Machine Learning in Smart Healthcare

Keynote - International Conference on Recent Advancements in Artificial Intelligence and Soft Computing (ICAISC) 2022

Hyderbad, India, 2-4 Dec 2022

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Outline

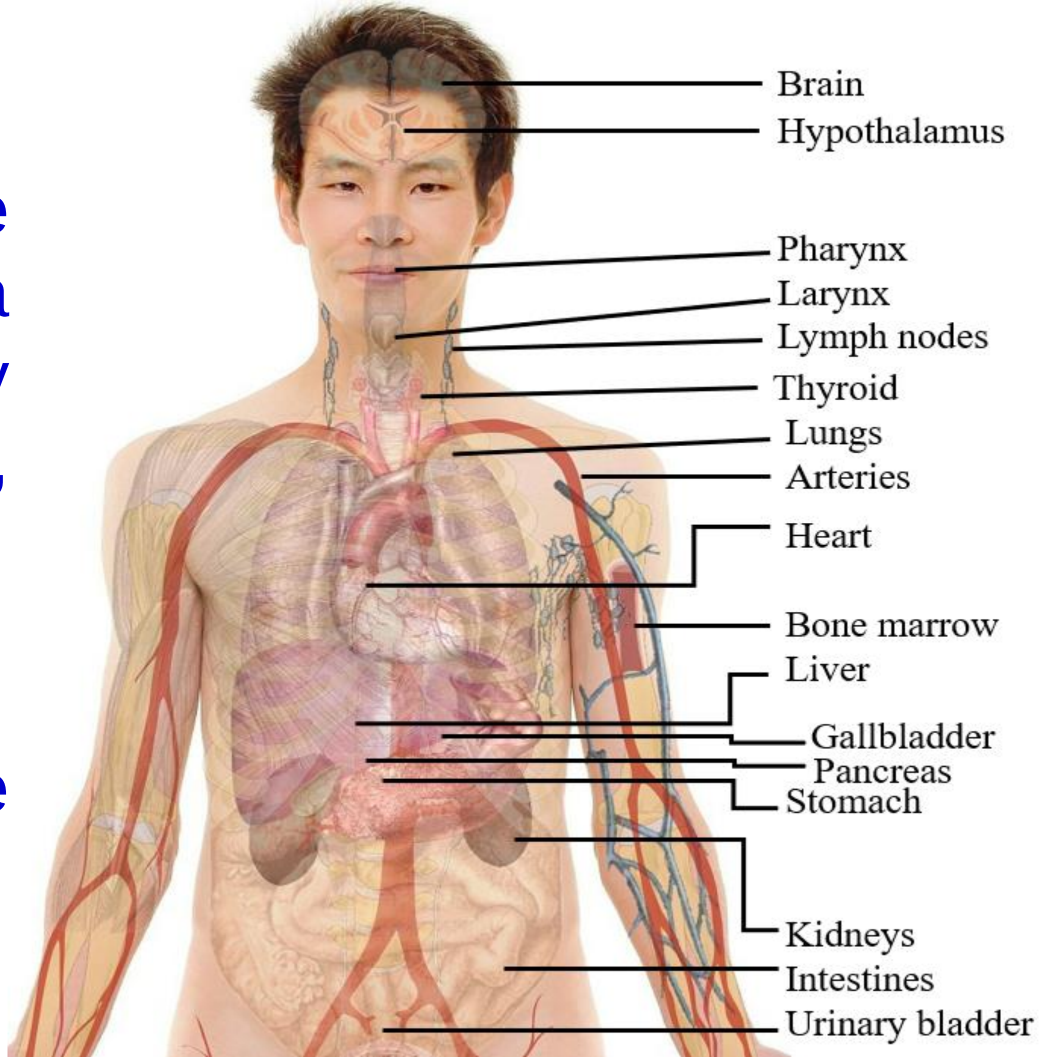
- Healthcare → Smart Healthcare
- Smart Healthcare - Characteristics
- Smart Healthcare - Components
- Smart Healthcare - Examples
- Smart Healthcare – Challenges
- Smart Healthcare – Solutions of Challenges
- Conclusions and Future Directions

Healthcare
to
Smart Healthcare

Human Body and Health

Human Body

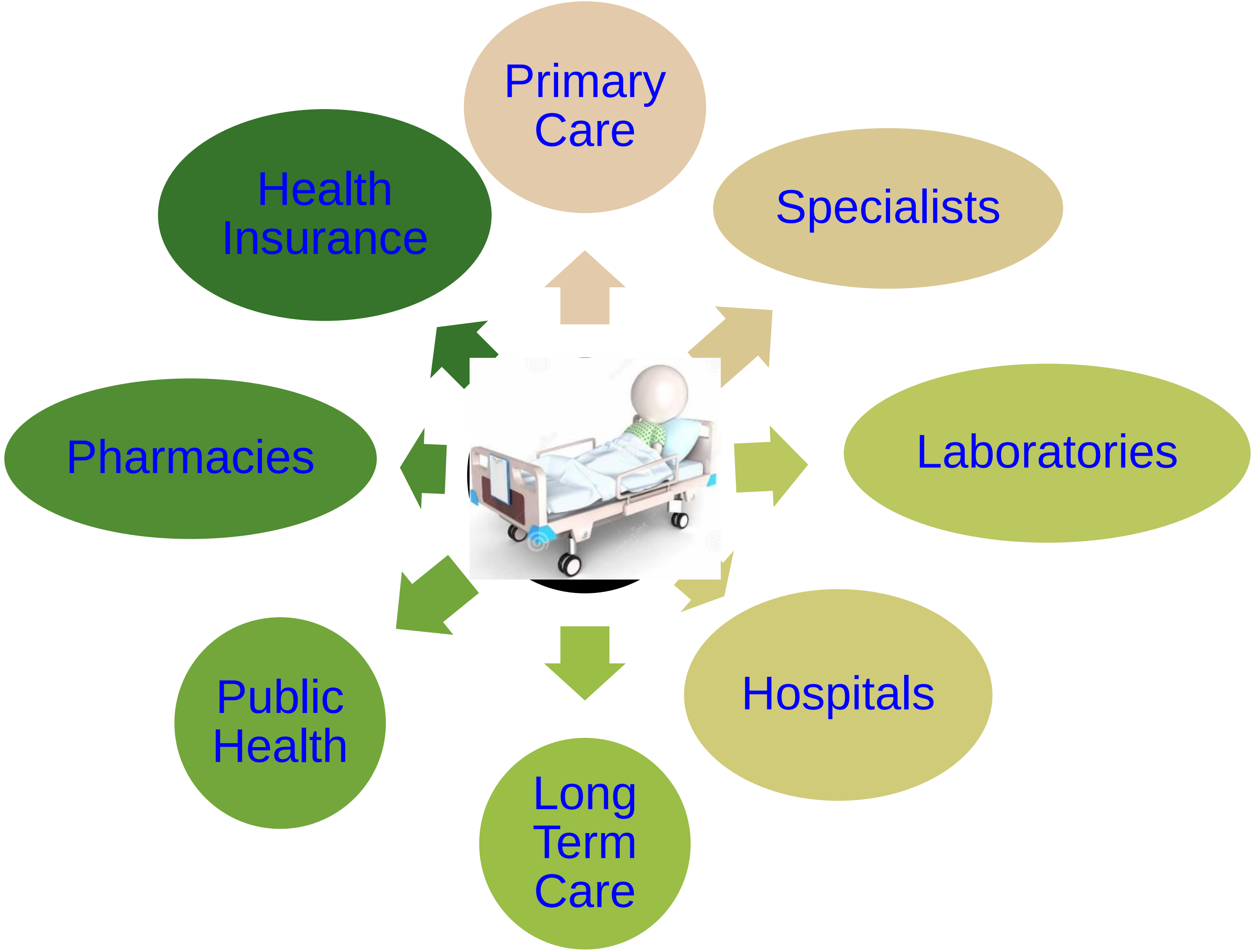
- From an engineering perspective, the human body can be defined as a combination of multi-disciplinary subsystems (electrical, mechanical, chemical …).



Health

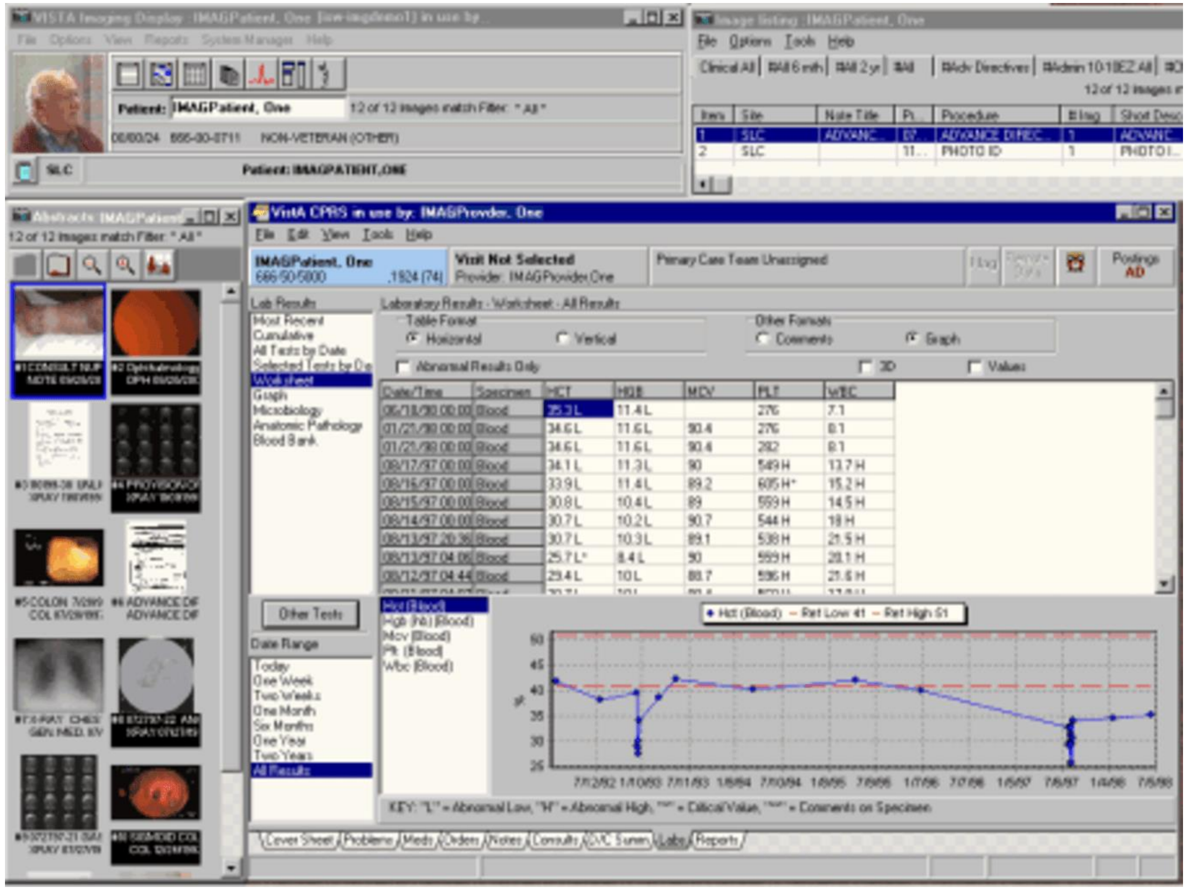
- Human health is a state of complete physical, mental and social well-being.

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

Electronic Health (eHealth)



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.

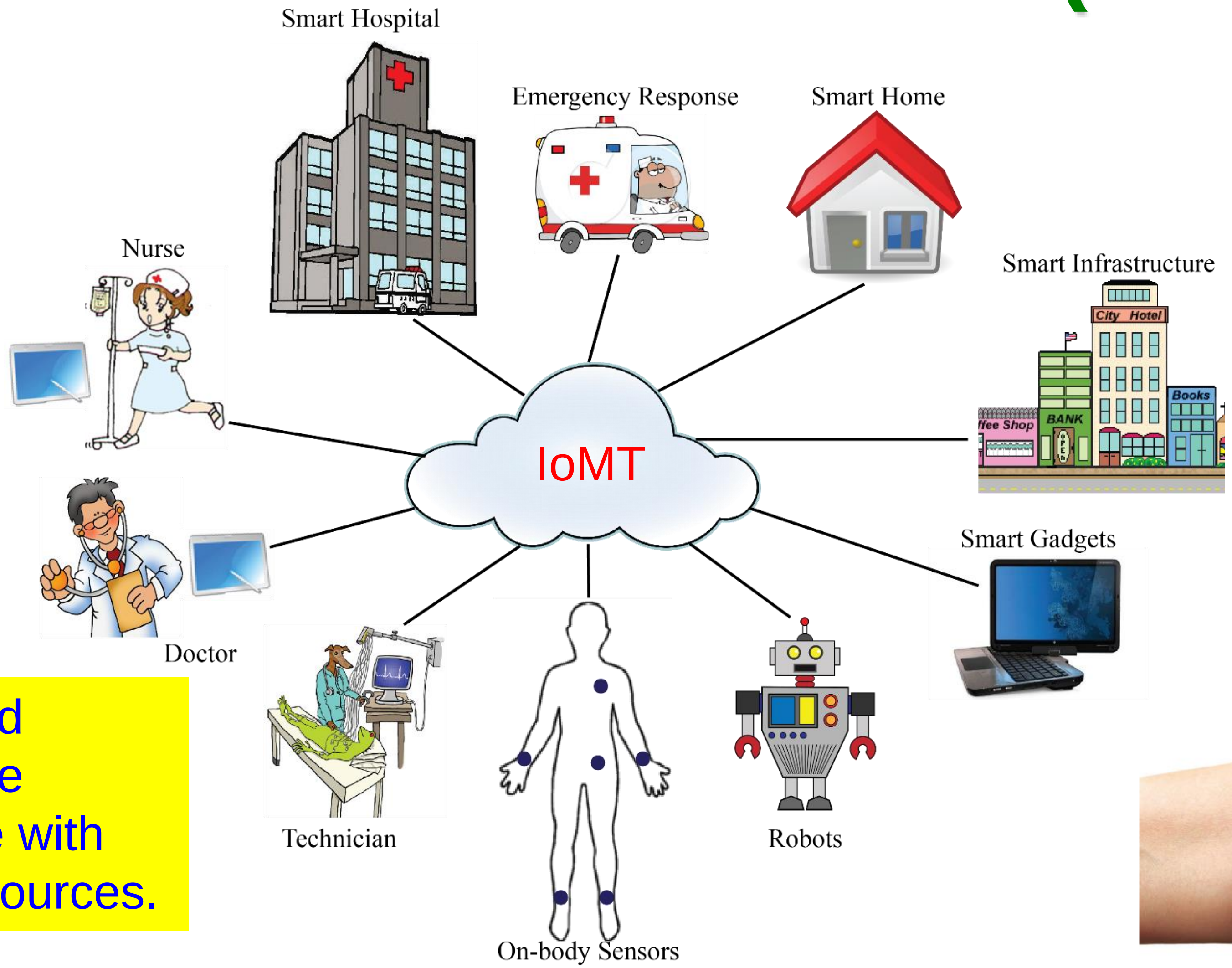
eHealth: The use of information and communication technologies (ICT) to improve healthcare services.

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.

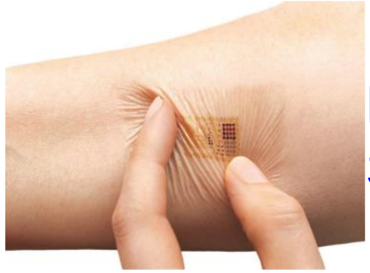
Source: H. Zhu, C. K. Wu, C. H. KOO, Y. T. Tsang, Y.Liu, H. R. Chi, and K. F. Tsang, "Smart Healthcare in the Era of Internet-of-Things", *IEEE Consumer Electronics Magazine*, vol. 8, no. 5, pp. 26-30, Sep 2019.

Smart Healthcare (sHealth)



Fitness Trackers

Headband with Embedded Neurosensors



Embedded Skin Patches

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.

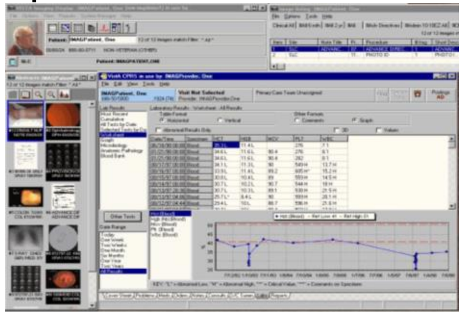
Healthcare → Smart Healthcare

Healthcare

eHealth → Telemedicine → mHealth → cHealth → sHealth

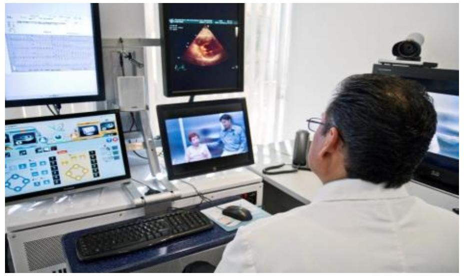
eHealth

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



Telemedicine

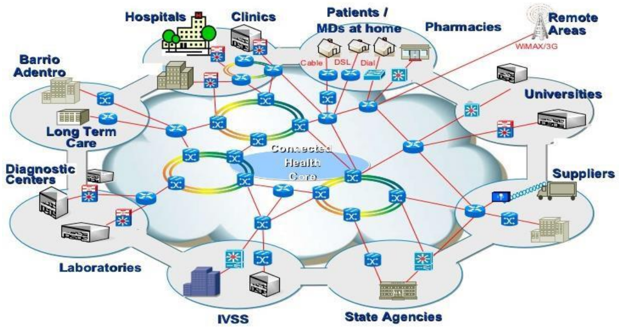
Telemedicine is the use of telecommunication and information technology to provide clinical healthcare from a distance.



mHealth

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

cHealth



sHealth

Spire Stone - Breath

Embedded Skin Patches

Thync's - UltrasoVibeund

Muse - EEG

Source: Saraju P. Mohanty, “Smart Healthcare: From Healthcare to Smart Healthcare”, ICCE 2020 Panel, Jan 2020.

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

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)

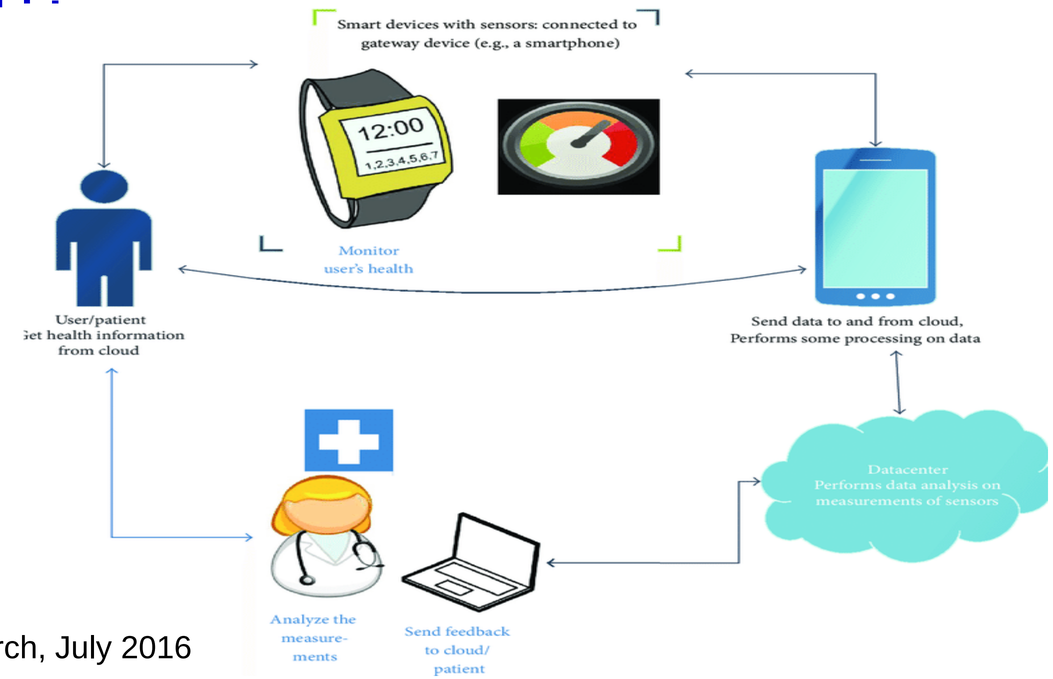
Healthcare Cyber-Physical Systems (H-CPS)

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 - IoMT

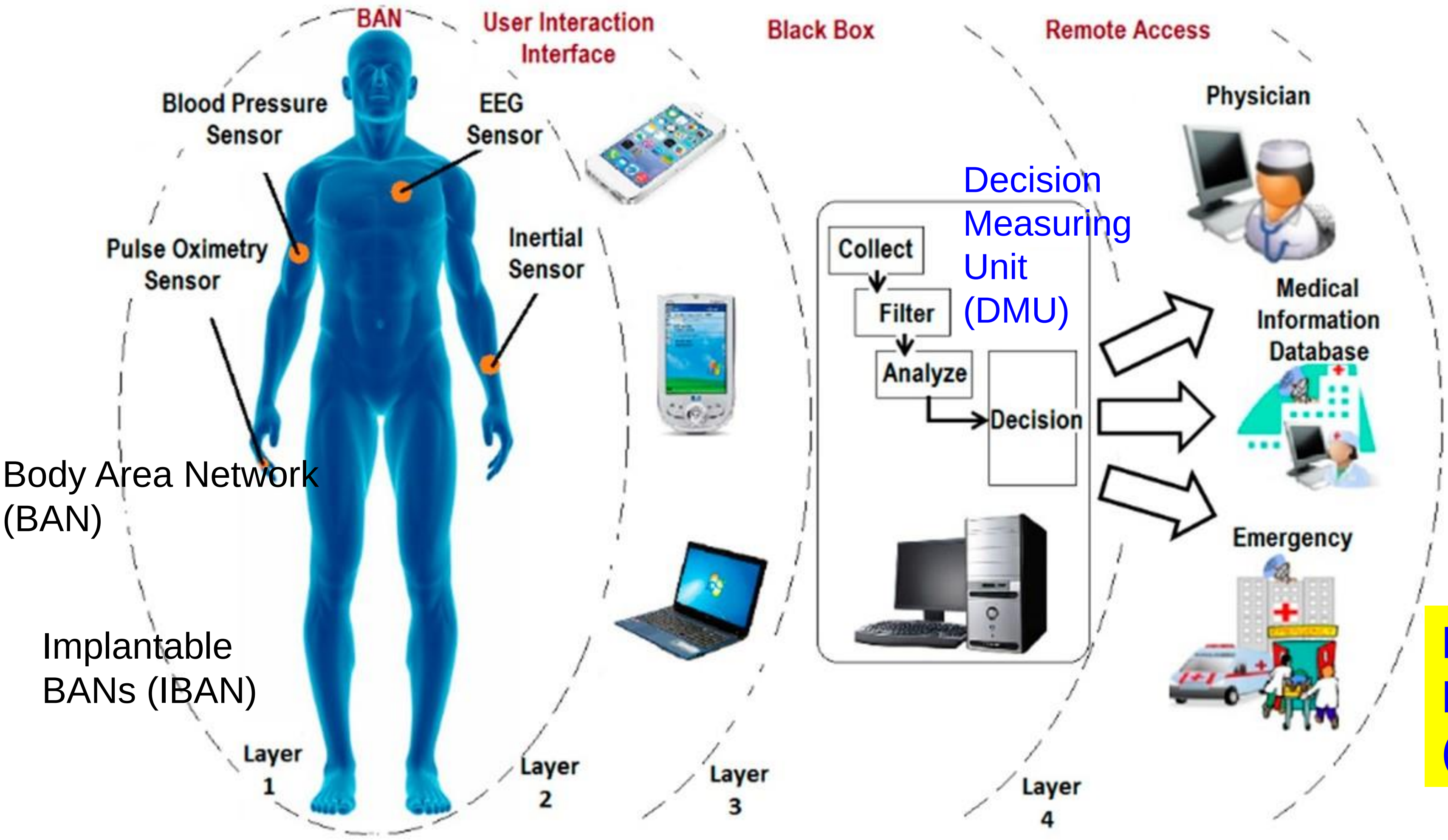
- The Internet of Medical Things (IoMT) is the collection of medical devices and applications that connect to healthcare IT systems through online computer networks.
- Medical devices equipped with Wi-Fi allow the machine-to-machine communication that is the basis of IoMT.

Smart Healthcare is defined by the technology that leads to better diagnostic tools, better treatment for patients, and devices that improves the quality of life for anyone and everyone.



Dimitrov 2016, Healthcare Informatics Research, July 2016

Smart Healthcare - 4-Layer Architecture



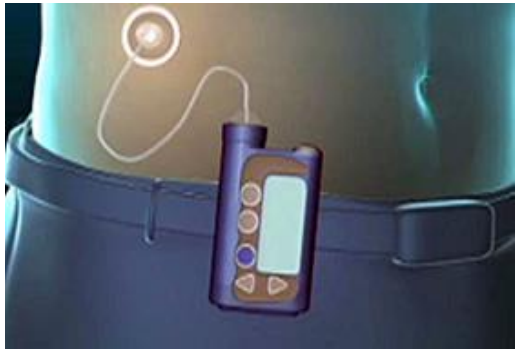
Healthcare Cyber-Physical Systems (H-CPS)

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.

Wearable Medical Devices (WMDs)

Fitness Trackers

Headband with Embedded Neurosensors

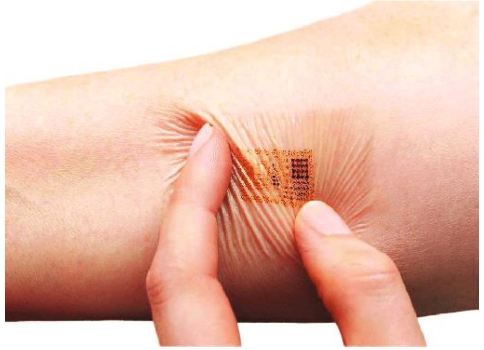


Source: https://www.webmd.com

Insulin Pump

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

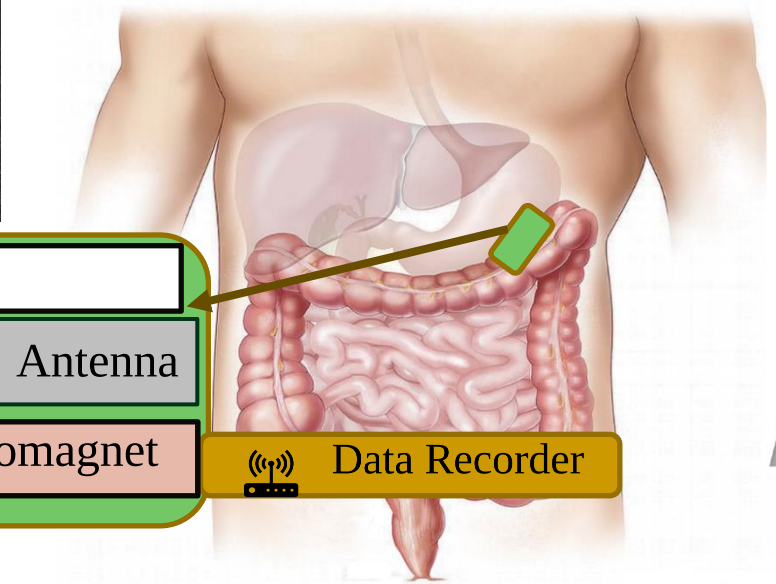
Medical grade smart watch to detect seizure

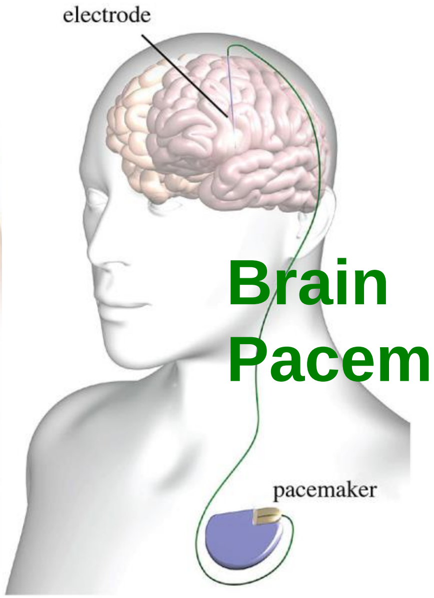


Embedded Skin Patches

Implantable Medical Devices (IMDs)

Pill Camera





Brain Pacemaker

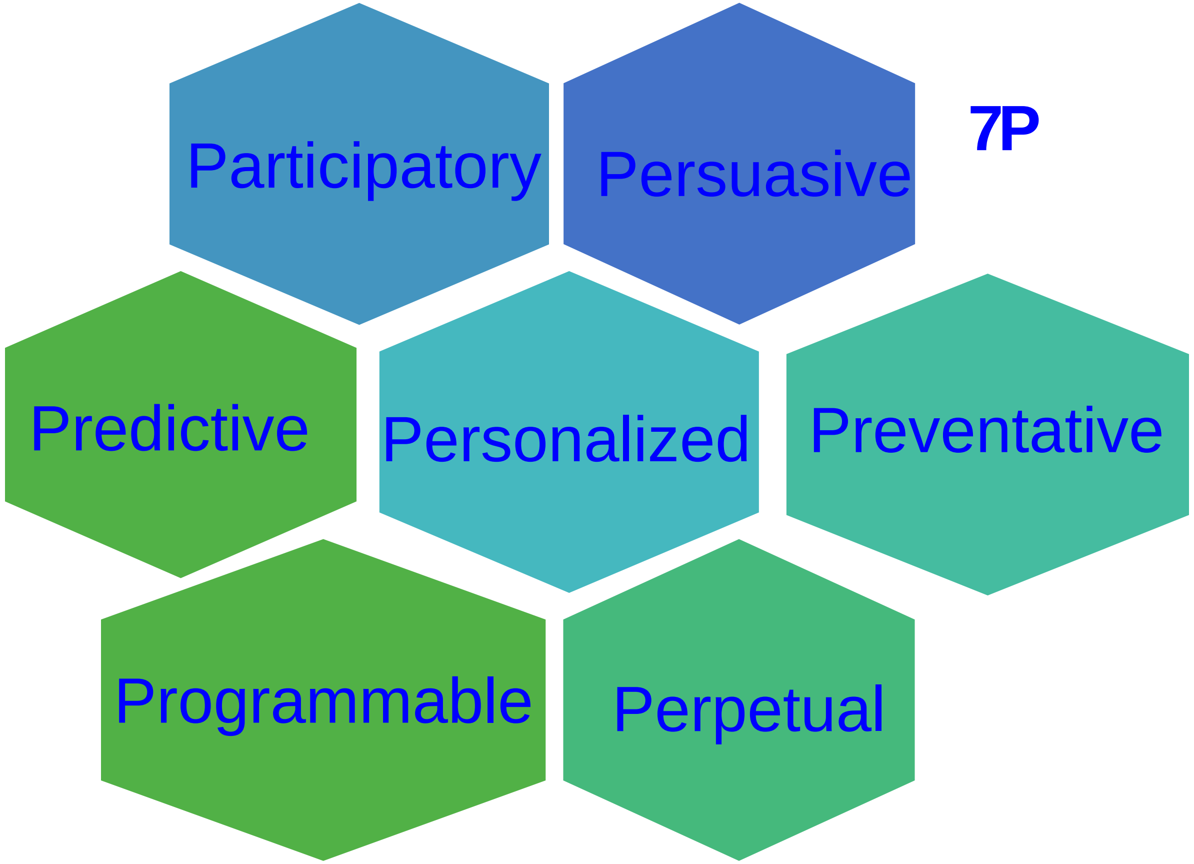
Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "*Everything You Wanted to Know about Smart Health Care*", IEEE Consumer Electronics Magazine (MCE), Volume 7, Issue 1, January 2018, pp. 18-28.

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 - 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

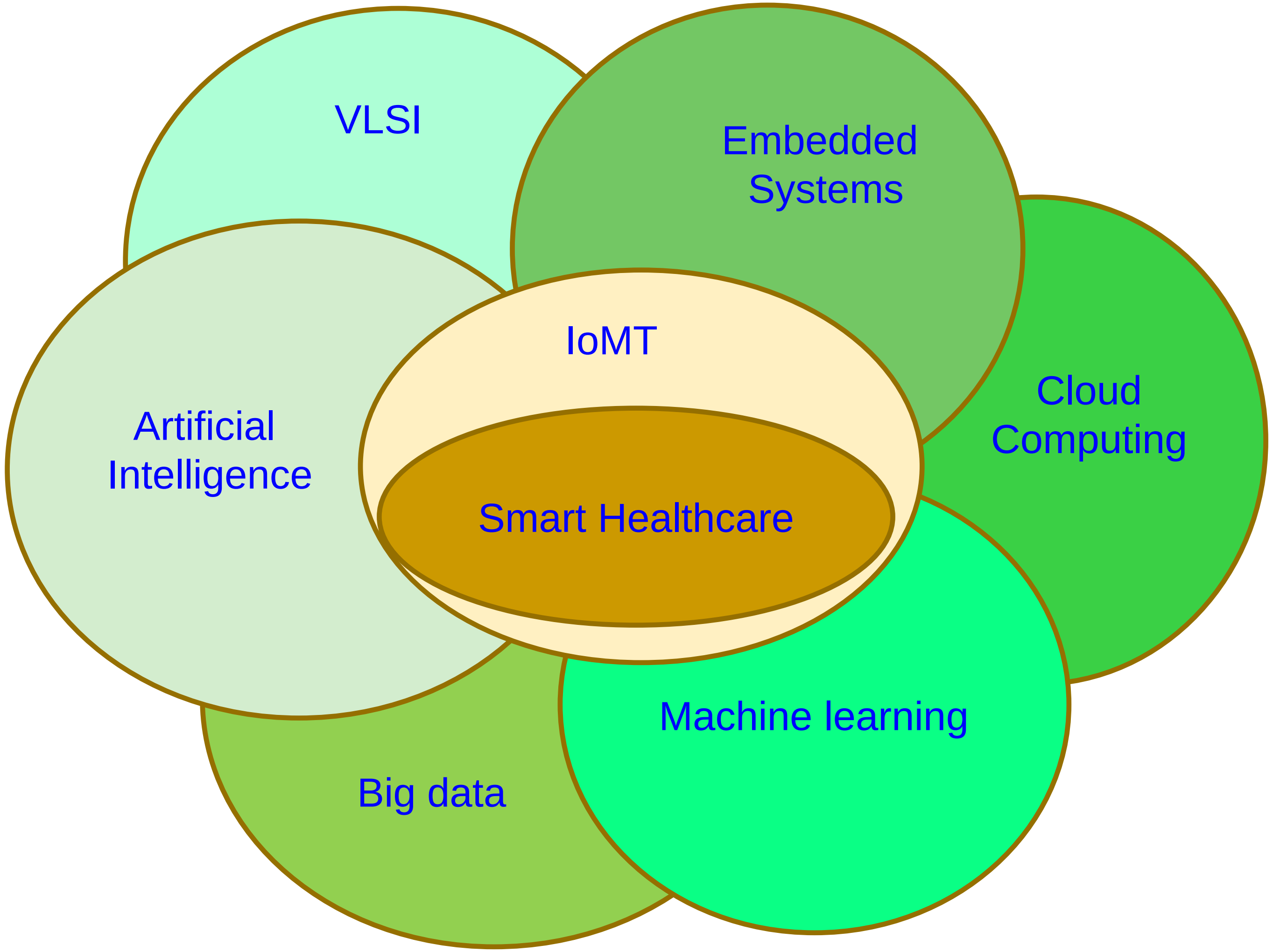
Market Challenges

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

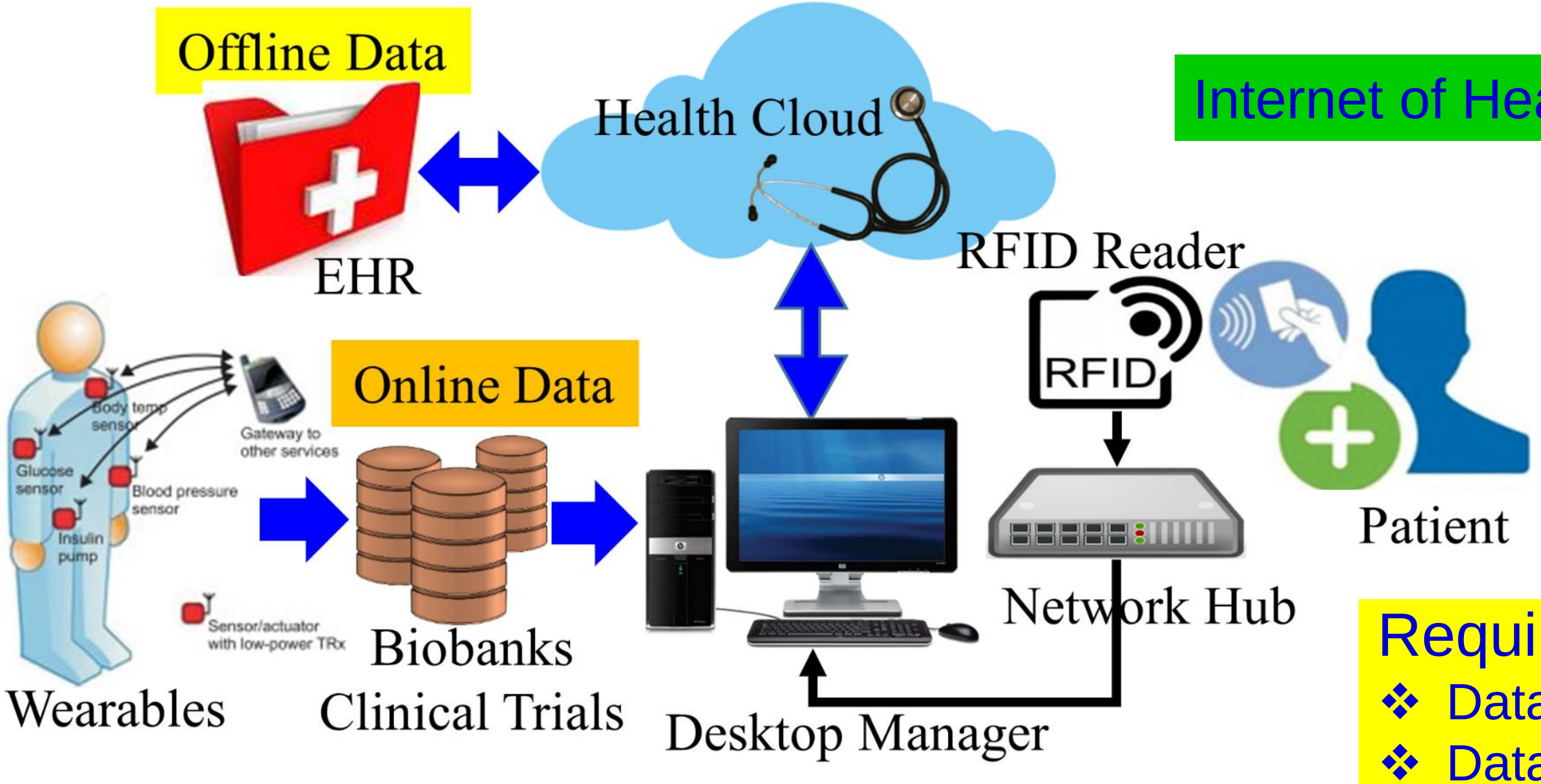
Source: Y. Shelke and A. Sharma, "Internet of Medical Things", 2016, Aranca, https://www.aranca.com/knowledge-library/special-reports/ip-research/the-internet-of-medical-things-iomt, Last Visited 10/18/2017.

Smart Healthcare - Components

Smart Healthcare - Verticals



Internet of Medical Things (IoMT)



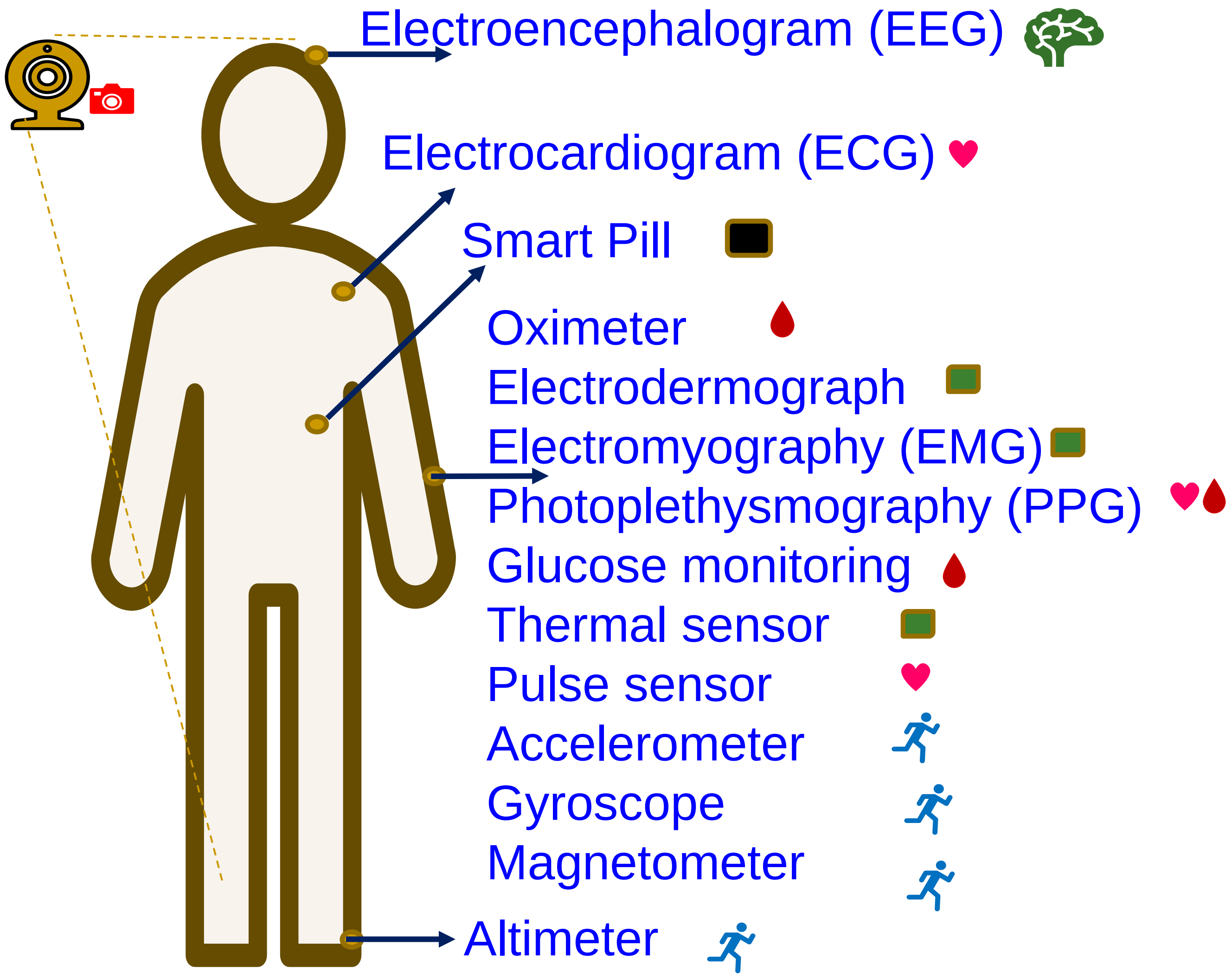
Internet of Health Things (IoHT)

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

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/

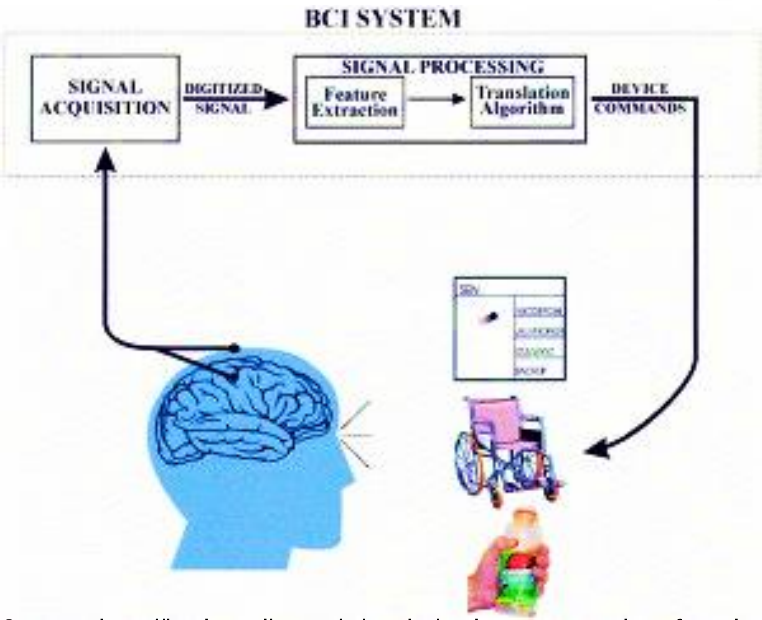
The body is a poor absorber of red light allowing the light to pass much deeper into the body and a larger volume of tissues to help provide more insightful data and could lead to improved accuracy with biometric data like heart rate.

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.

Brain Computer Interface (BCI)



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

BCI Allows paralysis patients move a wheelchair

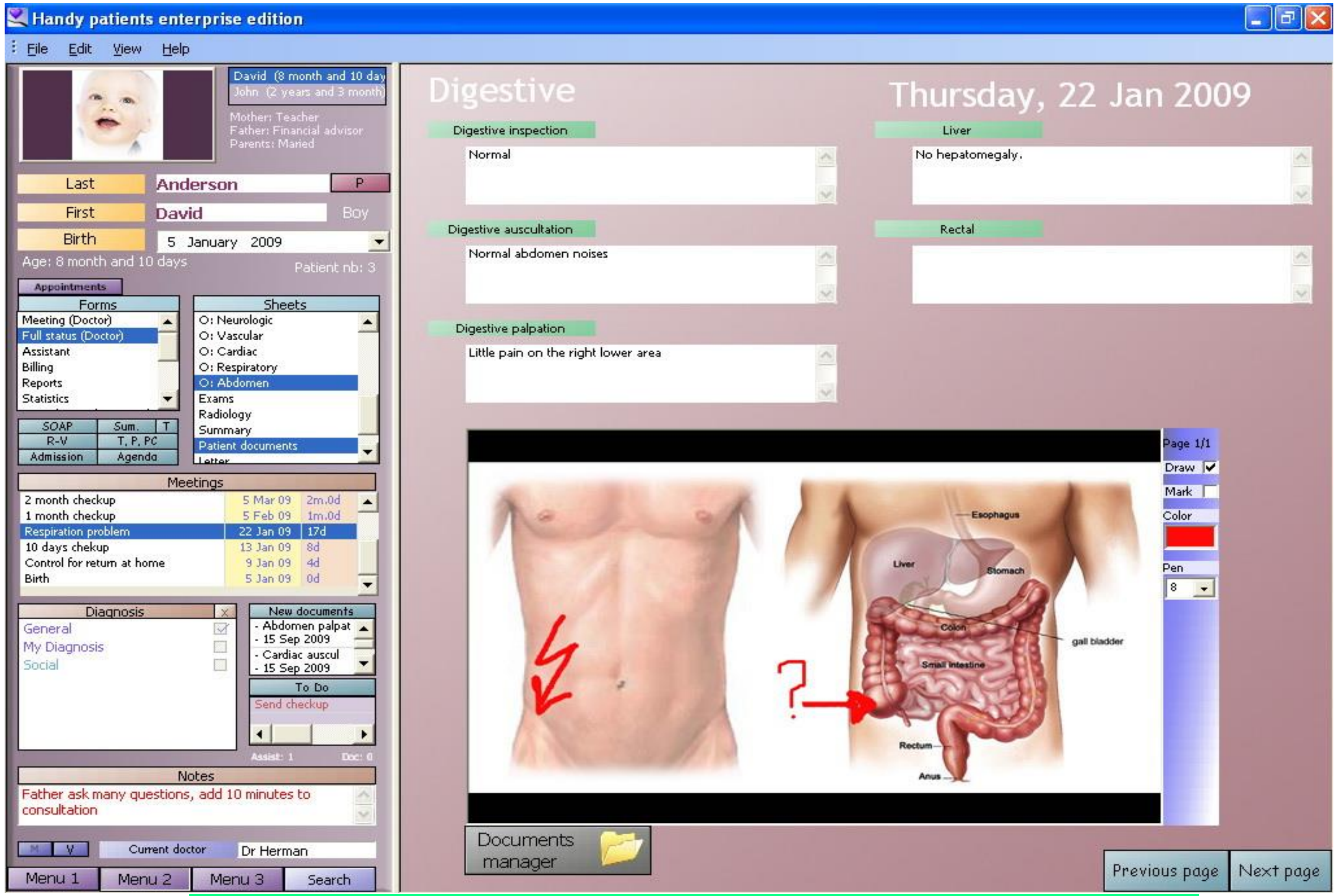
Source: http://brainpedia.org/brain-computer-interface-allows-paralysis-als-patients-type-much-faster/

BCI Allows paralysis patients to Type

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

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 Electronic Systems Laboratory (SESL)

Smart Healthcare – AI/ML 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

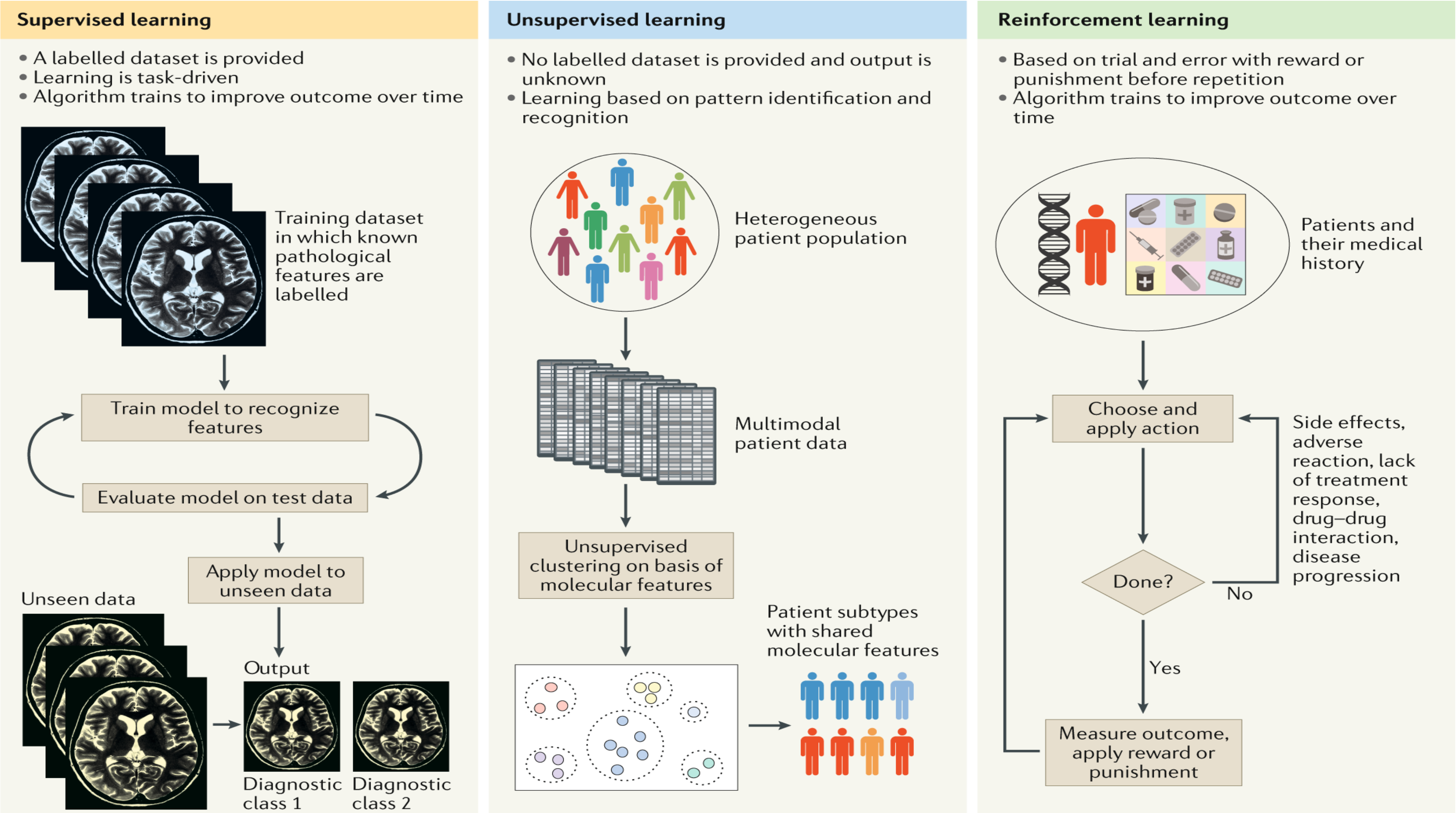
Smart Healthcare – AI/ML is Key

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*

AI Role Includes:

- Automatic diagnosis
- Disease predication
- Diet prediction
- Pandemic projection
- Automatic prescription

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

Smart Healthcare – Specific Examples

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/

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**

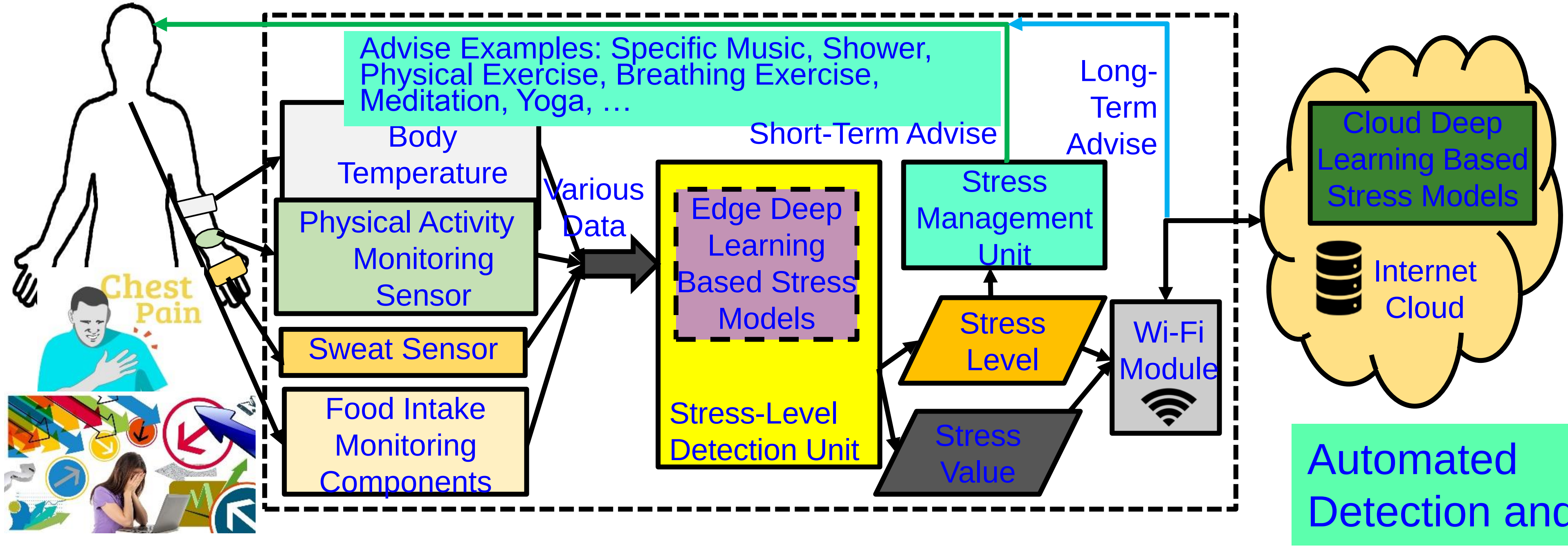
→Brain floods **body** with chemicals and hormones (adrenaline and cortisol)

- 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

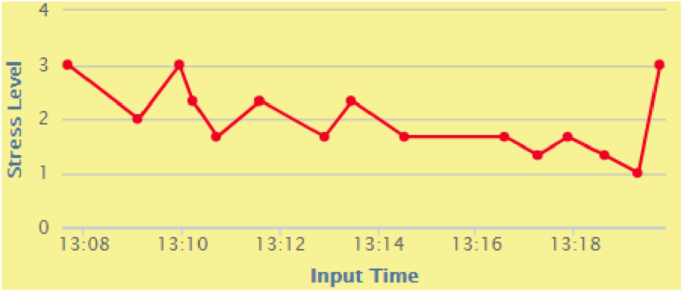
Eustress

Stress Monitoring & Control – Our Vision



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.

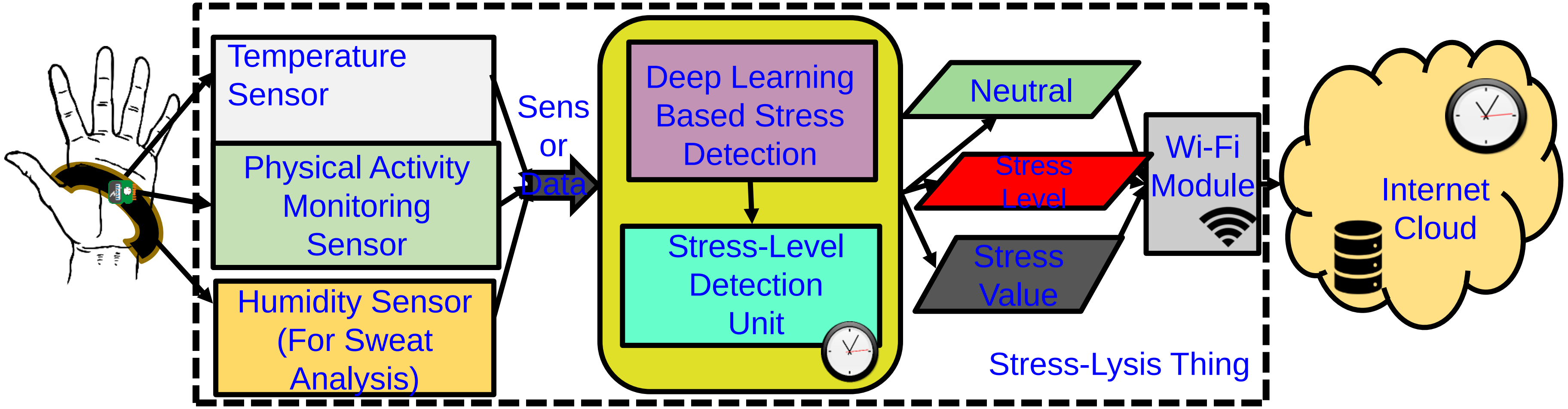
Consumer Electronics Devices – Can Provide Data for Stress Detection

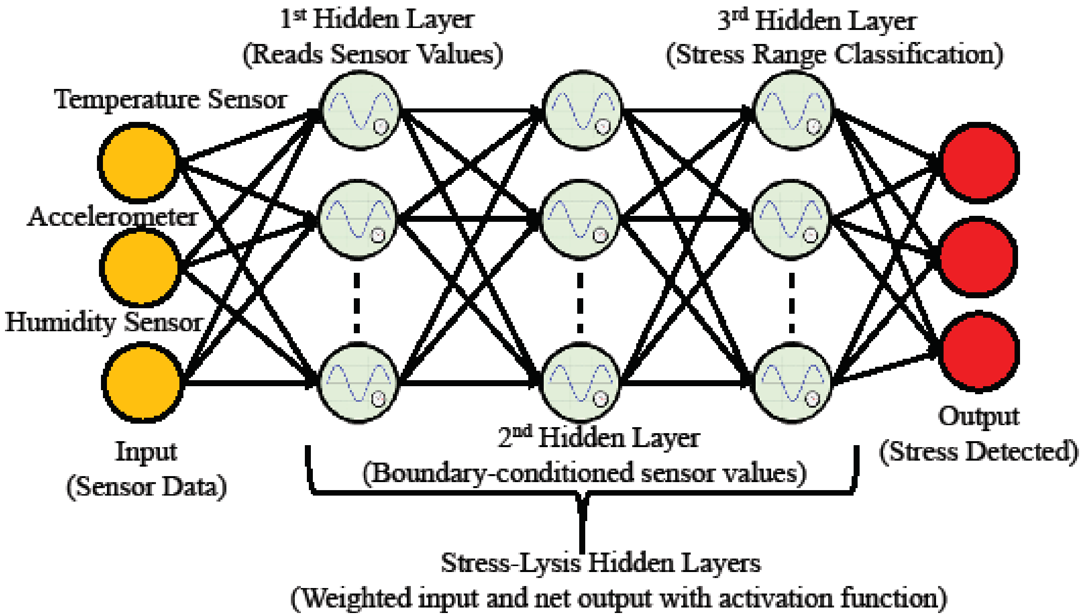
Brand	Device	Signals	RTI	Ambulant
Empatica	E4 wristband	PPG, GSR, HR, ACC, ST	Yes	Yes
Garmin	Vivosmart	HR, HRV, ACC	Yes	Yes
Zephyr	BioHarness 3.0	HR, HRV, GSR, ACC, ST	Yes	Yes
iMotions	Shimmer 3+ GSR	GSR, PPG	Yes	No
BIOPAC	Mobita Wearable	ECG, EEG, EGG EMG, and EOG	Yes	No

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, No. 5, September 2020, pp. 34--41.

Stress-Lysis: From Physiological Signals

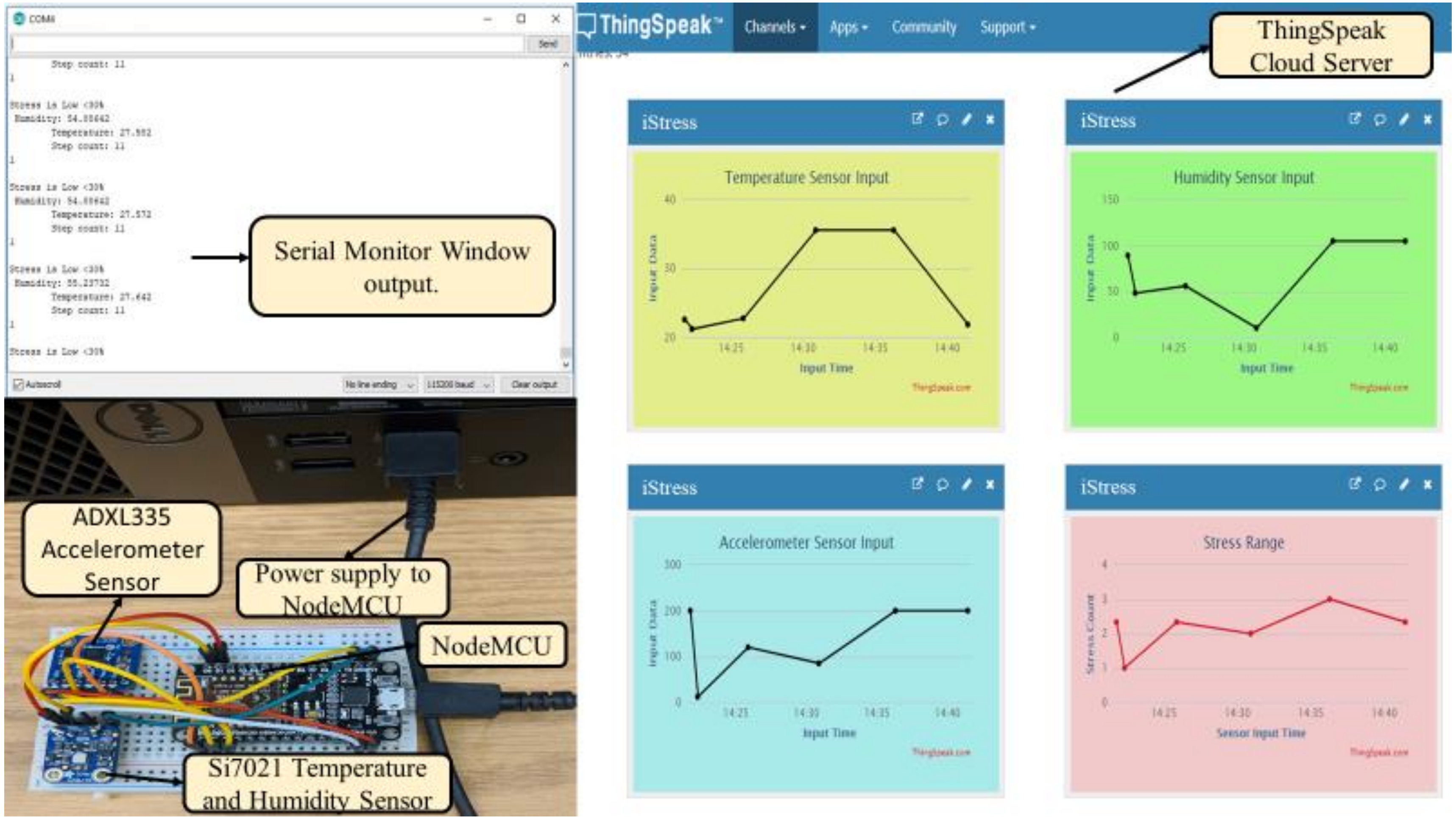




Stress-Lysis - DNN has been trained with a total of 26,000 samples per dataset and has accuracy upto 99.7%.

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



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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.

Smart-Yoga Pillow (SaYoPillow) - Sleeping Pattern

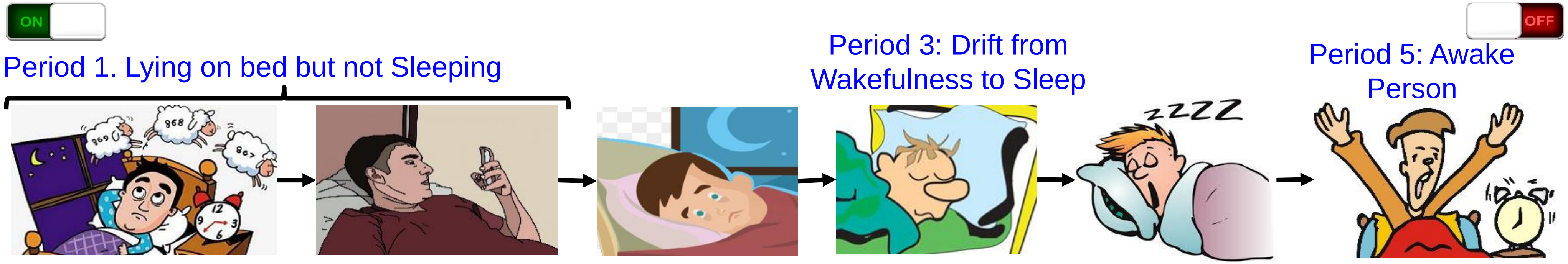
Person On Pillow:
Physiological Sensor Data Monitoring Starts

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.

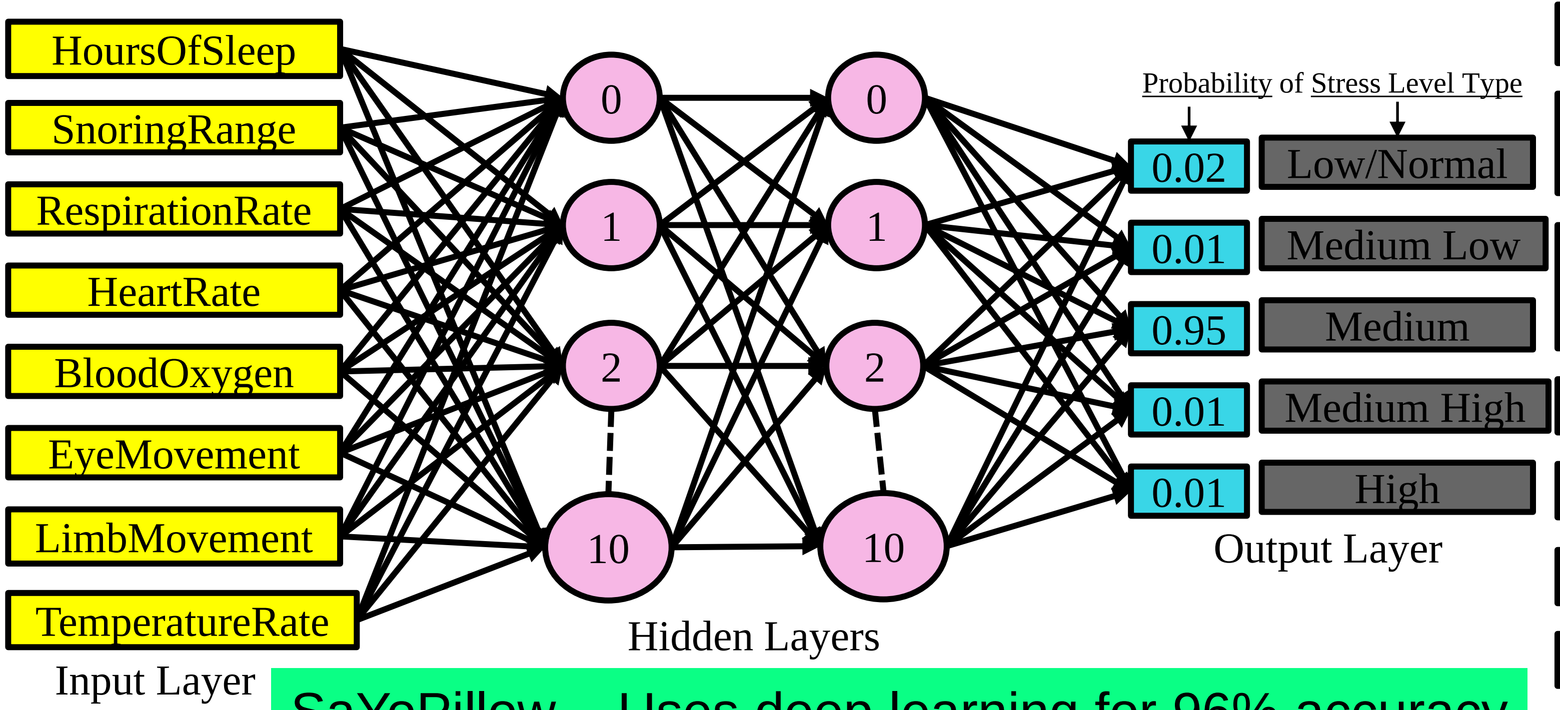
Data Processing

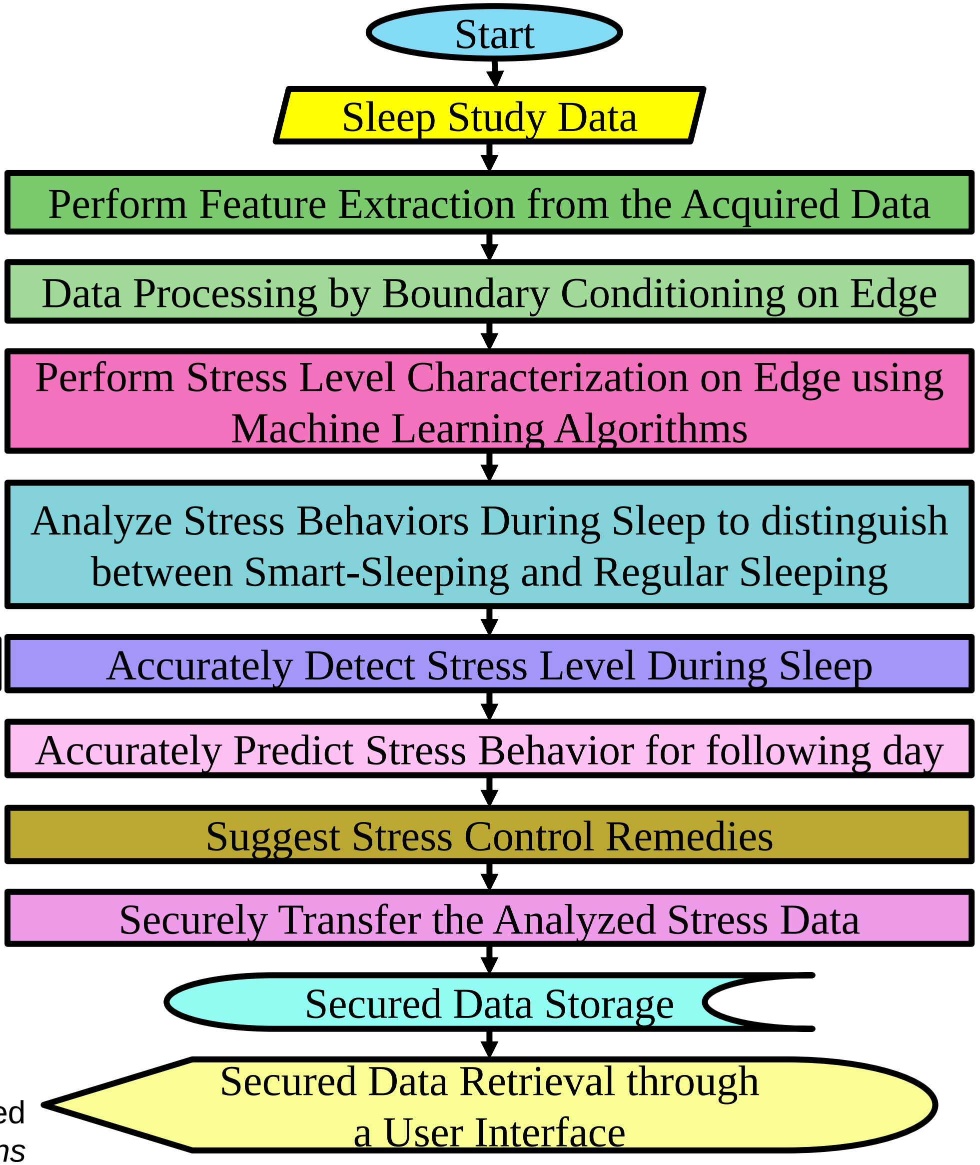
Secure Data Storage

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.

SaYoPillow – Stress Analysis Approach





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

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.

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:

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

Imbalance Diet – Impact on Hunan Body

Obesity

Inflammatory Disease

Reproductive Disease

Impact on Immune System

Kidney Disease

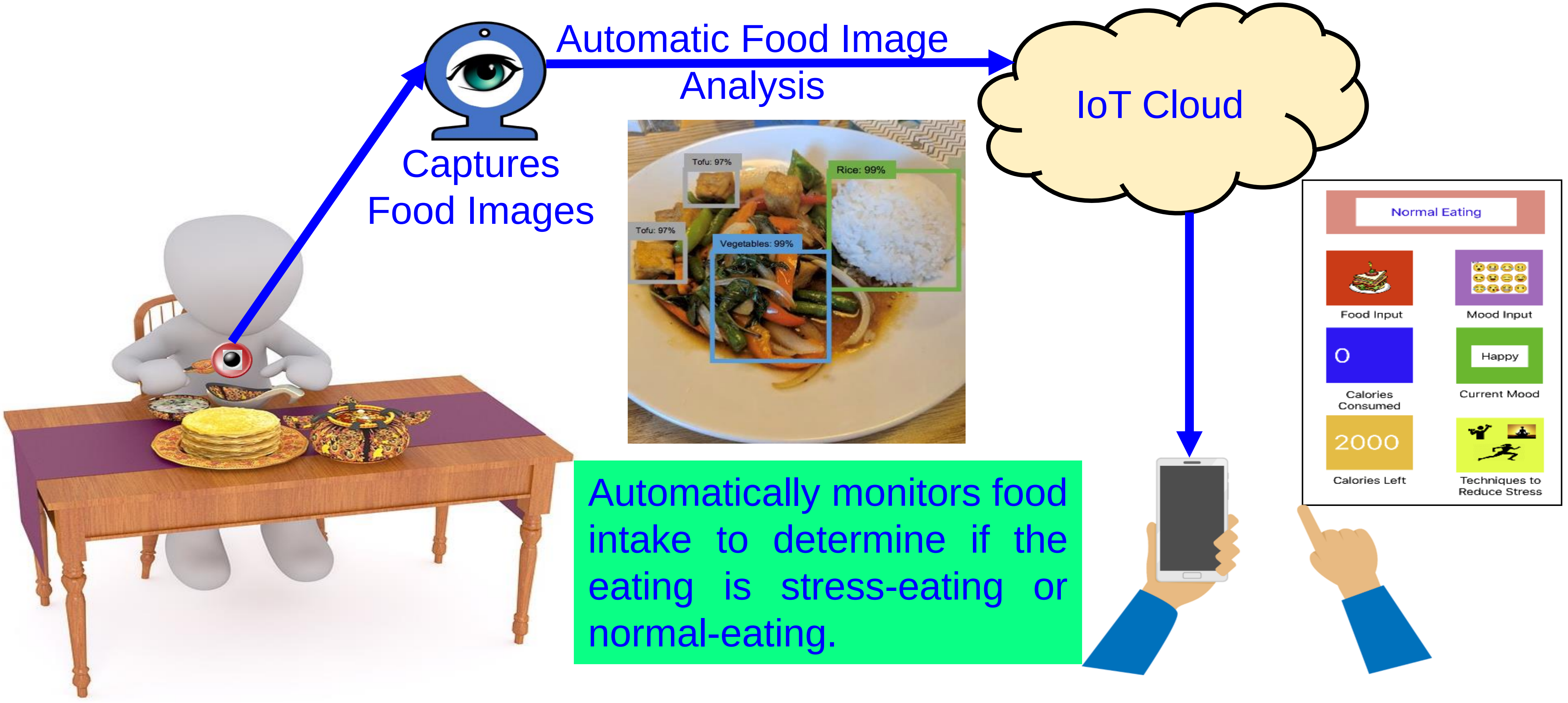
Insulin Secretion

Hypertension

Cardiac Disease

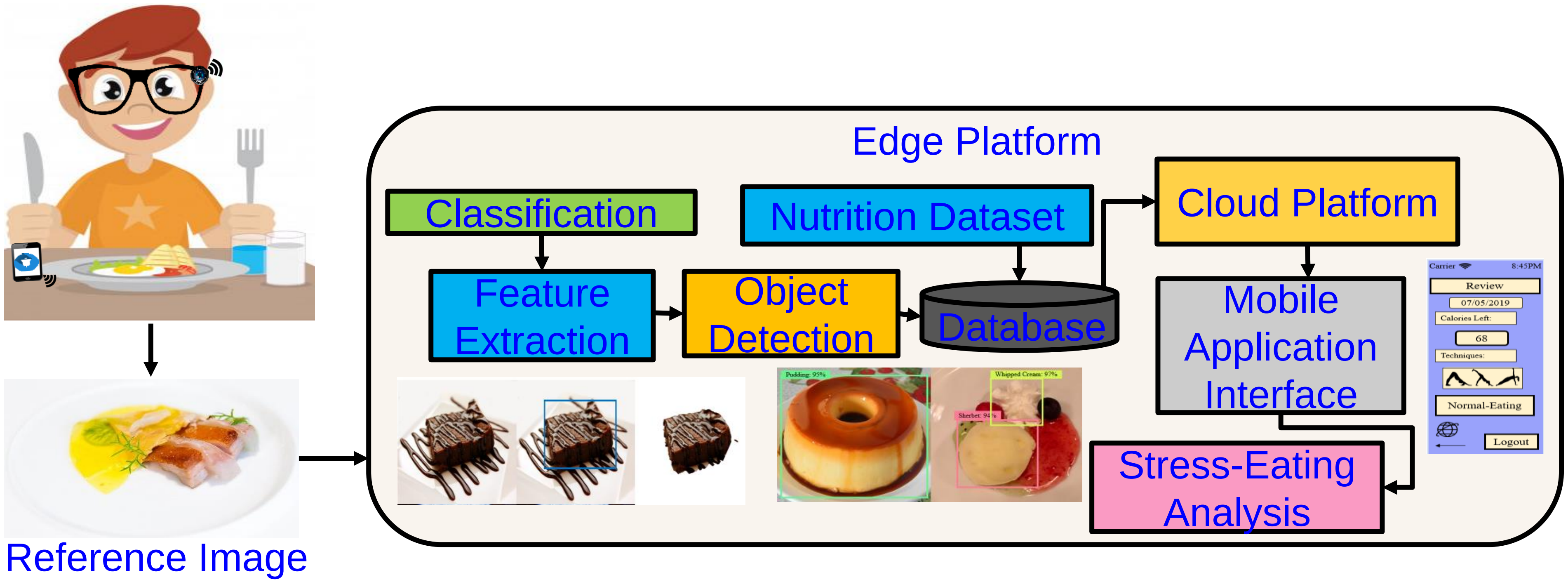
Source: A. Mitra, S. Goel, **S. P. Mohanty**, E. Kougianos, and L. Rachakonda, “iLog 2.0: A Novel Method for Food Nutritional Value Automatic Quantification in Smart Healthcare”, in *Proceedings of the IEEE International Symposium on Smart Electronic Systems (iSES)*, 2022, pp. Accepted.

Automatic Diet Monitoring & Control - Our Vision



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



iLog- Fully Automated Detection System with 98% accuracy.

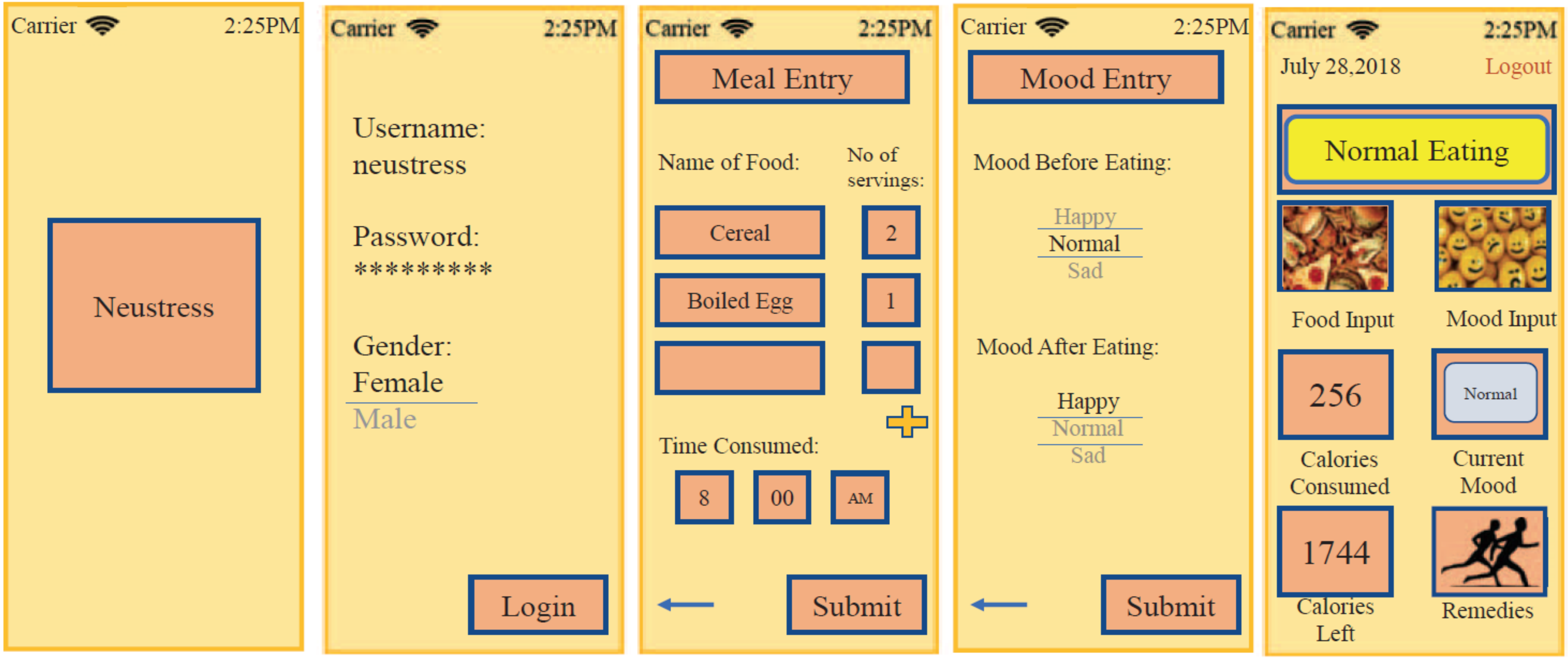
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, “iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT”, *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

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.

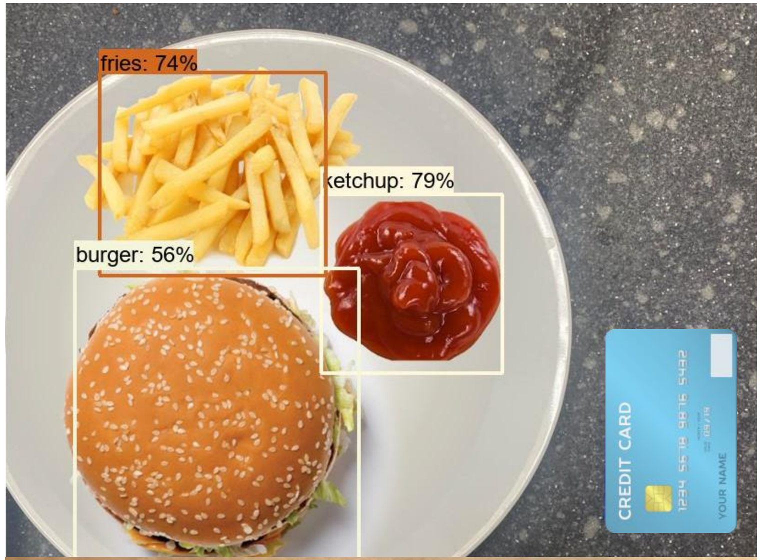
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare – iLog

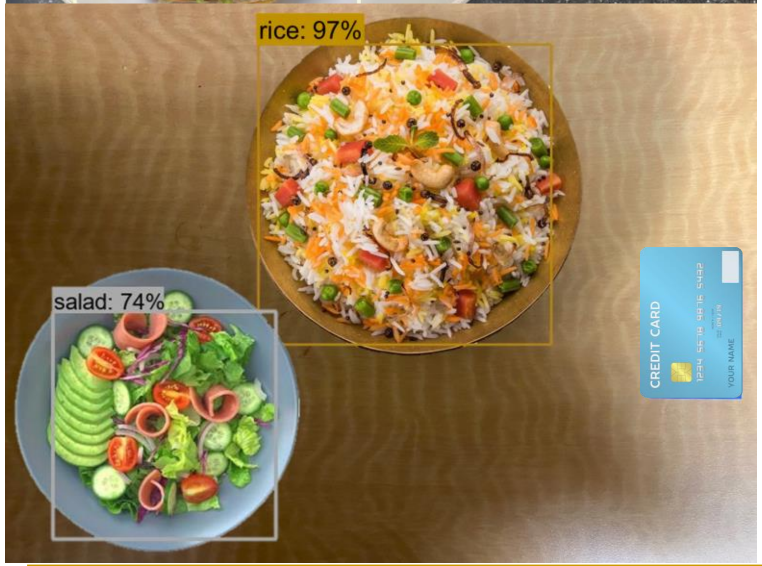


Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

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

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.

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

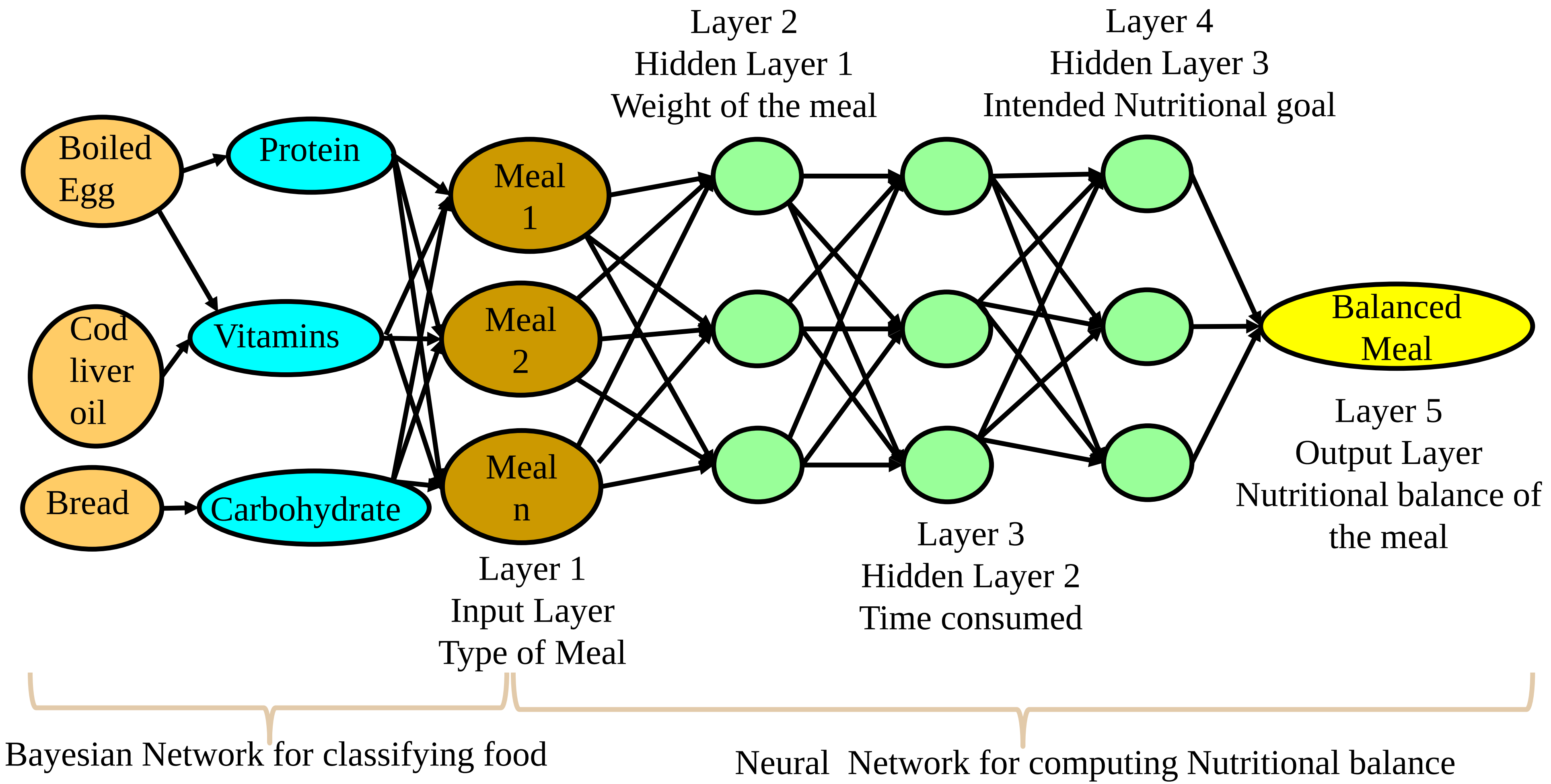
For Future Meal Predictions

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



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.

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.

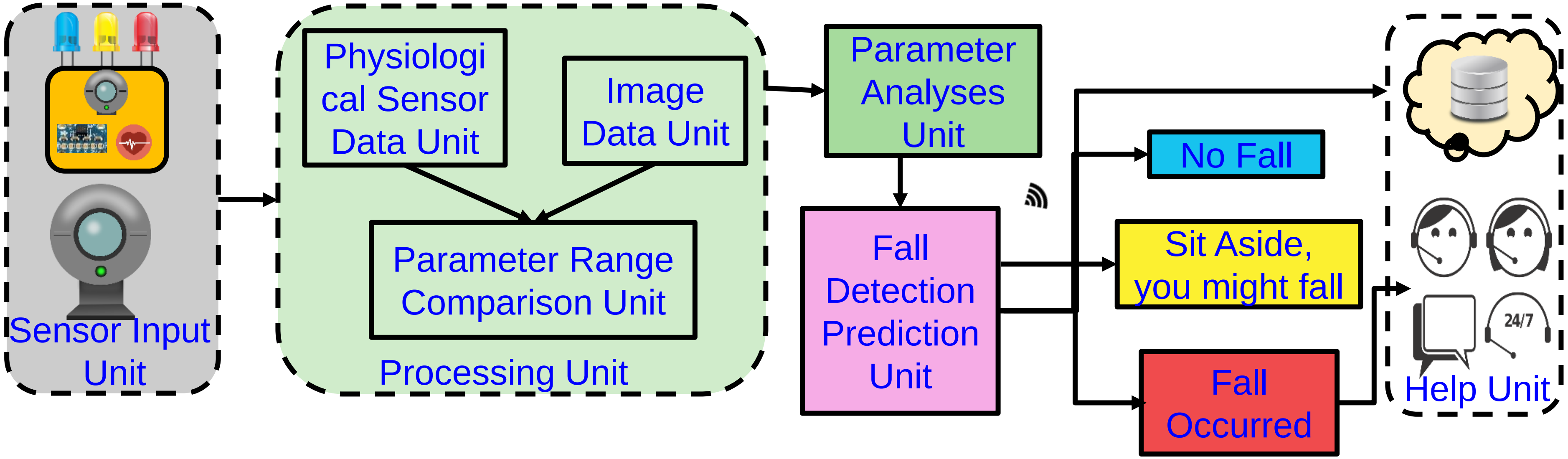
Consumer Electronics for Fall Detection

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

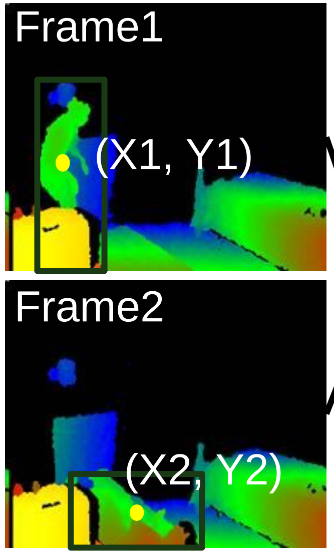
- Decisions of fall are dependent on the changes in accelerometer axes only.
- Some applications have user to give response after the fall and that can be time consuming as the user might not be conscious.
- Some applications are limited to a certain location and certain type of surroundings which add up the additional costs.
- 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: Our Multimodal Sensor System for Elderly Fall Prediction and Detection



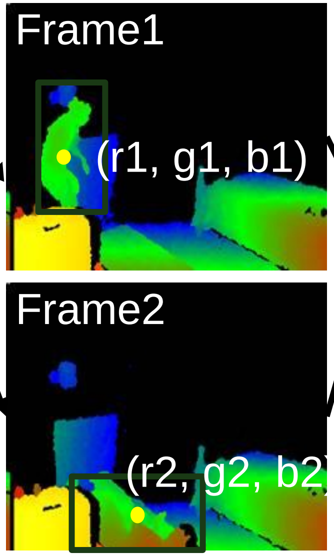
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019,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

Good-Eye: Elderly Fall Detection



Obtaining r,g,b values

```
func_r(x,y)
 { return x+y/100 * 256; }
 func_g(x,y)
{ return (1 – x+y/100) * 256; }
func_b(x,y)
 { return (1 - (0.5 – x+y/100)^2)
* 20; }
```



Distance Formula for r,g,b

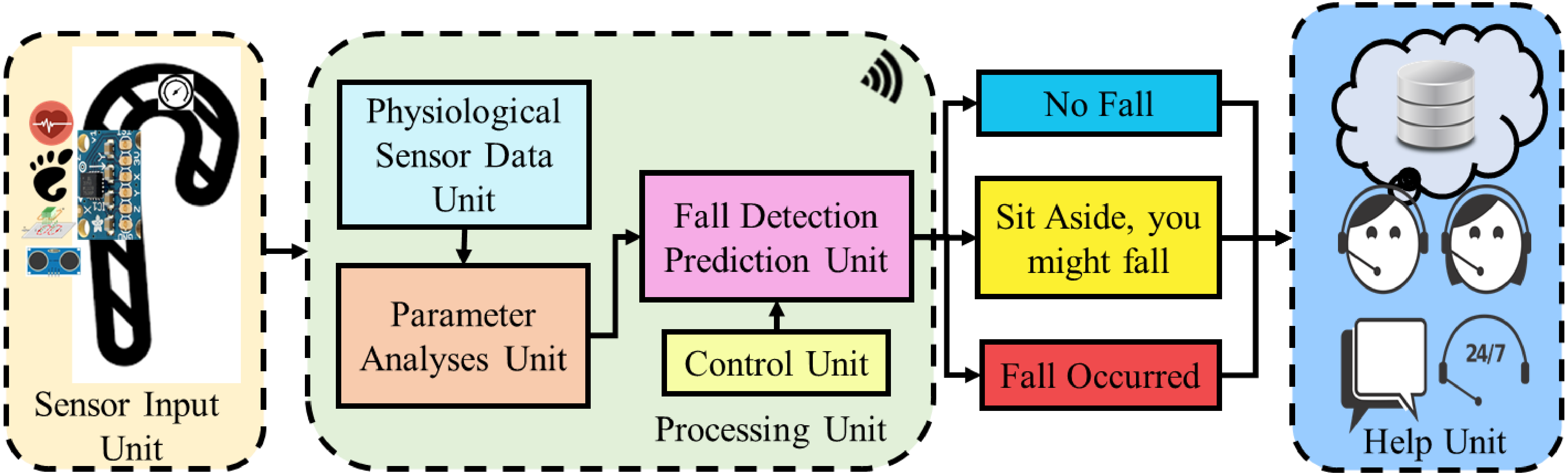
Check if the d is above the threshold

Decision of fall

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.

cStick: A Calm Stick for Fall Prediction, Detection and Control



Fall Monitoring
+ Body Vital Monitoring

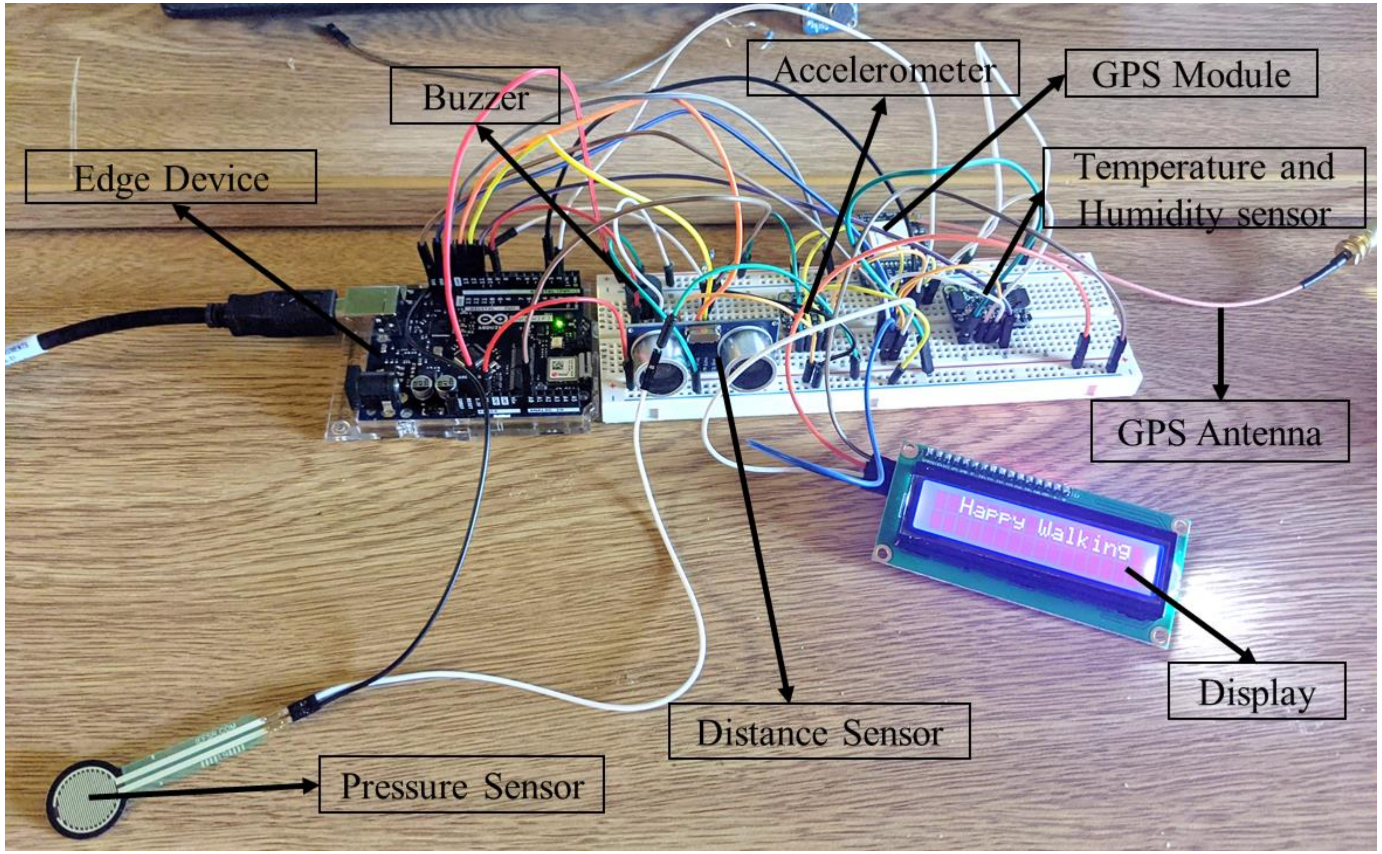
Accelerometer, Gyroscope, HRV,
Blood Pressure, Sugar levels, SpO2

Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, “cStick: A Calm Stick for Fall Prediction, Detection and Control in the IoMT Framework”, in *Proceedings of the 4th IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2021.

cStick - Prototyping

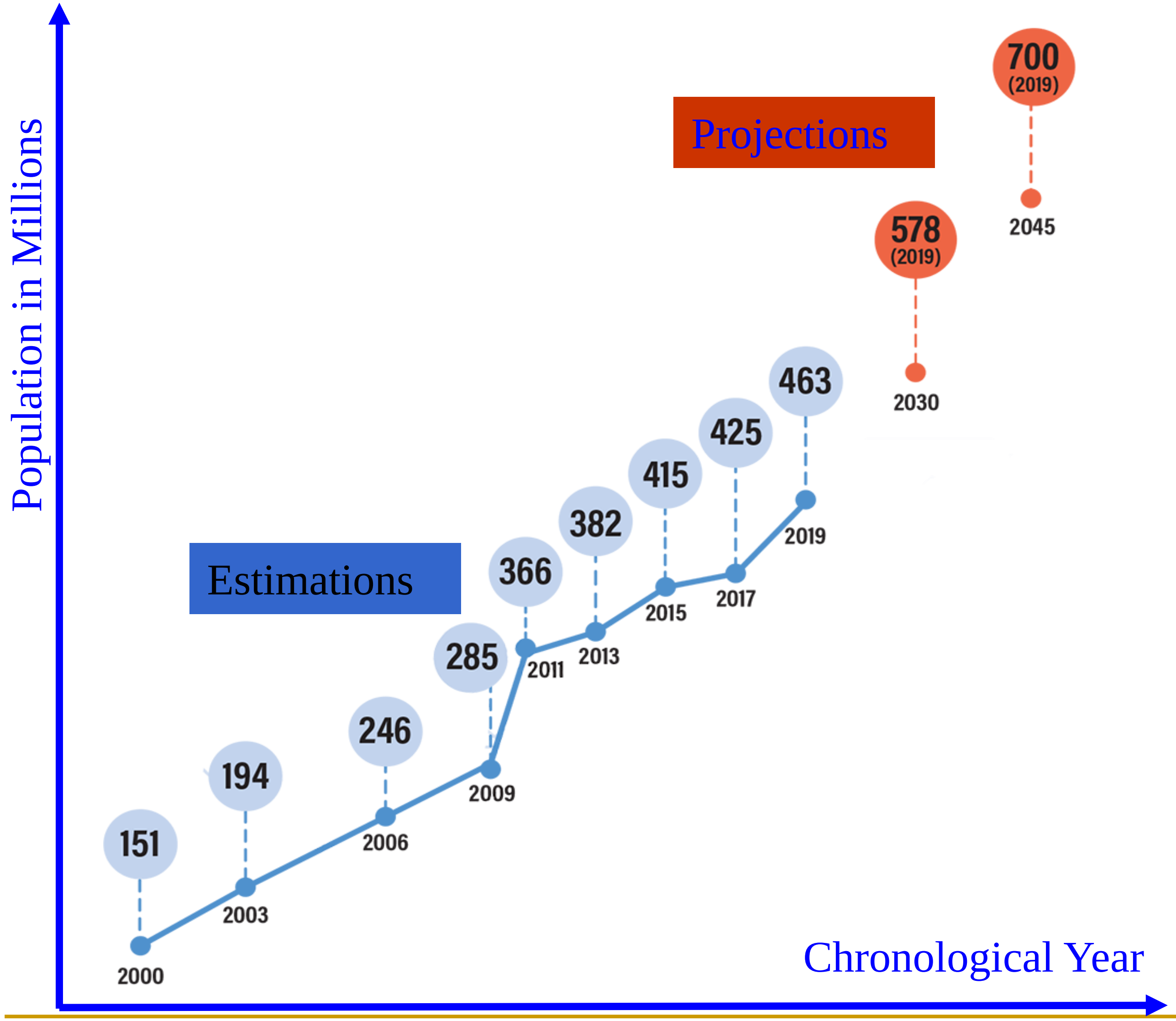
- For the IoMT-Edge computing, a controller has been chosen with real time sensor data from various sensors which monitor the required parameters.

cStick: Fall detection and prediction Accuracy – 96.7%.



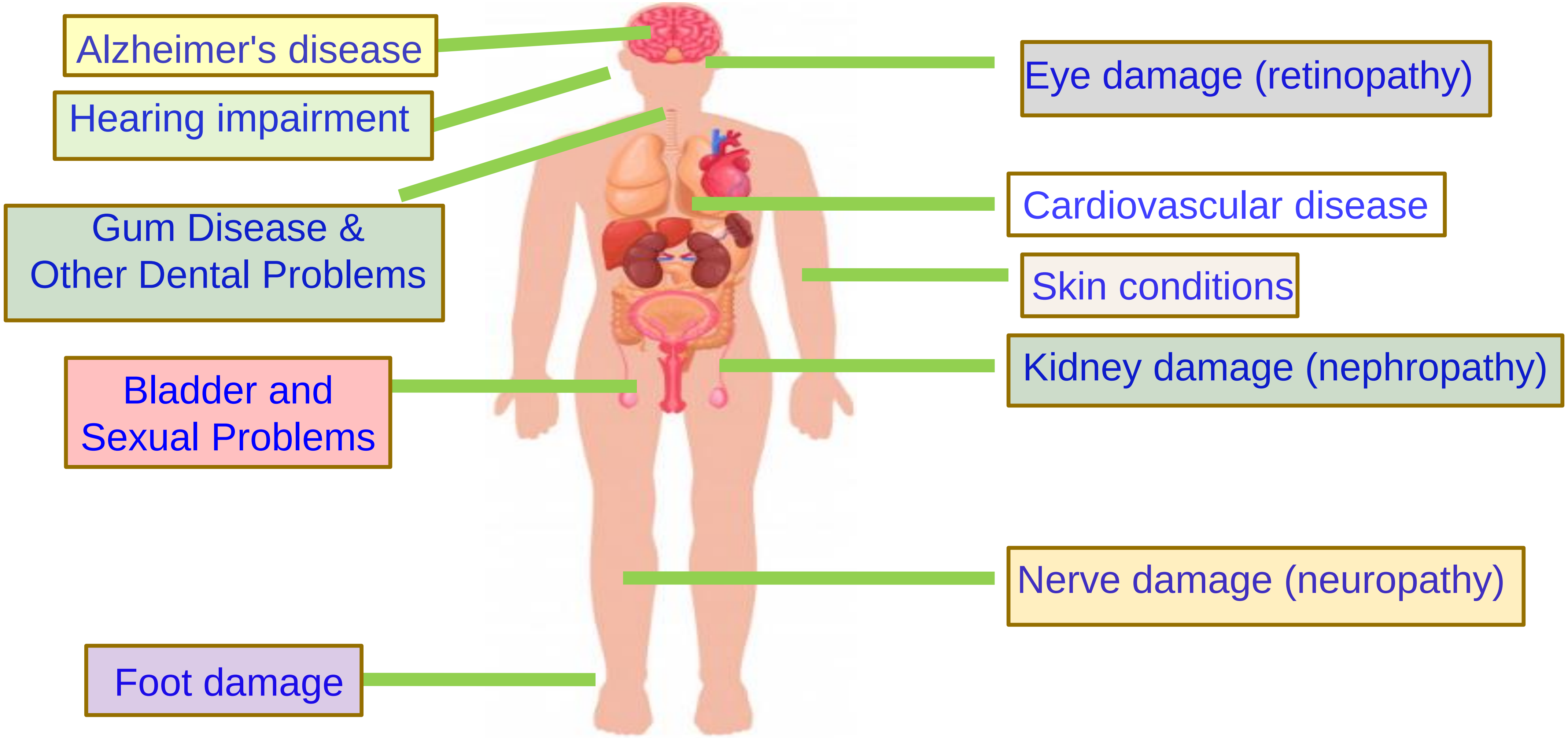
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "cStick: A Calm Stick for Fall Prediction, Detection and Control in the IoMT Framework", in *Proceedings of the 4th IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2021.

Diabetes is a Global Crisis



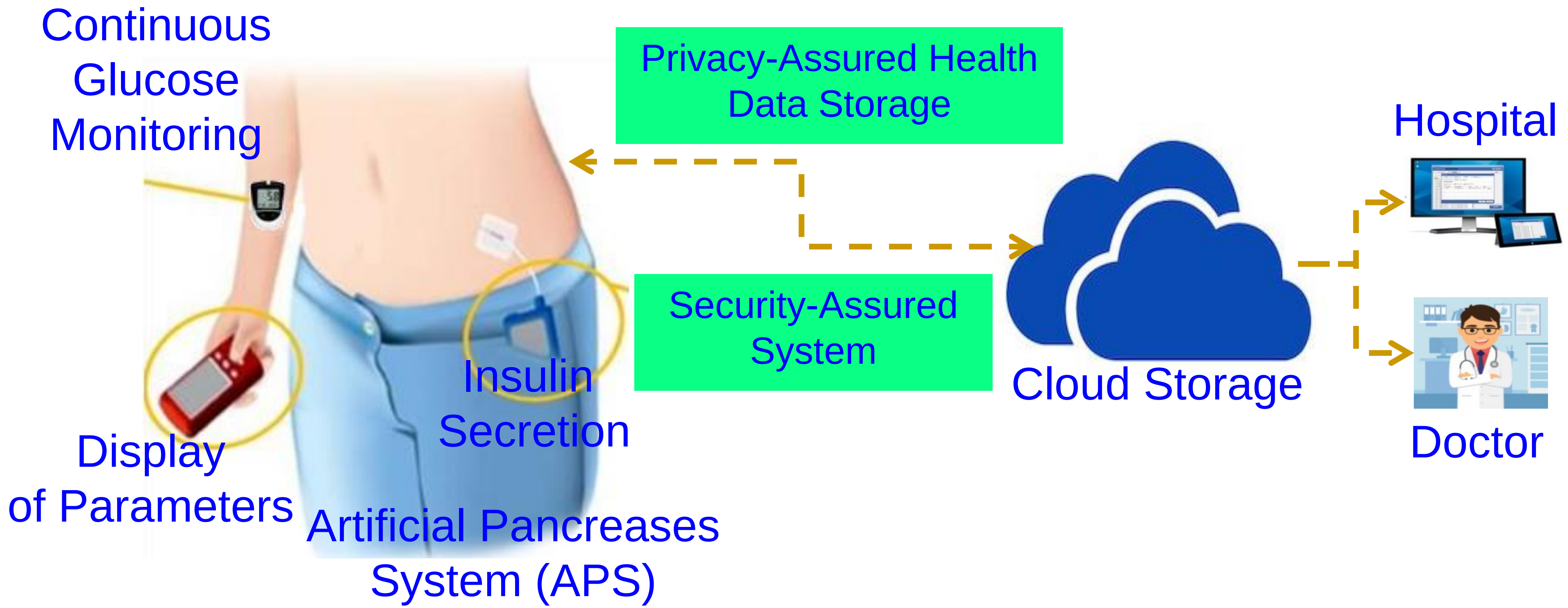
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

Diabetes – Impact on Human Body



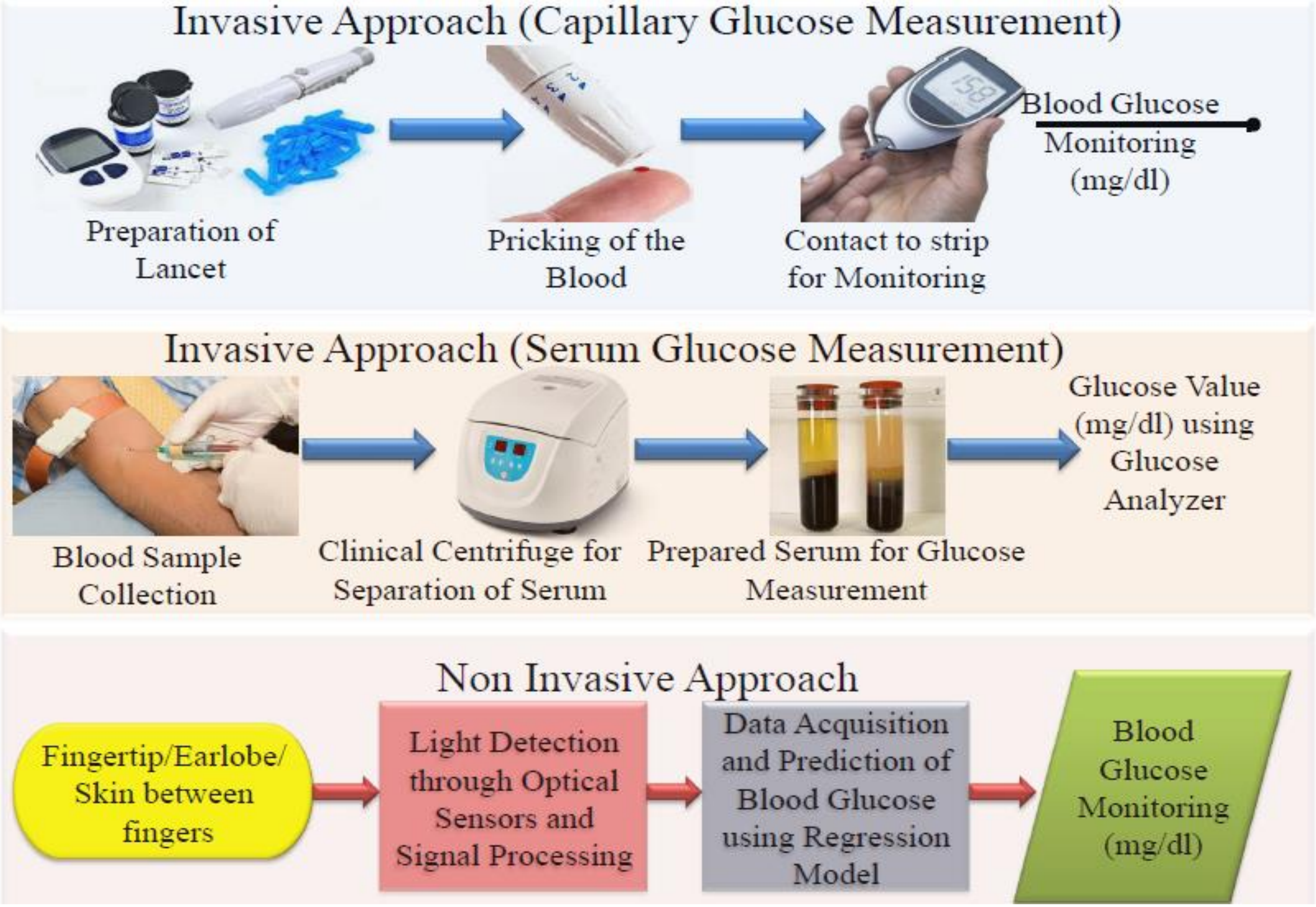
Source: P. Jain, A. M. Joshi, and **S. P. Mohanty**, "Everything You Wanted to Know About Noninvasive Glucose Measurement and Control", *arXiv Physics*, arXiv:2101.08996, January 2021, 51-pages.

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



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.

Blood Glucose Monitoring – Invasive Vs Noninvasive



Traditional – Finger Pricking

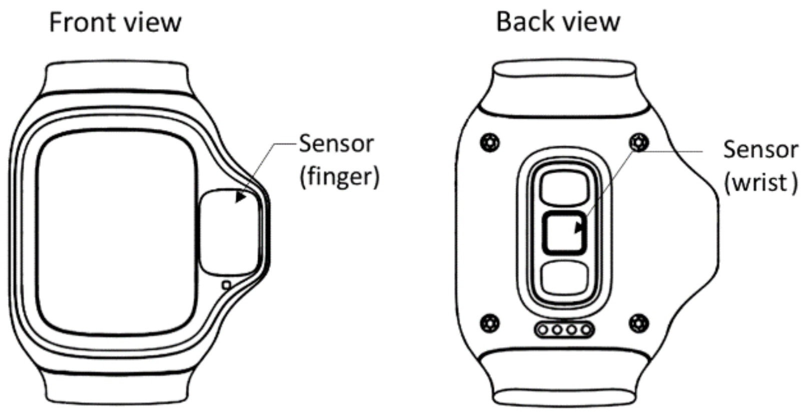
Invasive Approach – Processing Blood/Serum

Noninvasive – Wearable

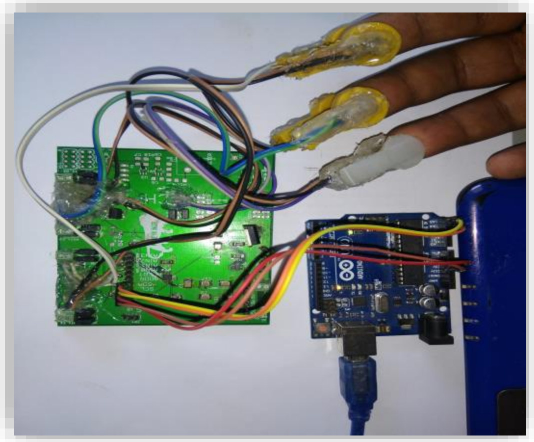
Noninvasive Approach – Processing Light

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.

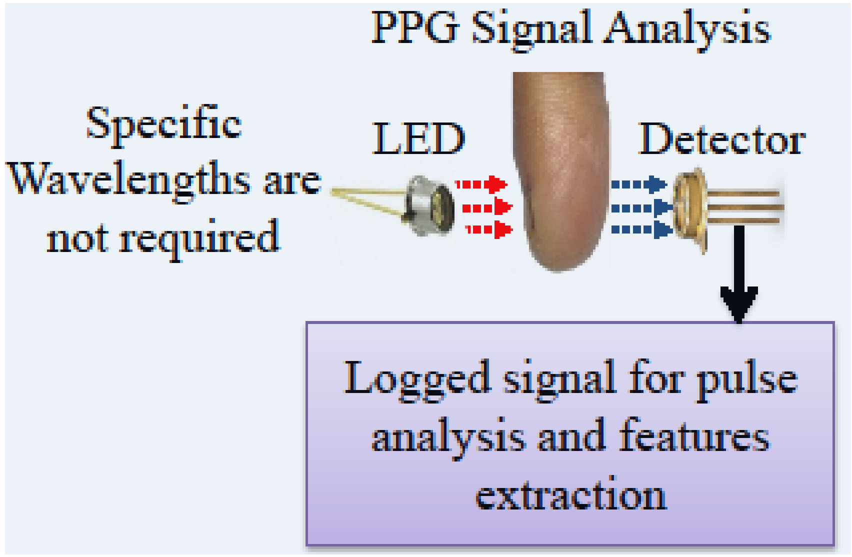
Noninvasive Glucose-Level Monitoring

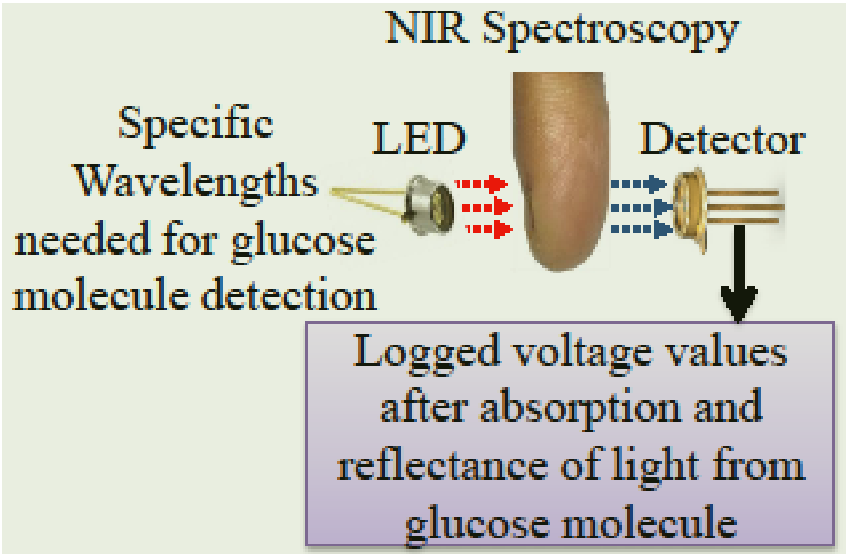


Photoplethysmogram (PPG)

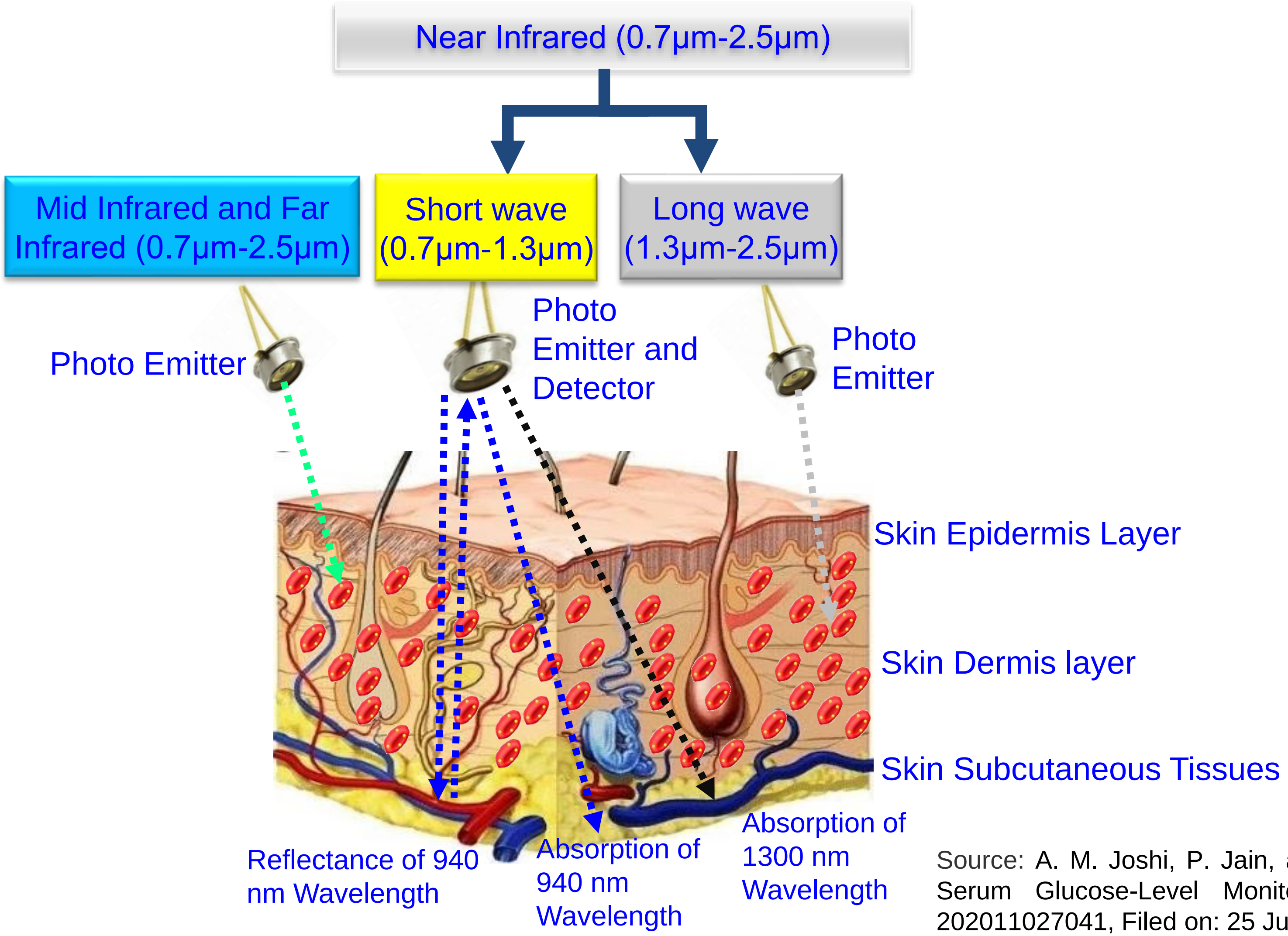


Near Infrared (NIR)



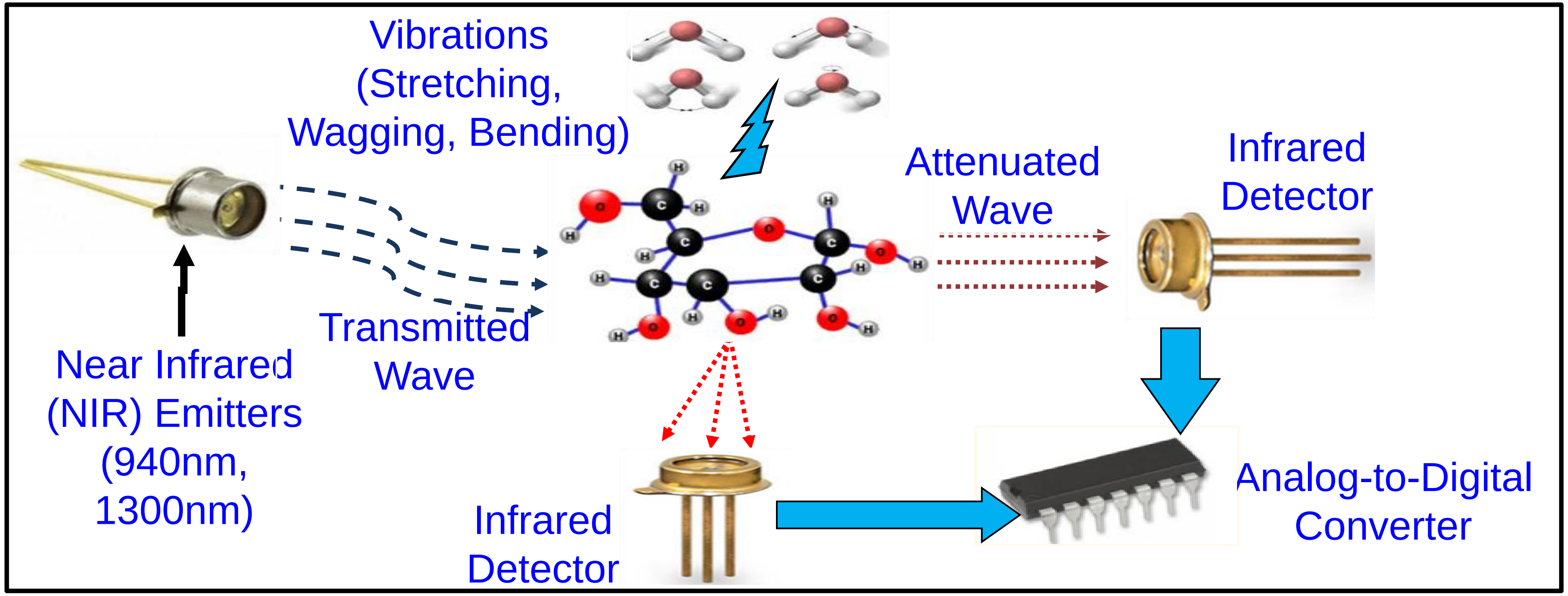


Unique Near Infrared Spectroscopy for iGLU



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

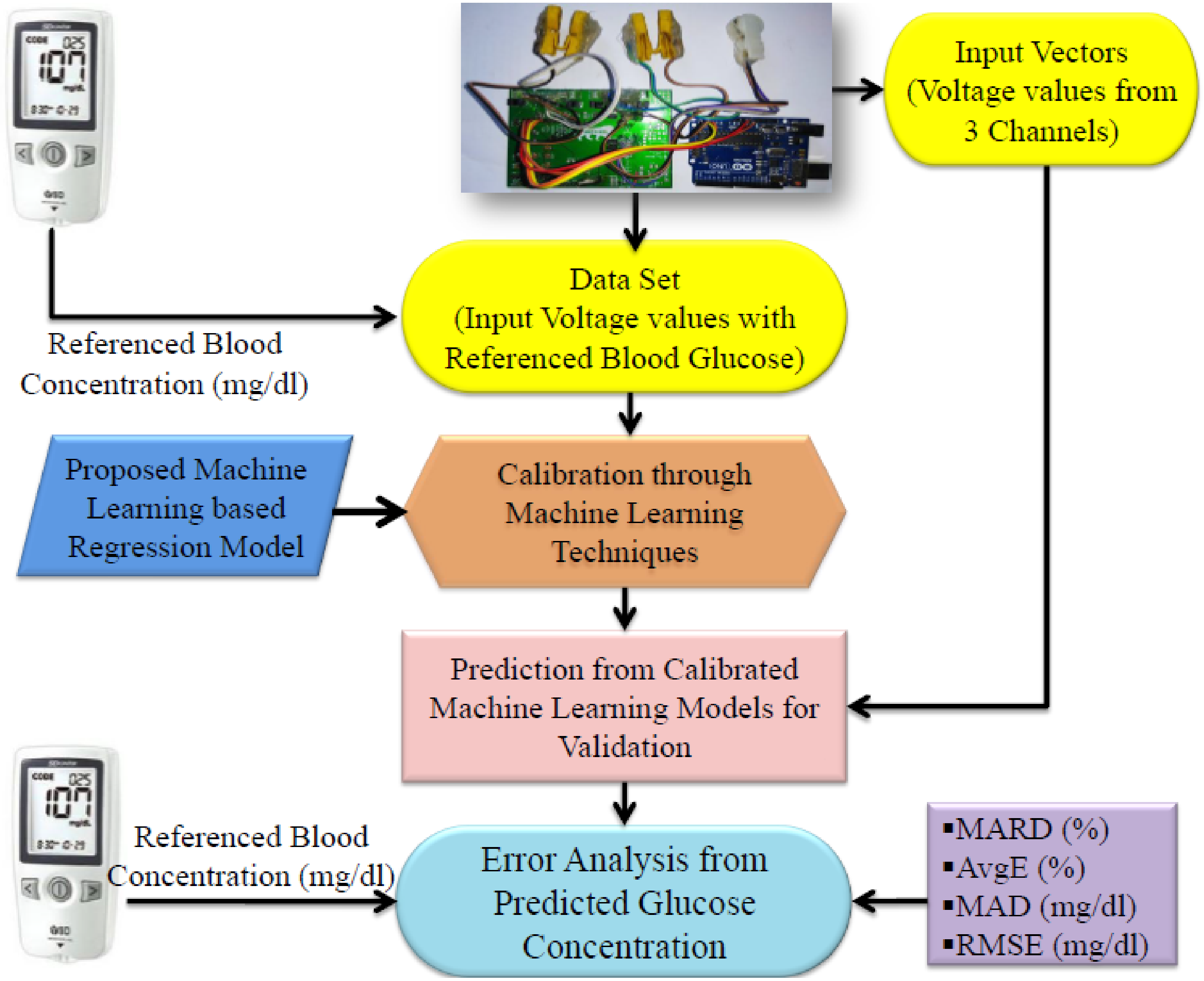


Clinically tested in an hospital.

Cost - US$ 20
Accuracy - 100%

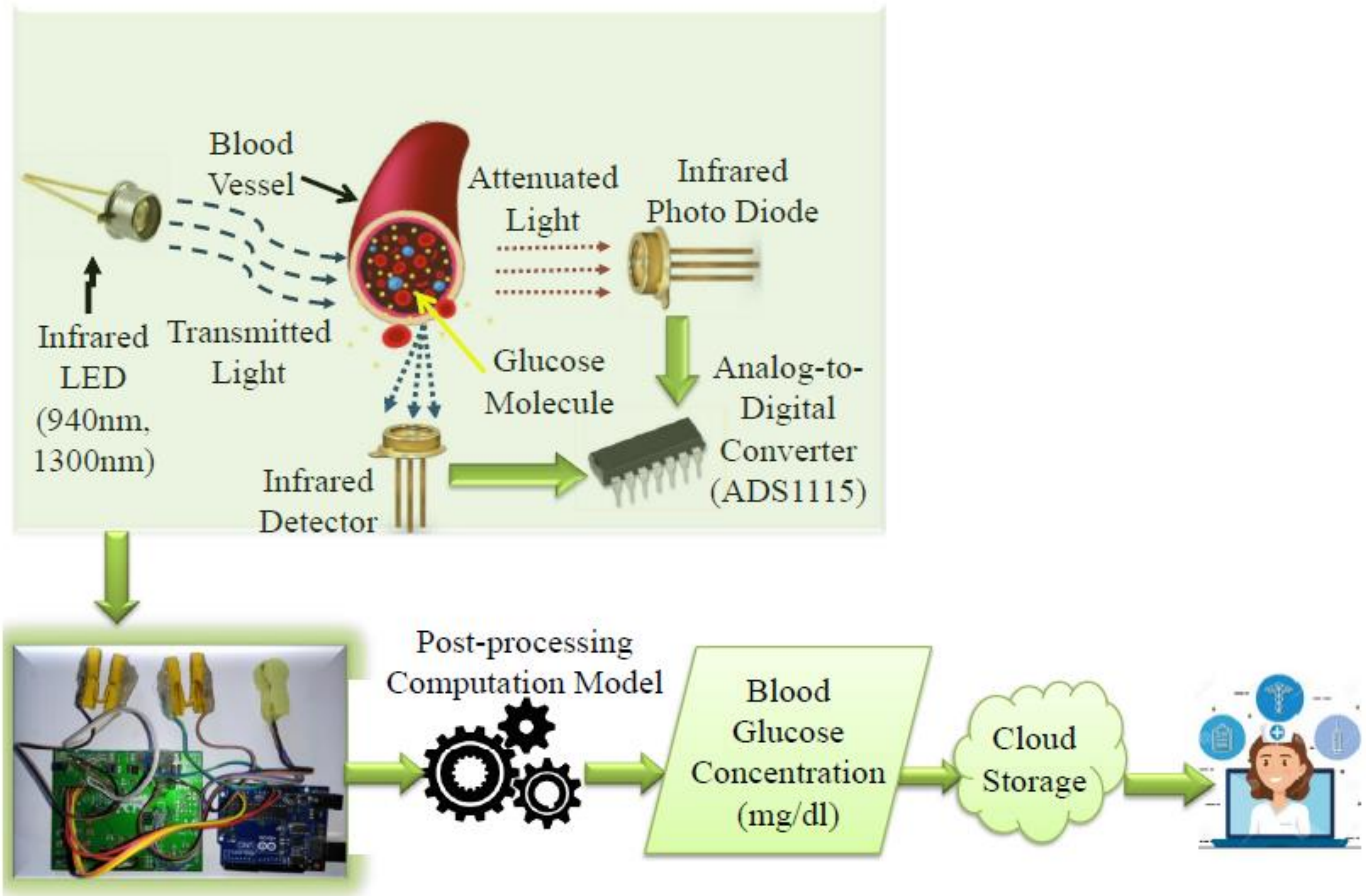
Source: P. Jain, A. M. Joshi, and S. P. Mohanty, "iGLU: An Intelligent Device for Accurate Non-Invasive Blood Glucose-Level Monitoring in Smart Healthcare", *IEEE Consumer Electronics Magazine (MCE),* Vol. 9, No. 1, January 2020, pp. 35-42.

iGLU 1.0: Modeling Flow



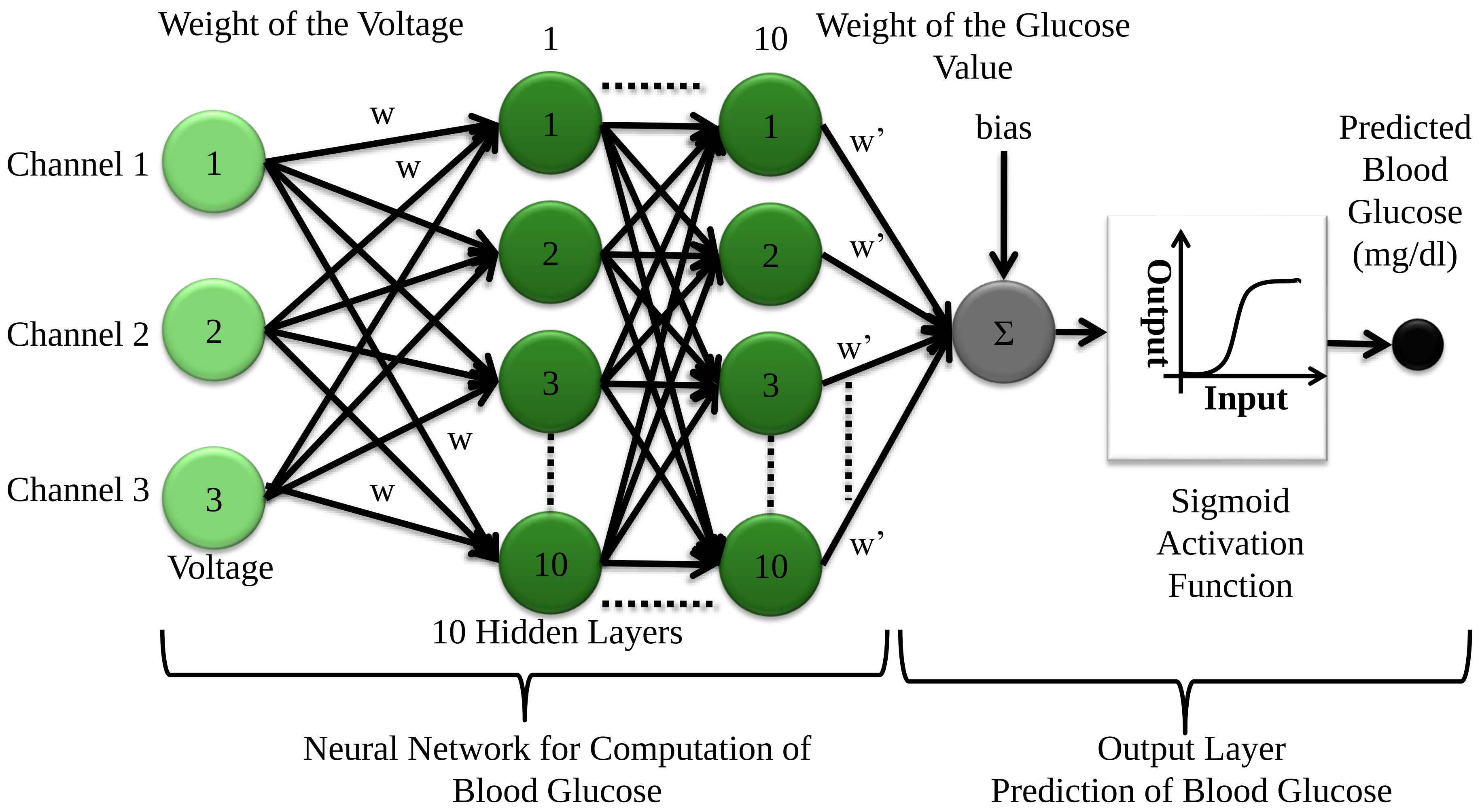
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

iGLU 2.0: Serum Glucose



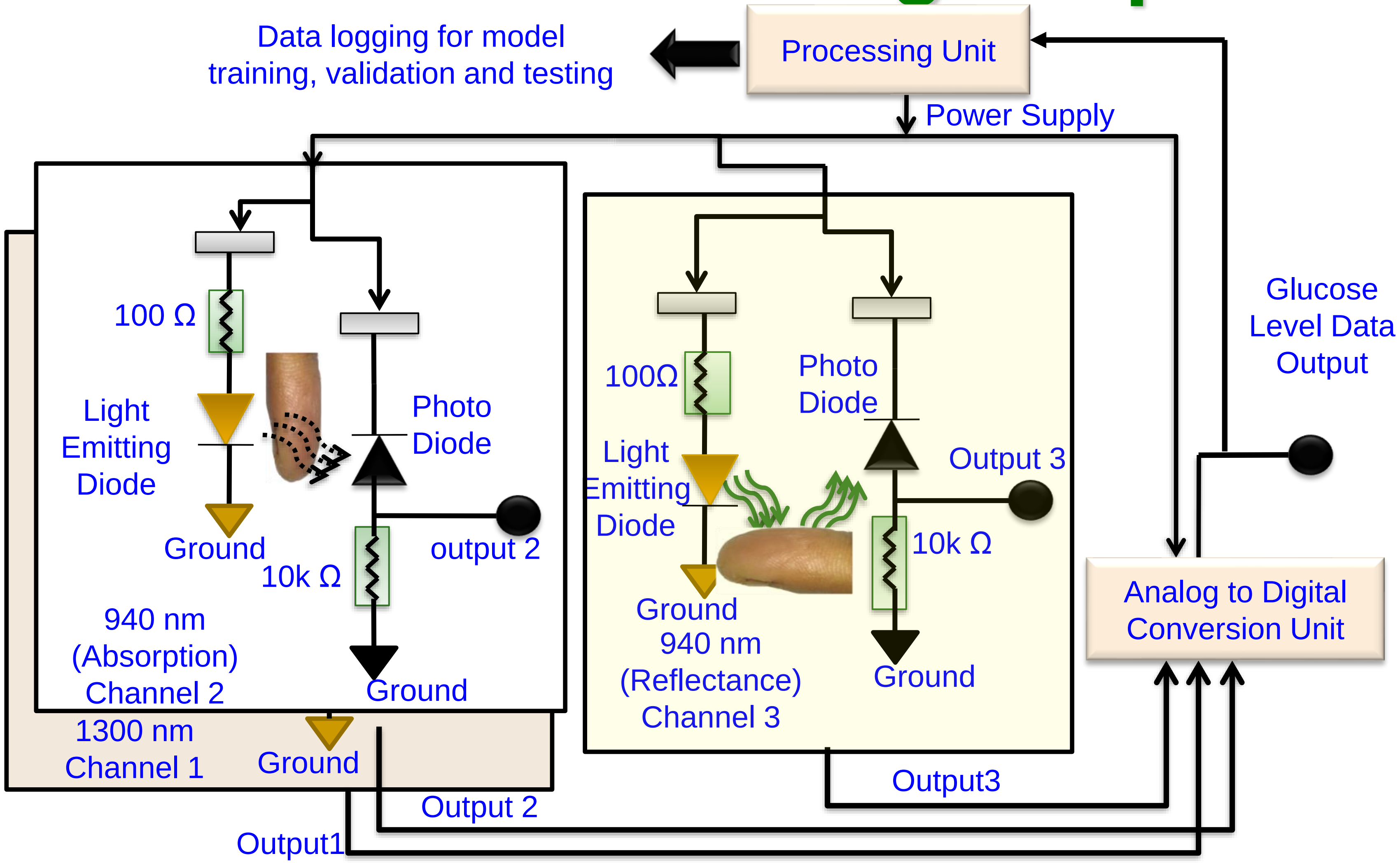
Source A. M. Joshi, P. Jain, S. P. Mohanty, and N. Agrawal, “iGLU 2.0: A New Wearable for Accurate Non-Invasive Continuous Serum Glucose Measurement in IoMT Framework”, *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 4, Nov 2020, pp. 327--335.

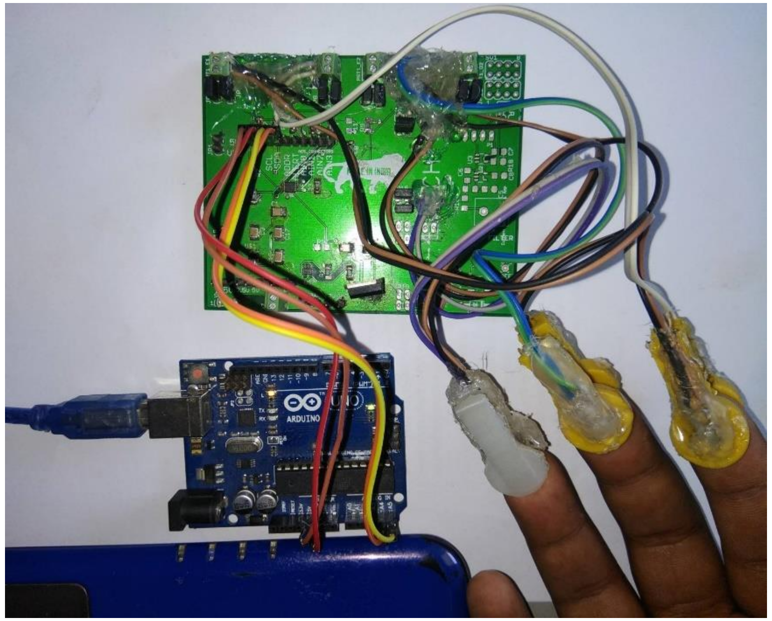
DNN Based Glucose Prediction



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.

iGLU – Design Implementation



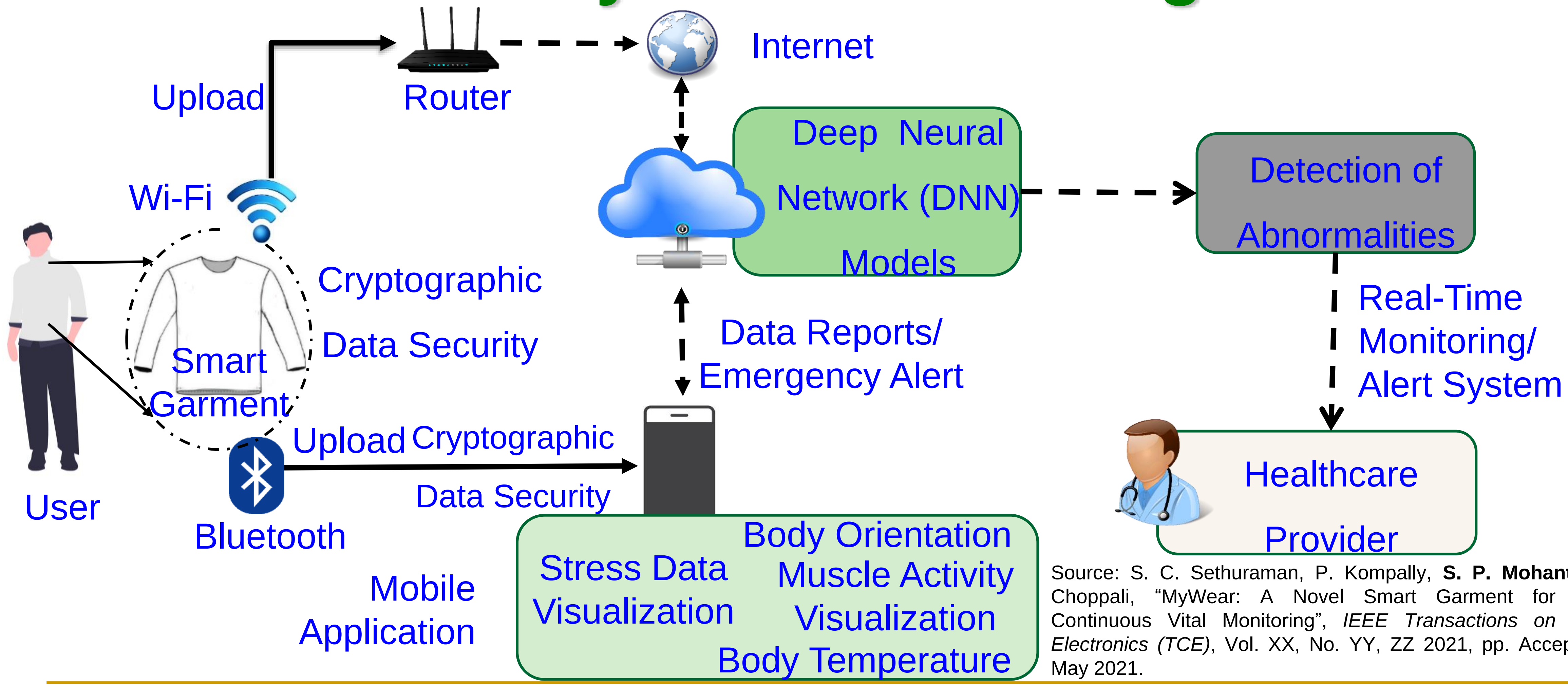


Clinically tested in an hospital.

Cost - US$ 20
Accuracy - 100%

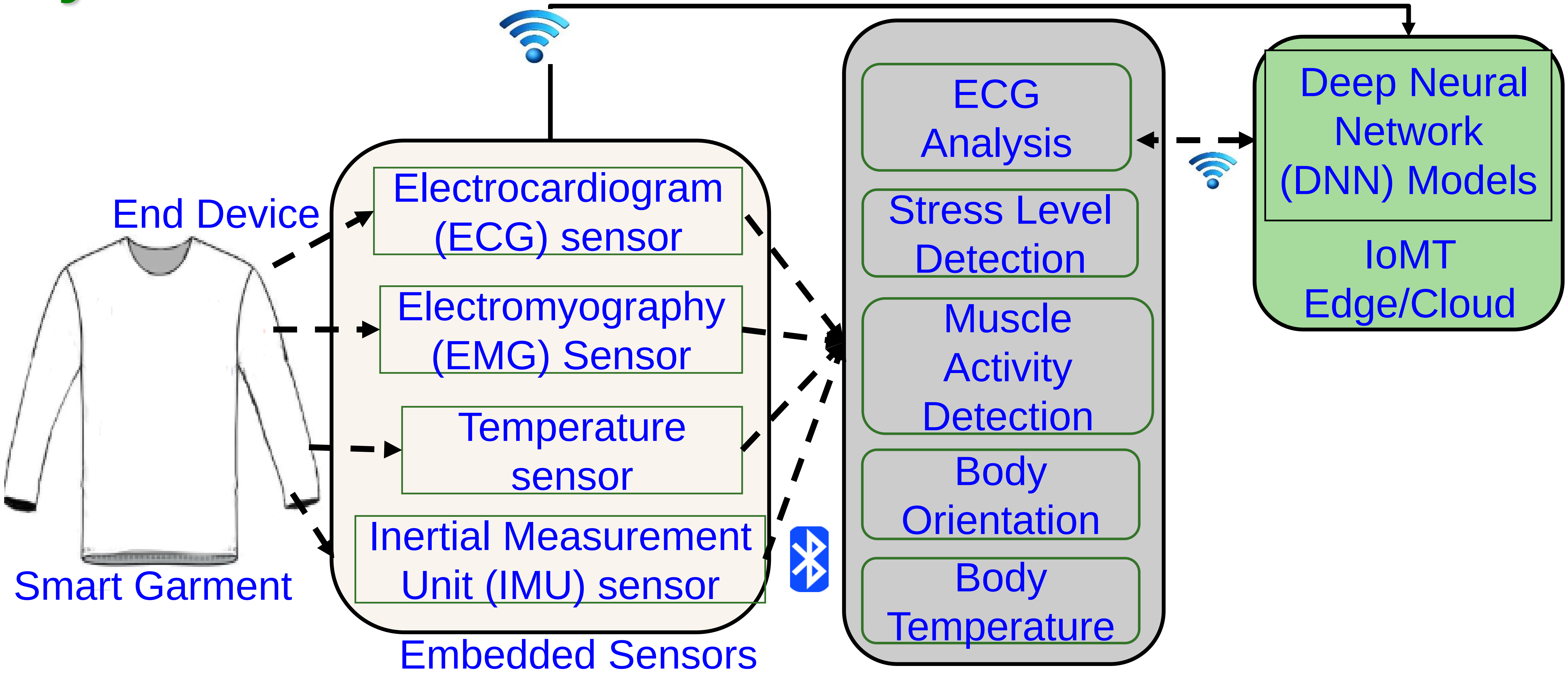
Source: A. M. Joshi, P. Jain, and S. P. Mohanty, A Device For Non-Invasive Blood and Serum Glucose-Level Monitoring and Control, India Patent Application Number: 202011027041, Filed on: 25 June 2020.

MyWear – A Smart Wear for Continuous Body Vital Monitoring



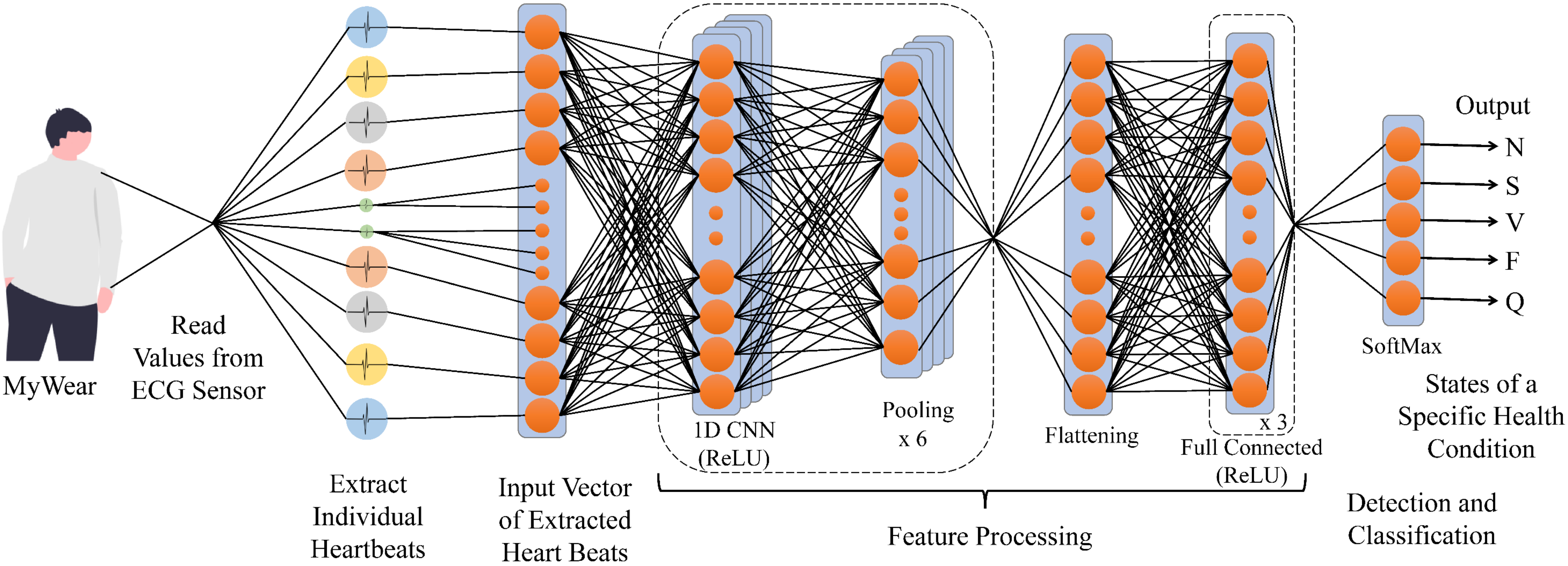
Source: S. C. Sethuraman, P. Kompally, **S. P. Mohanty**, and U. Choppali, "MyWear: A Novel Smart Garment for Automatic Continuous Vital Monitoring", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. XX, No. YY, ZZ 2021, pp. Accepted on 30 May 2021.

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.

MyWear – DNN Model for ECG Data

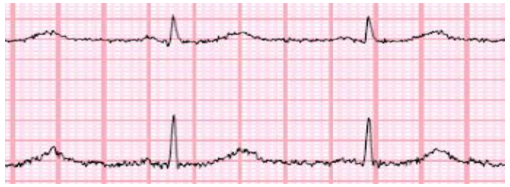


Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, “MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert”, *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

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

Display Standard Deviation of RR Intervals

Calculate the Successive Differences of two RR Intervals

Compute the Square of the obtained Successive Difference of RR Intervals

Calculate the Mean of the Successive Differences

Calculate the Root of the output Mean of Successive Differences

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

Compare RMSSD value with Stress Chart

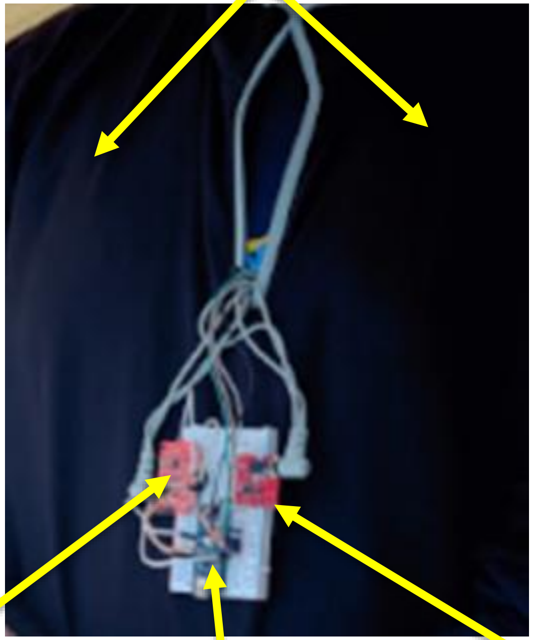
Obtain the Stress Level of the User

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.

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

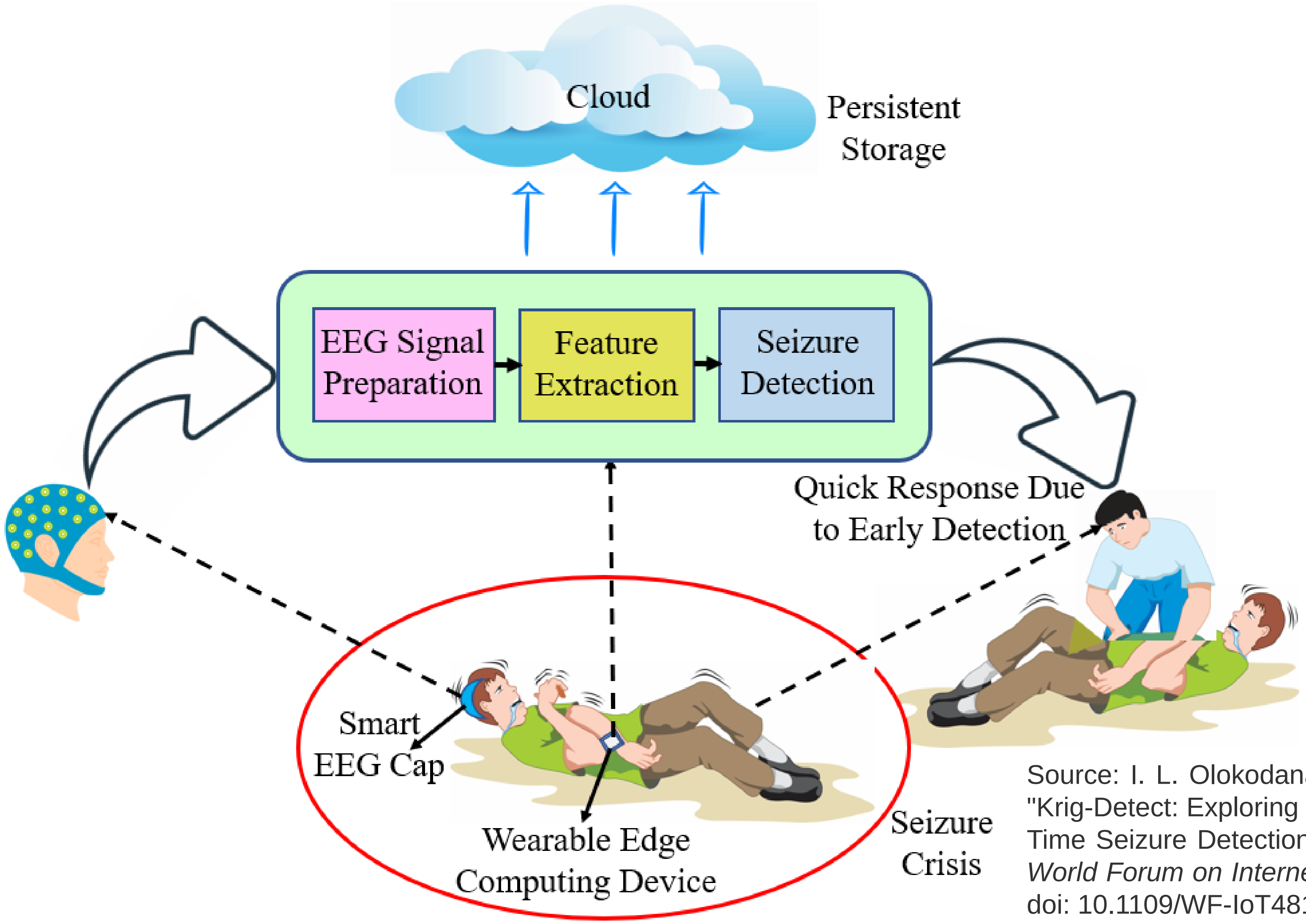
Source: S. C. Sethuraman, P. Kompally, **S. P. Mohanty**, and U. Choppali, "MyWear: A Novel Smart Garment for Automatic Continuous Vital Monitoring", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. XX, No. YY, ZZ 2021, pp. Accepted on 30 May 2021.

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

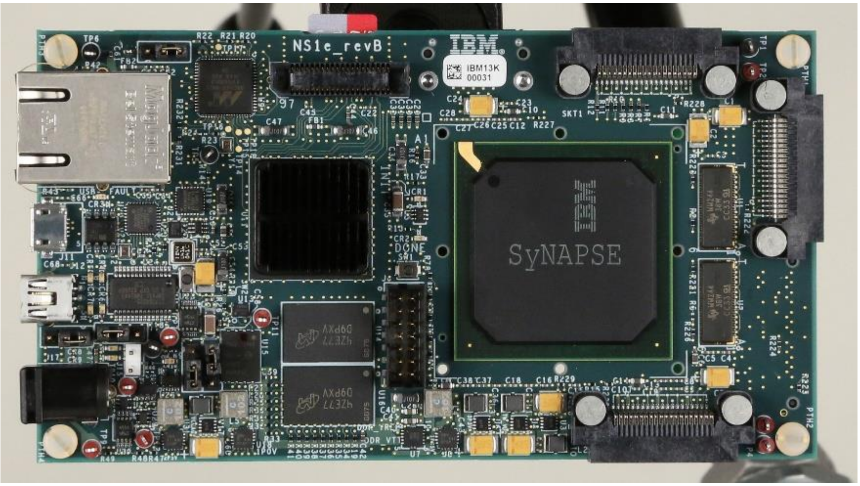
Epileptic Seizure – Our Research Vision



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.

IBM’s Implantable Seizure Detector

- 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

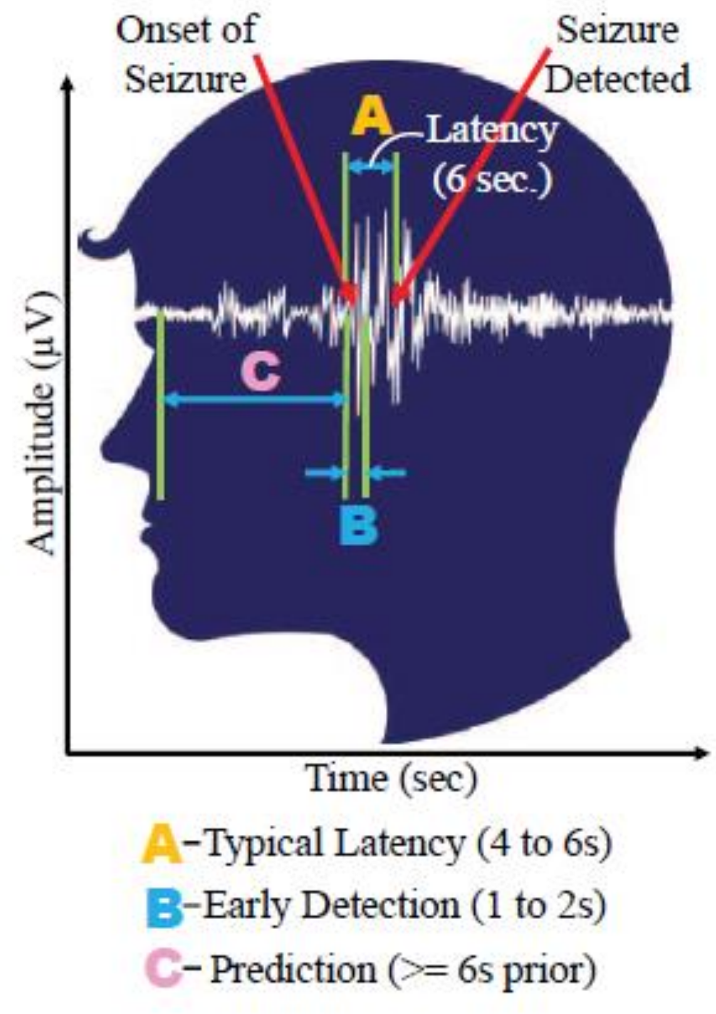
- Embrace2: Smart-band which uses machine learning to detect convulsive Seizures and notifies caregivers.

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

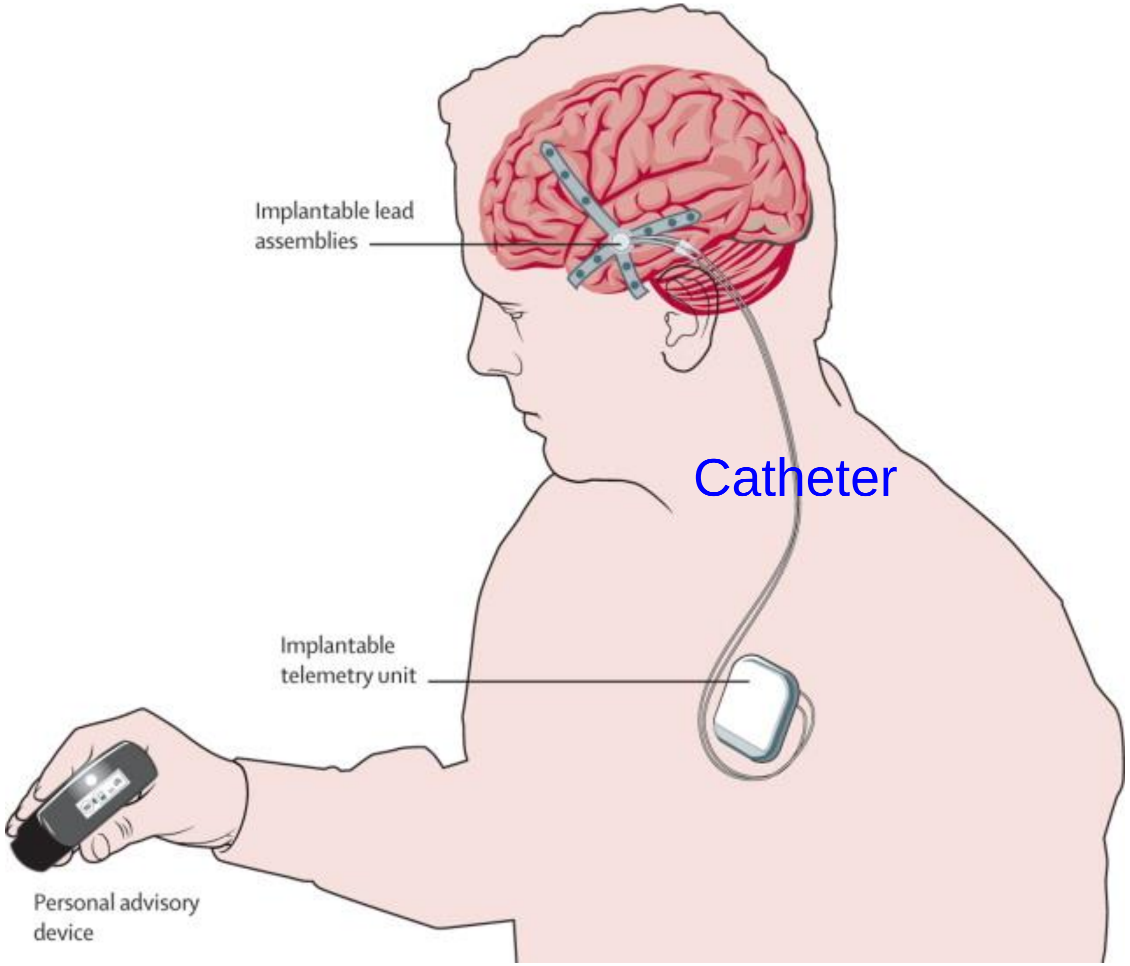
- Medical grade smart watch: It detects generalized clonic-tonic Seizures and notifies physicians.

Drawbacks of Existing Works?

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

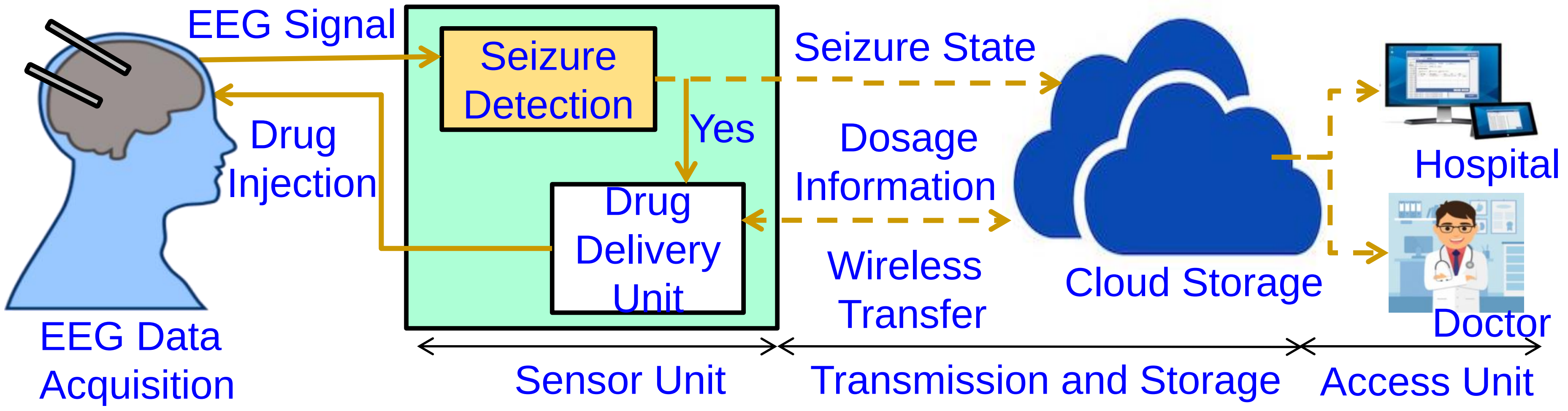


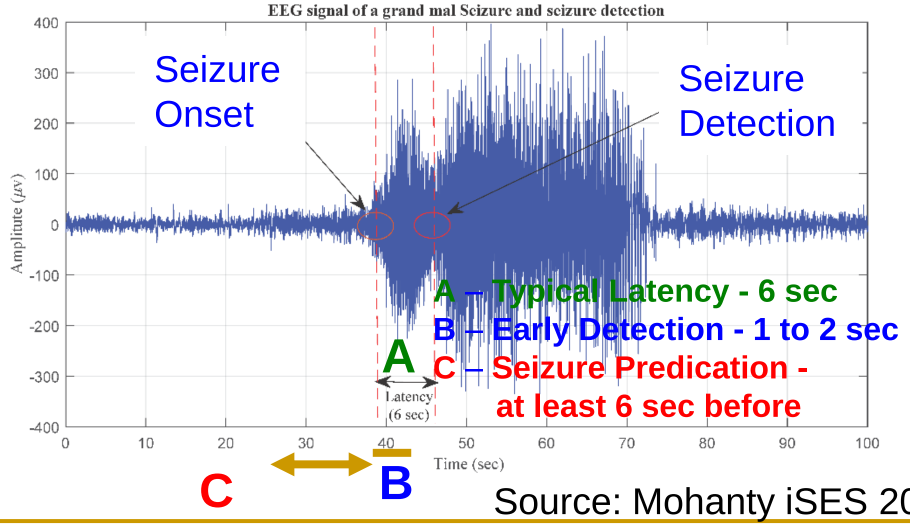
Implantable for Seizure Detection and Control



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

Smart Healthcare – Seizure Detection and Control



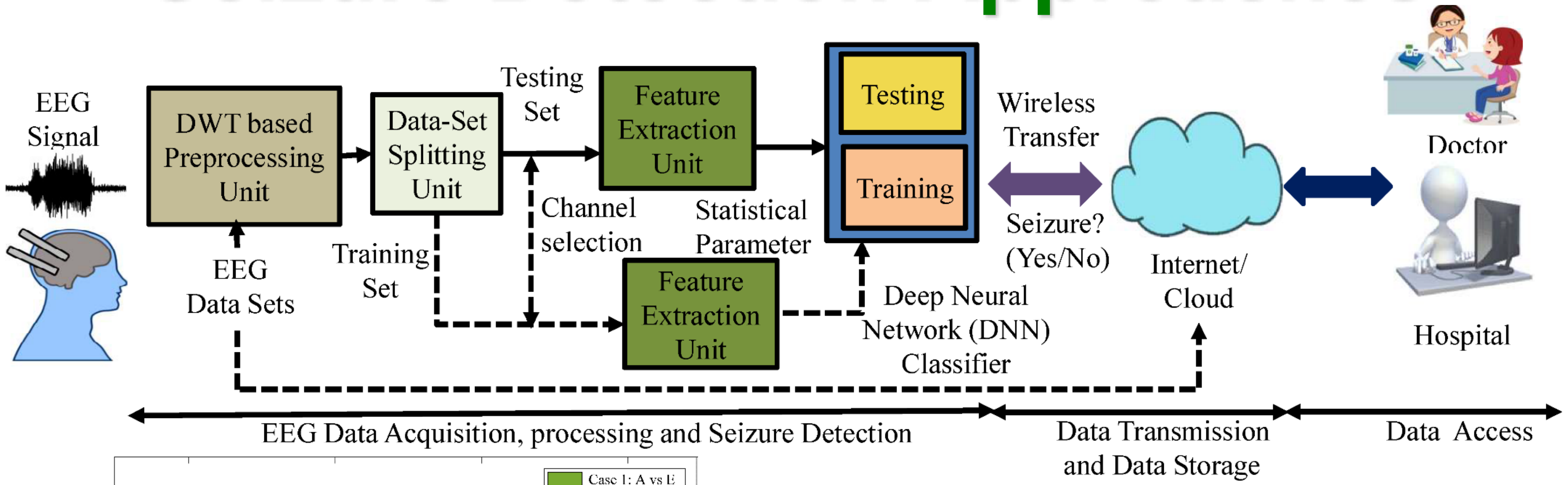


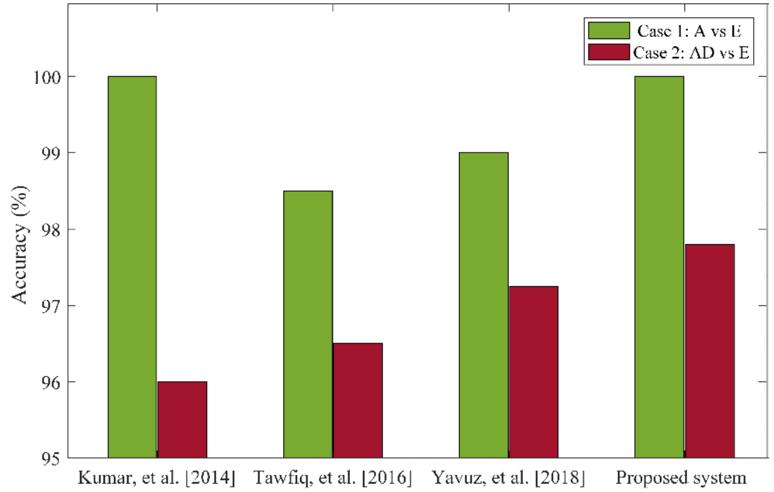
Automated Epileptic Seizure Detection and Control System

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

Source: Mohanty iSES 2018, IEEE Smart Cities 2018, and Mohanty ICCE 2019

Seizure Detection Approaches



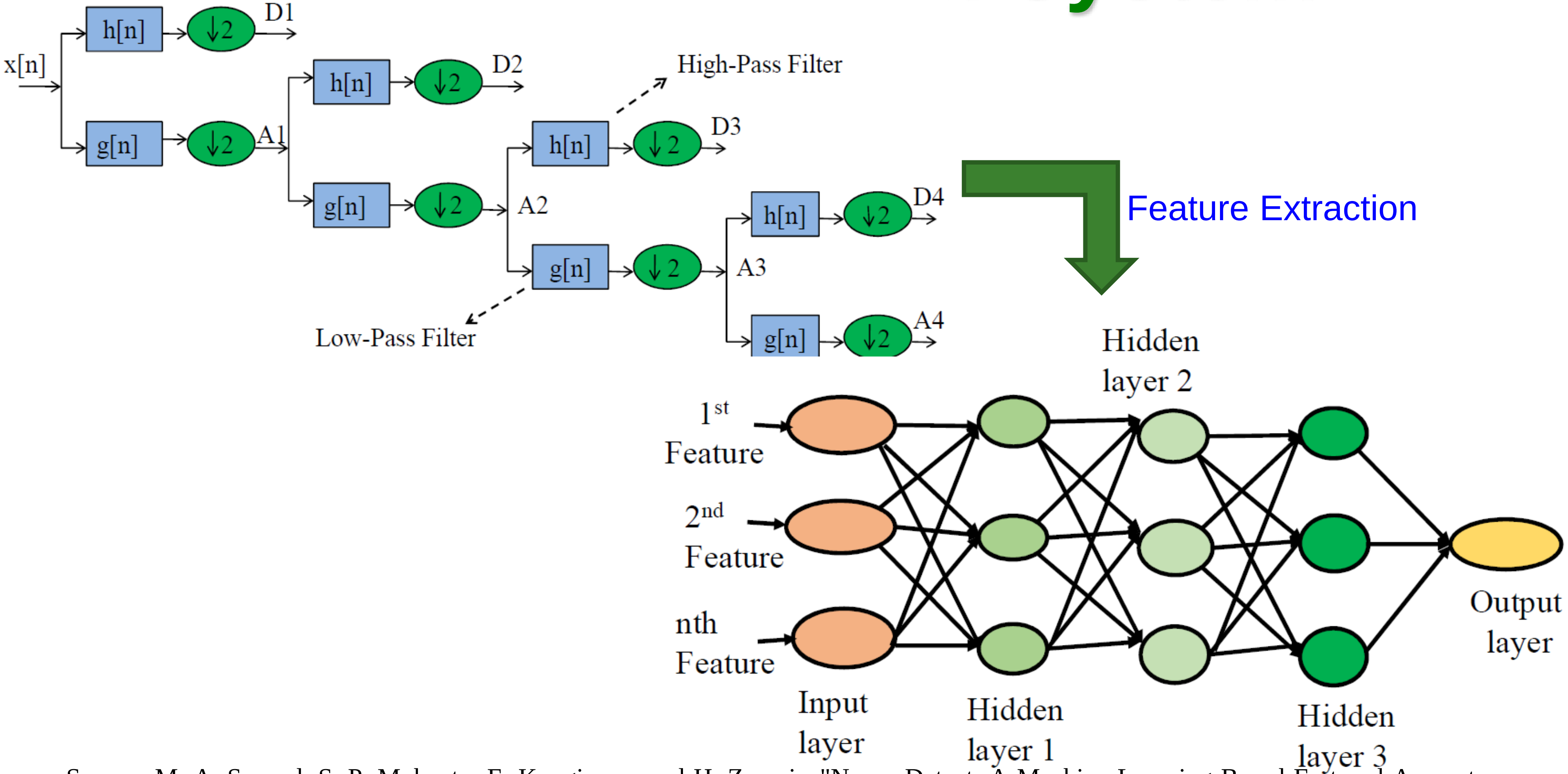


Cloud Vs Edge Computing

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



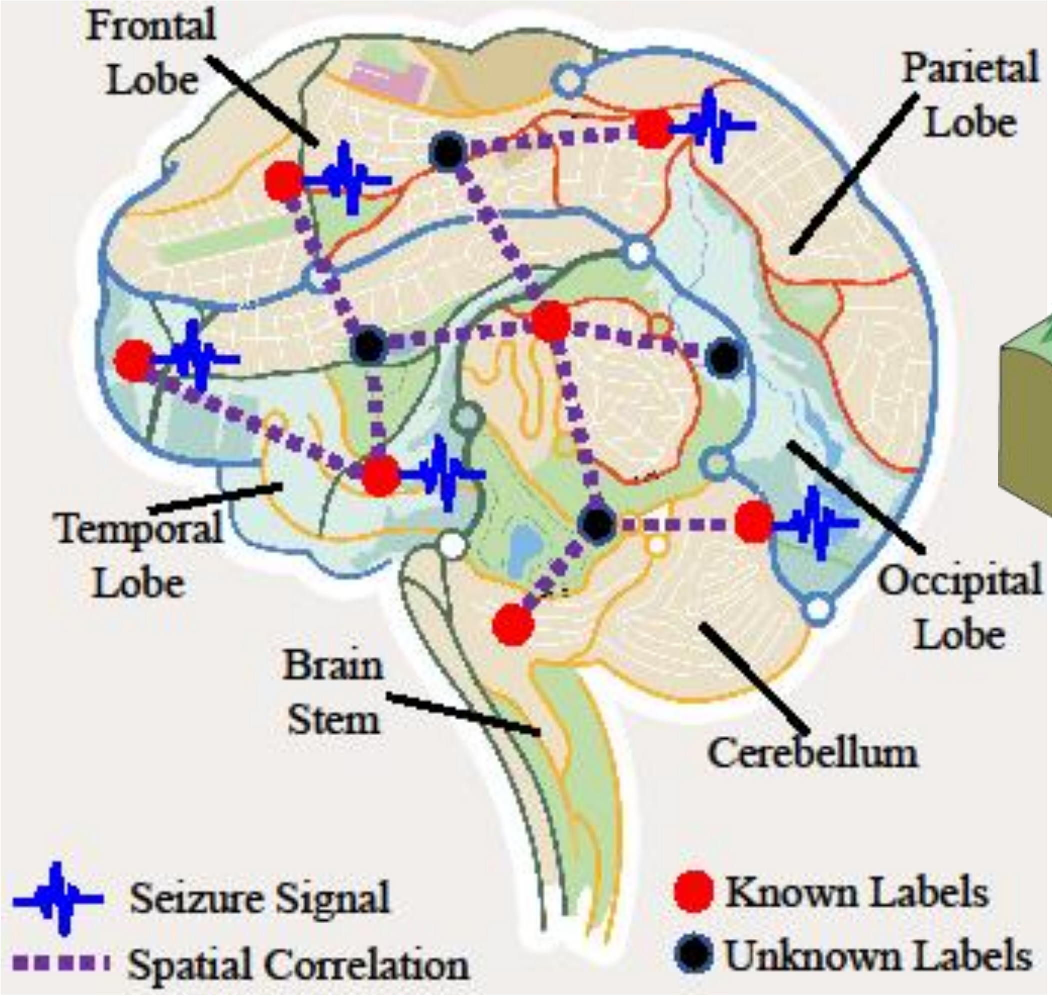
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri , "Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, Issue 3, Aug 2019, pp. 359-368.

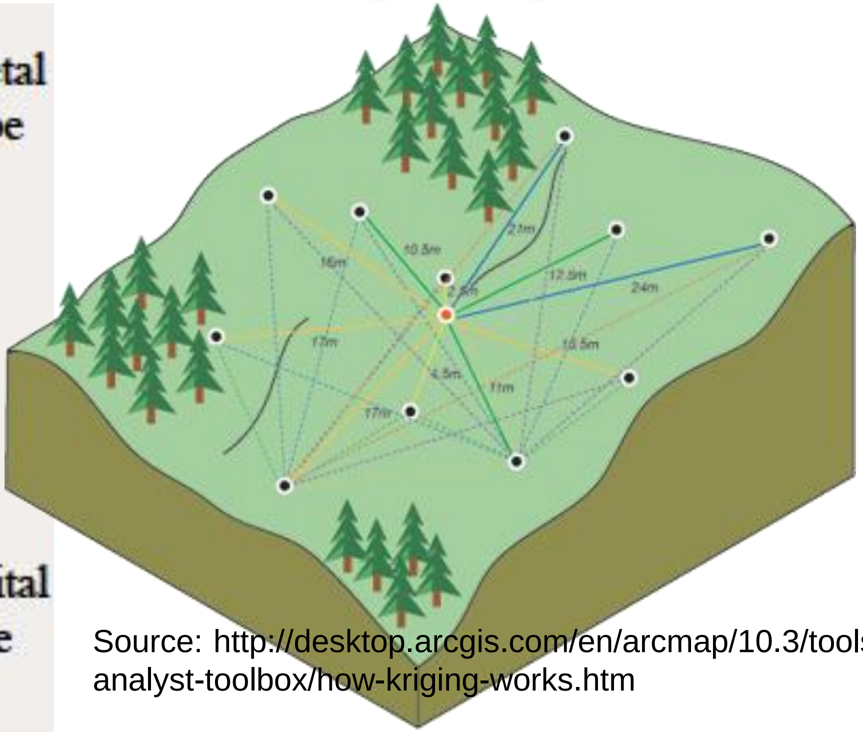
Krig-Detect: Exploring Kriging Methods for Real-Time Seizure Detection from EEG Signals

- To the best of the authors' knowledge, this is the first work where multiple Kriging methods have been used for real-time seizure detection in an edge computing paradigm.
- A novel achievement of an epileptic seizure detection latency of less than 1 second while maintaining a comparable accuracy with existing models and O(1) time and space complexity for edge computation.

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

Smart Healthcare – Brain as a Spatial Map → Kriging Methods





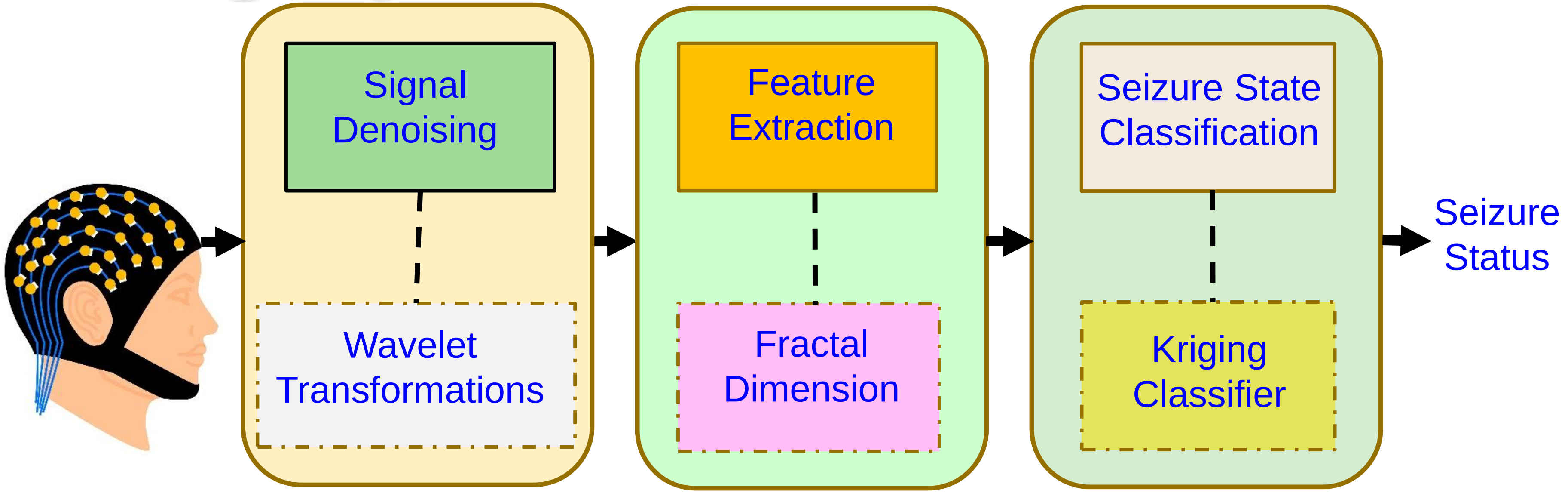
Source: http://desktop.arcgis.com/en/arcmap/10.3/tools/3d-analyst-toolbox/how-kriging-works.htm

Spatial modeling or Variography
- Correlation Function is “Variogram”

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

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.

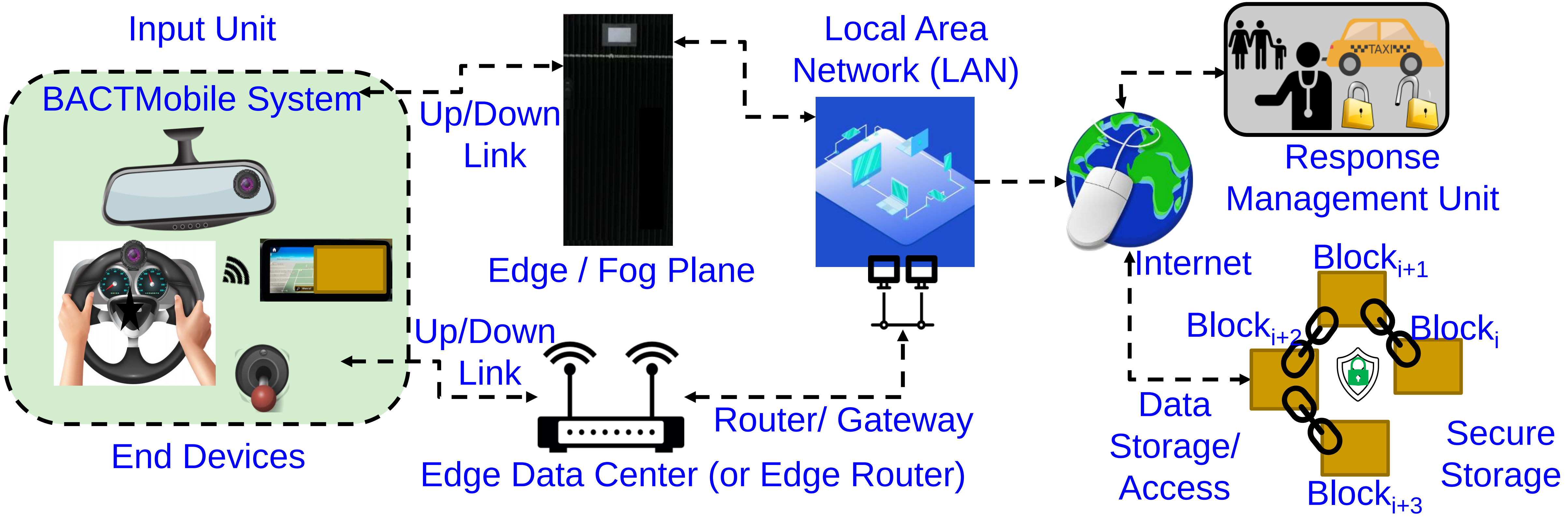
Kriging based Seizure Detection



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

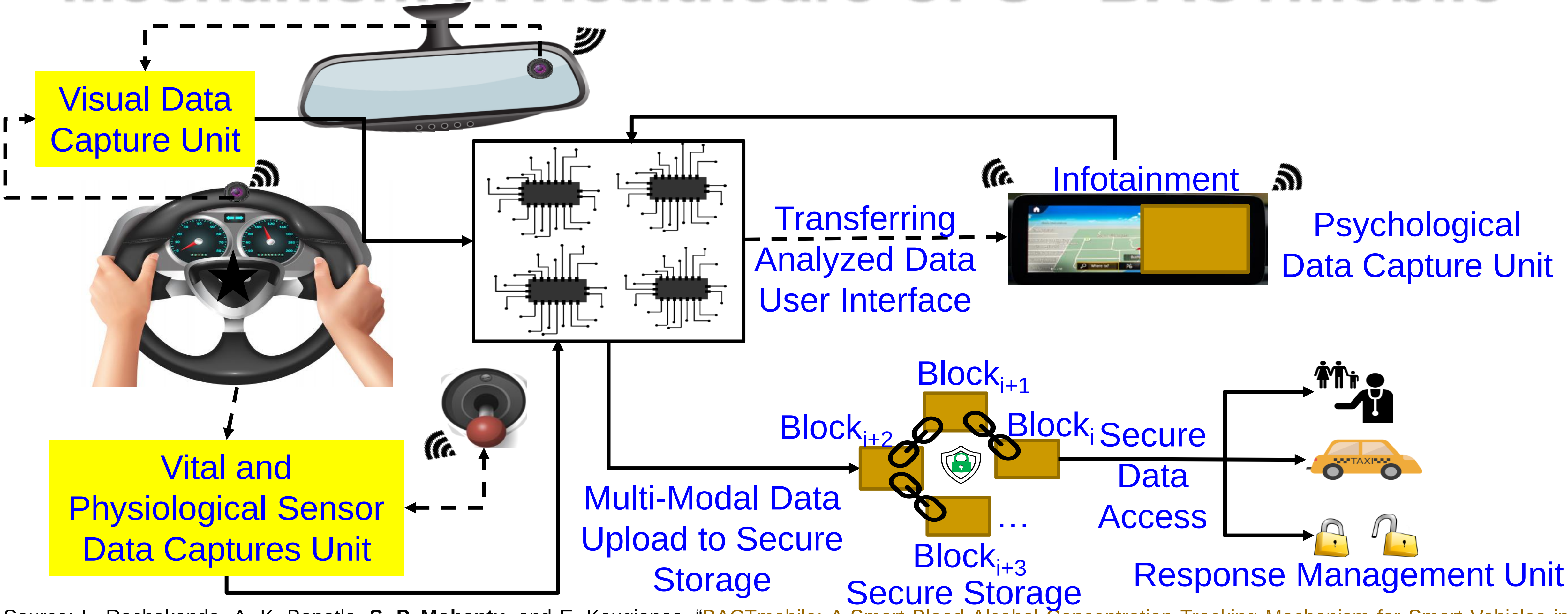
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Ordinary-Kriging Based Real-Time Seizure Detection in an Edge Computing Paradigm", in *Proceedings of the 38th IEEE International Conference on Consumer Electronics (ICCE)*, 2020, Accepted.

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



Source: L. Rachakonda, A. K. Bapatla, **S. P. Mohanty**, and E. Kougianos, "BACTmobile: A Smart Blood Alcohol Concentration Tracking Mechanism for Smart Vehicles in Healthcare CPS Framework", *Springer Nature Computer Science (SN-CS)*, Vol. 3, No. 3, May 2022, Article: 236, 24-pages, DOI: https://doi.org/10.1007/s42979-022-01142-9.

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



Source: L. Rachakonda, A. K. Bapatla, **S. P. Mohanty**, and E. Kougianos, "BACTmobile: A Smart Blood Alcohol Concentration Tracking Mechanism for Smart Vehicles in Healthcare CPS Framework", *Springer Nature Computer Science (SN-CS)*, Vol. 3, No. 3, May 2022, Article: 236, 24-pages, DOI: https://doi.org/10.1007/s42979-022-01142-9.

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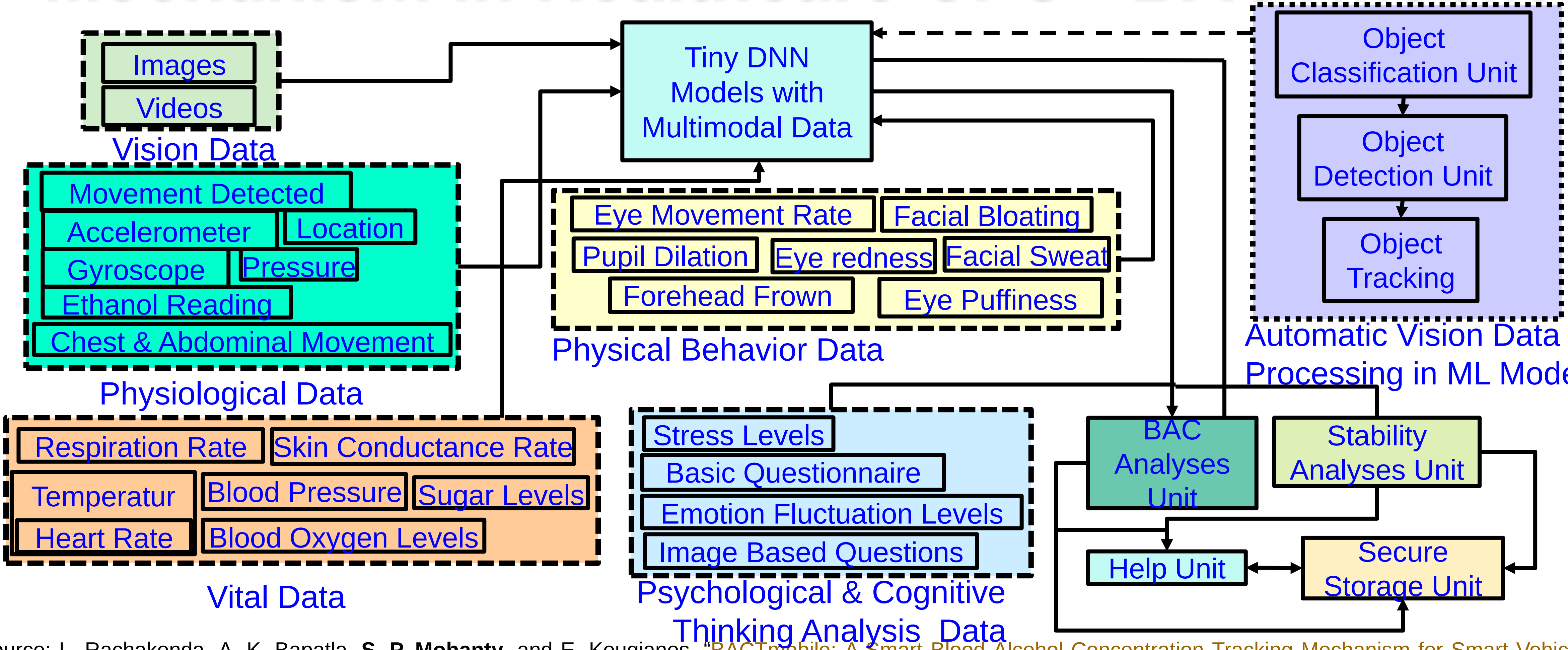

Source: L. Rachakonda, A. K. Bapatla, **S. P. Mohanty**, and E. Kougianos, "BACTmobile: A Smart Blood Alcohol Concentration Tracking Mechanism for Smart Vehicles in Healthcare CPS Framework", *Springer Nature Computer Science (SN-CS)*, Vol. 3, No. 3, May 2022, Article: 236, 24-pages, DOI: https://doi.org/10.1007/s42979-022-01142-9.

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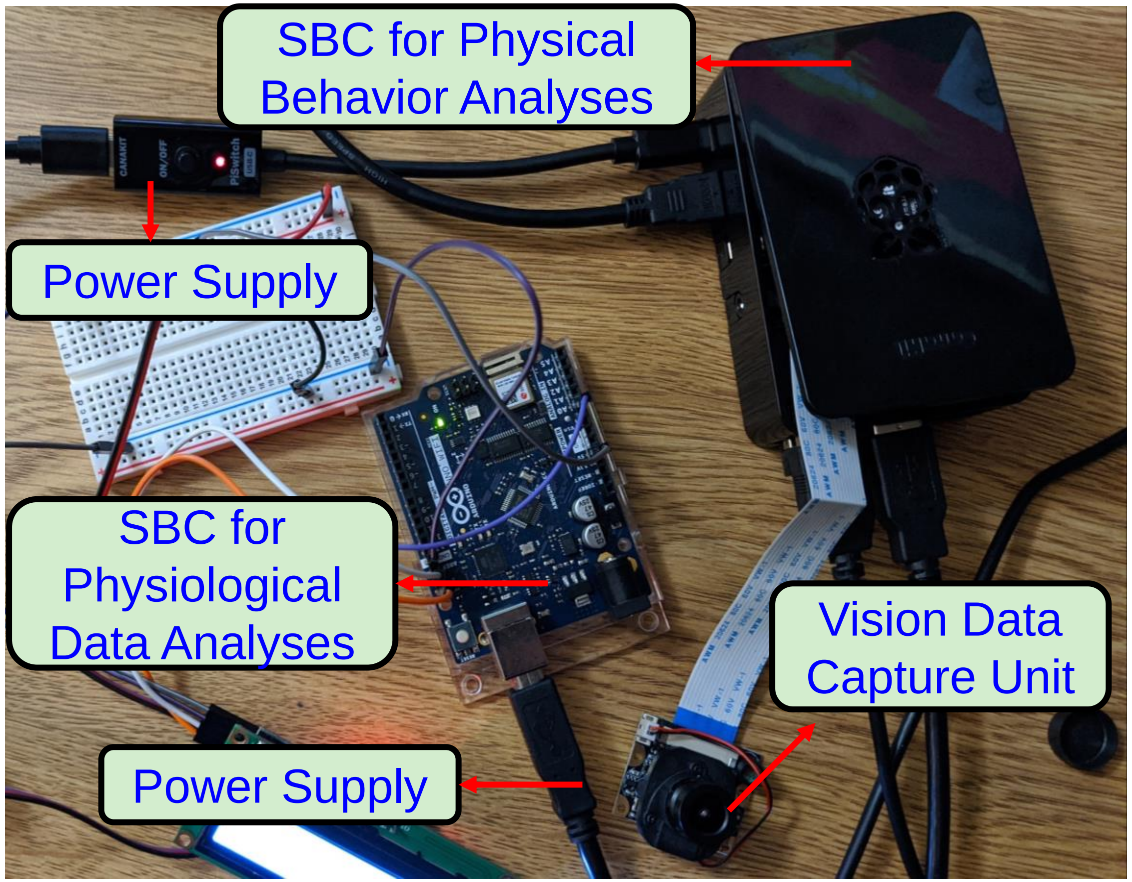
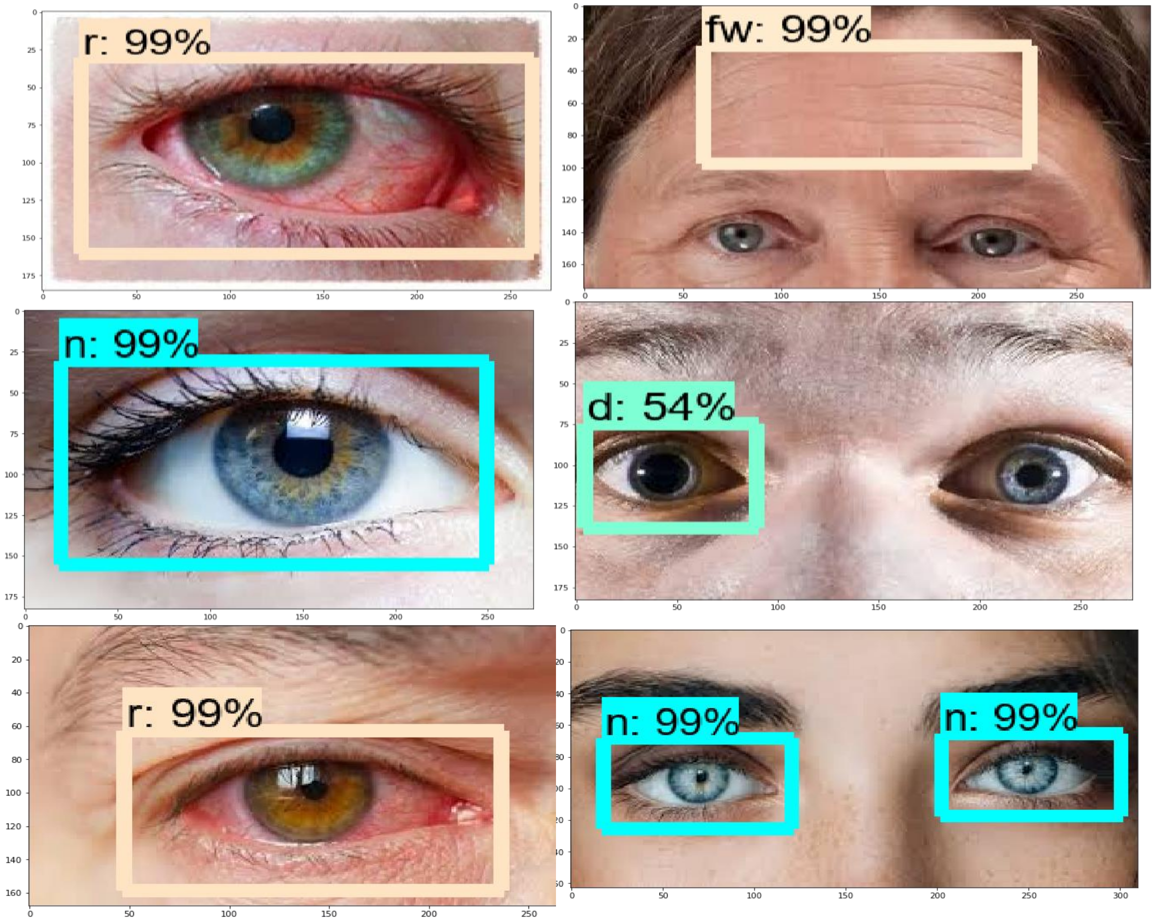
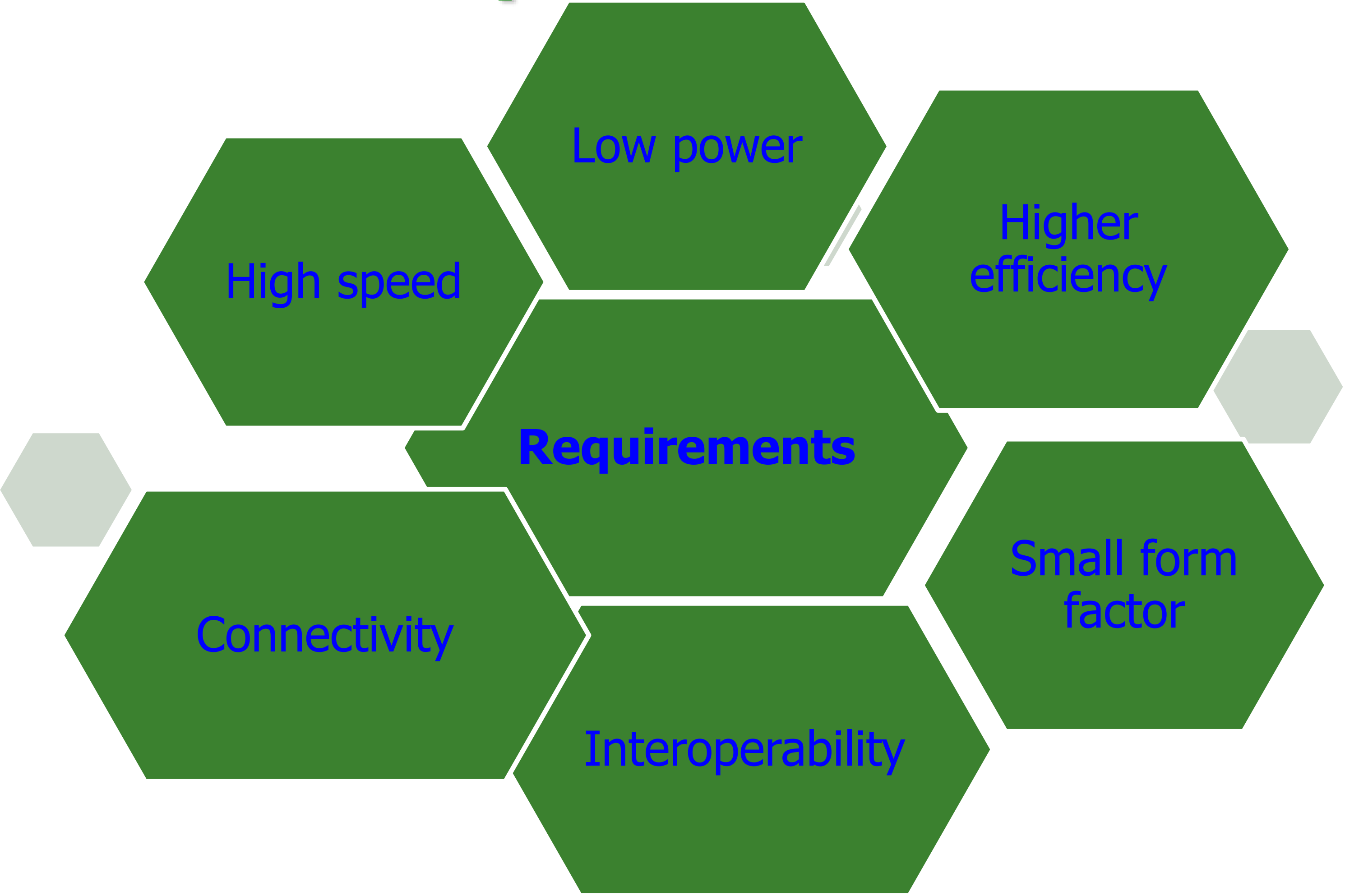




Source: L. Rachakonda, A. K. Bapatla, **S. P. Mohanty**, and E. Kougianos, "BACTmobile: A Smart Blood Alcohol Concentration Tracking Mechanism for Smart Vehicles in Healthcare CPS Framework", *Springer Nature Computer Science (SN-CS)*, Vol. 3, No. 3, May 2022, Article: 236, 24-pages, DOI: https://doi.org/10.1007/s42979-022-01142-9.

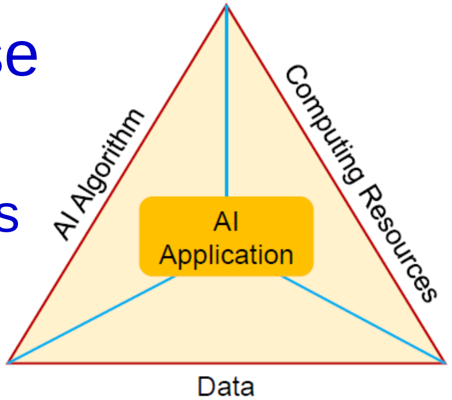
Smart Healthcare – Some Challenges

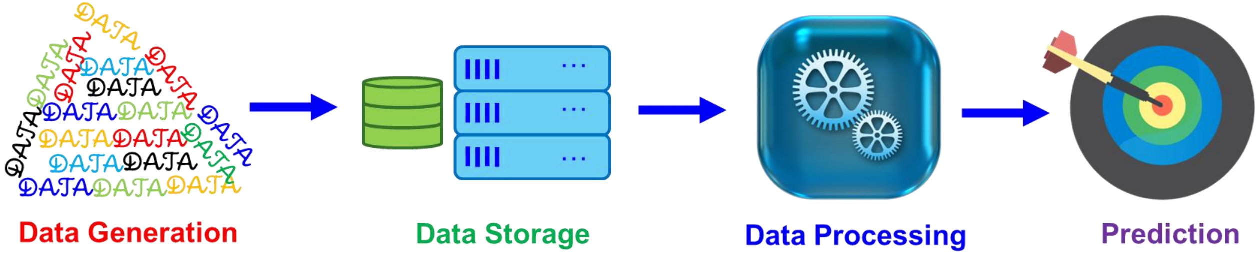
Smart Healthcare Architecture – Requirements



Overview - AI & Data

- AI flourished because
  - AI Algorithms
  - Computing Resources
  - Data



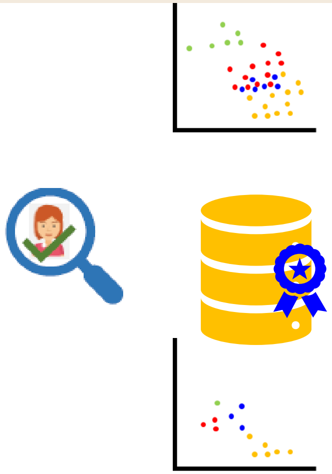


- AI/ ML/ Deep Learning Methods Data Driven.

Data Quality = Condition of Qualitative and Quantitative Information in Data

Data Generation

[Source: https://leanbi.ch/en/blog/iot-and-predictive-analytics-fog-and-edge-computing-for-industries-versus-cloud-19-1-2018]



Data Forgery
Data Scarcity
Data Insufficiency

Challenges of Data in IoT/CPS are Multifold

Data Curation

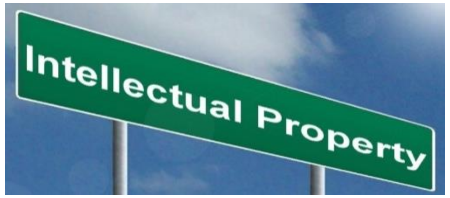
Data Cost

Lots of Data

Data Storage

Data Ownership

Data Modeling



Data Quality

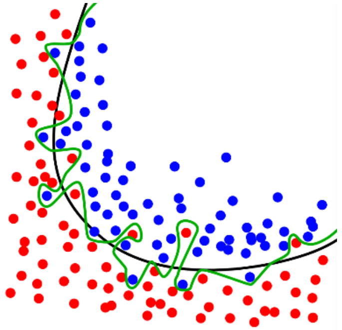
Smart Healthcare – Data Quality

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

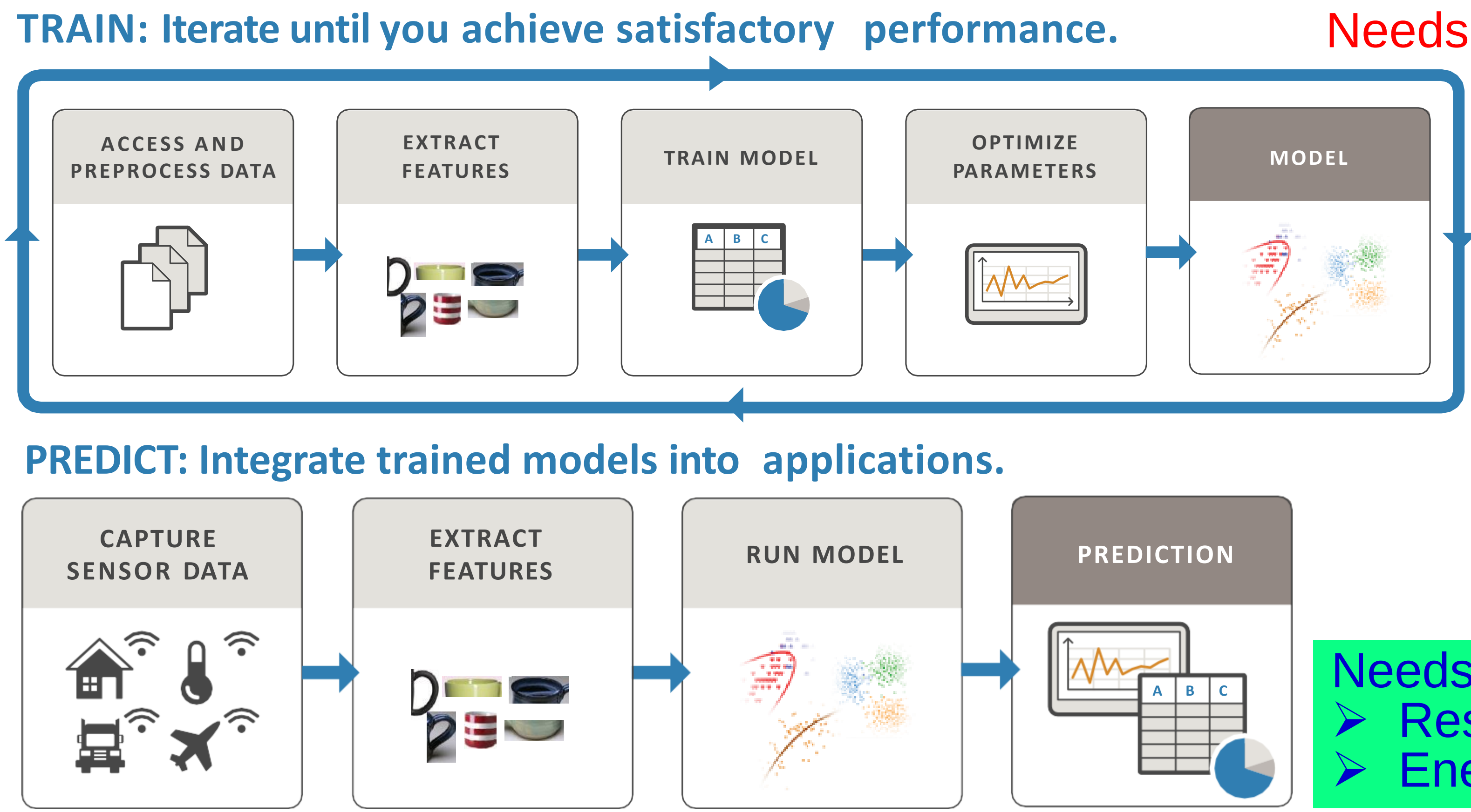
Machine Learning Issues

- 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

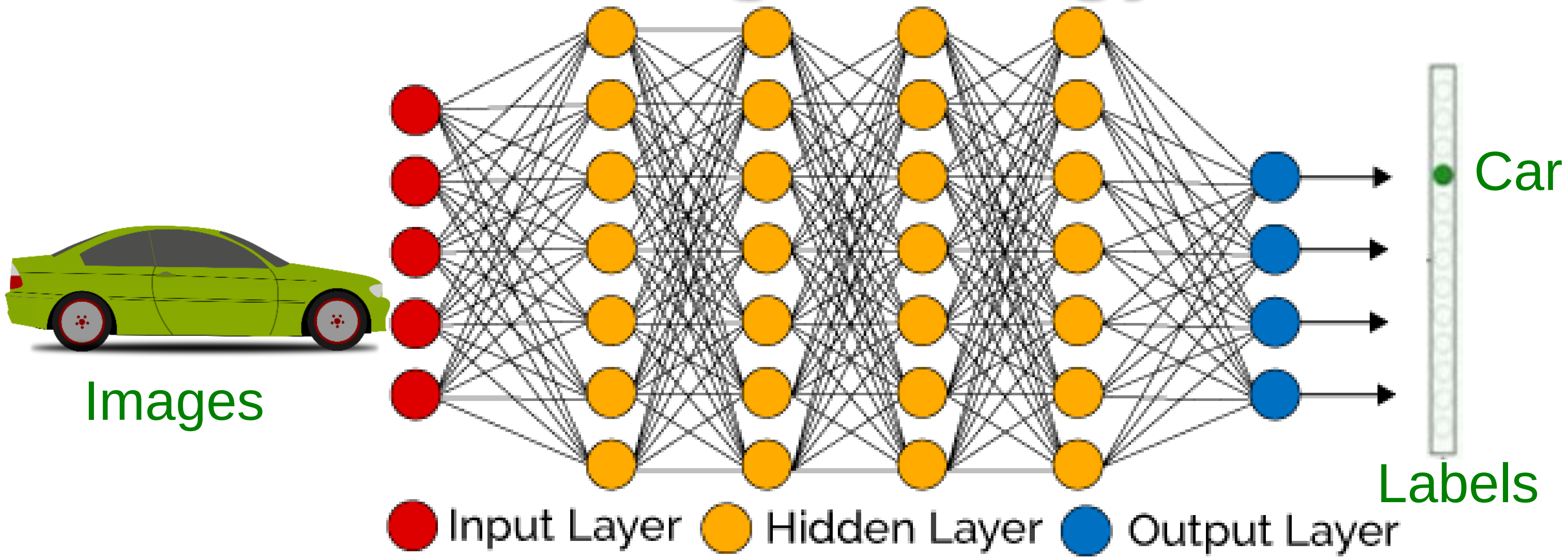


Needs Significant:
- Resource
- Energy

Needs:
- Resource
- Energy

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

DNN Training - Energy Issue



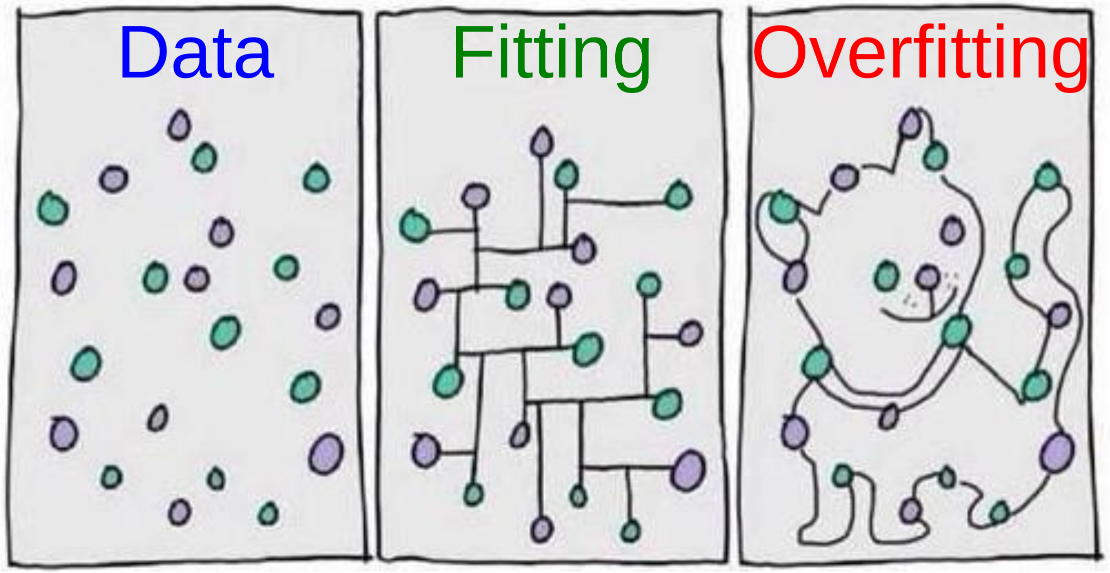
- DNN considers many training parameters, such as the size, the learning rate, and initial weights.
- High computational resource and time: For sweeping through the parameter space for optimal parameters.
- DNN needs: Multicore processors and batch processing.
- DNN training happens mostly in cloud not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

Source: Mohanty iSES 2018 Keynote

DNNs are not Always Smart

DNN - Overfitting or Inflation Issue

- DNN is overfitted or inflated - If the accuracy of DNN model is better than the training dataset
- DNN architecture may be more complex than it is required for a specific problem.
- Solutions: Different datasets, reduce complexity



Source: www.algotrading101.com

DNN - Class Imbalance Issue

- Class imbalance is a classification problems where the classes are not represented equally.
- Solutions: Use Precision, Recall, F-measure metrics

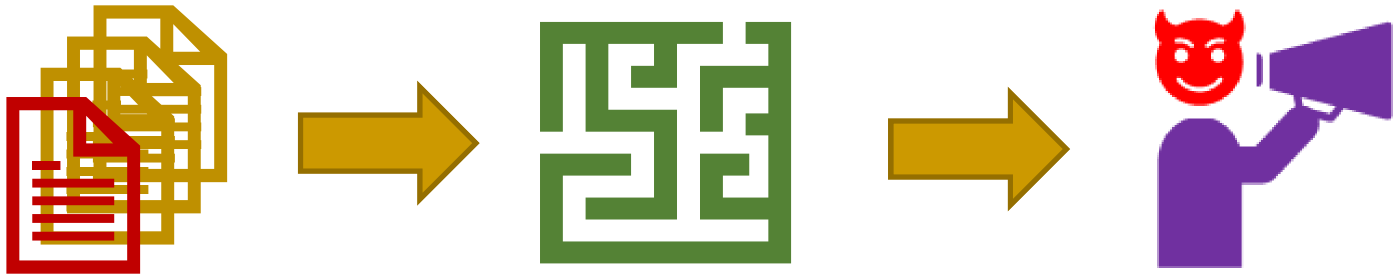
  Not only RMSE like accuracy metrics

AI/ML - Vulnerability

- Key vulnerabilities of machine learning systems
  - ML models often derived from fixed datasets
  - Assumption of similar distribution between training and real-world data
  - Coverage issues for complex use cases
  - Need large datasets, extensive data annotation, testing
- Strong adversaries against ML systems
  - ML algorithms established and public
  - Attacker can leverage ML knowledge for Adversarial Machine Learning (AML)
    - Reverse engineering model parameters, test data – Financial incentives
    - Tampering with the trained model – compromise security

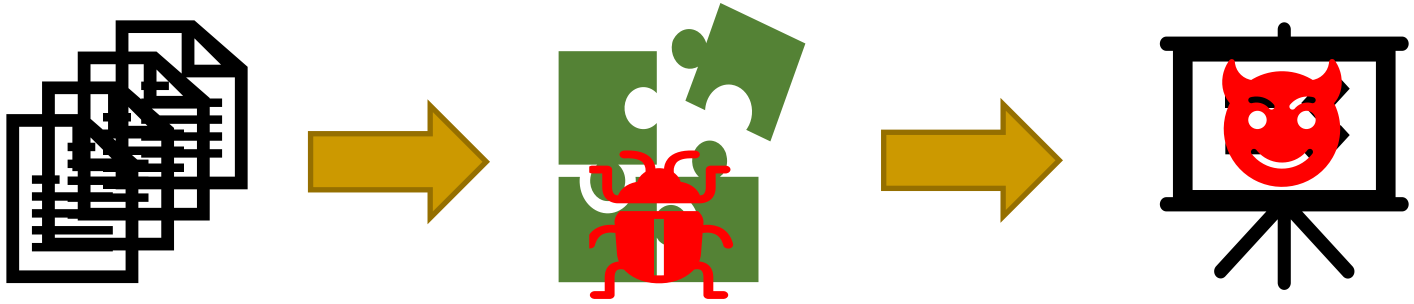
Source: Sandip Kundu ISVLSI 2019 Keynote.

AI/ML – Cybersecurity Issue



Corrupted Input Dataset | Predictive modelling | Corrupted Decision/ Prediction

Input attack in machine learning

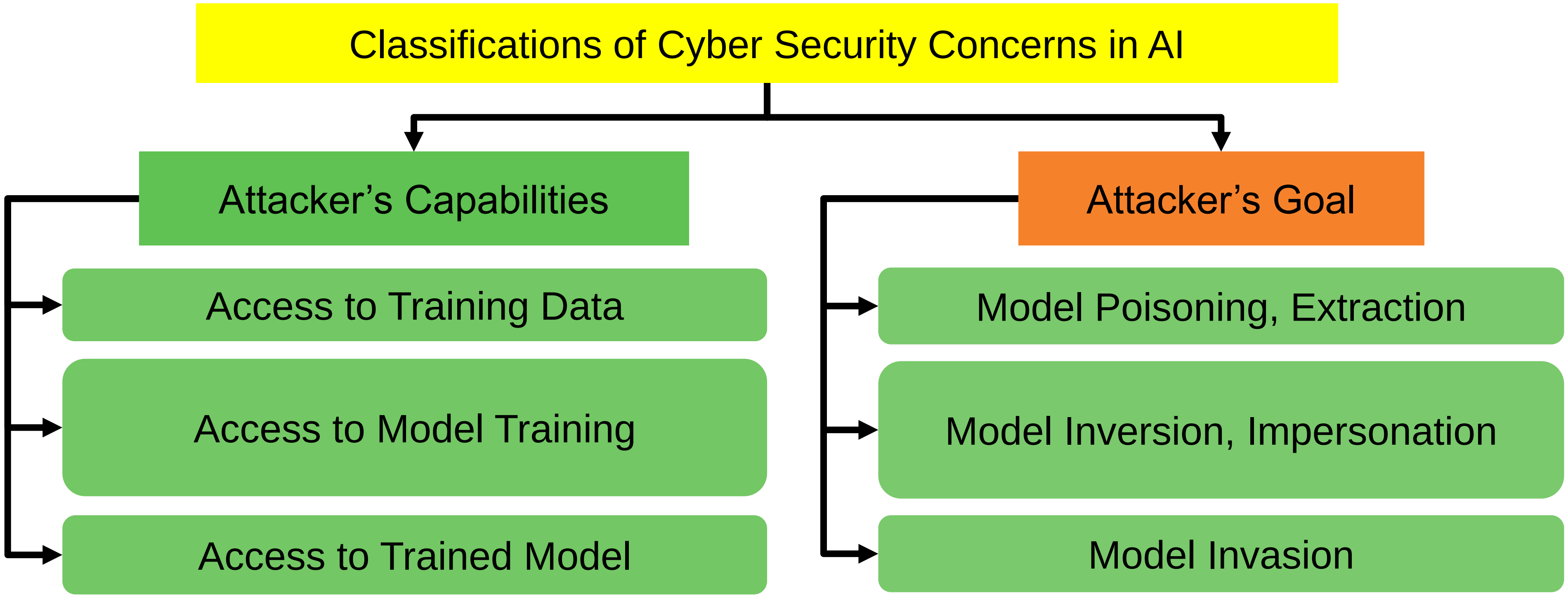


Input Dataset | Attacked training Process | Corrupt Classifications

Poisoning attack in training process

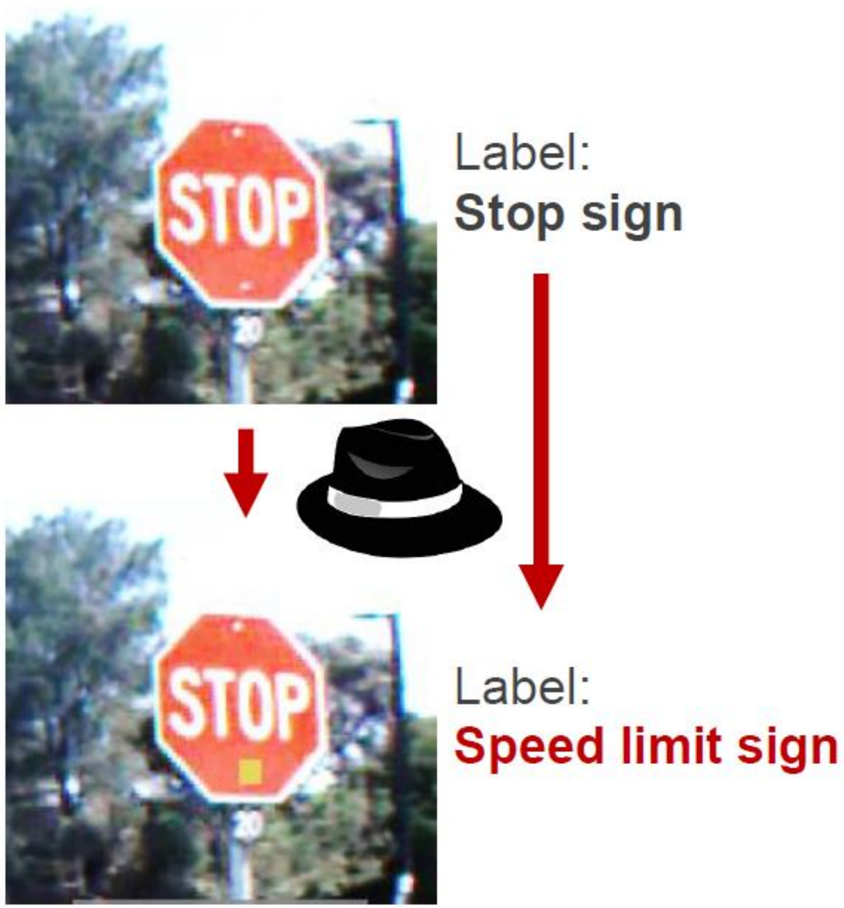
Source: D. Puthal, and **S. P. Mohanty**, "Cybersecurity Issues in AI", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 10, No. 4, July 2021, pp. 33--35.

AI/ML – Cybersecurity Issue



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.

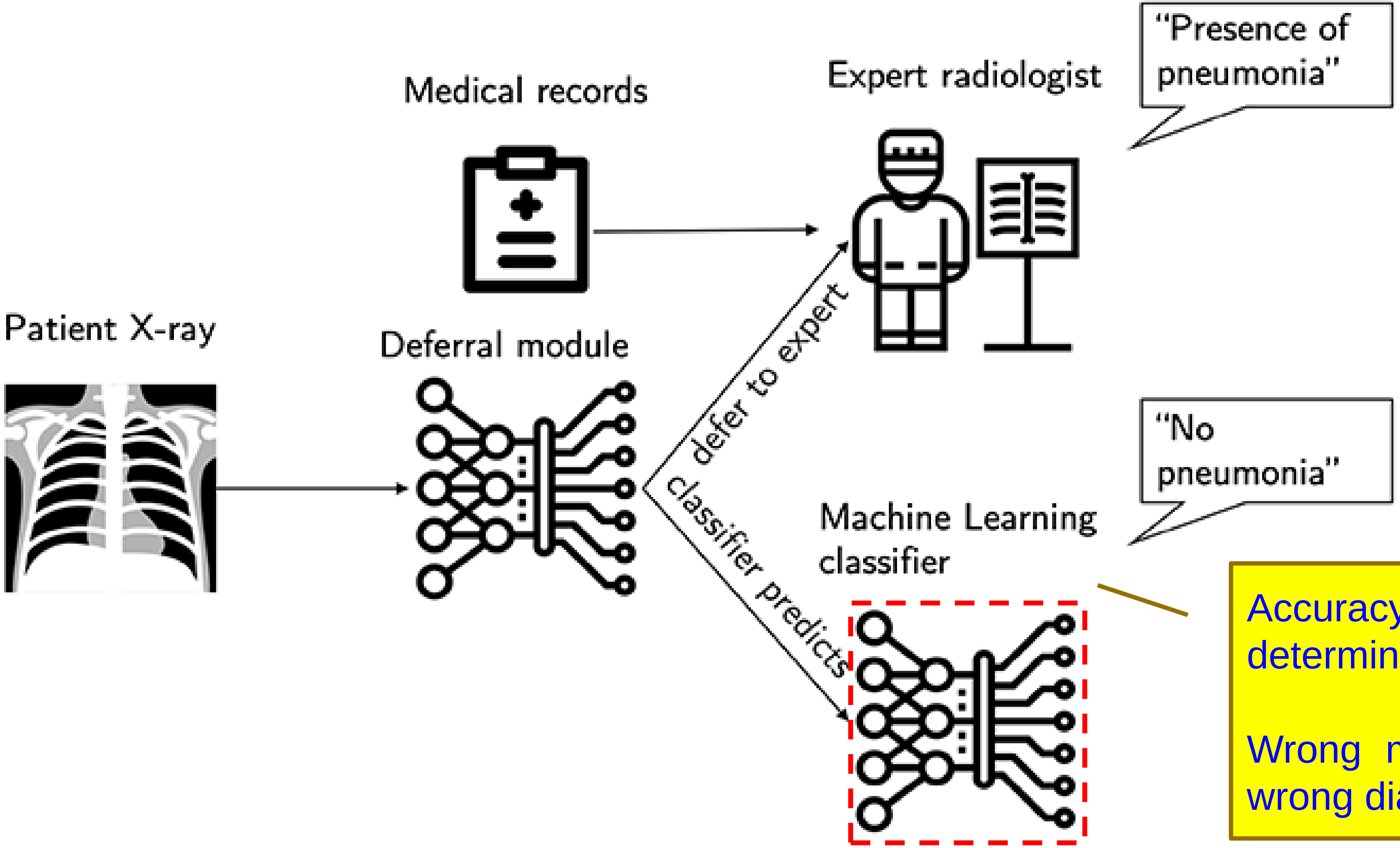
AI Security - Trojans in Artificial Intelligence (TrojAI)



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



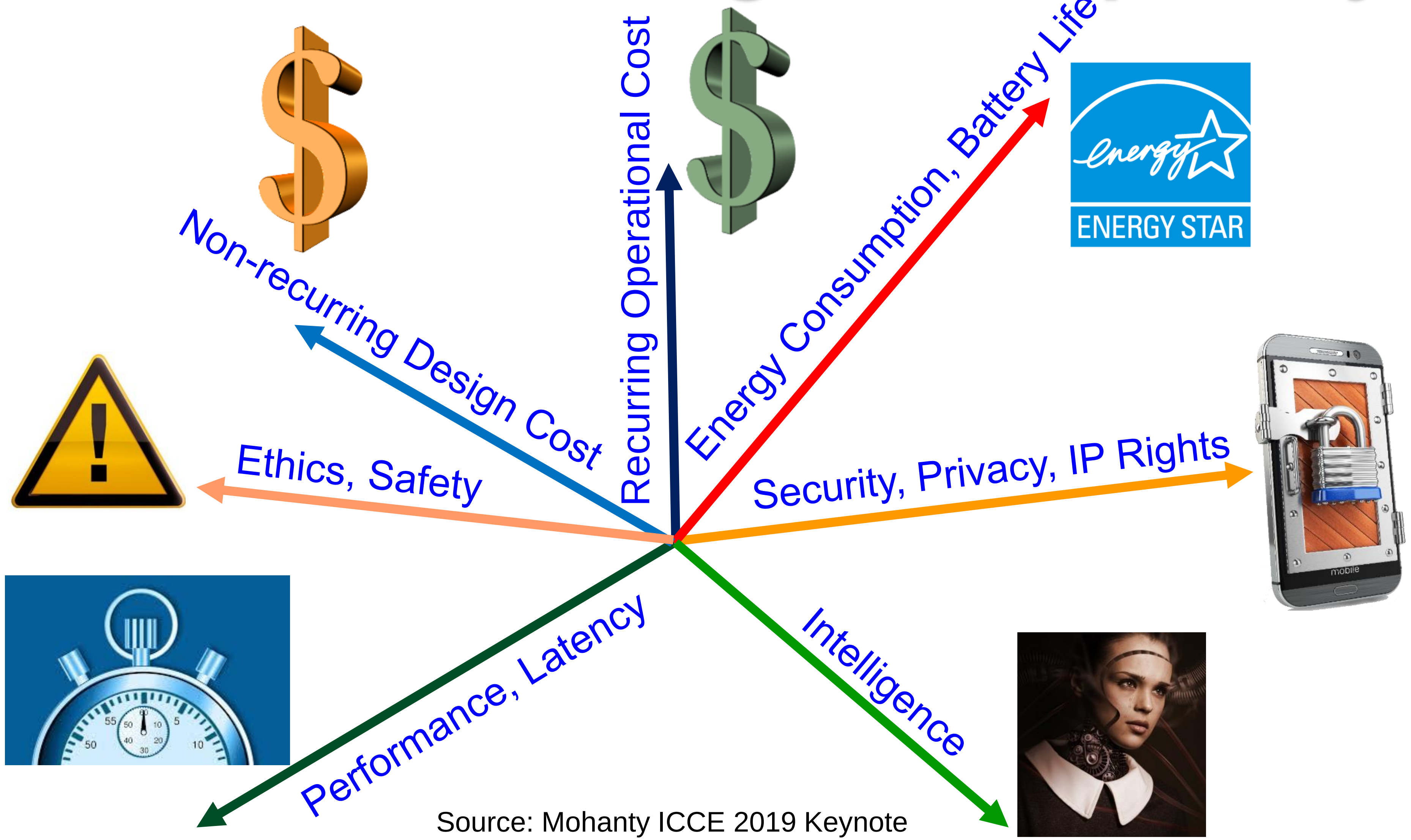
Accuracy is important determine pneumonia

Wrong model can lead to wrong diagnosis altogether

Source: https://www.healthcareitnews.com/news/new-ai-diagnostic-tool-knows-when-defer-human-mit-researchers-say

Smart Healthcare – Some Solutions

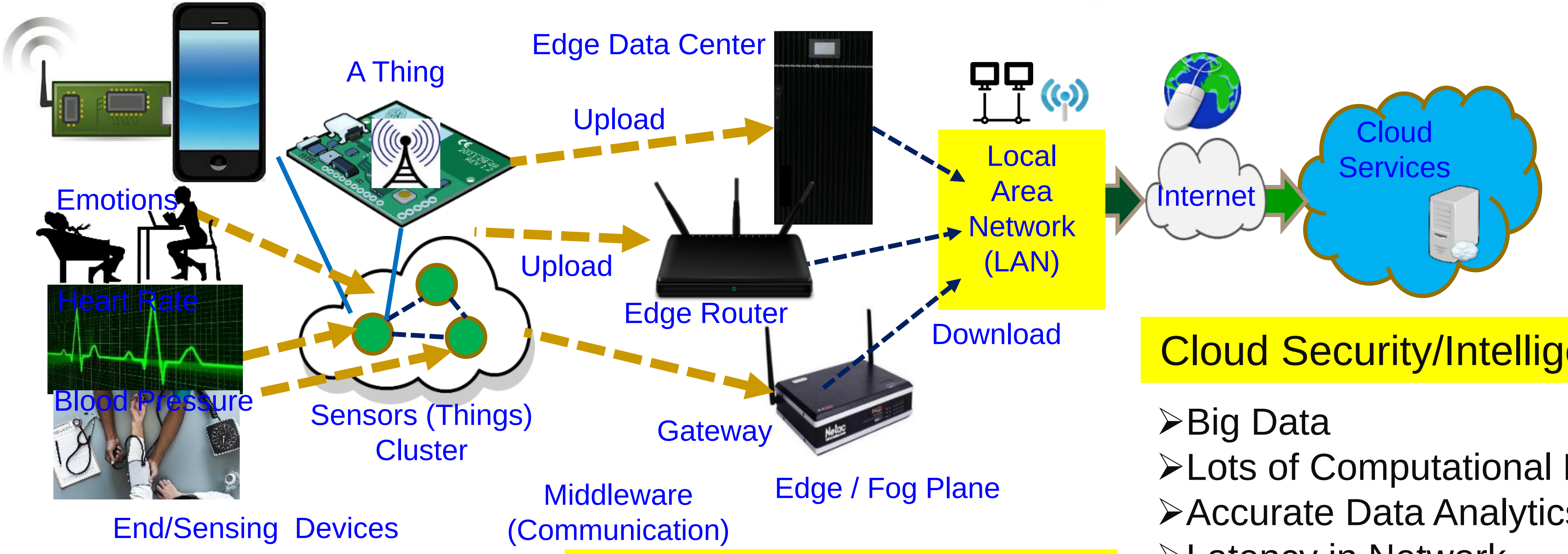
IoT/CPS Design – Multiple Objectives



Source: Mohanty ICCE 2019 Keynote

Smart Cities
Vs
Smart Villages

Smart Healthcare – Edge Vs Cloud



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

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

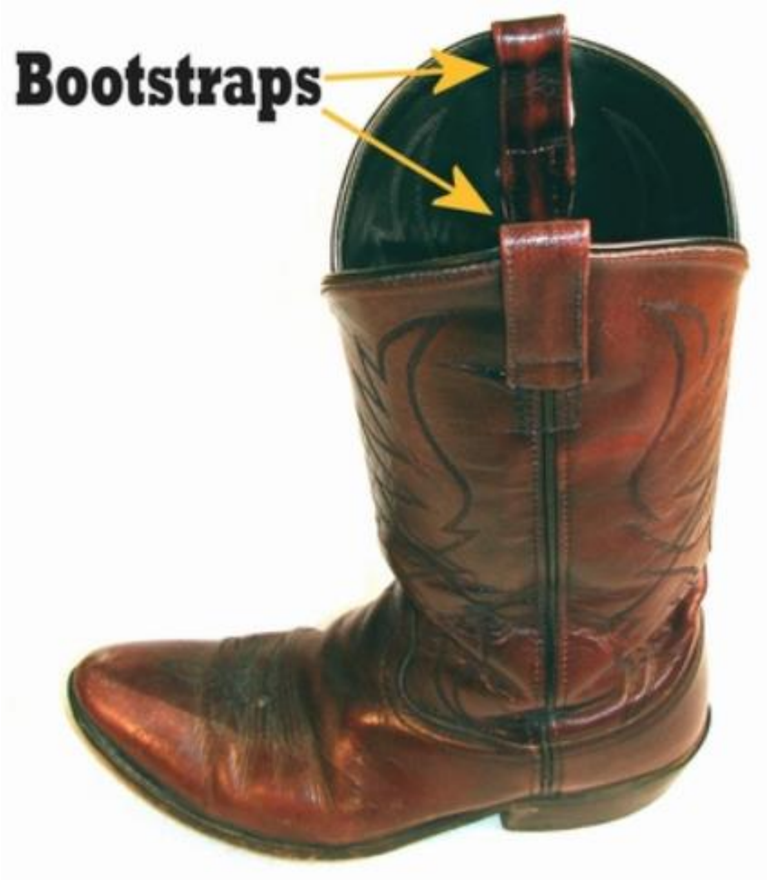
Cloud Security/Intelligence

- 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

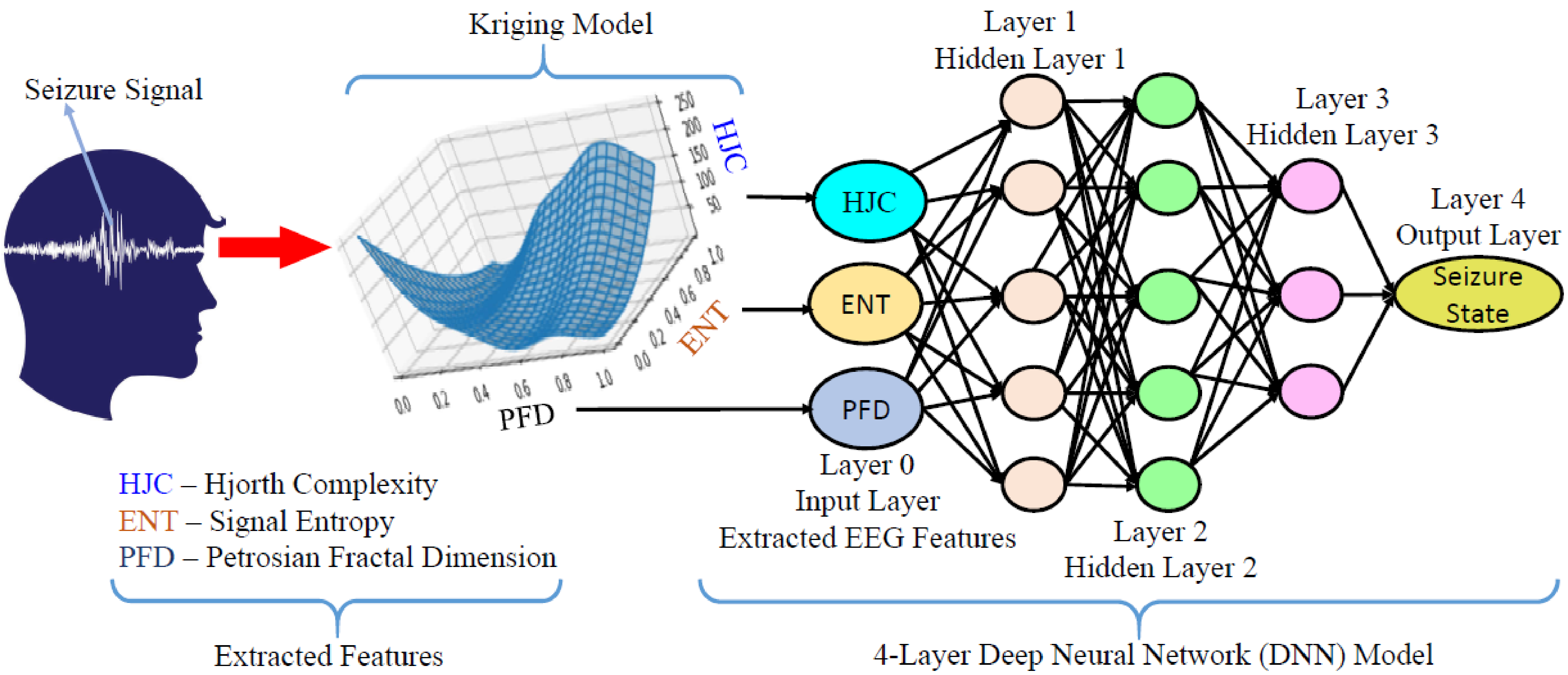
Hierarchical ML to Reduce Training Time - Bootstrapping

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



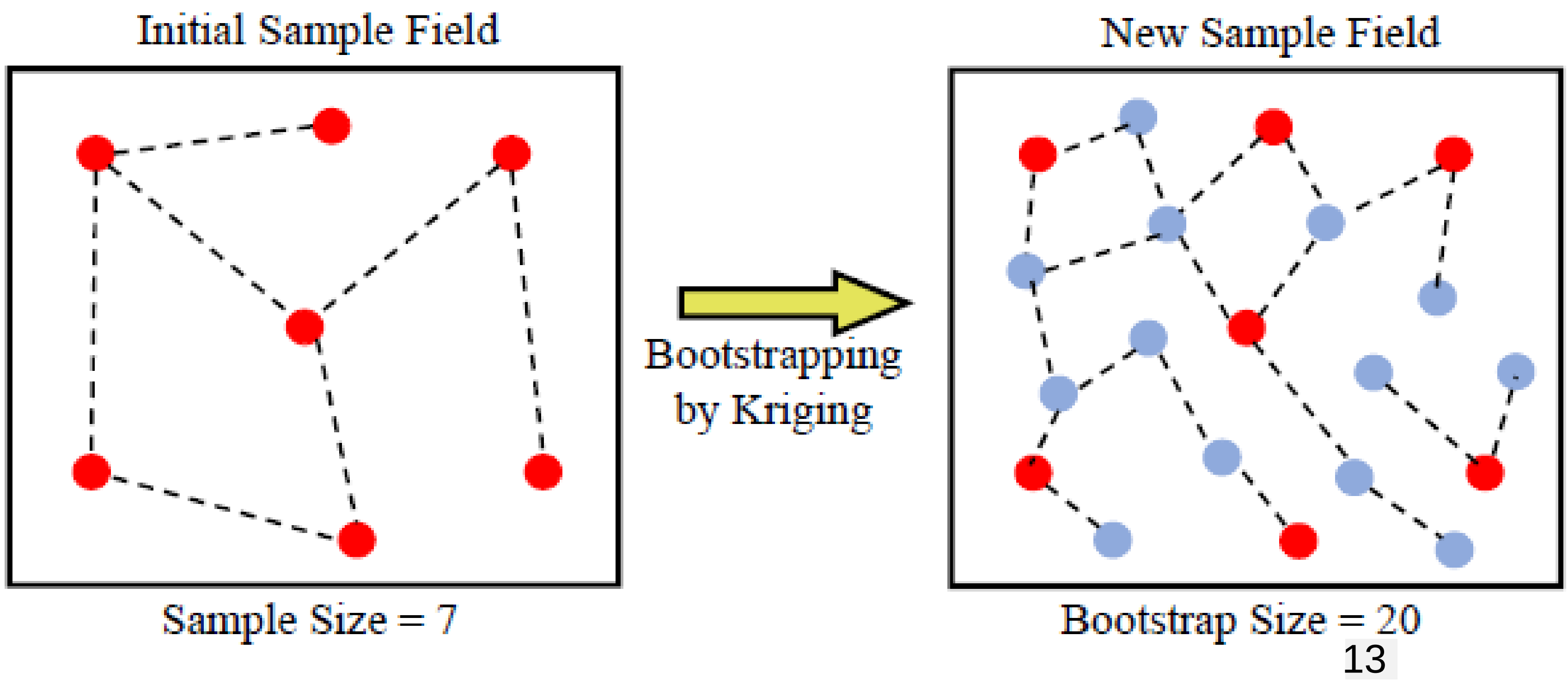
Source: http://www.lemen.com/dictionary-b.html#bootstrap

Our Kriging-Bootstrapped DNN Model



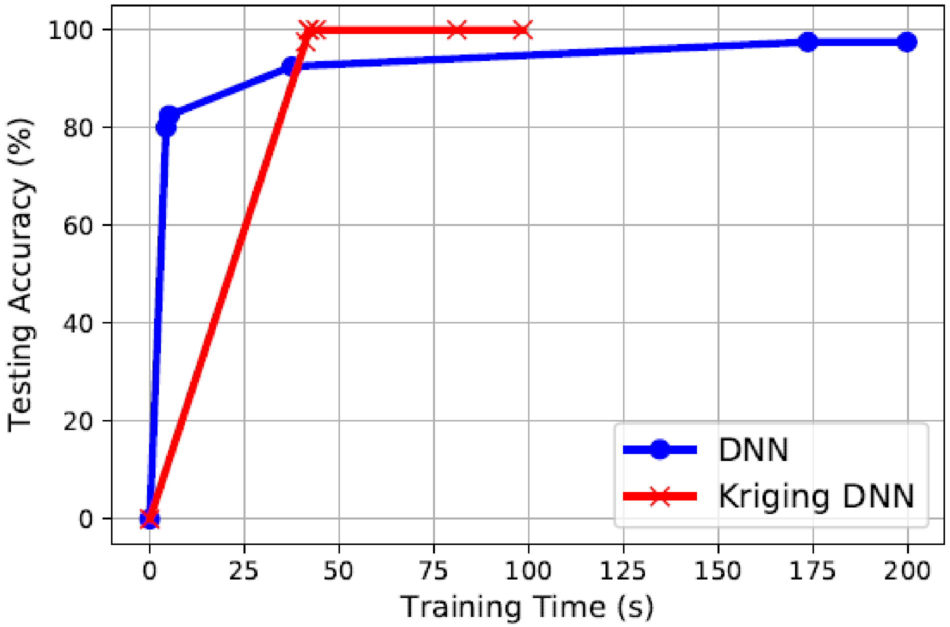
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

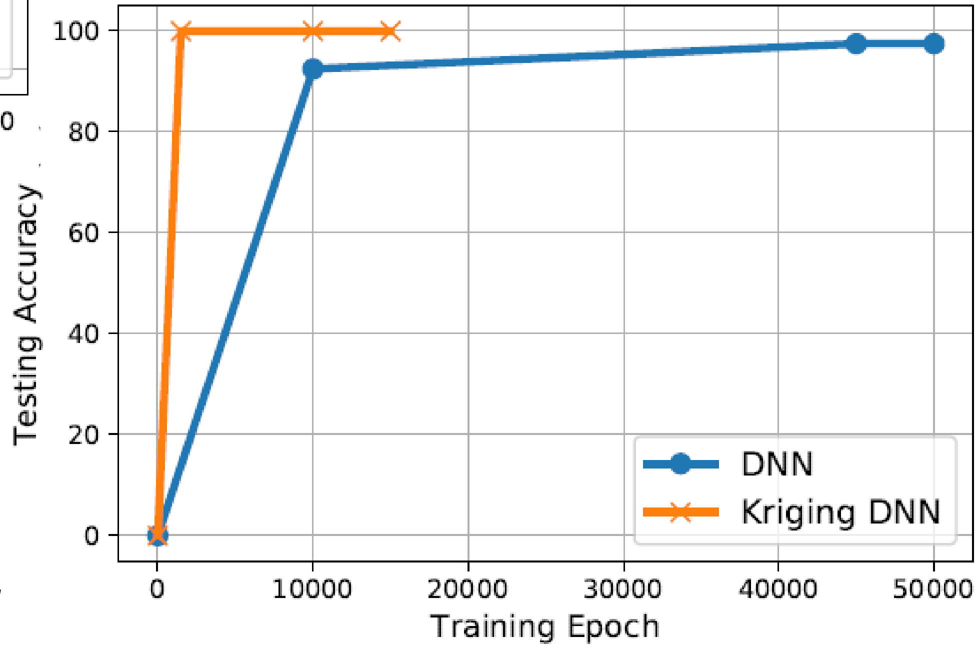
Bootstrapped Kriging



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

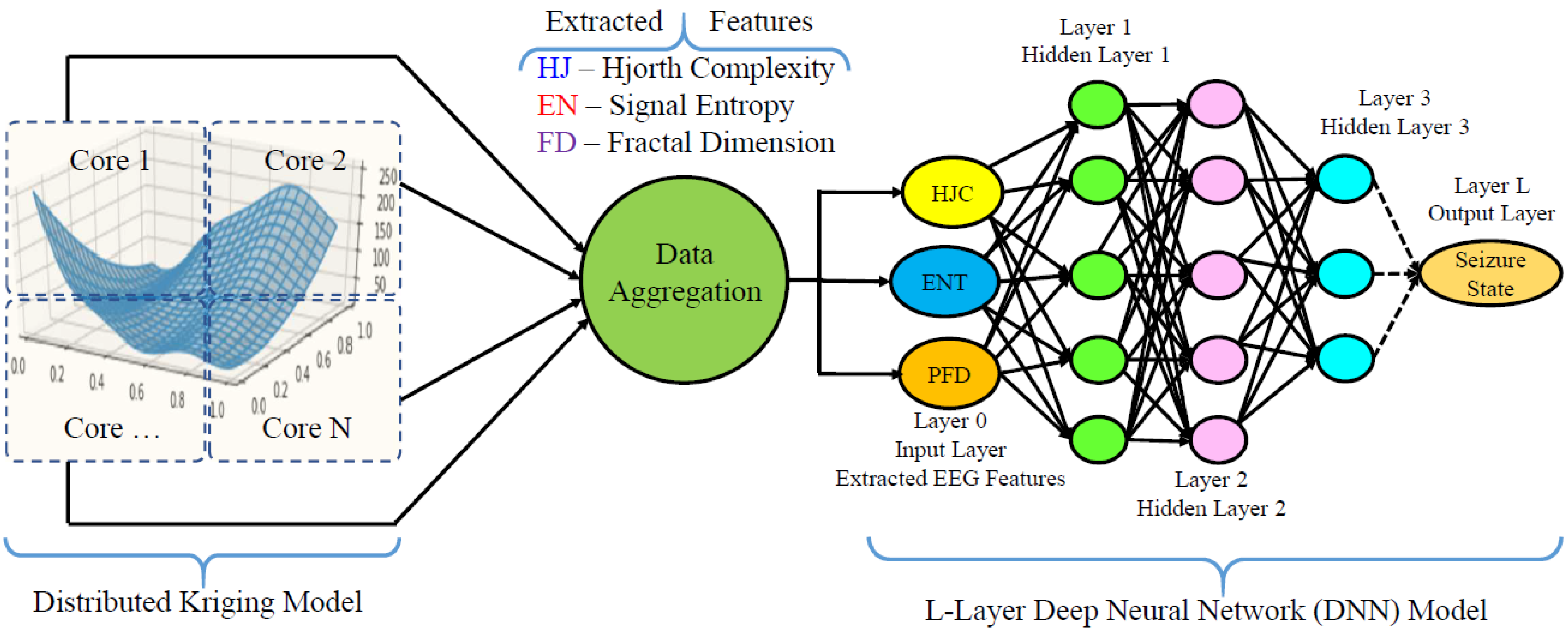
Experimental Results





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

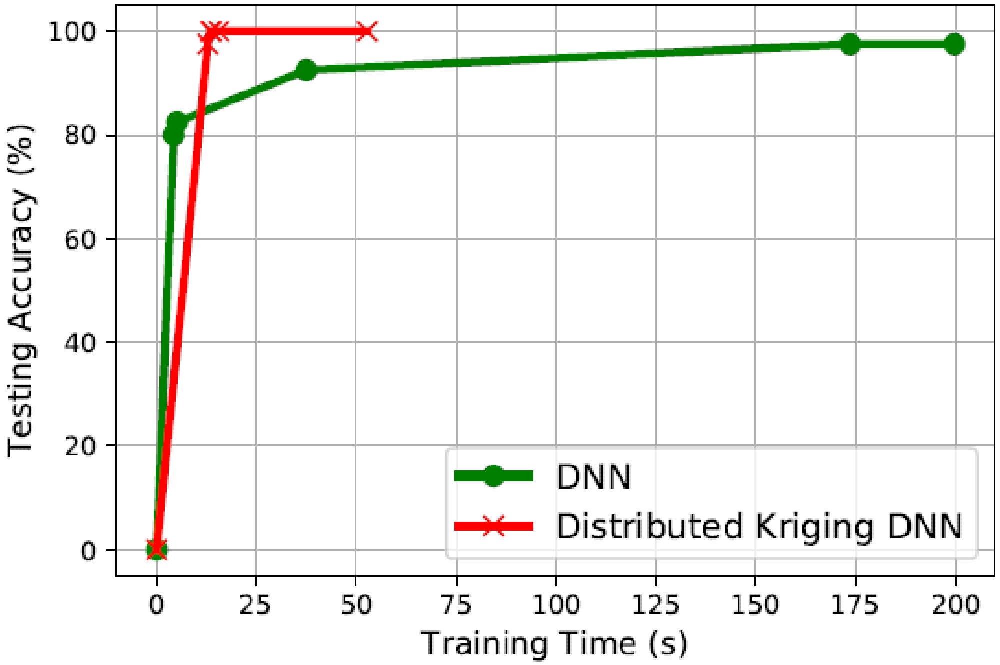
Our Distributed Kriging-Bootstrapped DNN Model



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**

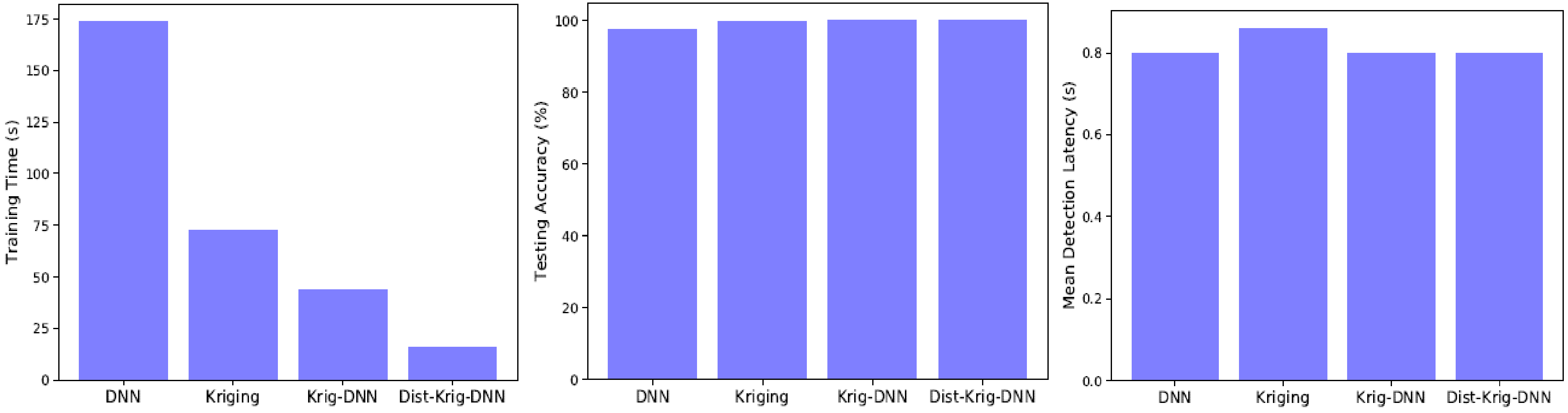


- Training Time reduced by 91%

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



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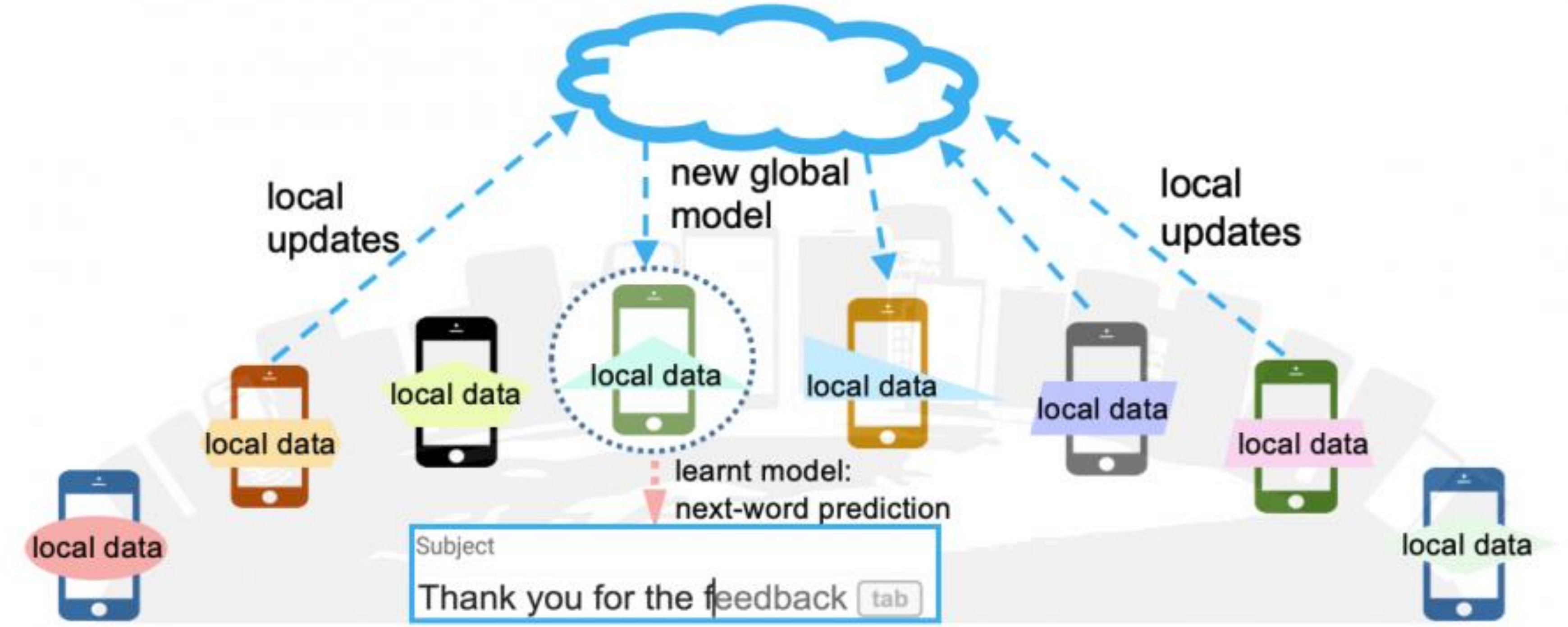
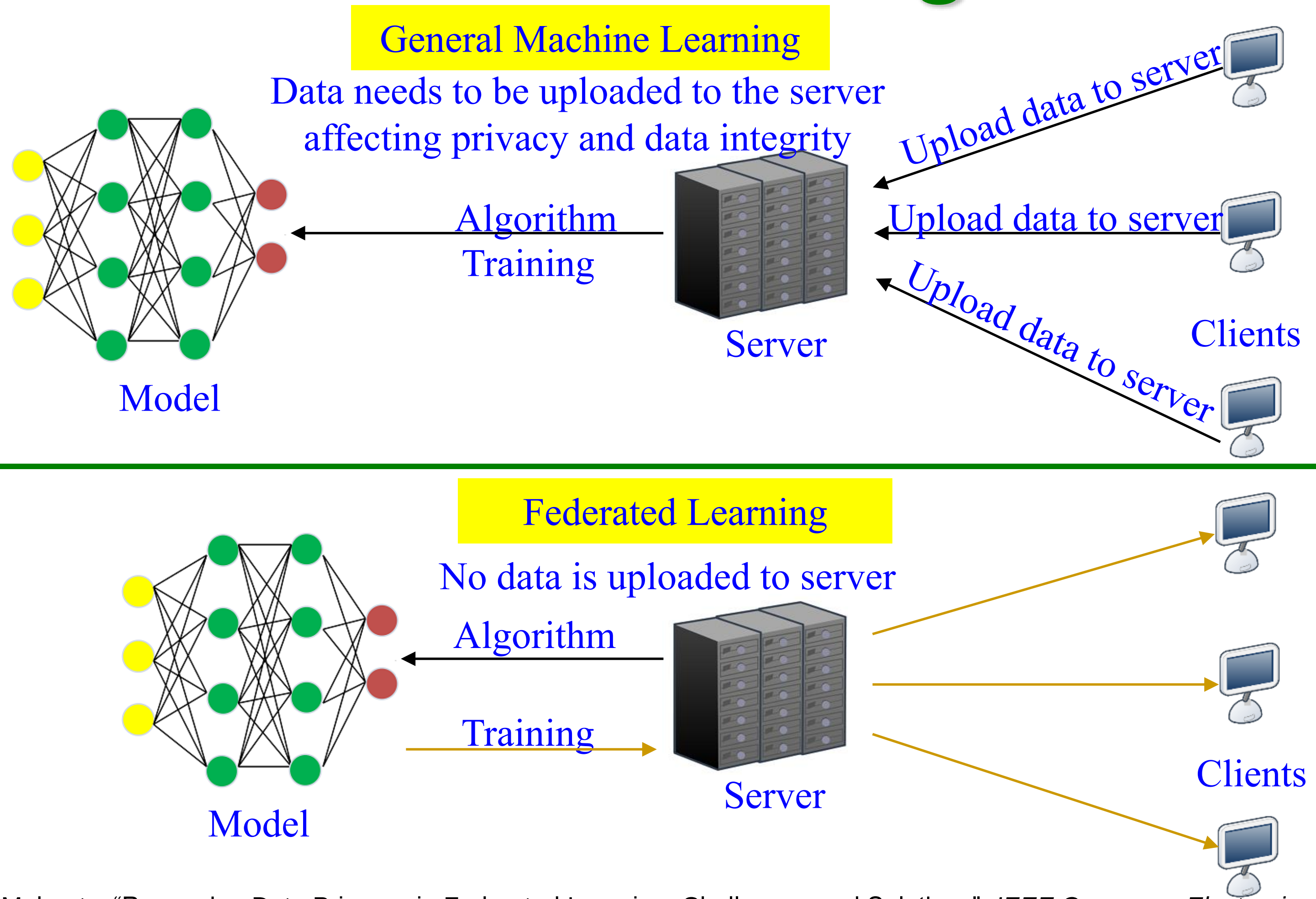
Motivation of Federated Learning (FL)



- Quality data exists at different location on various edge devices.
- Data privacy laws control the movement of data.
- FL is the way to provide ML solution without breaking privacy laws.

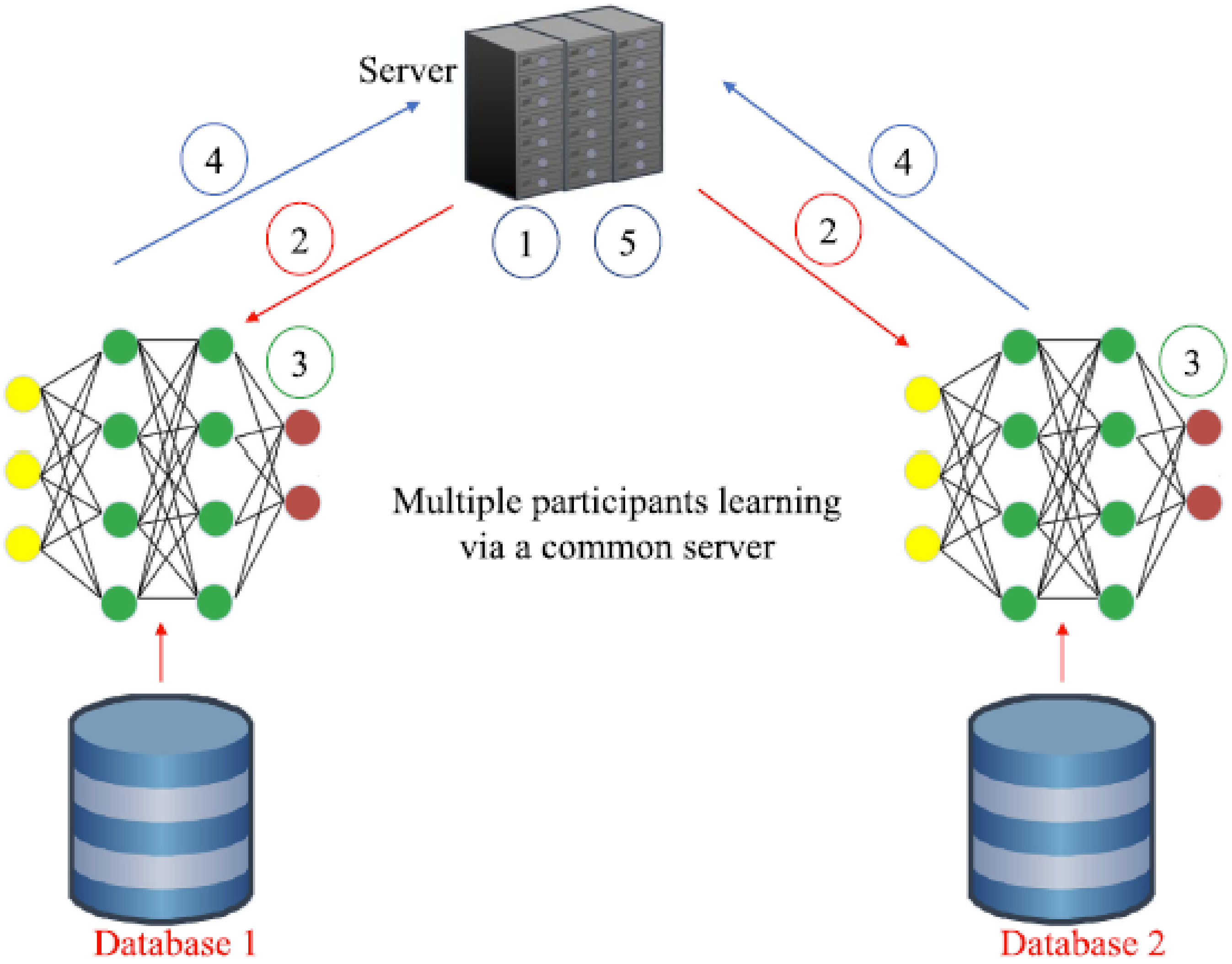
Source: Z. Li, V. Sharma, and S. P. Mohanty, “Preserving Data Privacy via Federated Learning: Challenges and Solutions”, *IEEE Consumer Electronics Magazine*, Vol. 9, No. 3, May 2020, pp. 8--16.

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.

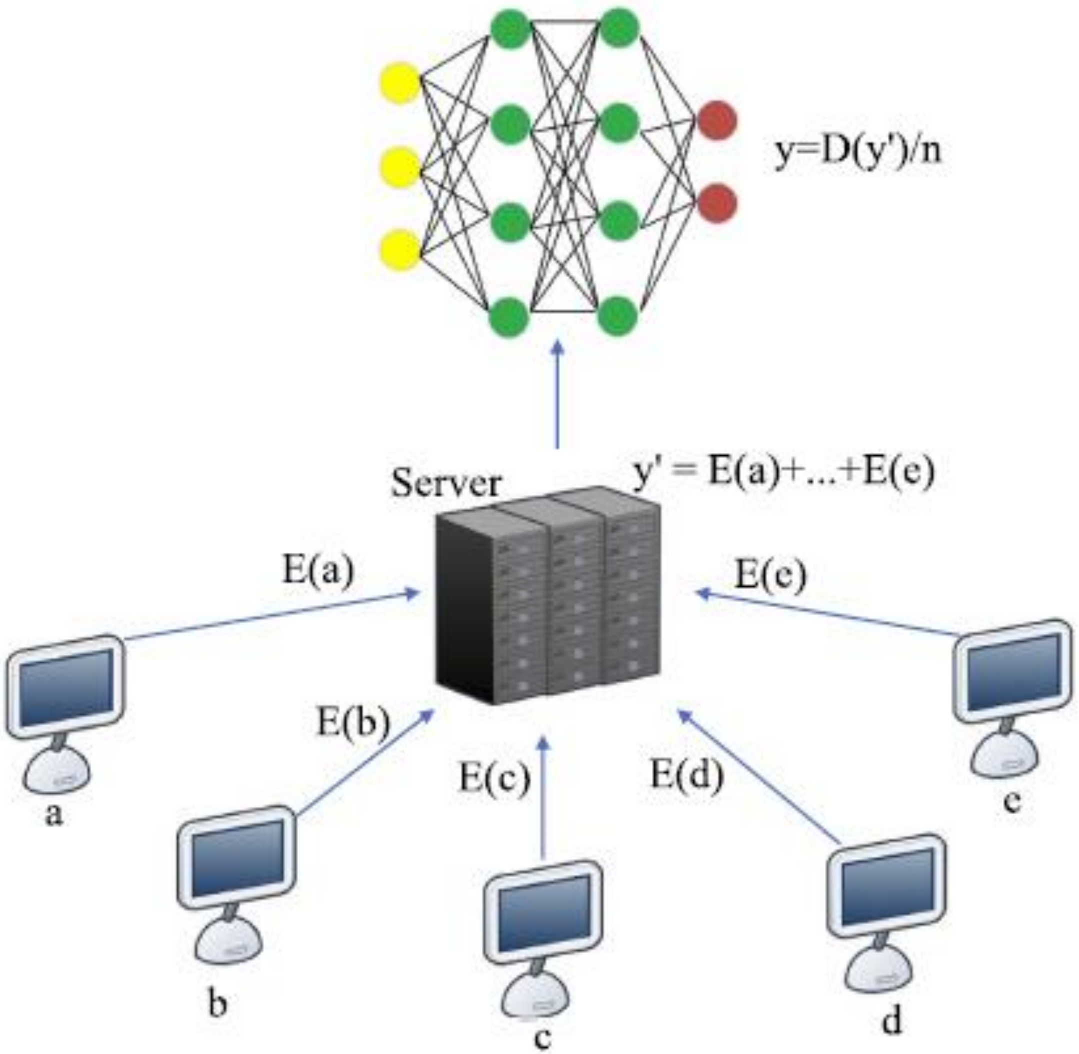
Horizontal FL System



1) Train global model in the server.
2) Deploy global model to edge devices.
3) Optimize model from each edge device.
4) Upload locally trained model update.
5) Average the update values and apply the average to the global model.
6) Repeat step 2 to step 5.

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.

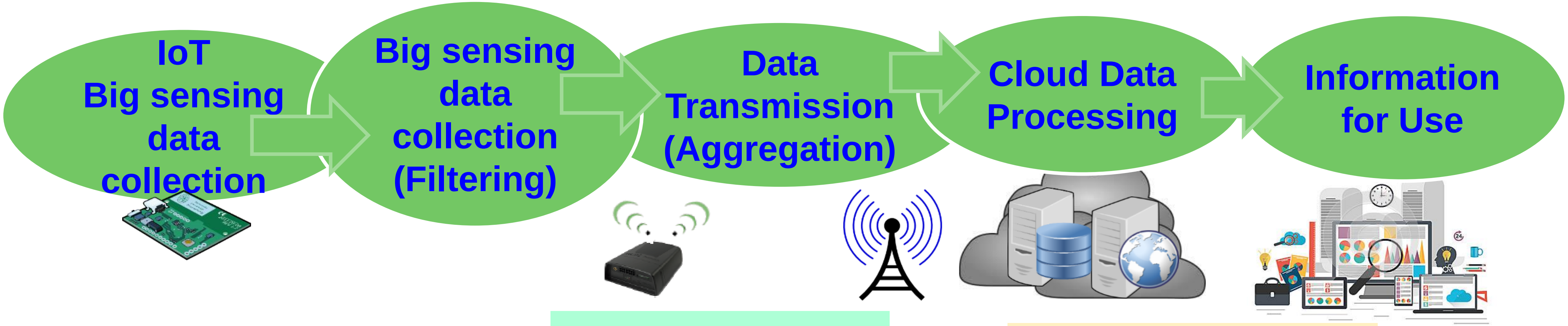
Aggregation of Vertical FL



Homomorphic Encryption

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.

Secure Data Curation a Solution for Fake Data?



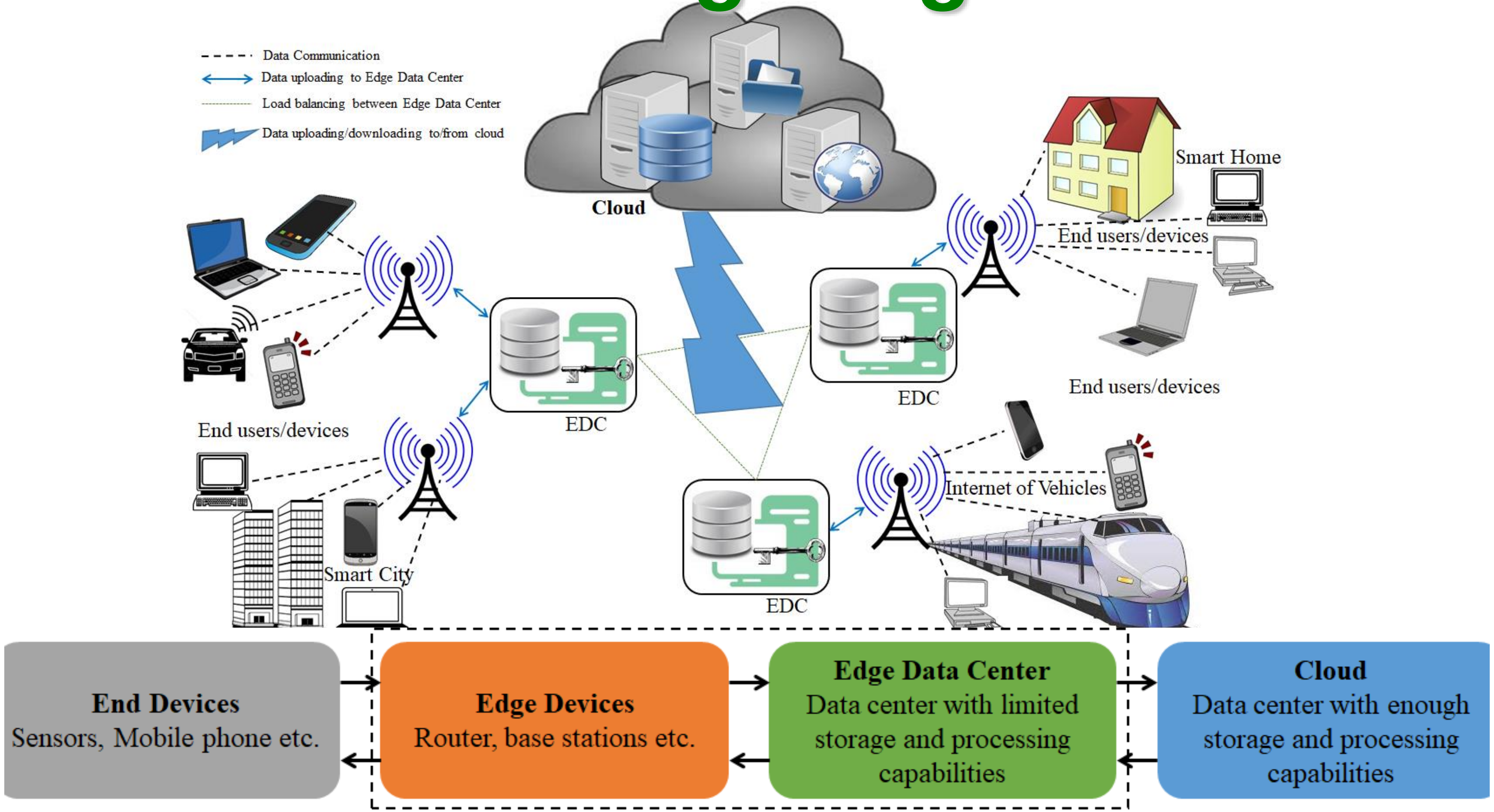
Edge Training:
- Data Signature
- Model Signature

Cloud Training:
- Data Signature
- Model Signature

Fake Data Defense:
- Stop (Shield)
- Detect

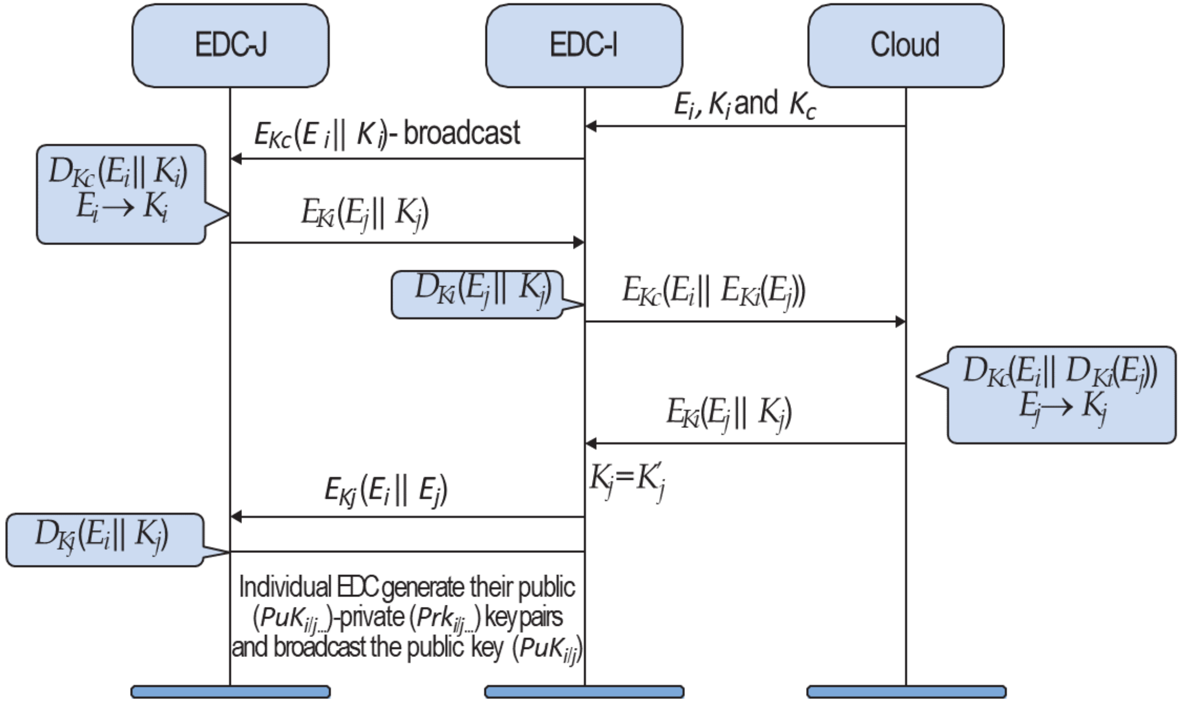
Source: C. Yang, D. Puthal, S. P. Mohanty, and E. Kougianos, "Big-Sensing-Data Curation for the Cloud is Coming", *IEEE Consumer Electronics Magazine (CEM)*, Volume 6, Issue 4, October 2017, pp. 48--56.

Data and Security Should be Distributed using Edge Datacenter



Source: D. Puthal, M. S. Obaidat, P. Nanda, M. Prasad, S. P. Mohanty, and A. Y. Zomaya, "Secure and Sustainable Load Balancing of Edge Data Centers in Fog Computing", *IEEE Communications Magazine*, Volume 56, Issue 5, May 2018, pp. 60--65.

Our Proposed Secure Edge Datacenter



Secure edge datacenter –
- Balances load among the EDCs
- Authenticates EDCs

Algorithm 1: Load Balancing Technique

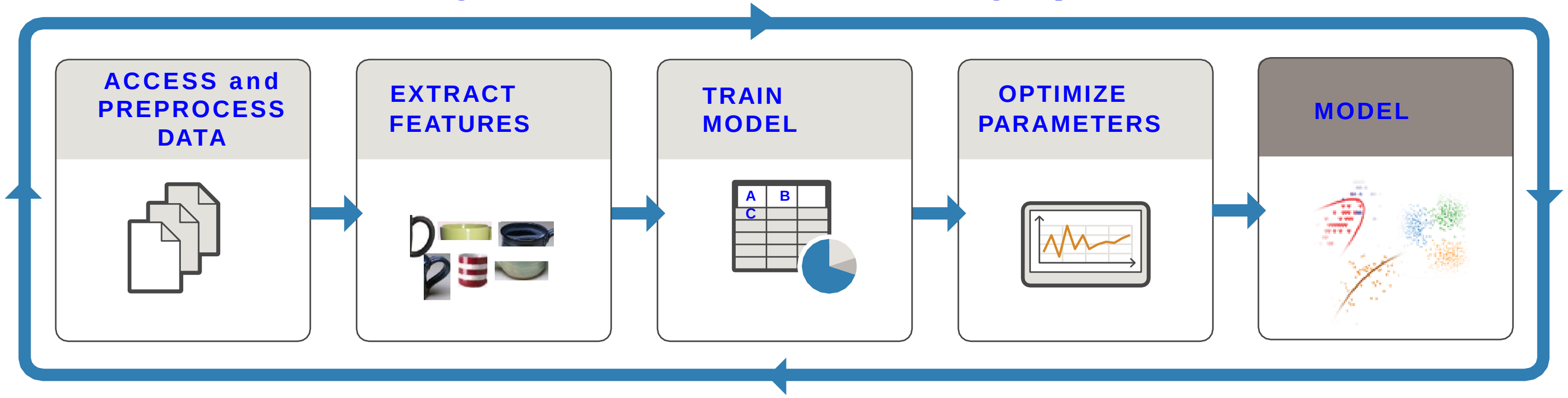
1. If (EDC-I is overloaded)
2. EDC-I broadcast (E_i, L_i)
3. EDC-J (neighbor EDC) verifies:
4. If (E_i is in database) & ($p \leq 0.6$ & $L_i << (n-m)$)
5. Response $E_{Kpu_i}(E_j || K_j || p)$
6. EDC-I perform $D_{Kpr_i}(E_j || K_j || p)$
7. $k'_j \leftarrow E_j$
8. If ($k'_j = k_j$)
9. EDC-I select EDC-J for load balancing.

Response time of the destination EDC has reduced by 20-30% using the proposed allocation approach.

Source: D. Puthal, M. S. Obaidat, P. Nanda, M. Prasad, S. P. Mohanty, and A. Y. Zomaya, "Secure and Sustainable Load Balancing of Edge Data Centers in Fog Computing", *IEEE Communications Magazine*, Volume 56, Issue 5, May 2018, pp. 60--65.

TinyML - Key for Smart Cities and Smart Villages

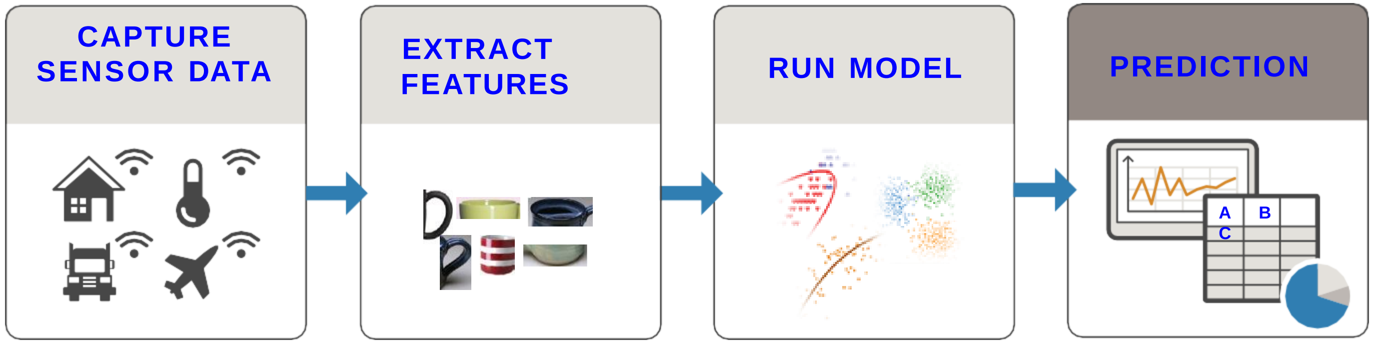
TRAIN: Iterate until you achieve satisfactory performance.



Needs Significant:
- ➢ Computational Resource
- ➢ Computation Energy

Solution: Reduce Training Time and/or Computational Resource

PREDICT: Integrate trained models into applications.

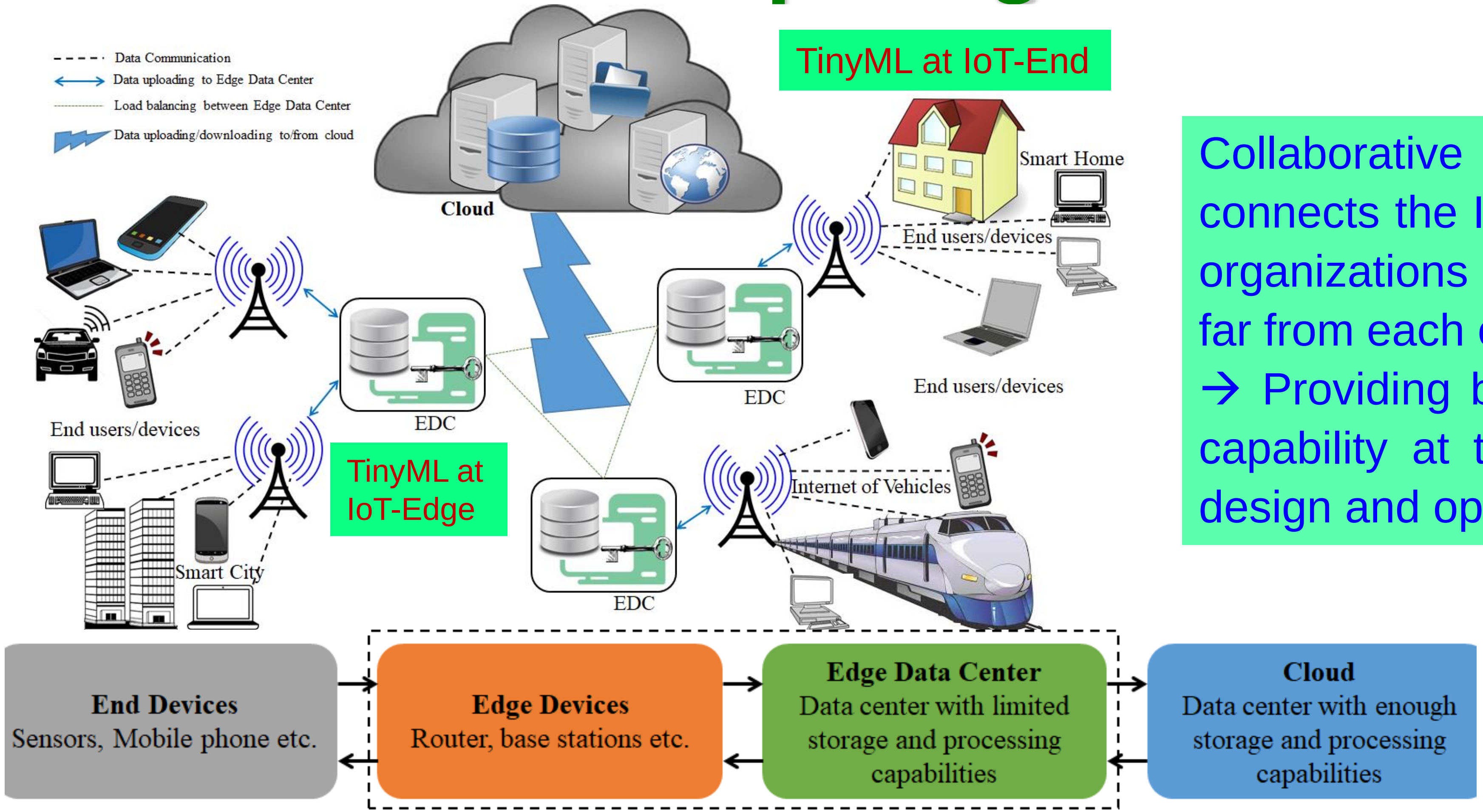


Needs:
- ➢ Computational Resource
- ➢ Computation Energy

Solution: TinyML

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

Collaborative Edge Computing is Cost Effective Sustainable Computing for Smart Villages

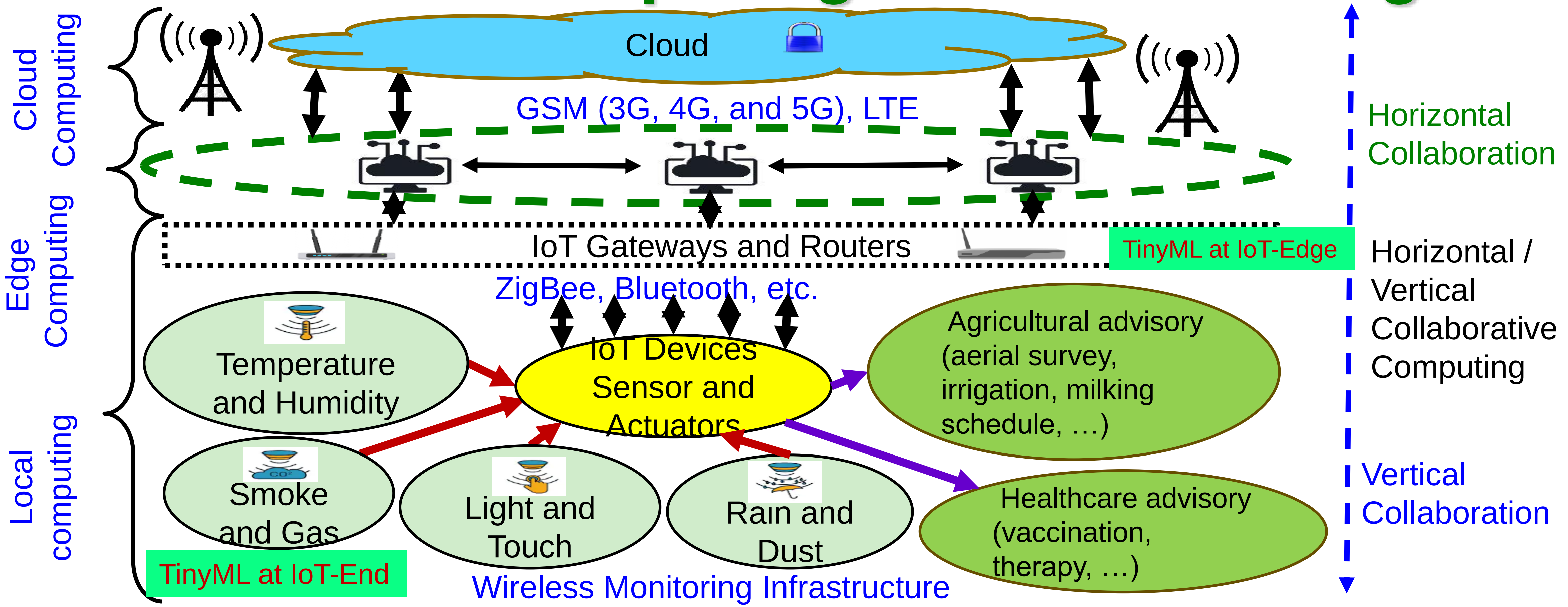


Collaborative edge computing connects the IoT-edges of multiple organizations that can be near or far from each other

→ Providing bigger computational capability at the edge with lower design and operation cost.

Source: D. Puthal, M. S. Obaidat, P. Nanda, M. Prasad, S. P. Mohanty, and A. Y. Zomaya, “Secure and Sustainable Load Balancing of Edge Data Centers in Fog Computing”, *IEEE Communications Mag*, Vol. 56, No 5, May 2018, pp. 60--65.

Collaborative Edge Computing is Cost Effective Sustainable Computing for Smart Villages



Source: D. Puthal, S. P. Mohanty, S. Wilson and U. Choppali, "Collaborative Edge Computing for Smart Villages", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 10, No. 03, May 2021, pp. 68-71.

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, and privacy.

Future Research

- Machine learning (ML) models for smart healthcare needs research.
- Internet-of-Everything (IoE) with Human as active part as crowdsourcing need research.
- Tiny-ML or Edge-AI for smart healthcare needs research.
- Security of IWMDs needs to have extremely minimal energy overhead to be useful and hence needs research.