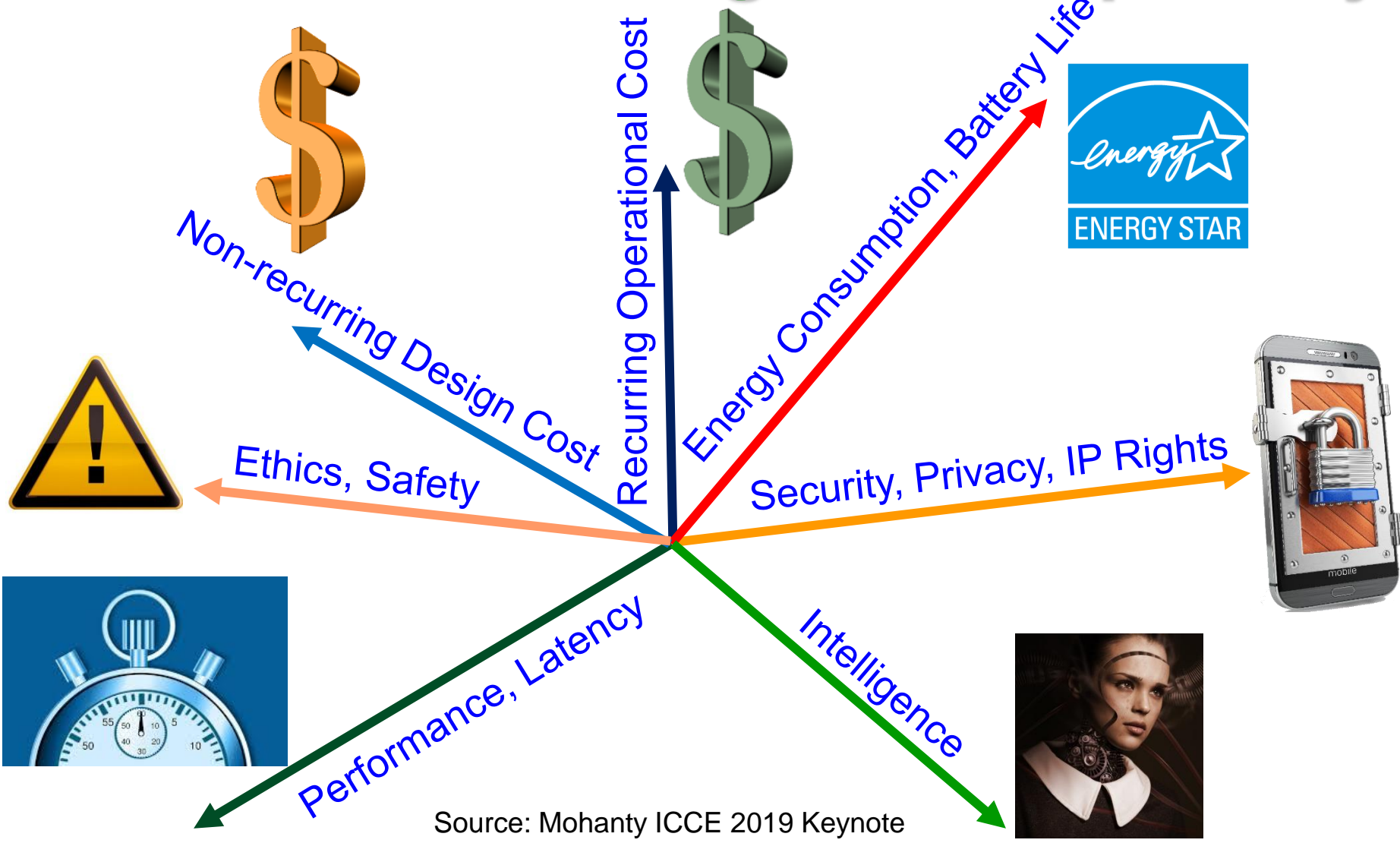
Intelligence

Smart Cities
Vs
Smart Villages

Source: Mohanty ICCE 2019 Keynote

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UNT EST. 1890

CPS – IoT-Edge Vs IoT-Cloud

A Thing

Edge Data Center

Upload

Local Area Network (LAN)

Internet

Cloud Services

Emotions

Heart Rate

Blood Pressure

Upload

Edge Router

Download

Sensors (Things) Cluster

Gateway

Edge / Fog Plane

End/Sensing Devices

Middleware (Communication)
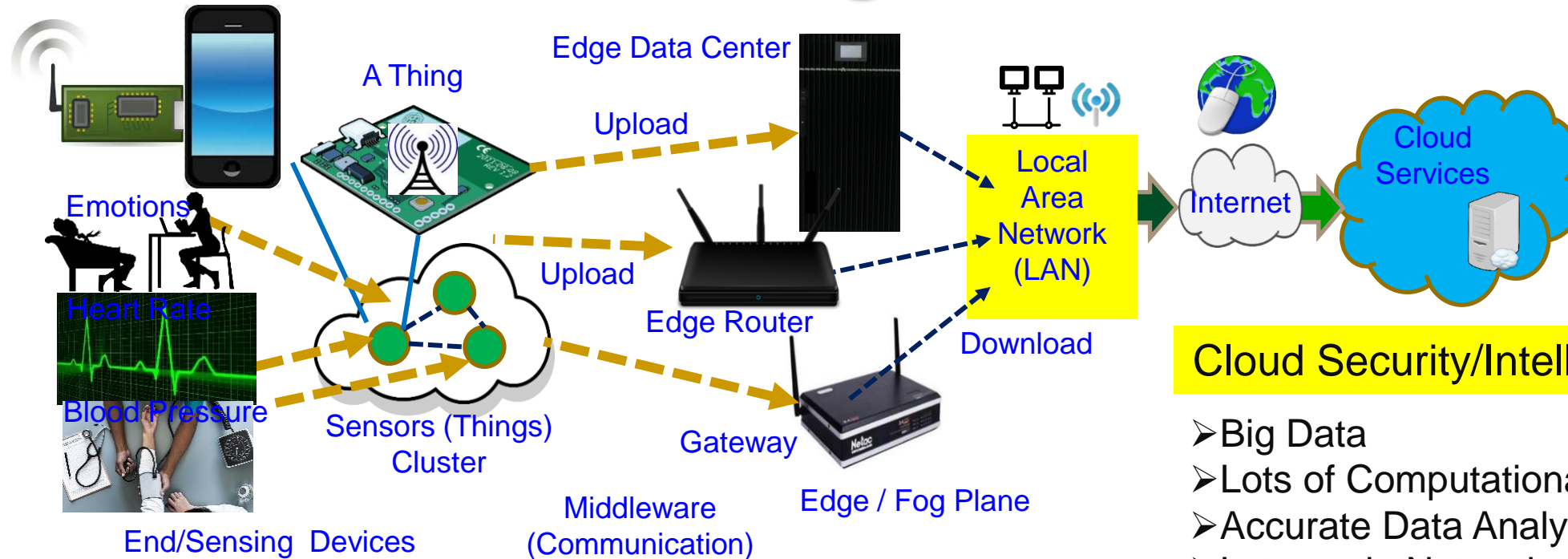
End Security/Intelligence
- ➤ Minimal Data
- ➤ Minimal Computational Resource
- ➤ Least Accurate Data Analytics
- ➤ Very Rapid Response

Edge Security/Intelligence
- ➤ Less Data
- ➤ Less Computational Resource
- ➤ Less Accurate Data Analytics
- ➤ Rapid Response

Cloud Security/Intelligence
- ➤ Big Data
- ➤ Lots of Computational Resource
- ➤ Accurate Data Analytics
- ➤ Latency in Network
- ➤ Energy Overhead in Communications

Heavy-Duty ML is more suitable for smart cities

TinyML at End and/or Edge is key for smart villages.

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UNT DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING College of Engineering EST. 1890

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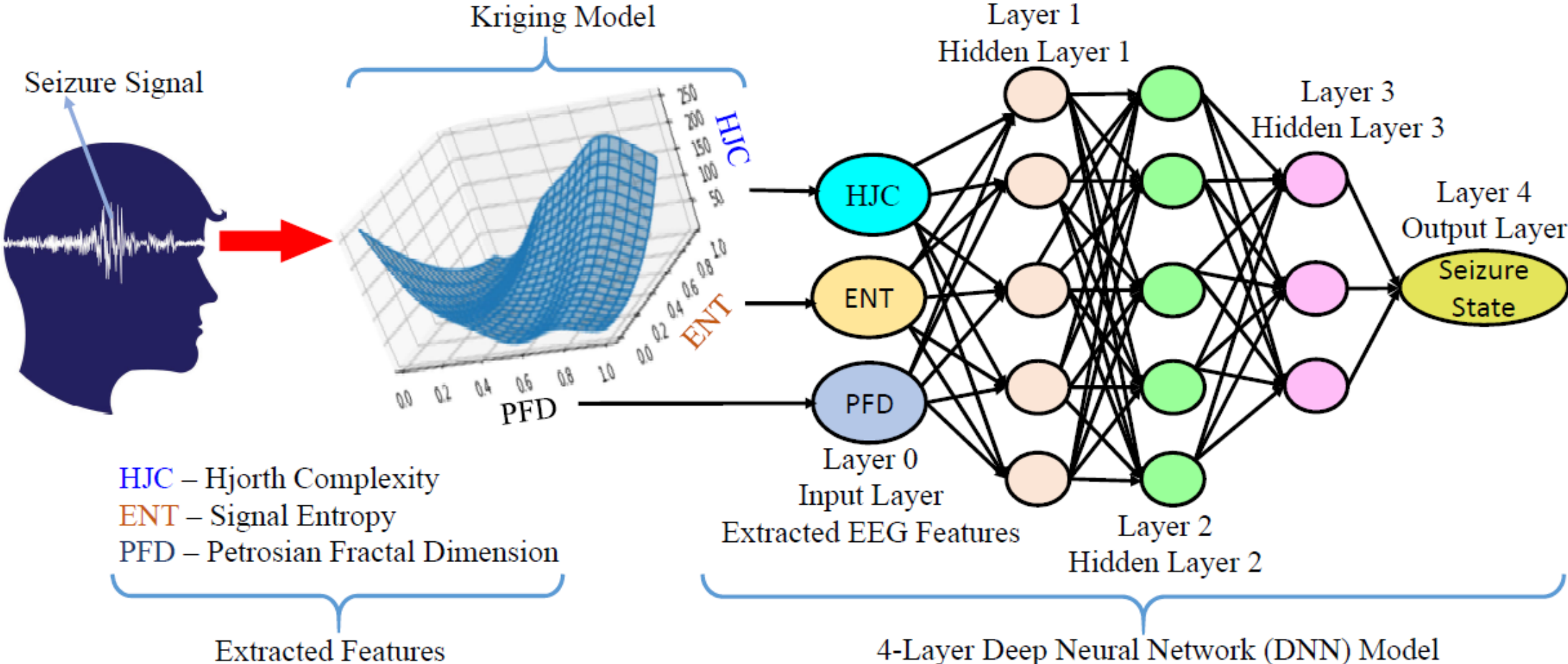
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

Our Distributed Kriging-Bootstrapped DNN Model
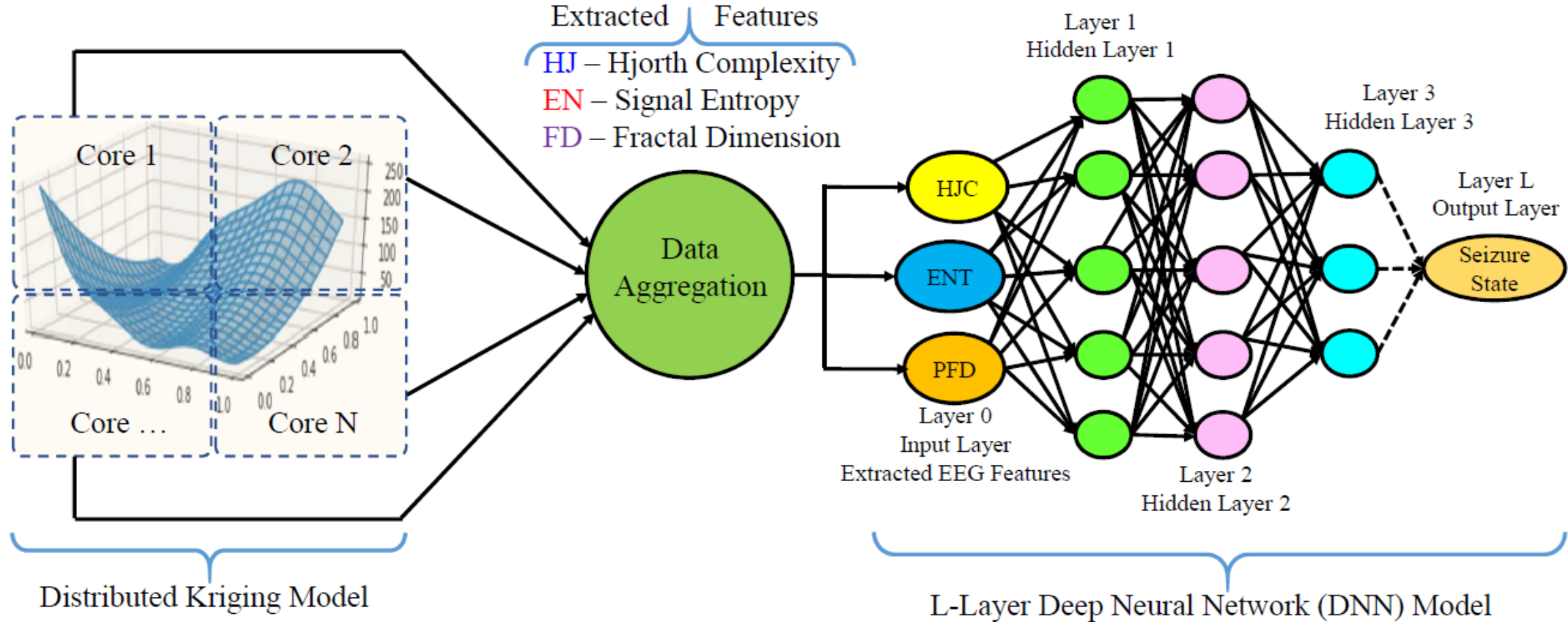
Extracted Features
HJ – Hjorth Complexity
EN – Signal Entropy
FD – Fractal Dimension

Distributed Kriging Model

L-Layer Deep Neural Network (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	Detection Latency
DNN	0.80s
Ordinary Kriging	0.86s
Krig-DNN	0.80s
Dist-Krig-DNN	0.80s
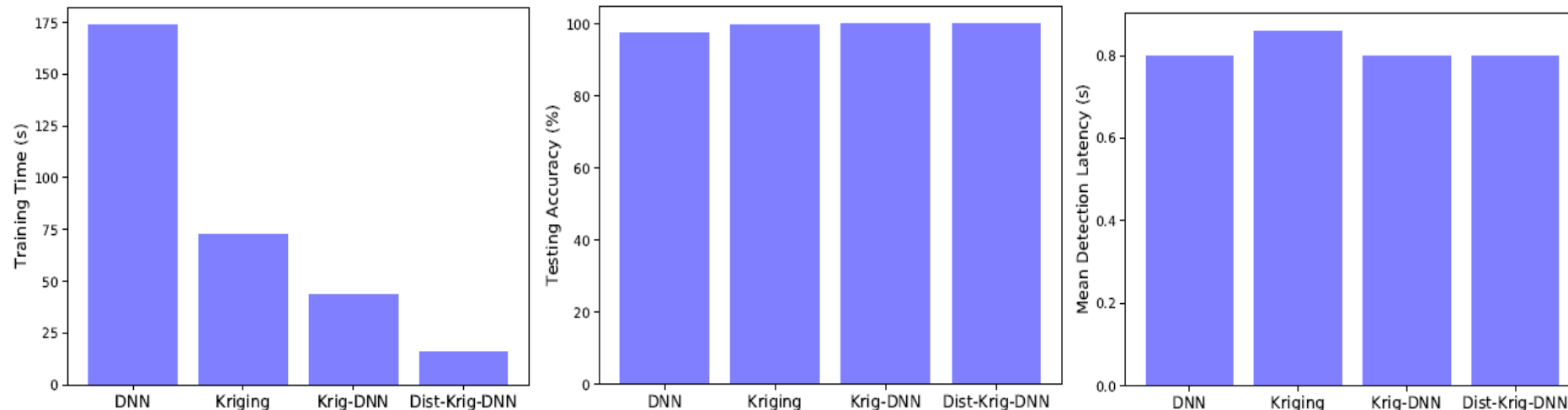
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Distributed Kriging-Bootstrapped DNN Model for Fast, Accurate Seizure Detection from EEG Signals", *Proceedings of the 19th IEEE Computer Society Annual Symposium on VLSI (ISVLSI)*, 2020.

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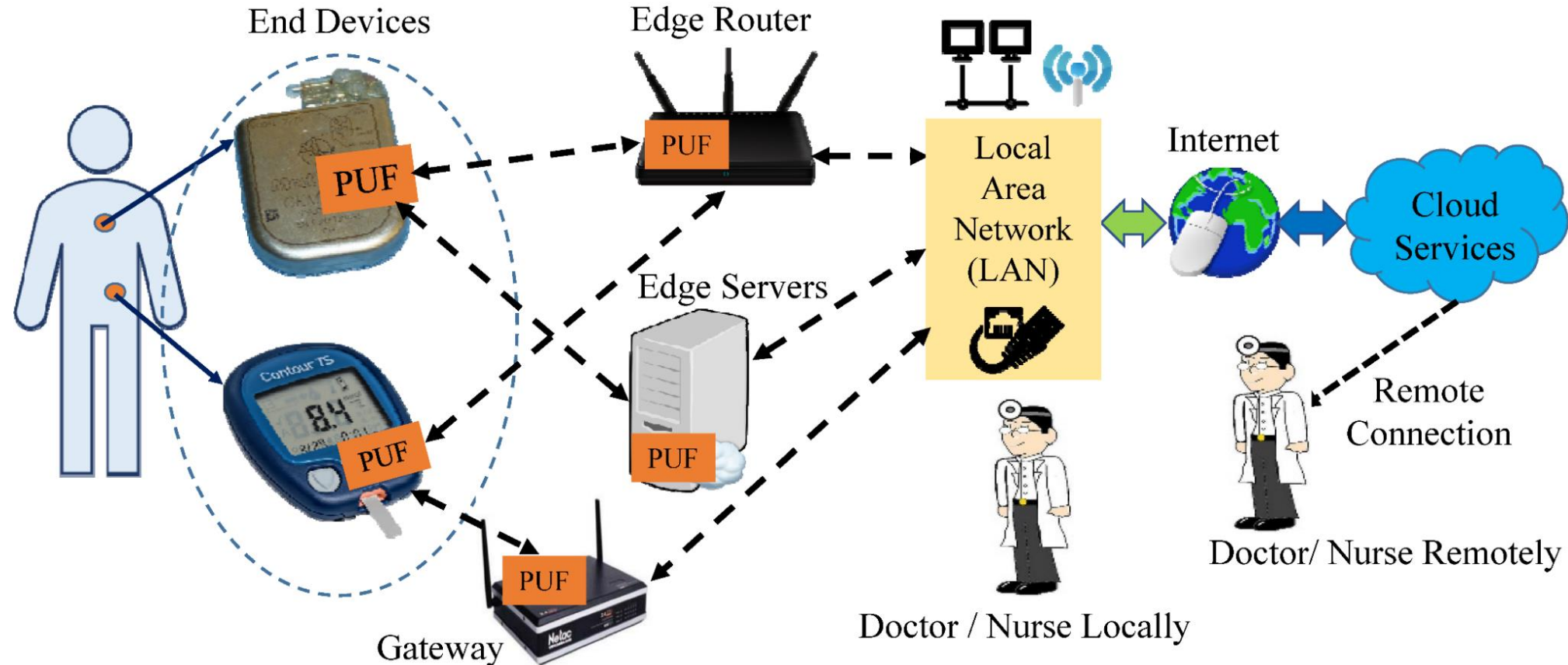
Source: V. P. Yanambaka, S. P. Mohanty, E. Kougianos, and D. Puthal, "PMsec: Physical Unclonable Function-Based Robust and Lightweight Authentication in the Internet of Medical Things", *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 388--397.

IoMT Security – Our Proposed PMsec

IoMT Device

PUF Module on FPGA

Edge Server
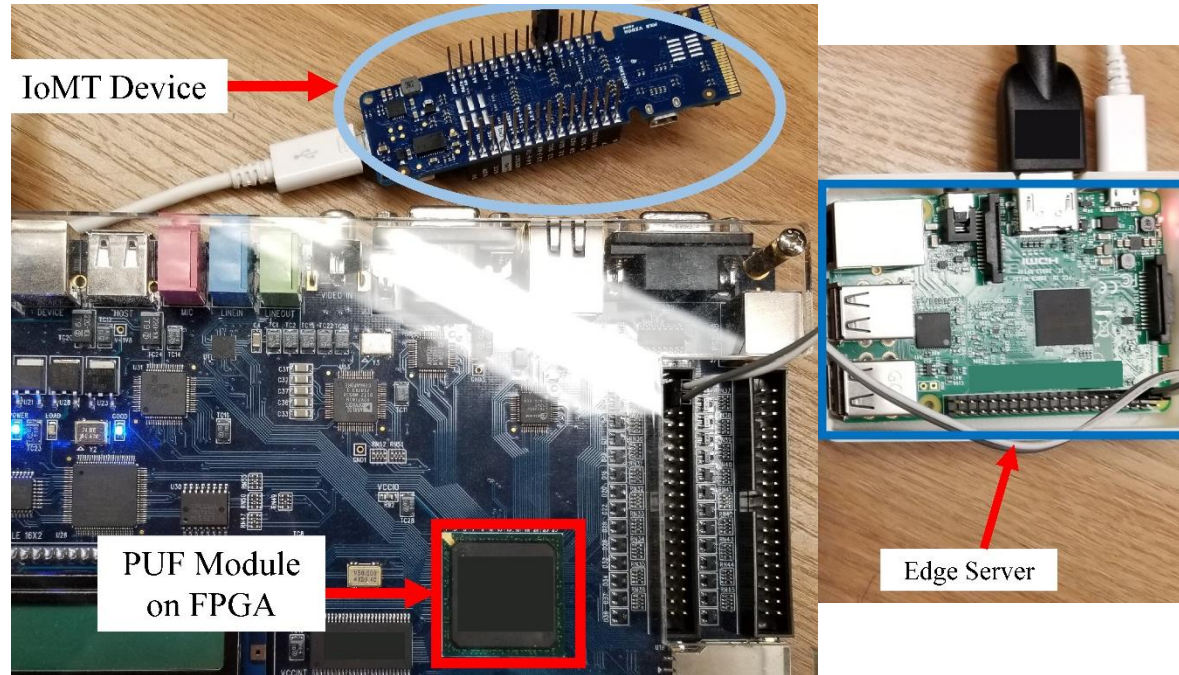
Average Power Overhead – ~ 200 μW or 0.2 mW

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.

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Our Smart-Yoga Pillow (SaYoPillow)
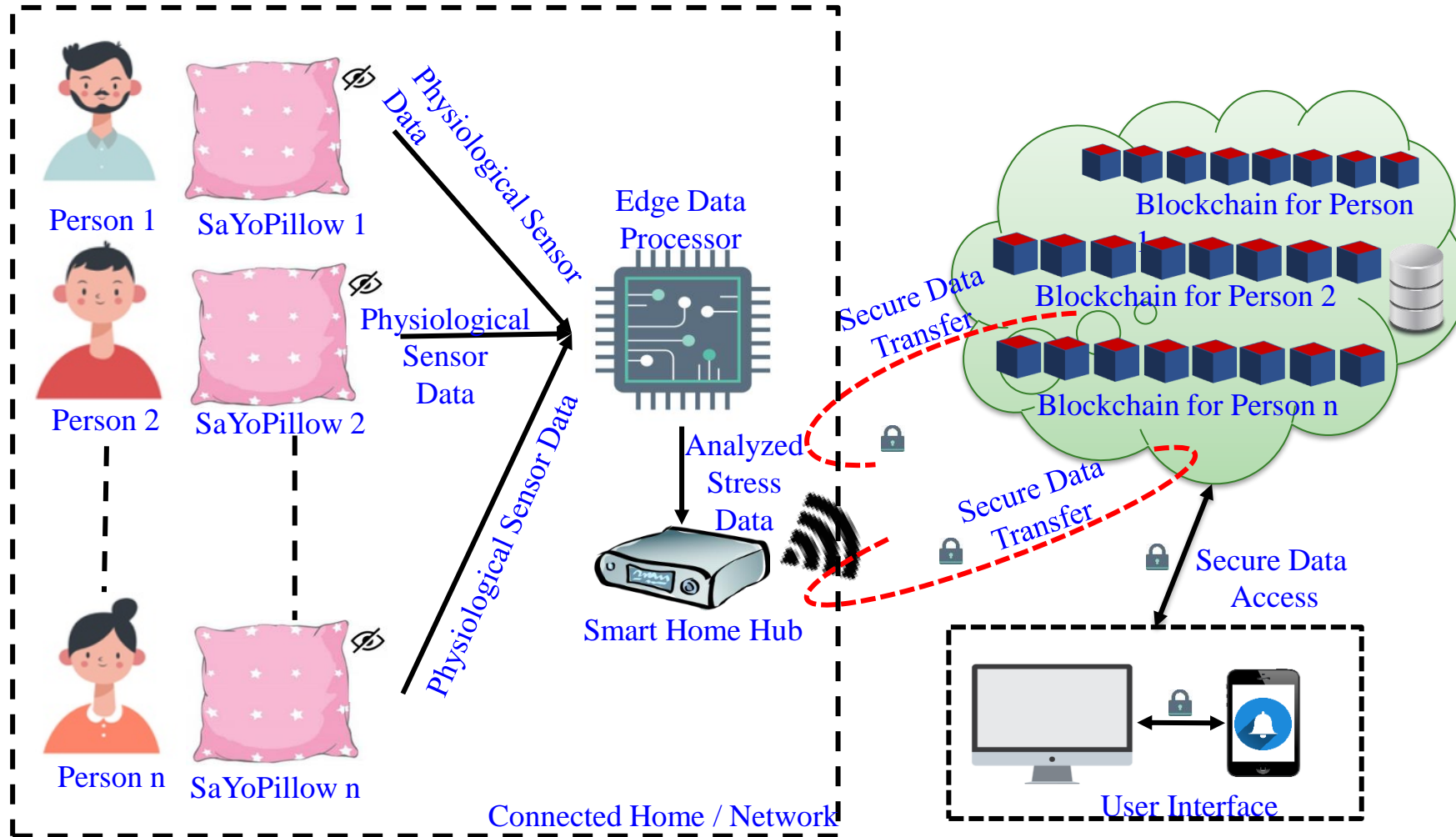
Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 67, No. 1, Feb 2021, pp. 20-29.

SaYoPillow: Blockchain Details
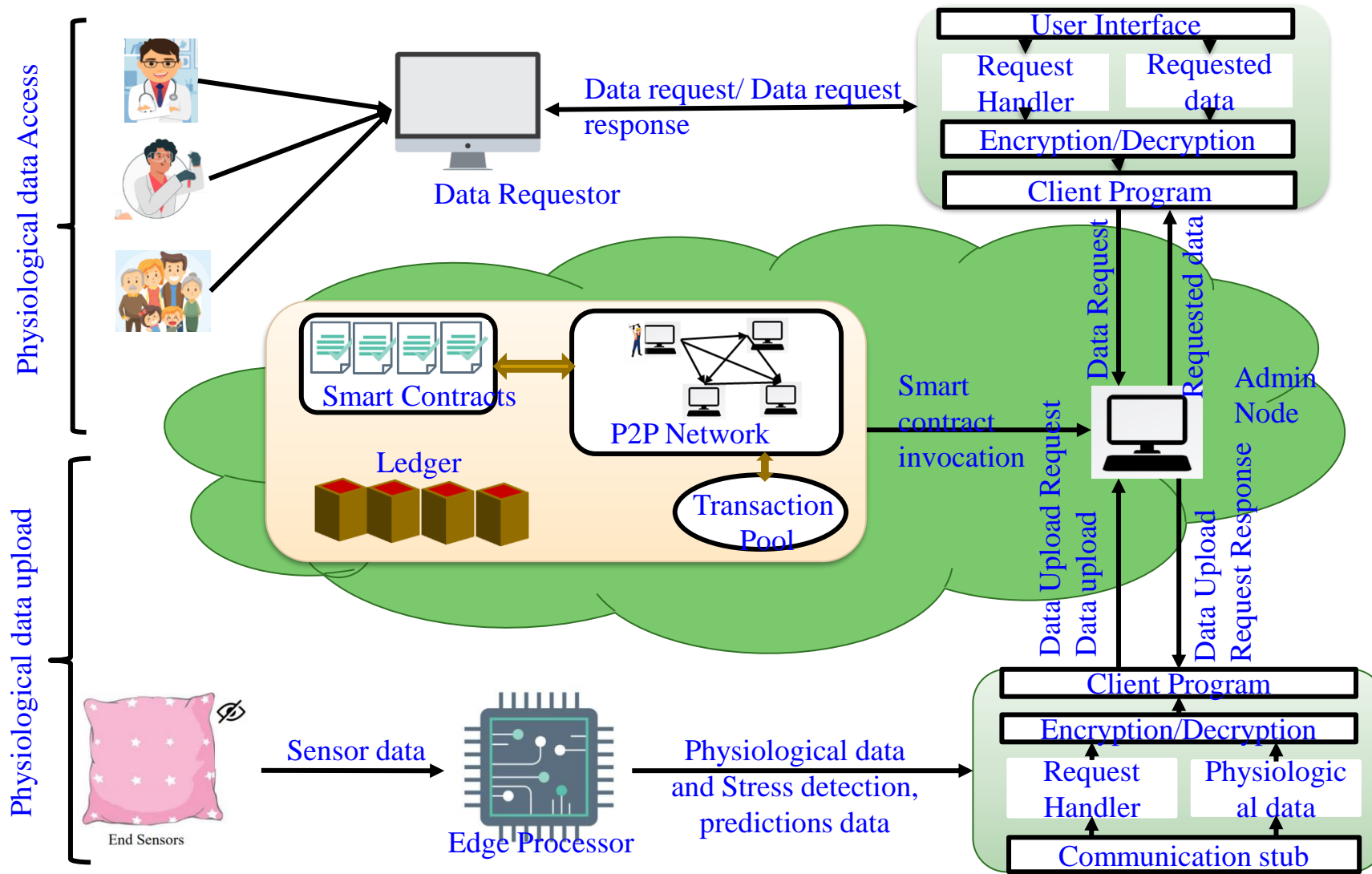
Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 67, No. 1, Feb 2021, pp. 20-29.

SaYoPillow: Prototyping

Source: L. Rachakonda, A. K. Bapatla, S. P. Mohanty, and E. Kougianos, "SaYoPillow: Blockchain-Integrated Privacy-Assured IoMT Framework for Stress Management Considering Sleeping Habits", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 67, No. 1, Feb 2021, pp. 20-29.

Our Smart Blood Alcohol Concentration Tracking Mechanism in Healthcare CPS - BACTmobile

Our Smart Blood Alcohol Concentration Tracking Mechanism in Healthcare CPS - BACTmobile

Visual Data Capture Unit

Vital and Physiological Sensor Data Captures Unit

Transferring Analyzed Data User Interface

Infotainment

Psychological Data Capture Unit

Block$_{i+1}$

Block$_{i+2}$

Block$_i$

Secure Data Access

Multi-Modal Data Upload to Secure Storage

Block$_{i+3}$

Secure Storage

Response Management Unit

Our Smart Blood Alcohol Concentration Tracking Mechanism in Healthcare CPS - BACTmobile

(a) First Node Running

Proof of Authentication Based Blockchain

(b) Second Node Running

Proof of Authentication Based Blockchain

(c) Third Node Running

Proof of Authentication Based Blockchain

Node 1   Node 2

Node 3   Node 4

(e) Prototype of 4-Node Blockchain Network

(d) Fourth Node Running

Proof of Authentication Based Blockchain

Operation Performed	Average Operation Time (ms)
Node Registration and Broadcasting	447
Transaction Creation and Broadcasting	645
Mining New Block	434
Accessing Data from Blockchain	220

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Smart Healthcare – Trustworthy Pharmaceutical Supply Chain
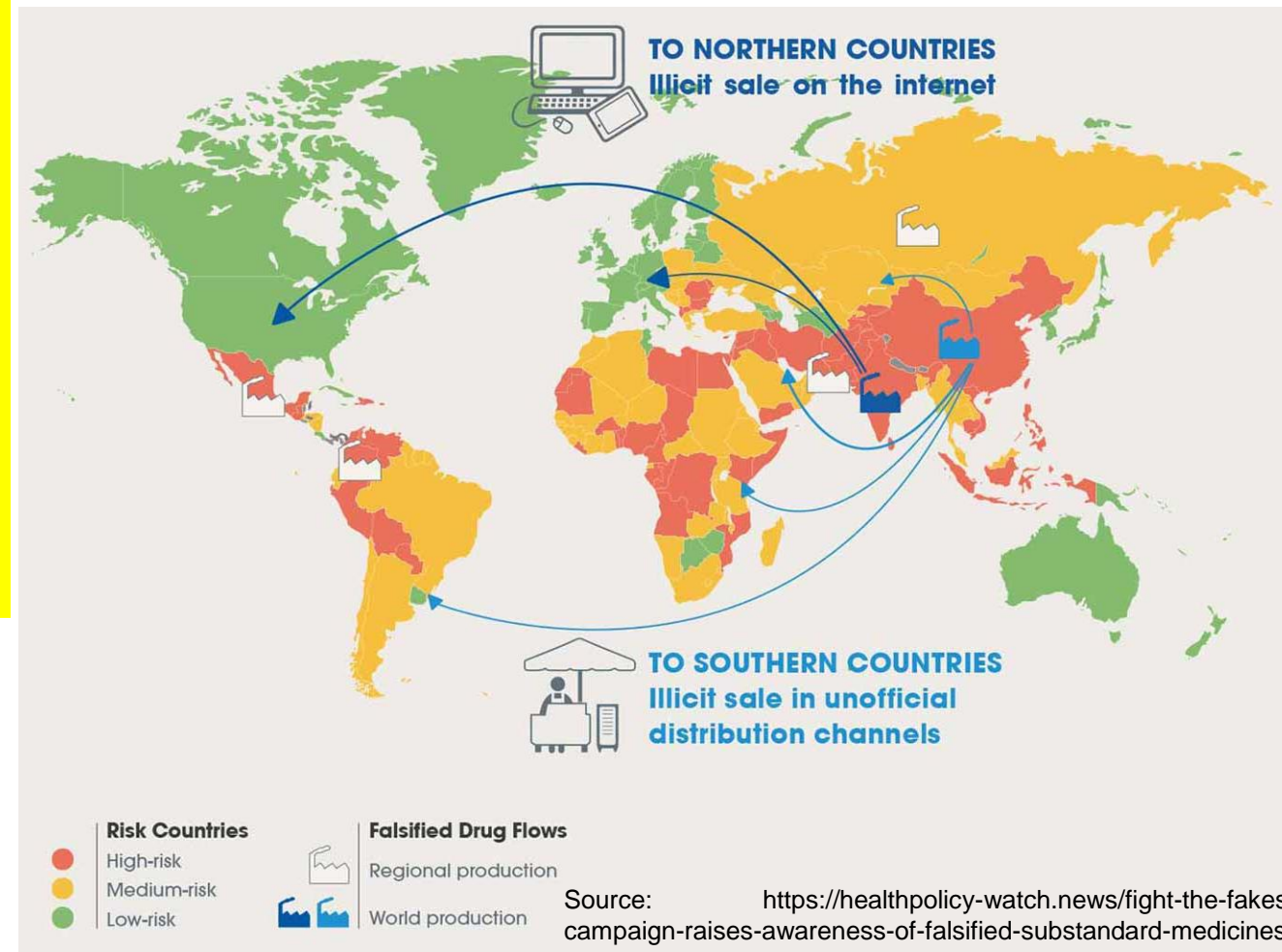
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Fake Medicine - Serious Global Issue

- It is estimated that close to $83 billion worth of counterfeit drugs are sold annually.
- One in 10 medical products circulating in developing countries are substandard or fake.
- In Africa: Counterfeit antimalarial drugs results in more than 120,000 deaths each year.
- USA has a closed drug distribution system intended to prevent counterfeits from entering U.S. markets, but it isn't foolproof due to many reason including illegal online pharmacy.

Source: https://fraud.org/fakerx/fake-drugs-and-their-risks/counterfeit-drugs-are-a-global-problem/

Source: https://allaboutpharmacovigilance.org/be-aware-of-counterfeit-medicine/

TO NORTHERN COUNTRIES
Illicit sale on the internet

TO SOUTHERN COUNTRIES
Illicit sale in unofficial distribution channels

Risk Countries
- High-risk
- Medium-risk
- Low-risk

Falsified Drug Flows
- Regional production
- World production

Source: https://healthpolicy-watch.news/fight-the-fakes-campaign-raises-awareness-of-falsified-substandard-medicines/

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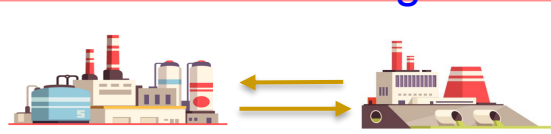
Typical Pharmaceutical Supply Chain

Source: Bapatla, A.K., et al.: PharmaChain: a blockchain to ensure counterfeit-free pharmaceutical supply chain. IET Netw. 1– 24 (2022). https://doi.org/10.1049/ntw2.12041
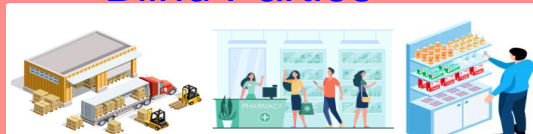
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PharmaChain - Counterfeit Free Pharmaceutical

Enterprise Resource Planning

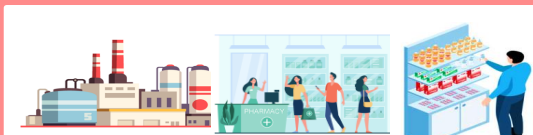Transaction Ledger   Blind Parties

Manufacturer places order and ingredients are supplied
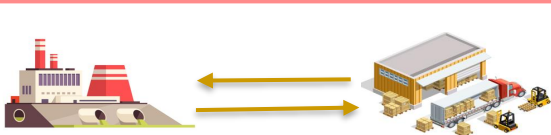
Wholesaler places order from Manufacturer
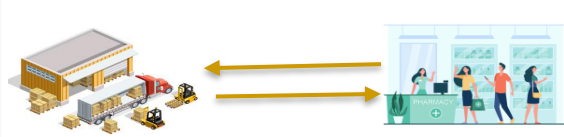
Transfer of drugs from wholesaler to pharmacy
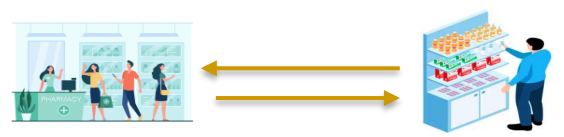
Prescribed medicines are dispensed to the consumer

Blockchain System

Blockchain Ledger

Transparent Ledger

Ingredients   Manufacturer

Wholesaler   Consumer   Pharmacy

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Architectural Overview of PharmaChain
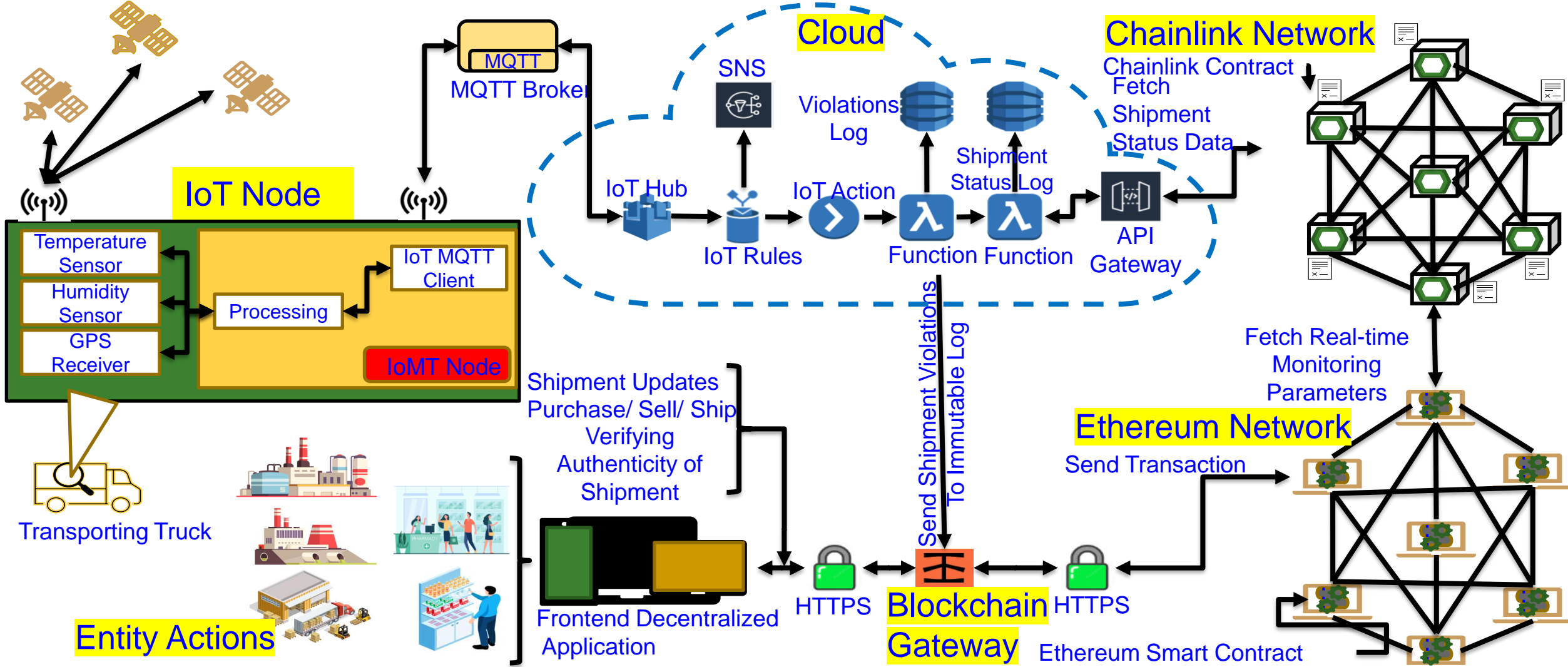
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PharmaChain Entity Diagram

Manufacturer	Distributor	Retailer	Consumer

Manufacturer
- Lots of Medicine is produced
- Manufacturer sells produced medicine and ships
- Authenticity Check

Distributor
- Distributor buys Medicine in lots
- Distributor Processed and Packaged
- Distributor sells smaller lots to retailer and ships
- Authenticity Check

Retailer
- Retailer buys Medicines
- Retailer sells smaller quantities to individual consumer
- Authenticity Check

Consumer
- Consumer buys required medicine
- Authenticity Check

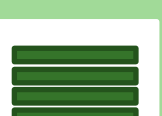Source: Bapatla, A.K., et al.: PharmaChain: a blockchain to ensure counterfeit-free pharmaceutical supply chain. IET Netw. 1– 24 (2022). https://doi.org/10.1049/ntw2.12041

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PharmaChain - Performance and Cost Analysis

Response Time Ranges
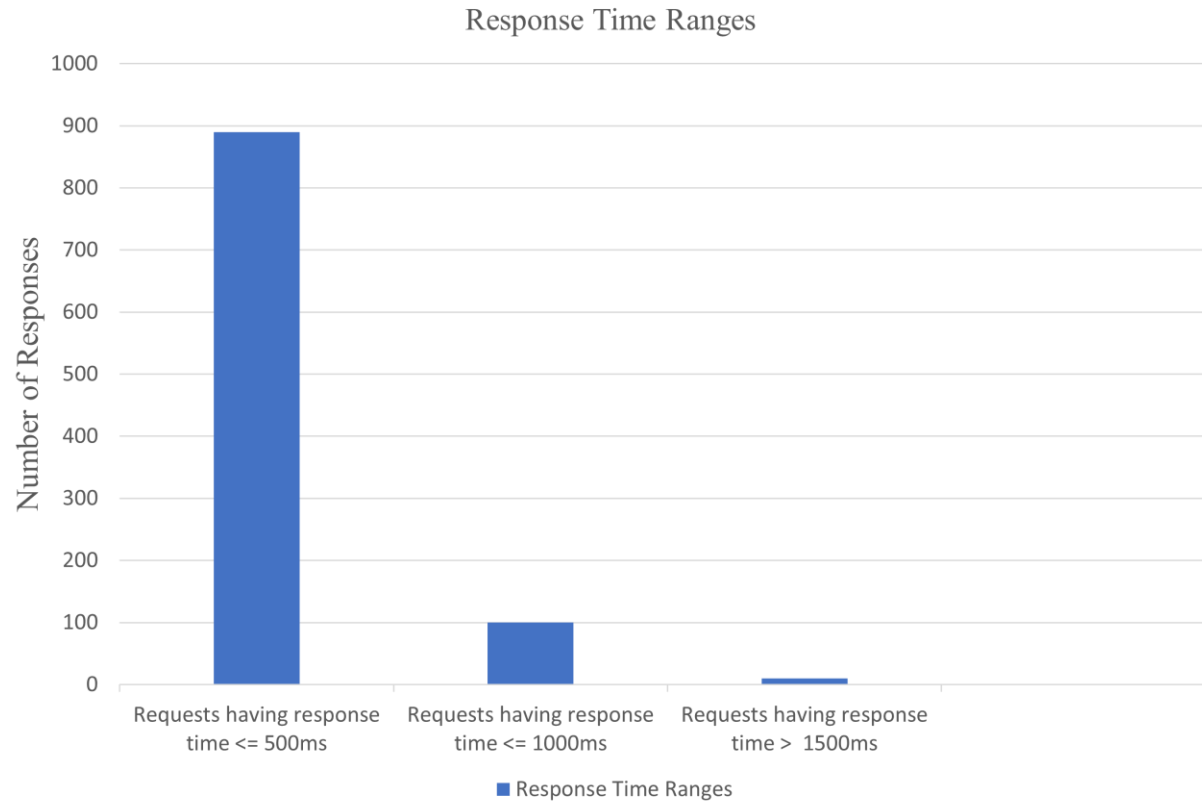
Parameters	Value
Number of Oracle Requests sent	1000
Load Duration	2 Seconds
Failed Requests	0
Percentage of Error	0%
Average Response Time (ms)	285.196 ms
Maximum Response Time (ms)	78ms
Throughput (requests/sec)	16.66

Source: Bapatla, A.K., et al.: PharmaChain: a blockchain to ensure counterfeit-free pharmaceutical supply chain. IET Netw. 1– 24 (2022). https://doi.org/10.1049/ntw2.12041

PharmaChain 2.0 - Architecture Overview

End Node

Edge Device

MQTT Protocol

Parameters Data

Control Command

Violation Data

End Node

Edge Device

Parameters Data

Control Command

End Node

MQTT Protocol

Violation Data

Monitoring and Controlling Environmental Parameters

SNS

IoT Hub

IoT Rules

Violations Log IoT Action

Function

Manufacturer

Distributor

Shipping

Secure Storage for Violation Data

Blockchain Structure

P2P Network

Retrieving Violation Data

Consumer

Source: A. K. Bapatla, **S. P. Mohanty**, E. Kougianos, and D. Puthal, "PharmaChain 2.0: A Blockchain Framework for Secure Remote Monitoring of Drug Environmental Parameters in Pharmaceutical Cold Supply Chain", in *Proceedings of the IEEE International Symposium on Smart Electronic Systems (iSES)*, 2022, pp. Accepted.

PharmaChain Versus PharmaChain 2.0

PharmaChain	PharmaChain 2.0
Tracking and Tracing in Pharmaceutical Supply Chain	Both Tracking & Tracing along with Monitoring and Controlling Temperature Excursions
Ethereum Blockchain	PoAh Consensus Based Blockchain (our EasyChain)
Proof-of-Authority (PoA) with less throughput compared to PoAh	Proof-of-Authentication (PoAh) with higher throughput
Private Blockchain with only nodes participating from Entities	Private Blockchain with only nodes participating from Entities
Not IoT friendly Consensus	IoT Friendly Consensus with less power and computations
Average transaction processing time is 5.6 sec.	Average transaction time has been improved significantly to 322.28 ms

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PharmaChain 2.0 - Comparative Analysis

Comparison of Proposed PharmaChain 2.0 solution with Existing Solutions					
Features	**Blockchain**	**Consensus Protocol**	**Openness**	**IoT Friendly Consensus**	**Average Time**
CryptoCargo [15]	Ethereum	Proof-of-Work (PoW)	Public	No	43.36 sec
PharmaChain [9]	Ethereum	Proof-of-Authority (PoA)	Private	No	5.6 sec
Current Paper (PharmaChain 2.0)	PoAh Consensus Based Blockchain	Proof-of-Authentication (PoAh)	Private	Yes	322.28ms

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PharmaChain 3.0 - Architectural Overview

QR Code Label Generation

QR Code with Contract Address

Label Assigned to Lot

Scan QR Code

Contract Address

Labeled Drug Lot

Manufacturer

Blockchain Network

Blockchain Structure

Smart Contract Interactions

Distributor

P2P Network

Smart Contract Interactions

Retrieved Product Information and IPFS Hash

Consumer

Shipping

Response Hash

Upload Files

Request Files using IPFS Hash

Retrieved Files

Inter Planetary File System

Source: A. K. Bapatla, **S. P. Mohanty**, E. Kougianos, and D. Puthal, "PharmaChain 3.0: Blockchain Integrated Efficient QR Code Mechanism for Pharmaceutical Supply Chain", in *Proceedings of the OITS International Conference on Information Technology (OCIT)*, 2022, pp. Accepted.

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PharmaChain 2.0 Versus PharmaChain 3.0

PharmaChain 2.0	PharmaChain 3.0
Both Tracking & Tracing along with Monitoring and Controlling Temperature Excursions	Integrating QR Code Mechanism for easy Tracking and Tracing and Drug Information
PoAh Consensus Based Blockchain (Our EasyChain)	Ethereum Blockchain into the CPS
Proof-of-Authentication (PoAh) with higher throughput	Proof-of-Stake (PoS) Consensus mechanism is used with lesser throughput than PoAh
Private Blockchain with only nodes participating from Entities	Private Blockchain with only nodes participating from Entities
IoT Friendly Consensus with less power and computations. Doesn't support smart Contracts.	P2P nodes are maintained by the entities and are computationally capable. No need for IoT-Friendly Consensus
The average transaction time is 322.28ms	The average Transaction time is 16.2 Sec
Less information storage capabilities	More information can be stored

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PharmaChain 3.0 - Comparative Analysis

Works	Blockchain	Consensus Mechanism	Computational Needs	Openness	QR Code Integrated	Storage	Handling Large data
Crypto Cargo [11]	Ethereum	Proof-of-Work (PoW)	High	Public	No	On-Chain and Cloud	No
Kumar et.al. [9]	NA	NA	NA	NA	Yes	On-chain	No
PharmaChain [12]	Ethereum	Proof-of-Authority (PoA)	Low	Private	No	On-Chain and Cloud	No
PharmaChain 2.0	Our EasyChain	Proof-of-Authentication (PoAh)	Low	Private	No	On-Chain and Cloud	No
Current Solution (PharmaChain 3.0)	Ethereum	Proof-of-Stake (PoS)	Low	Private	Yes	On-Chain and off-Chain	Yes

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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.

- AI/ML is a key component of smart healthcare.

- IoMT provides advantages but also has limitations in terms of cybersecurity and privacy.

- Edge-AI for smart healthcare needs research.

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Future Research

- Smart Healthcare will need robust data, device, and H-CPS security need more research.

- Cybersecurity of IWMDs needs to have very 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.

- Privacy-aware limited healthcare data sharing in global scale to reduce spread of pandemic outbreak.

- Pharmaceutical supply chain needs research to ensure counterfeit free medicine and vaccinees.

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Smart Healthcare – Reality?

- Short answer - Yes

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Smart Healthcare – Hype?

■ Still long way to go …

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Acknowledgement(s)