Machine Learning in Smart Healthcare

Electronics and ICT Academy
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Outline

- Healthcare → Smart Healthcare
- Smart Healthcare - Characteristics
- Smart Healthcare - Components
- Smart Healthcare - Examples
- Smart Healthcare - Challenges
- AI/ML Fundamentals
- Conclusions and Future Directions

Healthcare
to
Smart Healthcare

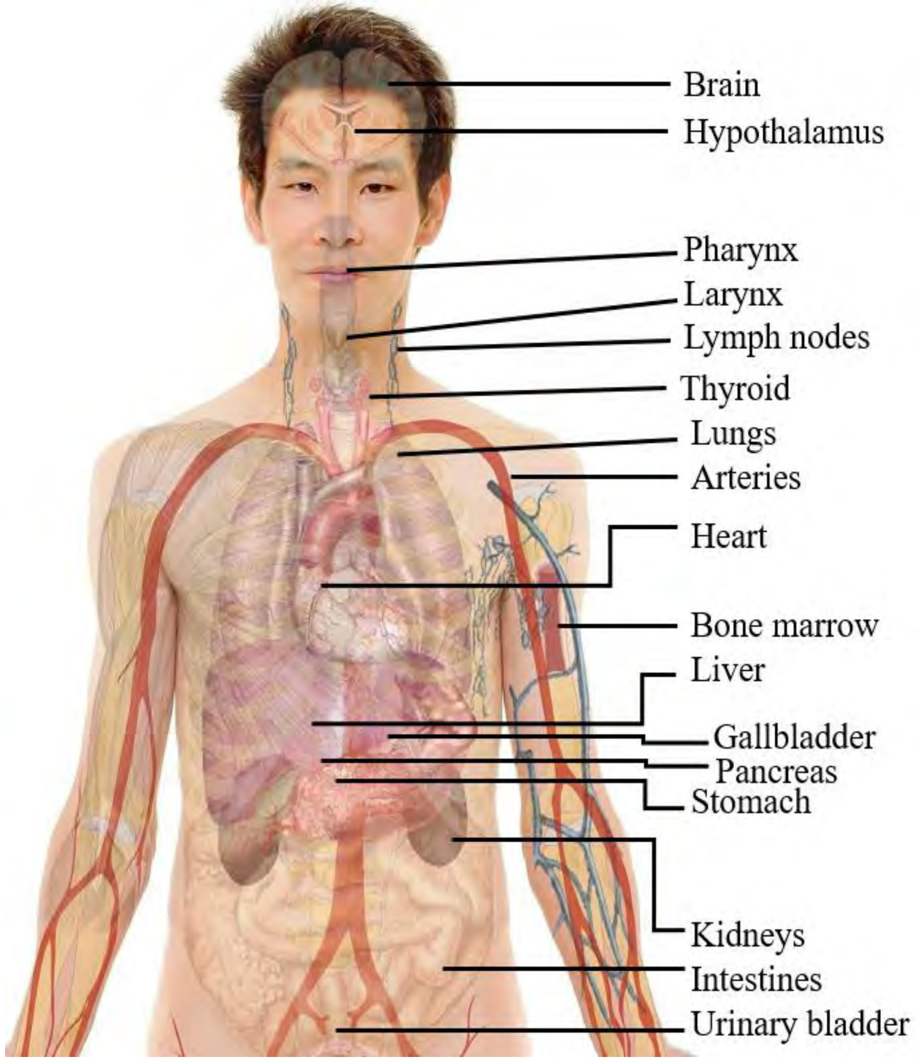
Human Body and Health

Human Body

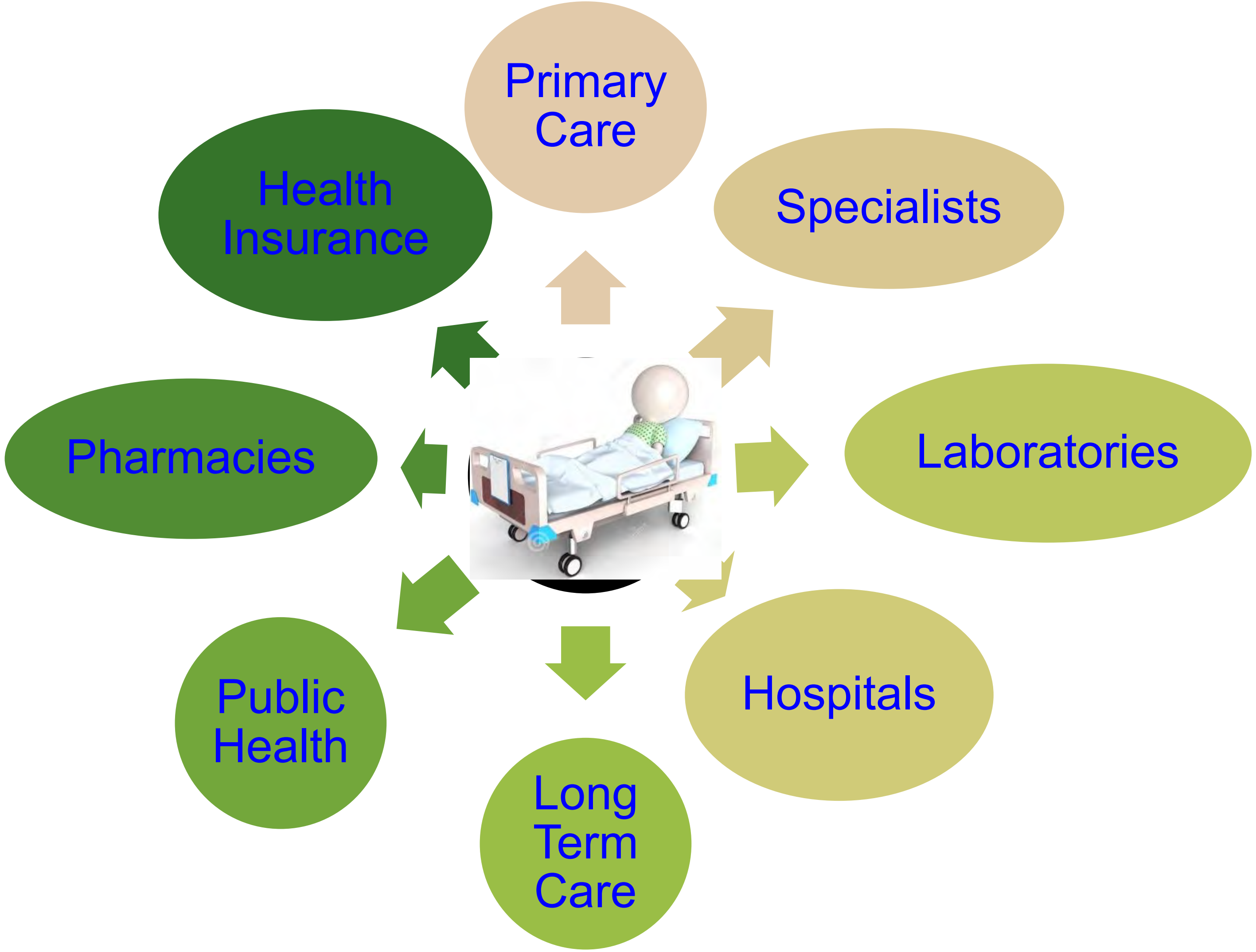
- From an engineering perspective, the human body can be defined as a combination of multi-disciplinary subsystems (electrical, mechanical, chemical …).

Health

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



Traditional Healthcare

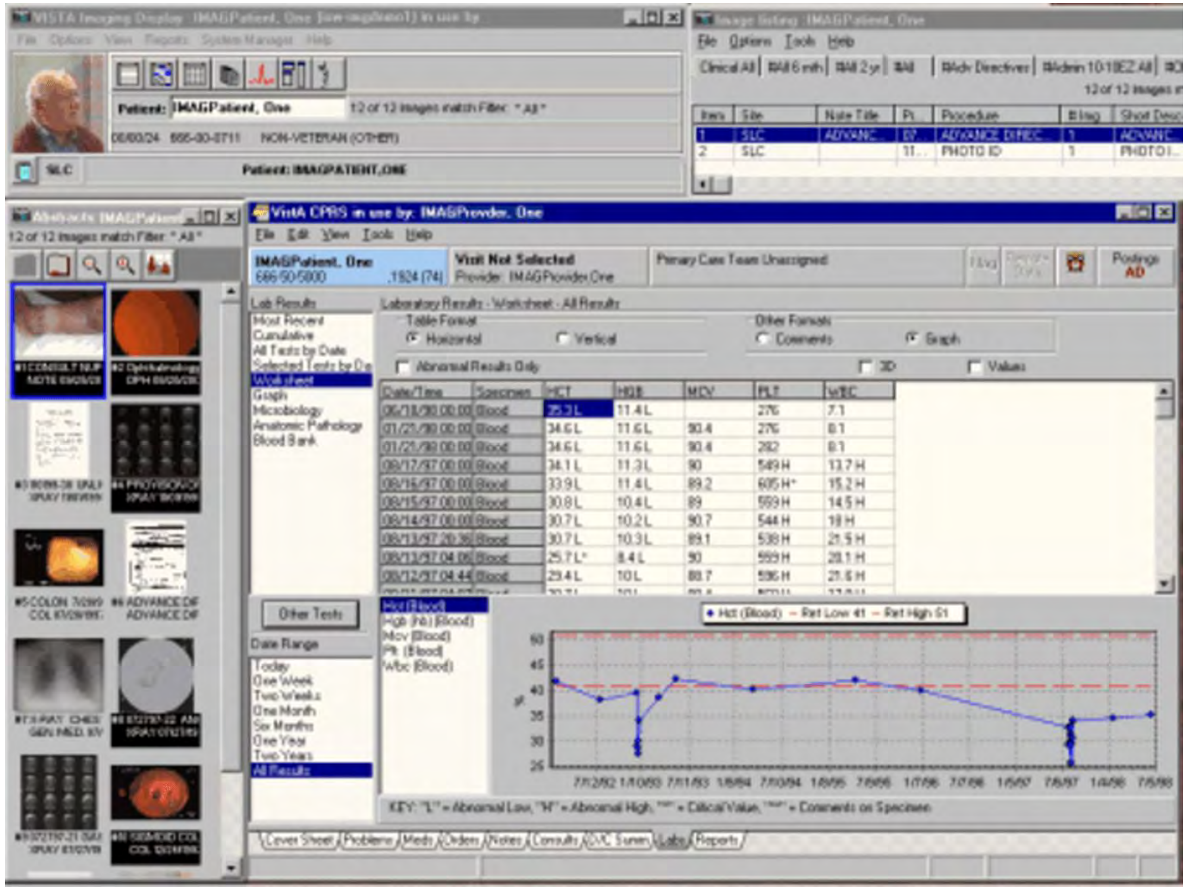


- Physical presence needed
- Deals with many stakeholders
- Stakeholders may not interact
- May not be personalized
- Not much active feedback
- No follow-up from physicians

Telemedicine

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

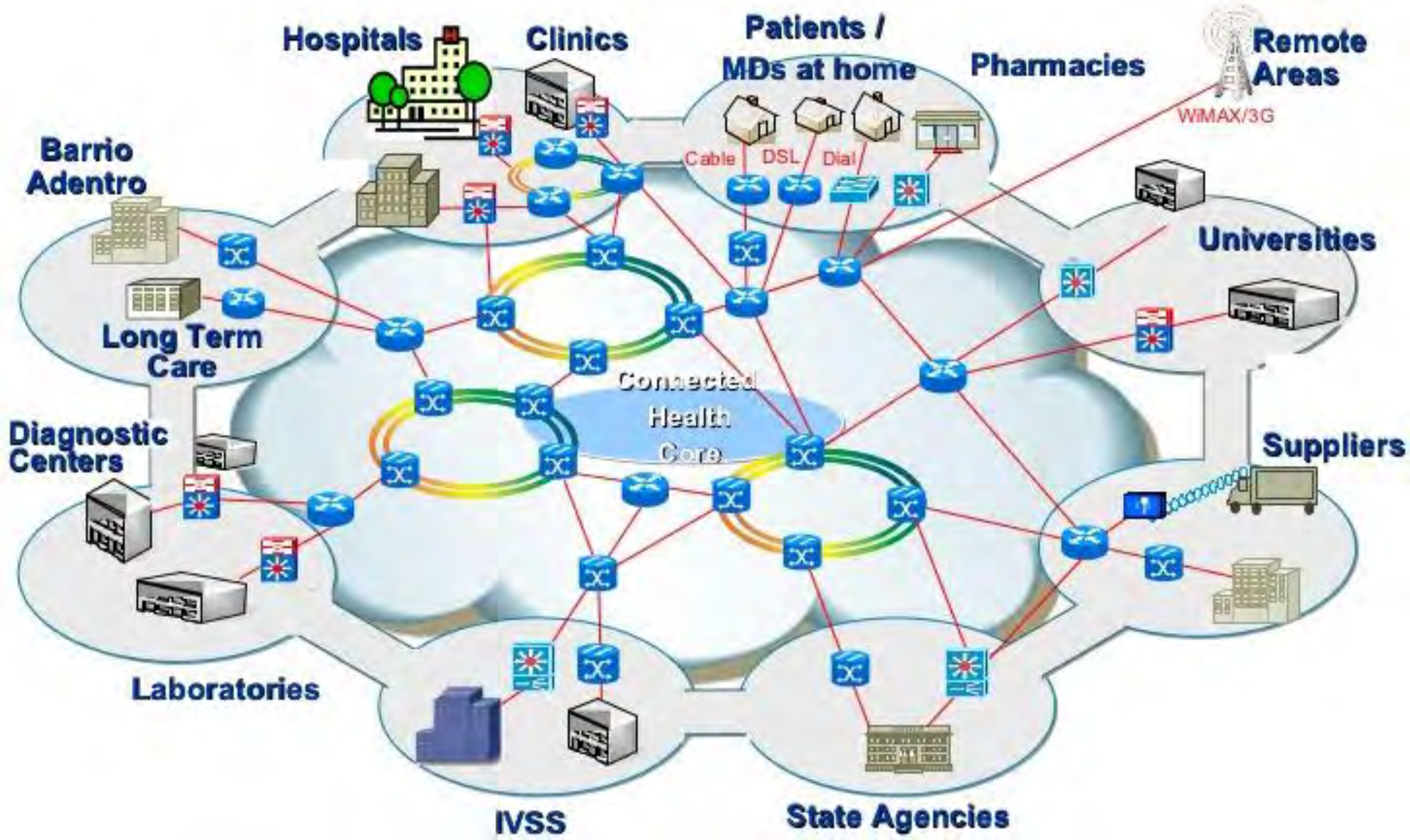
Electronic Health (eHealth)



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.

Connected Health (cHealth)



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

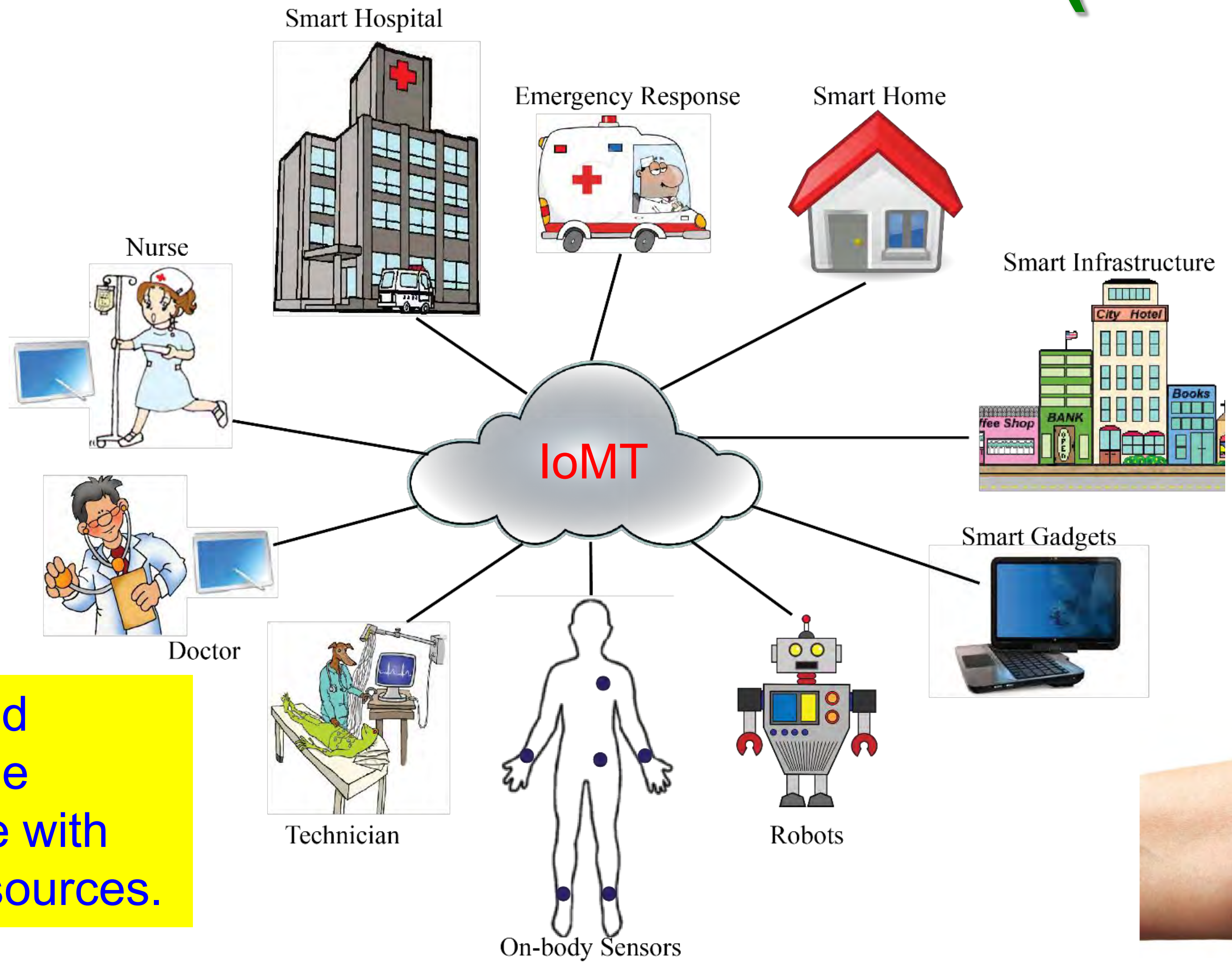
cHealth: Connections of the various healthcare stake holders through Internet to share appropriate data to better serve the patients.

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.

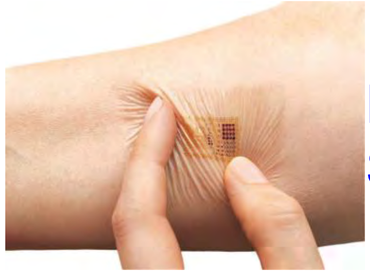
Source: H. Zhu, C. K. Wu, C. H. KOO, Y. T. Tsang, Y.Liu, H. R. Chi, and K. F. Tsang, "Smart Healthcare in the Era of Internet-of-Things", *IEEE Consumer Electronics Magazine*, vol. 8, no. 5, pp. 26-30, Sep 2019.

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.

Smart Healthcare

Healthy Living
- Fitness Tracking
- Disease Prevention
- Food monitoring

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

Acute Care
- Hospital
- Specialty clinic
- Nursing Home
- Community Hospital

Internet of Medical Things (IoMT)

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

January 2018

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

Transitions in Healthcare

Healthcare

eHealth

The use of information 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

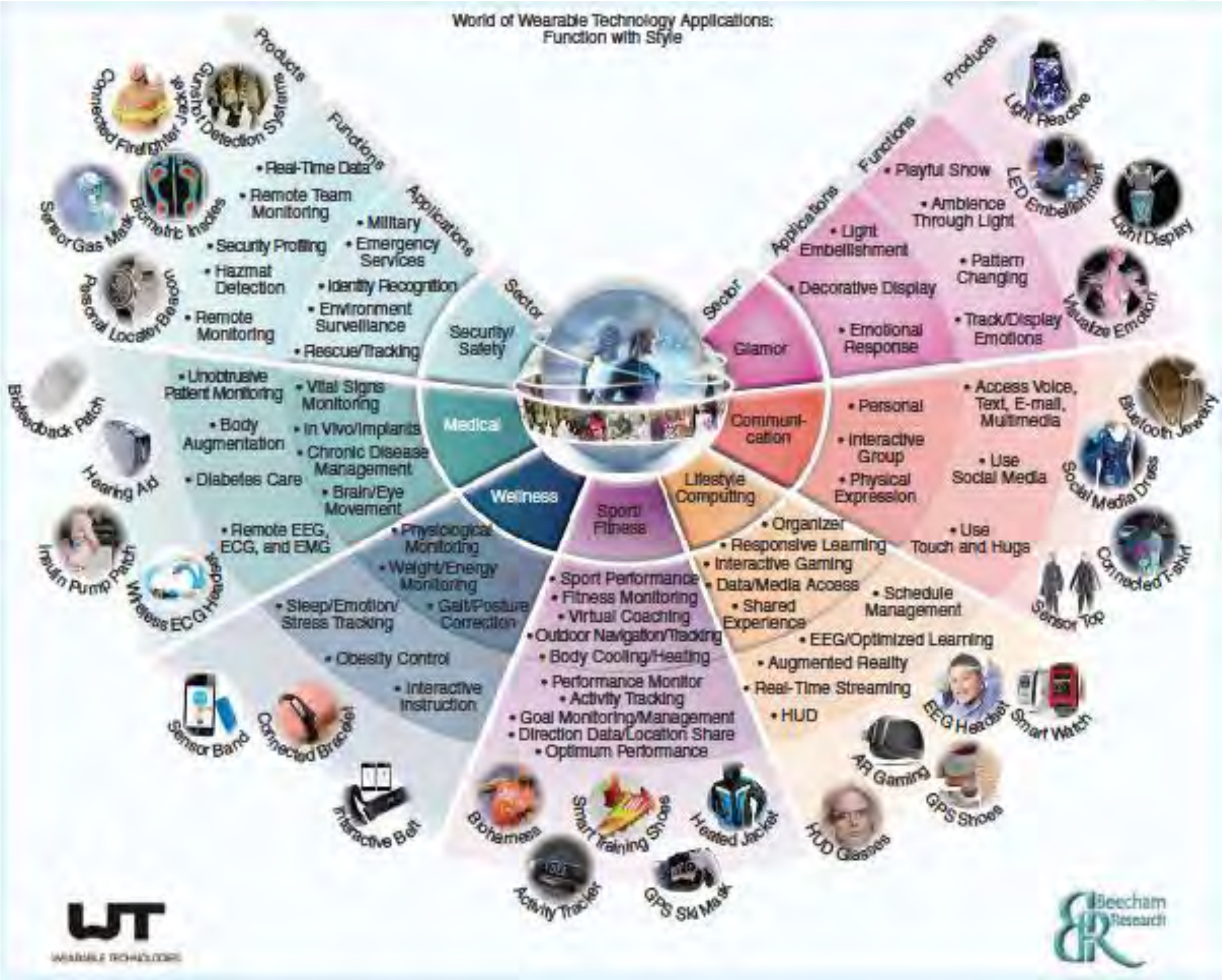
Muse - EEG

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

Selected Healthcare Products

Source: Islam, D. Kwak, M. H. Kabir, M. Hossain and K. Kwak, "The Internet of Things for Health Care: A Comprehensive Survey," IEEE Access, vol. 3, pp. 678-708, 2015. doi: 10.1109/ACCESS.2015.

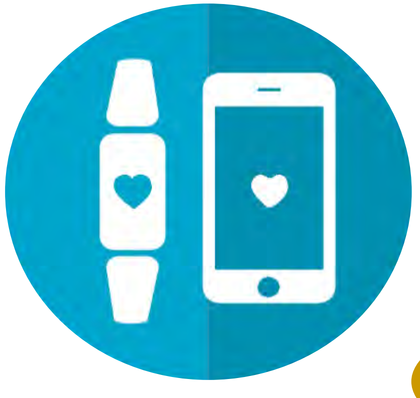
Wearable Technology - Applications



The diversified wearable market - (Photo courtesy of Johanna Mischke, Wearable Technologies, AG.)

Source: J. Wei, "How Wearables Intersect with the Cloud and the Internet of Things : Considerations for the developers of wearables.," *IEEE Consumer Electronics Magazine*, vol. 3, no. 3, pp. 53-56, July 2014.

Smart Healthcare Wearables

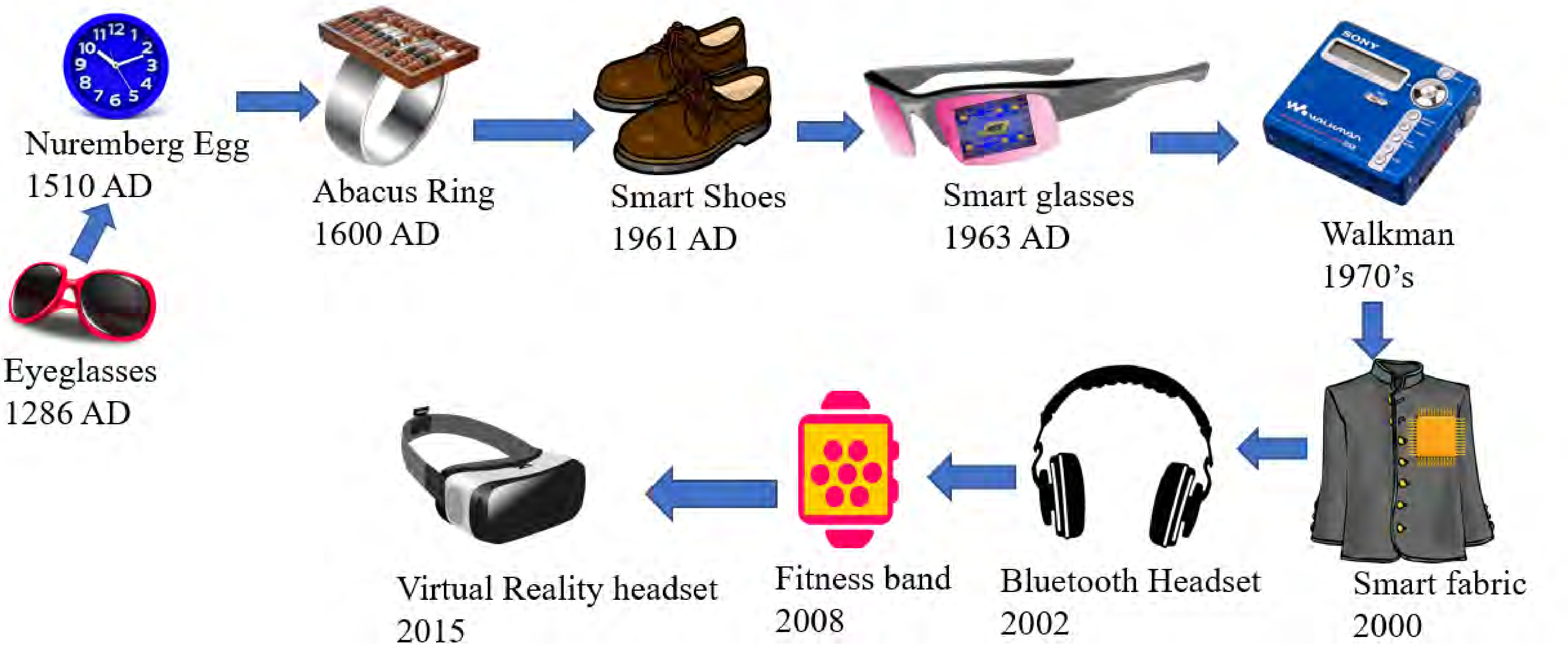


Advantages
- Enriched user experience
- Personalized remote assistance

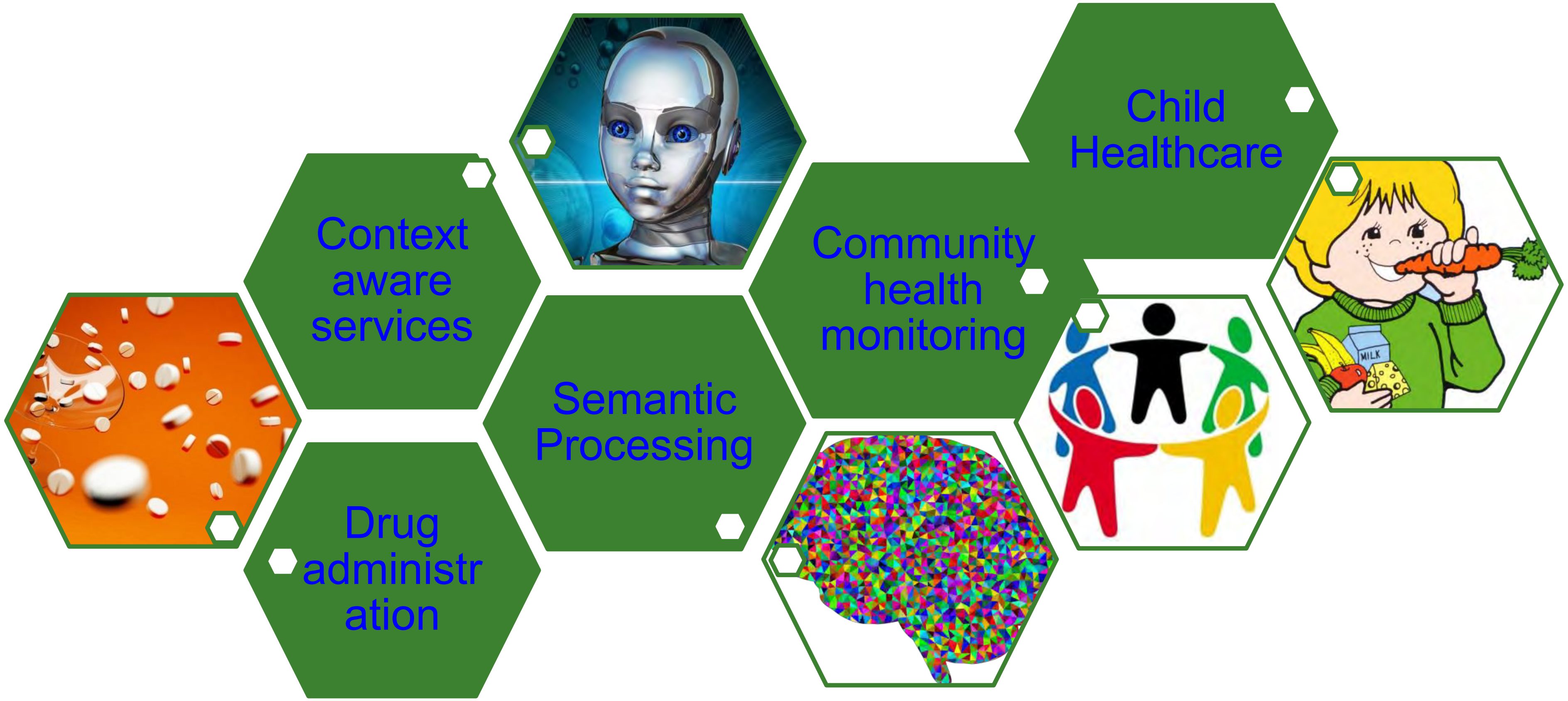
Applications
- Single condition
- Clustered condition

Research
- Pre data acquisition phase
- Post data acquisition phase

Wearables - Evoluation



Smart Healthcare - Services



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Smart Healthcare - Applications

Applications

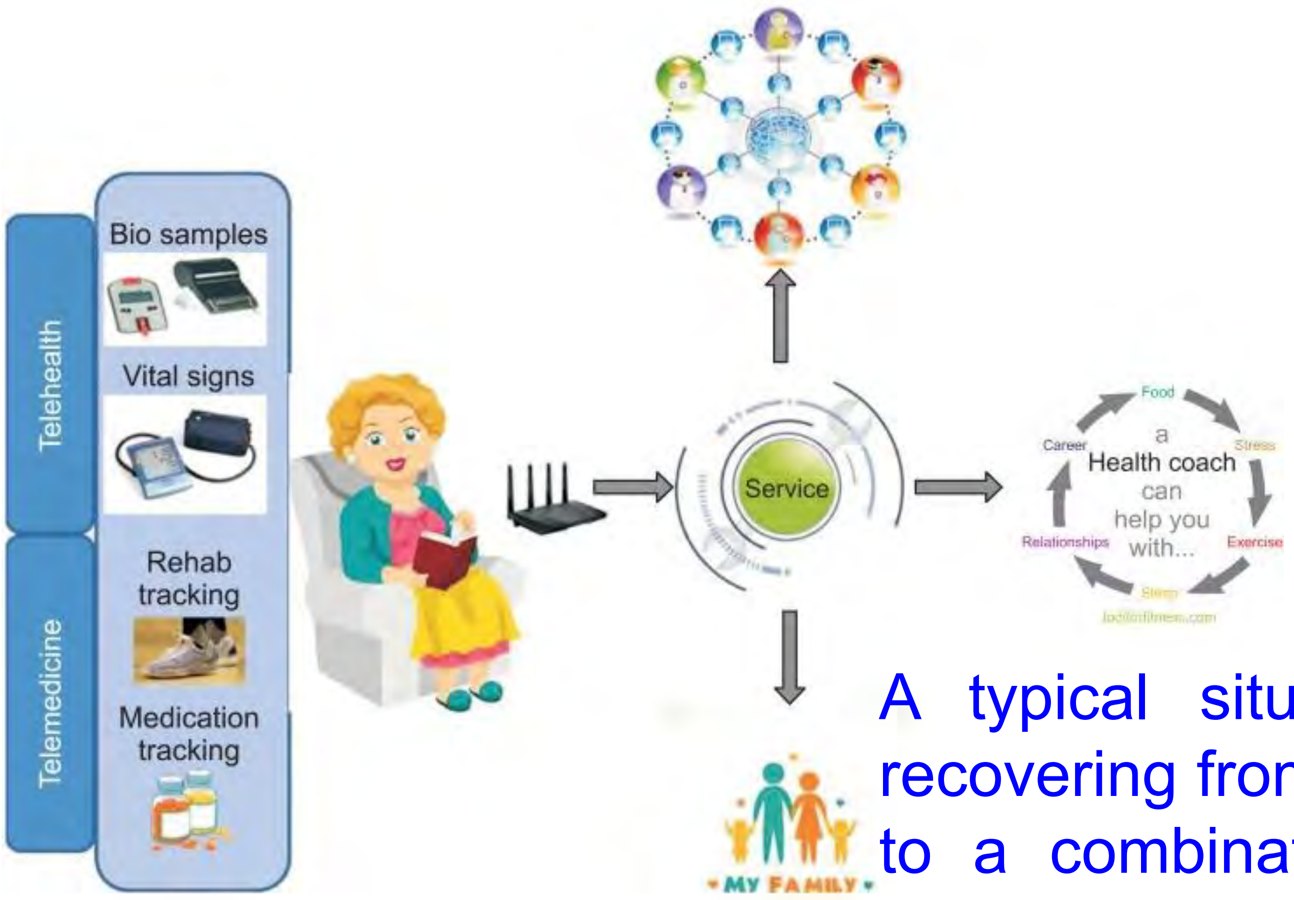
Single-condition

- Glucose level sensing
- ECG monitoring
- Blood pressure monitoring
- Body temperature monitoring
- Oxygen saturation monitoring

Clustered condition

- Rehabilitation system
- Medication management
- Wheelchair management
- Smartphone healthcare solutions

Smart Healthcare - IoMT



Dimitrov 2016, Healthcare Informatics Research, July 2016

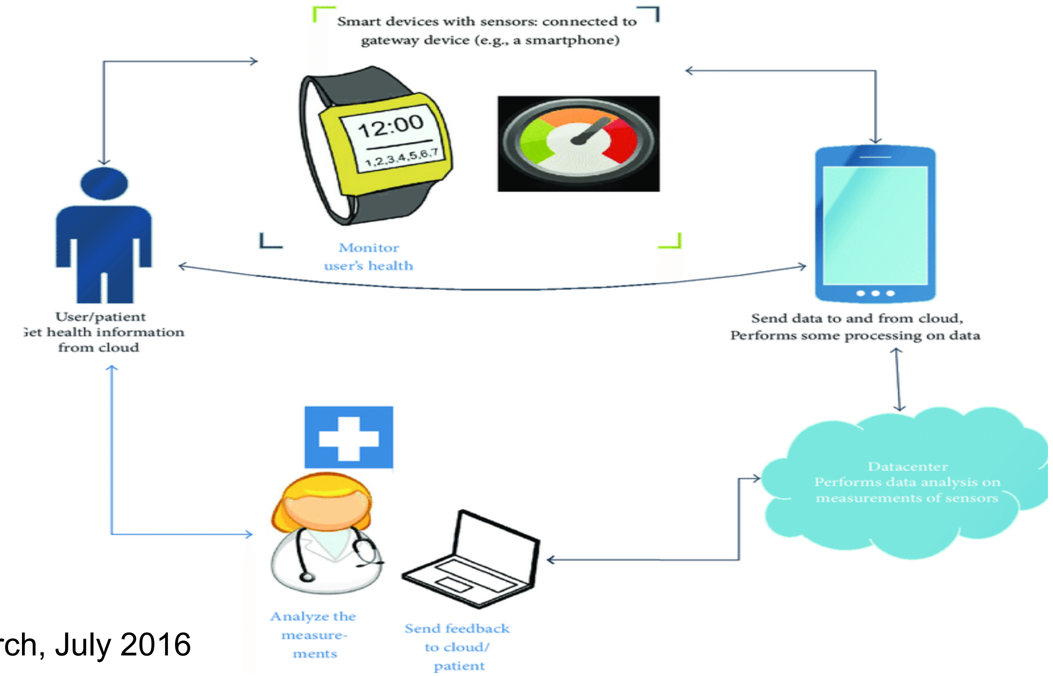
A typical situation involved an elderly person, recovering from a medical condition at home, linked to a combination of several connected services streaming data towards different parties, such as family members, tele-carer and physicians.

Smart Healthcare - Characteristics

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

What is Smart Healthcare?

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

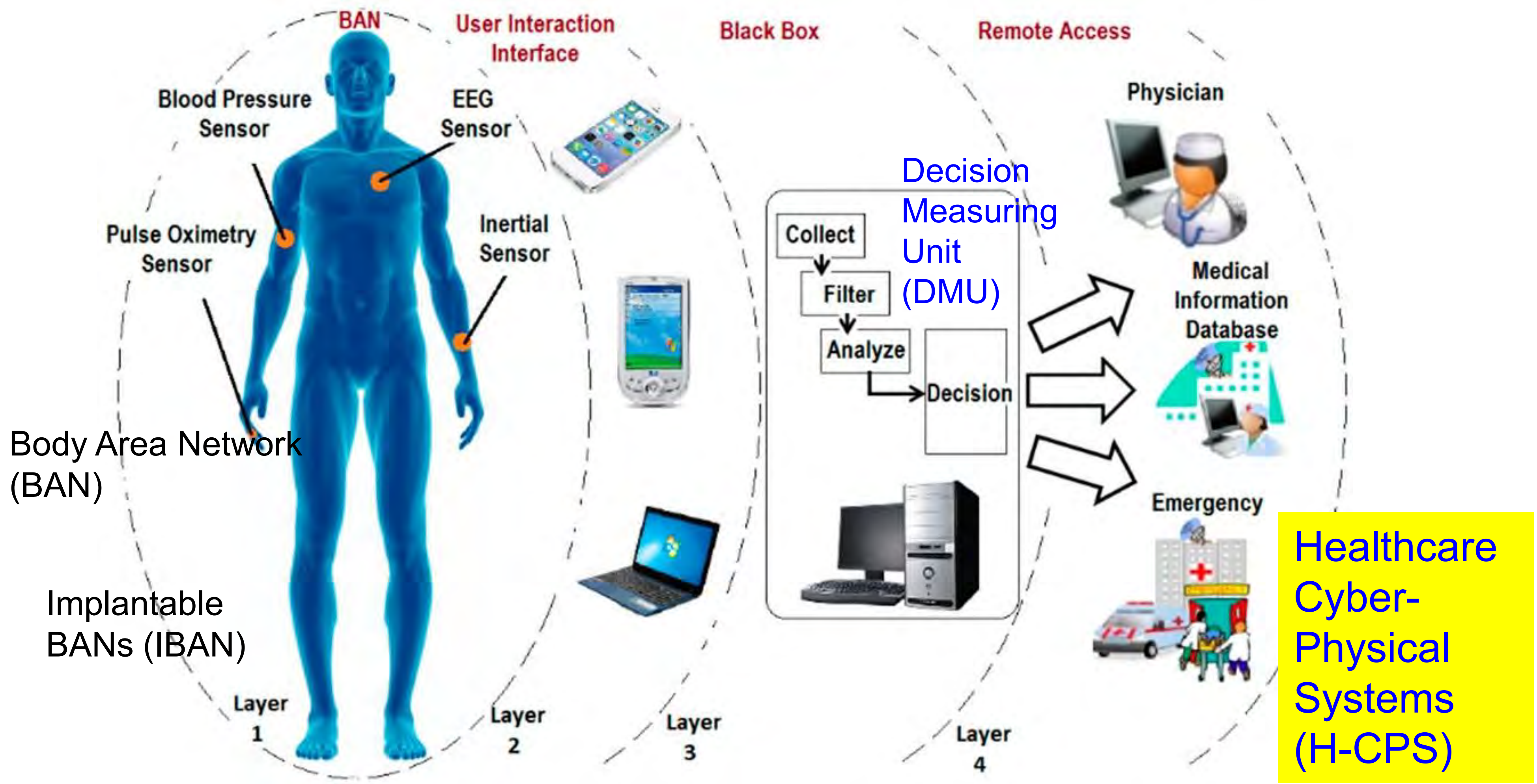
Internet of Medical Things (IoMT)

Internet of Health Things (IoHT)

Healthcare Cyber-Physical Systems (H-CPS)

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

Smart Healthcare - 4-Layer Architecture



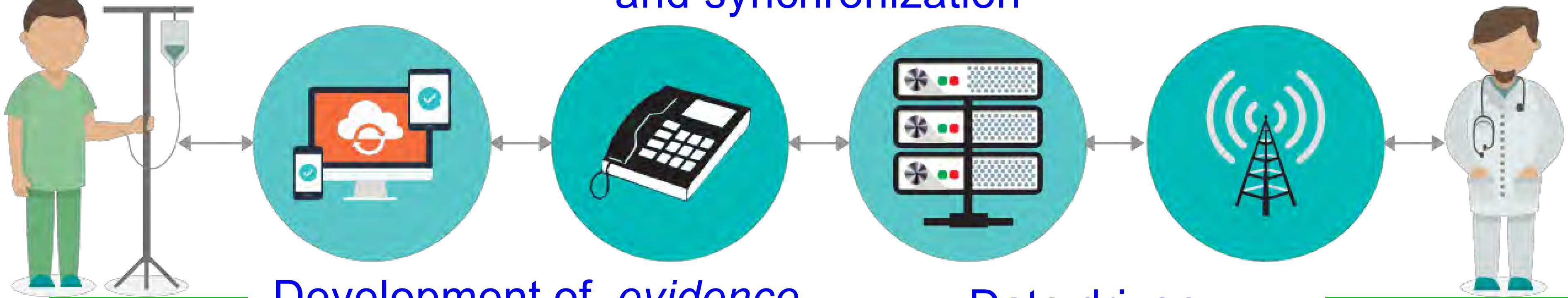
Source: M. Ghamari, B. Janko, R.S. Sherratt, W. Harwin, R. Piechockic, and C. Soltanpur, "A Survey on Wireless Body Area Networks for eHealthcare Systems in Residential Environments", *Sensors*, 2016. 16(6): p. 831.

IoMT based H-CPS

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

Improved inter-device connection and synchronization

Real-time *tracking* and intervention



Patient

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

Data driven health *prediction*

Healthcare Provider

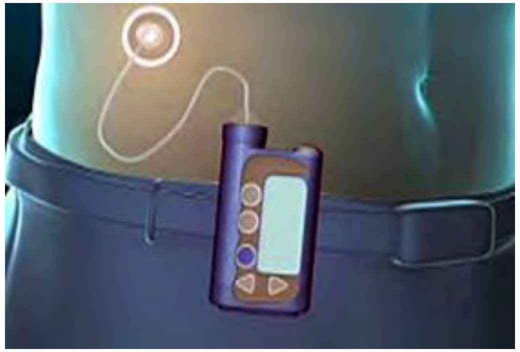
Healthcare Cyber-Physical Systems (H-CPS)

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

Wearable Medical Devices (WMDs)

Fitness Trackers

Headband with Embedded Neurosensors

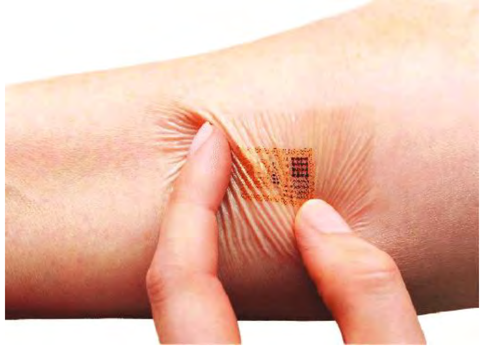


Insulin Pump

Source: https://www.webmd.com

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

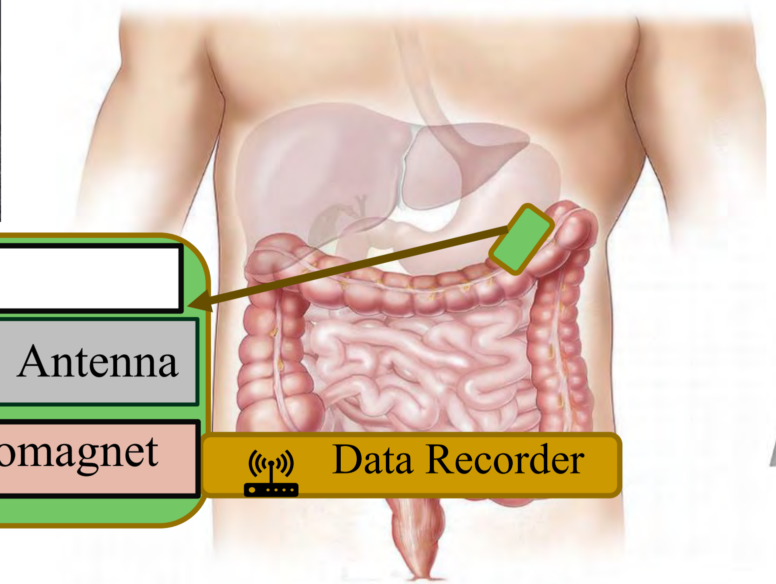
Medical grade smart watch to detect seizure

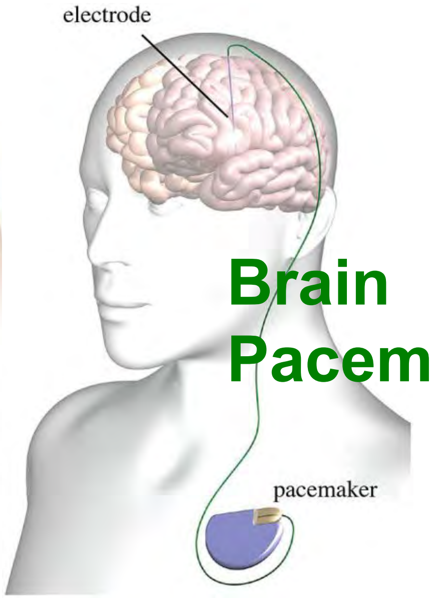


Embedded Skin Patches

Implantable Medical Devices (IMDs)

Pill Camera





Brain Pacemaker

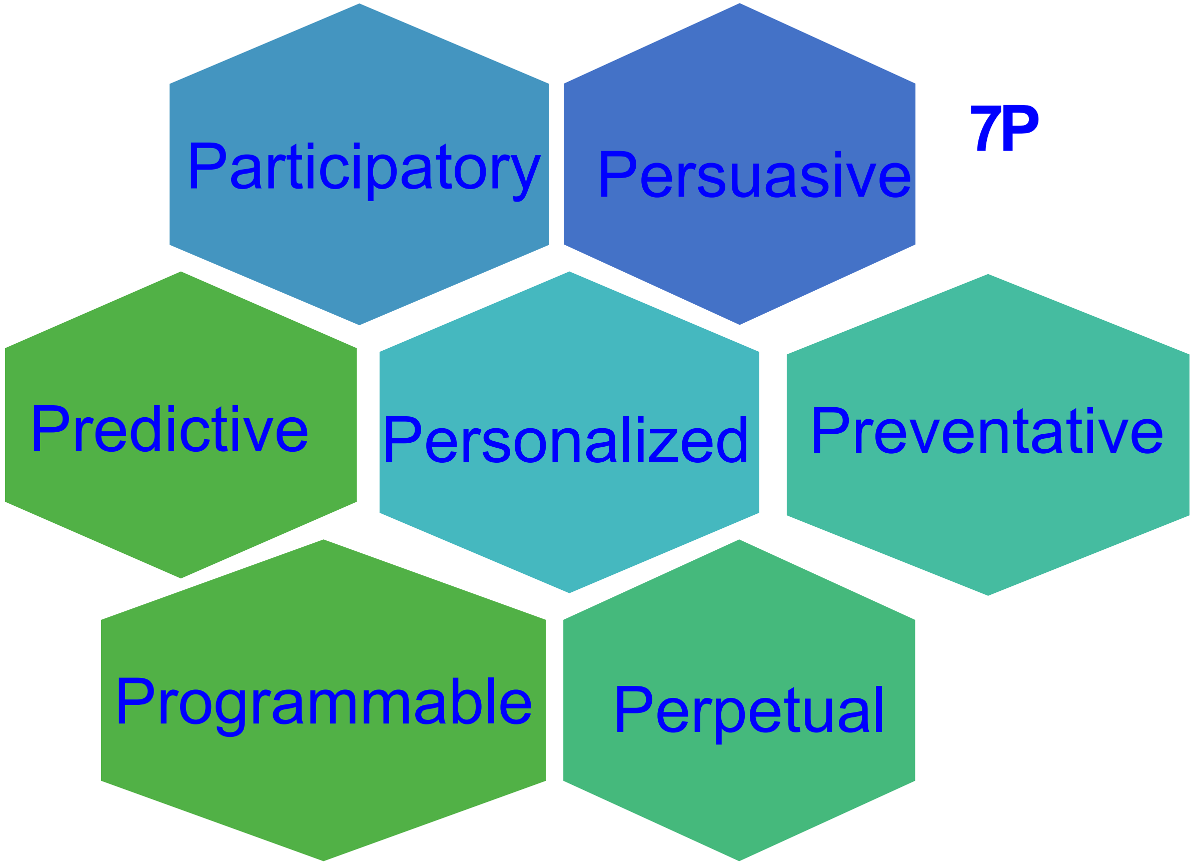
Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "*Everything You Wanted to Know about Smart Health Care*", IEEE Consumer Electronics Magazine (MCE), Volume 7, Issue 1, January 2018, pp. 18-28.

Collectively:
Implantable and Wearable Medical Devices (IWMDs)

Implantable MEMS Device

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

Smart Healthcare – 7Ps



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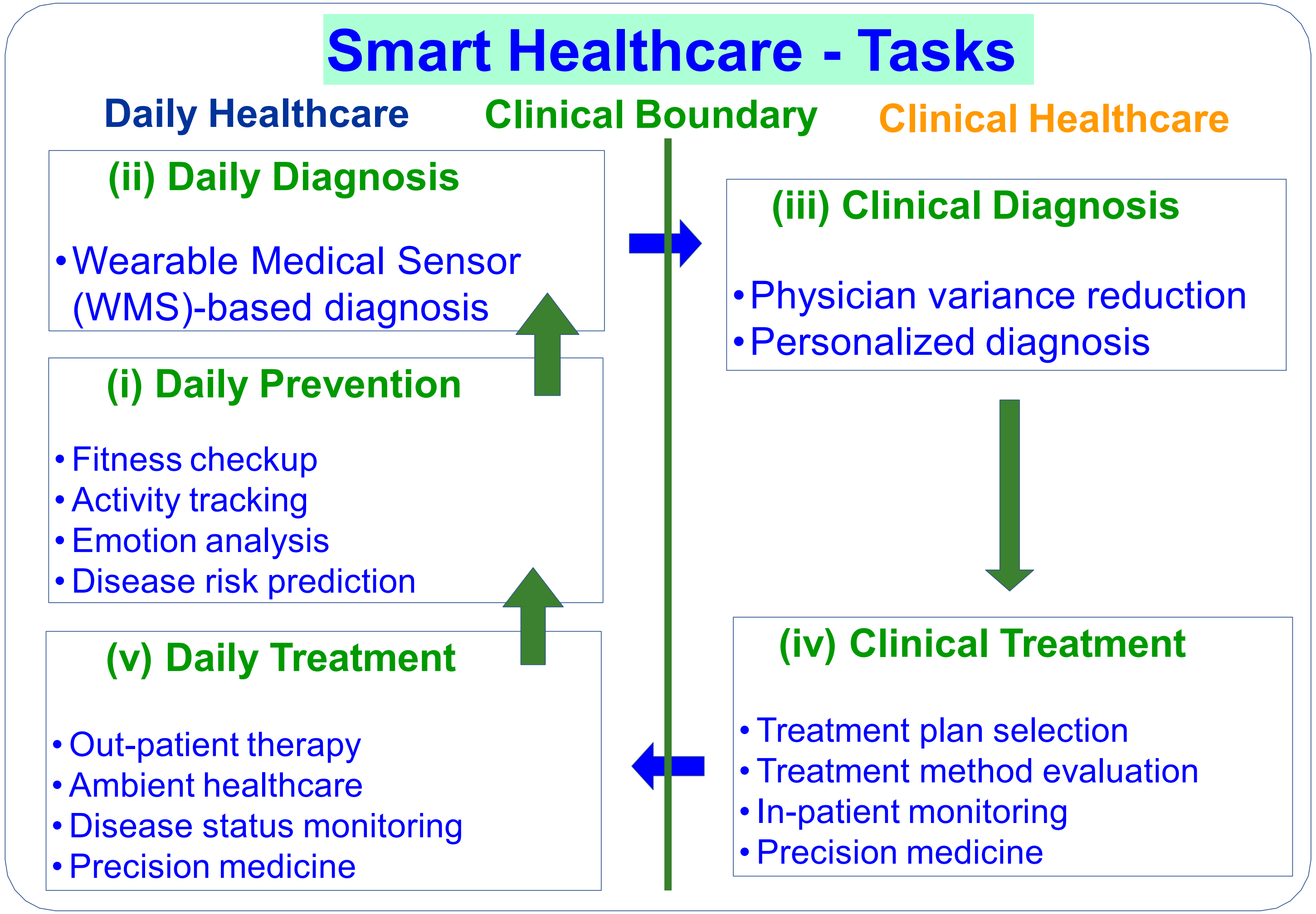
Smart Healthcare - Tasks



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 Tasks

Personal & Community

- Remote Monitoring
- Self-management of chronic conditions
- Performance improvement
- Behavior modification
- Stress Monitoring
- Therapy Result Measurement
- Social Activities
- Diet Management
- Detection & Diagnosis
- Remote Treatment

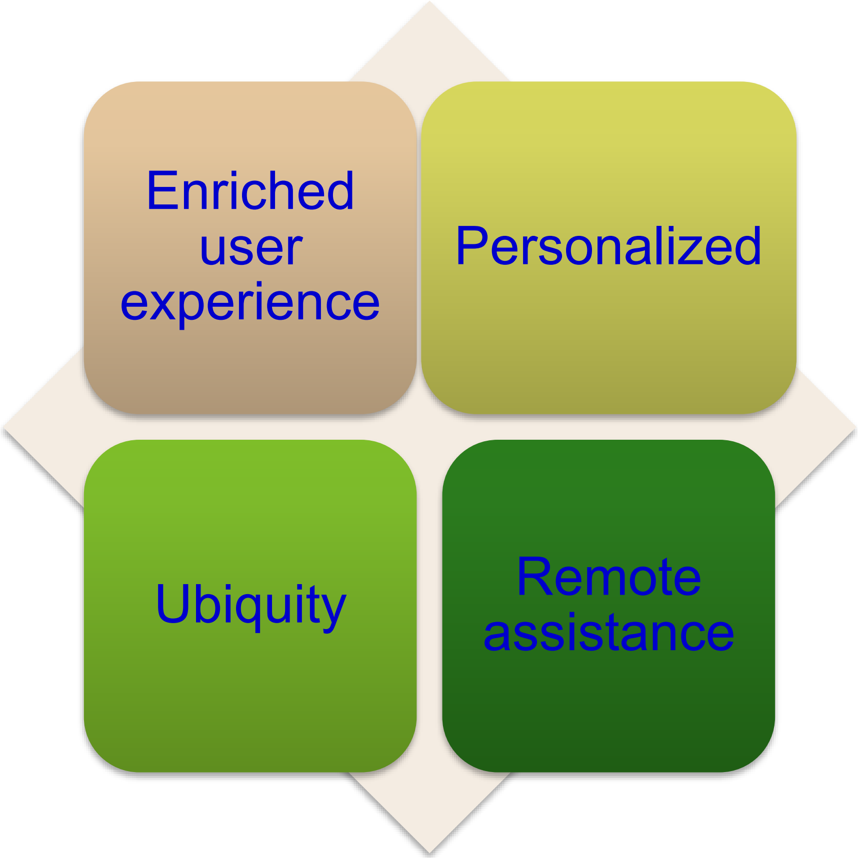
In Hospitals

- Real-time Patient Monitoring
- Equipment Tracking
- Performance improvement
- Behavior modification
- Detection & diagnosis
- Treatment
- Product Recalls
- Prevent Medication Error
- Smart Alert System

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, 2019, Accepted.

Smart Healthcare - Advantages

- Smart healthcare empowers the users to self-manage emergency situations and keeps them health-aware.
- It aids in remote monitoring of patients which helps in using the available resources to maximum potential.



IoMT Advantages & Limitations

Advantages

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

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

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

Limitations

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

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

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

Smart Healthcare - Architectures

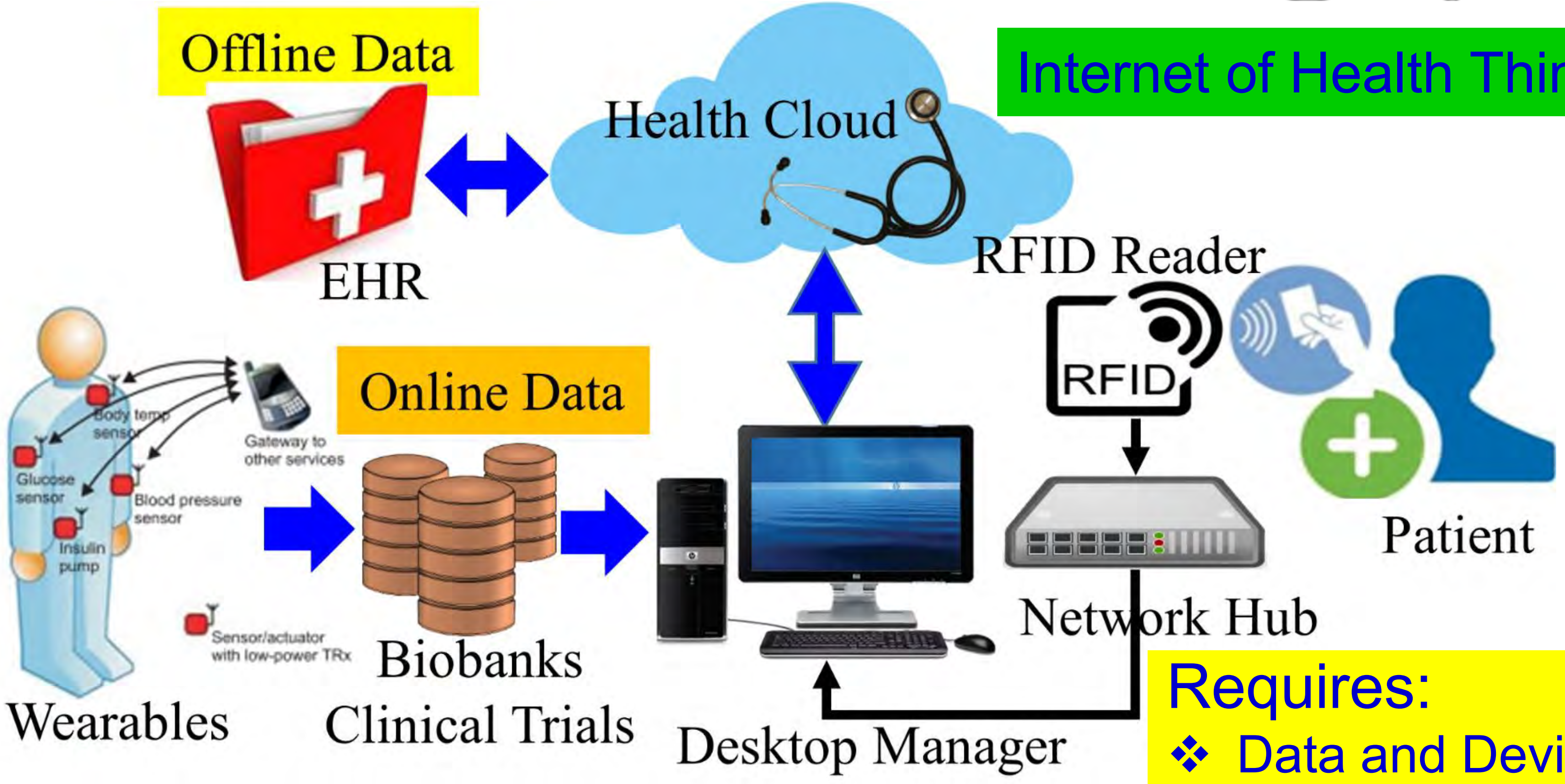
Problem?

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

Smart Healthcare - Components

Internet of Medical Things (IoMT)

Internet of Health Things (IoHT)



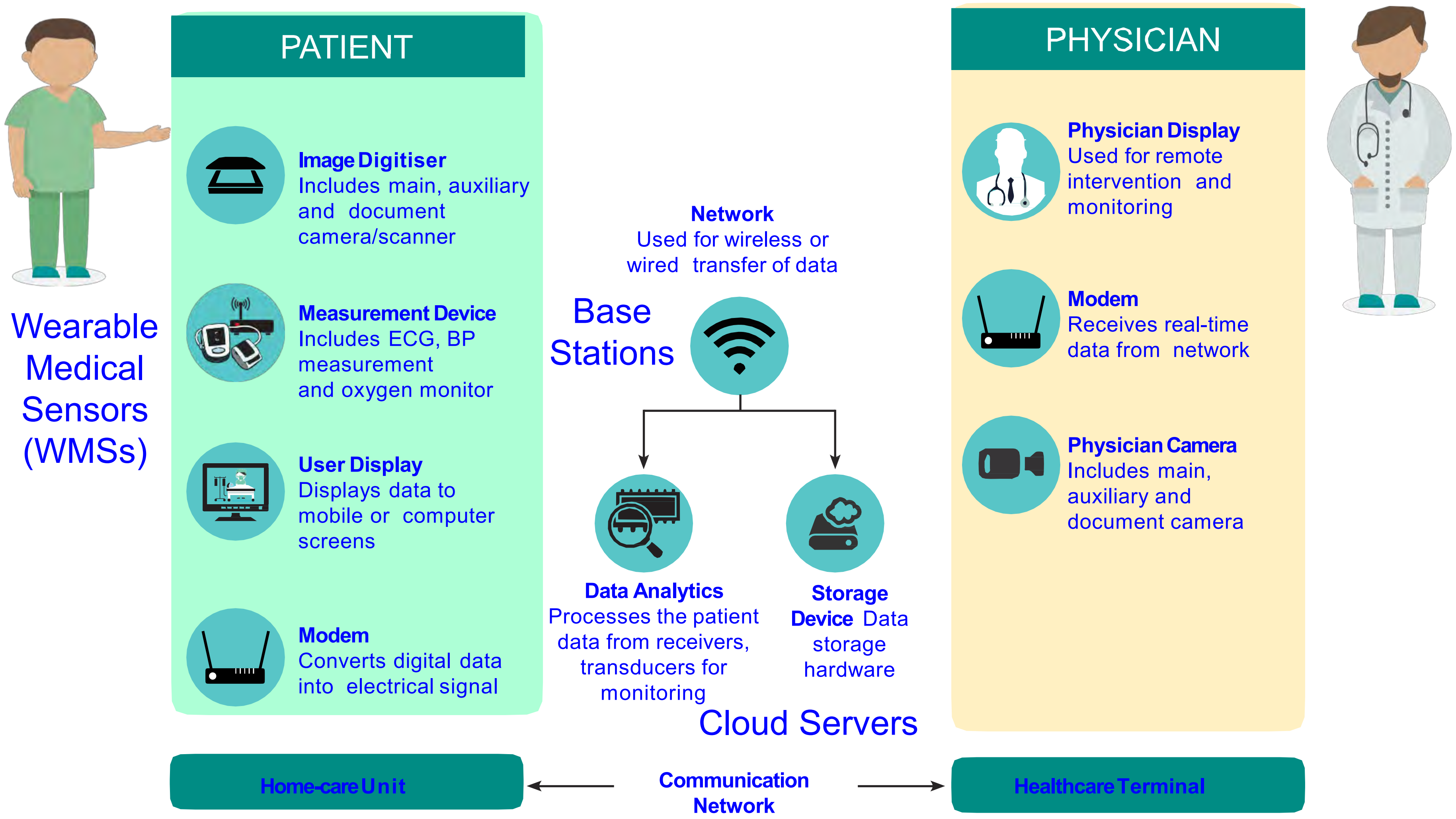
Requires:

- ❖ Data and Device Security
- ❖ Data Privacy

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

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

IoMT - Components



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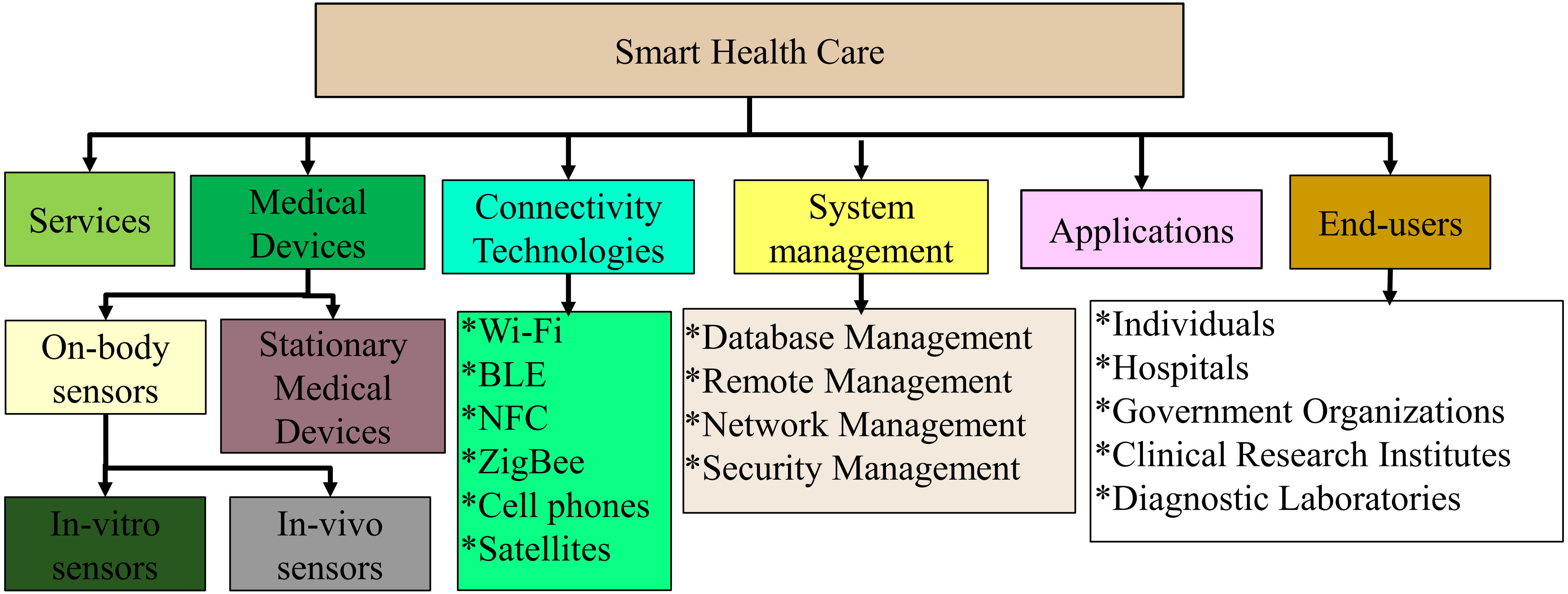
Smart Healthcare – Components



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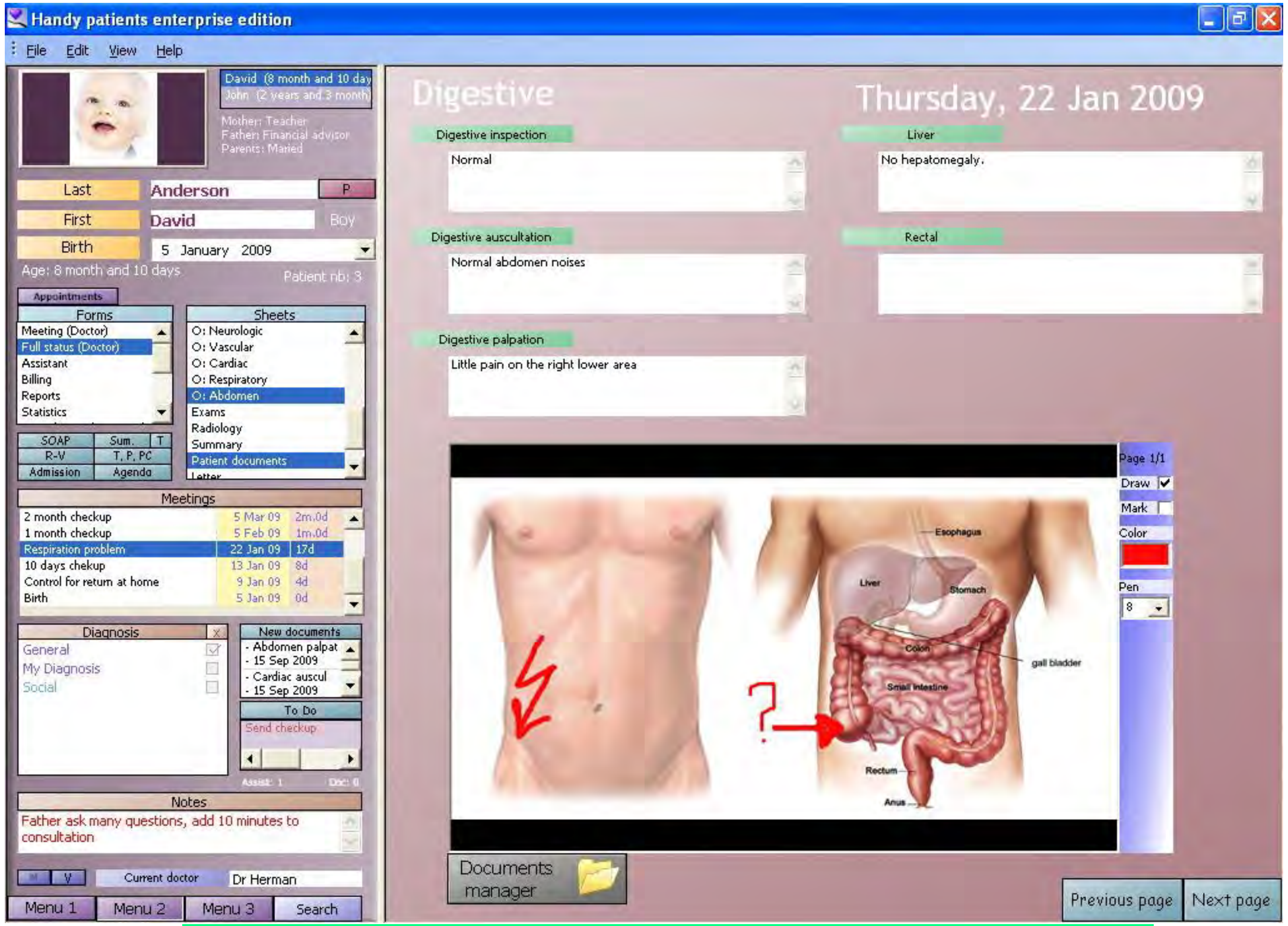
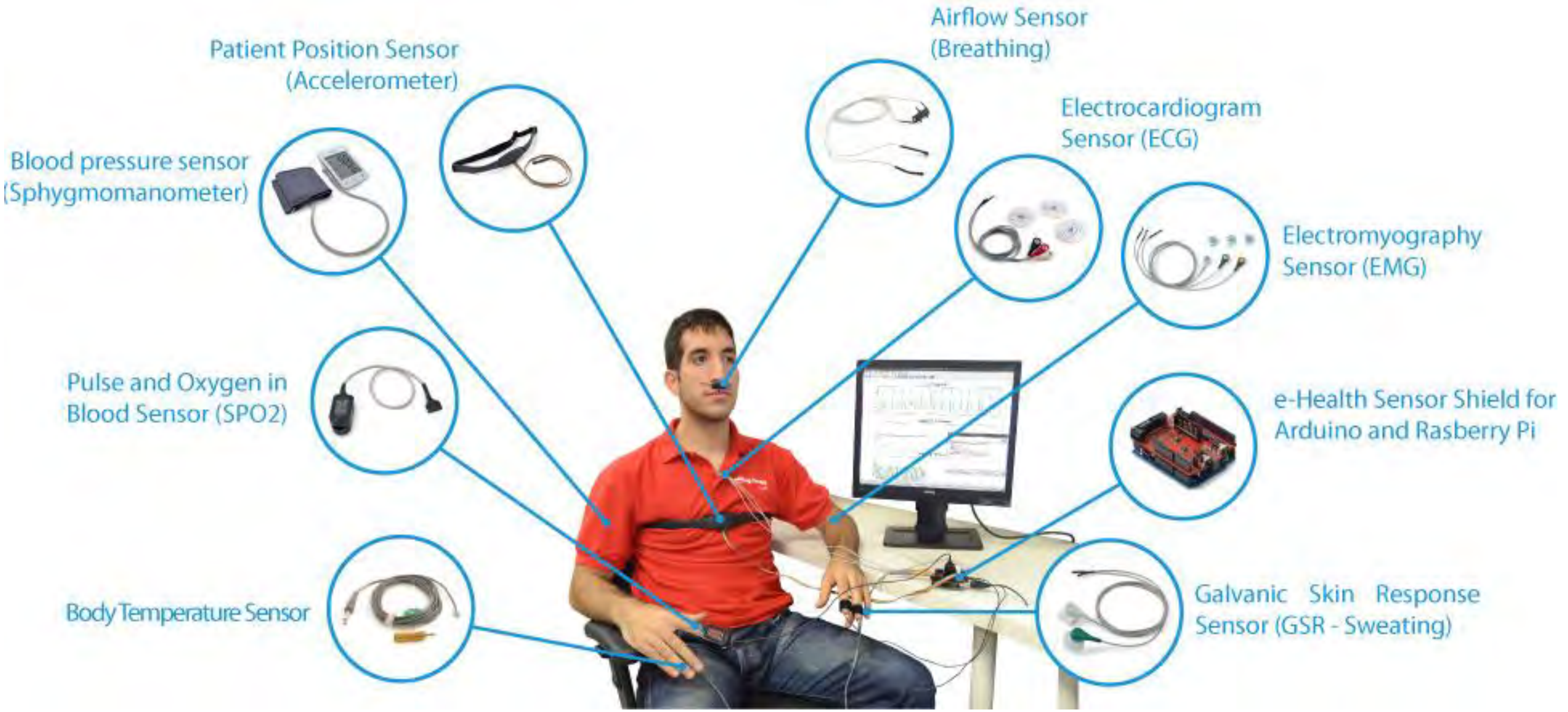
Electronics Health Record (EHR)

- 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.



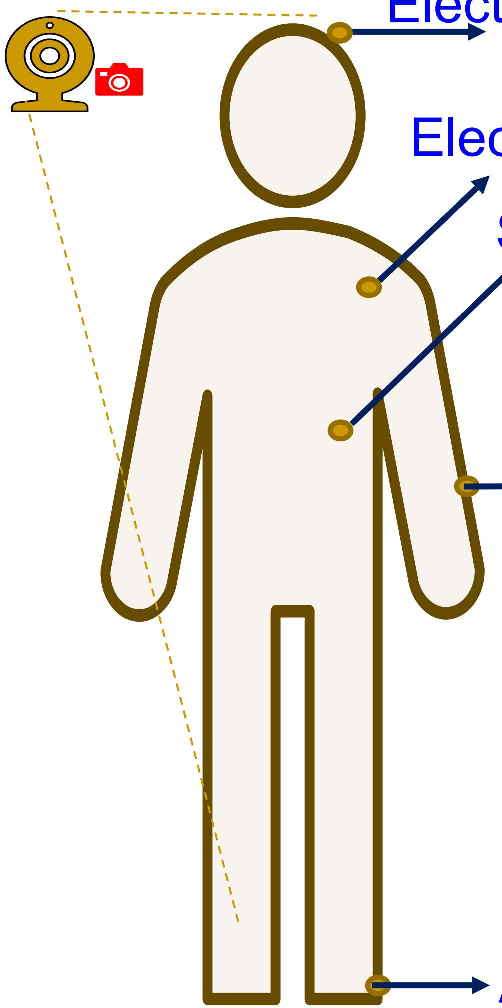
Electronic Medical Record (EMR)

Sensor Technology - Healthcare



Source: http://www.libelium.com/e-health-low-cost-sensors-for-early-detection-of-childhood-disease-inspire-project-hope/

Smart Healthcare Sensors

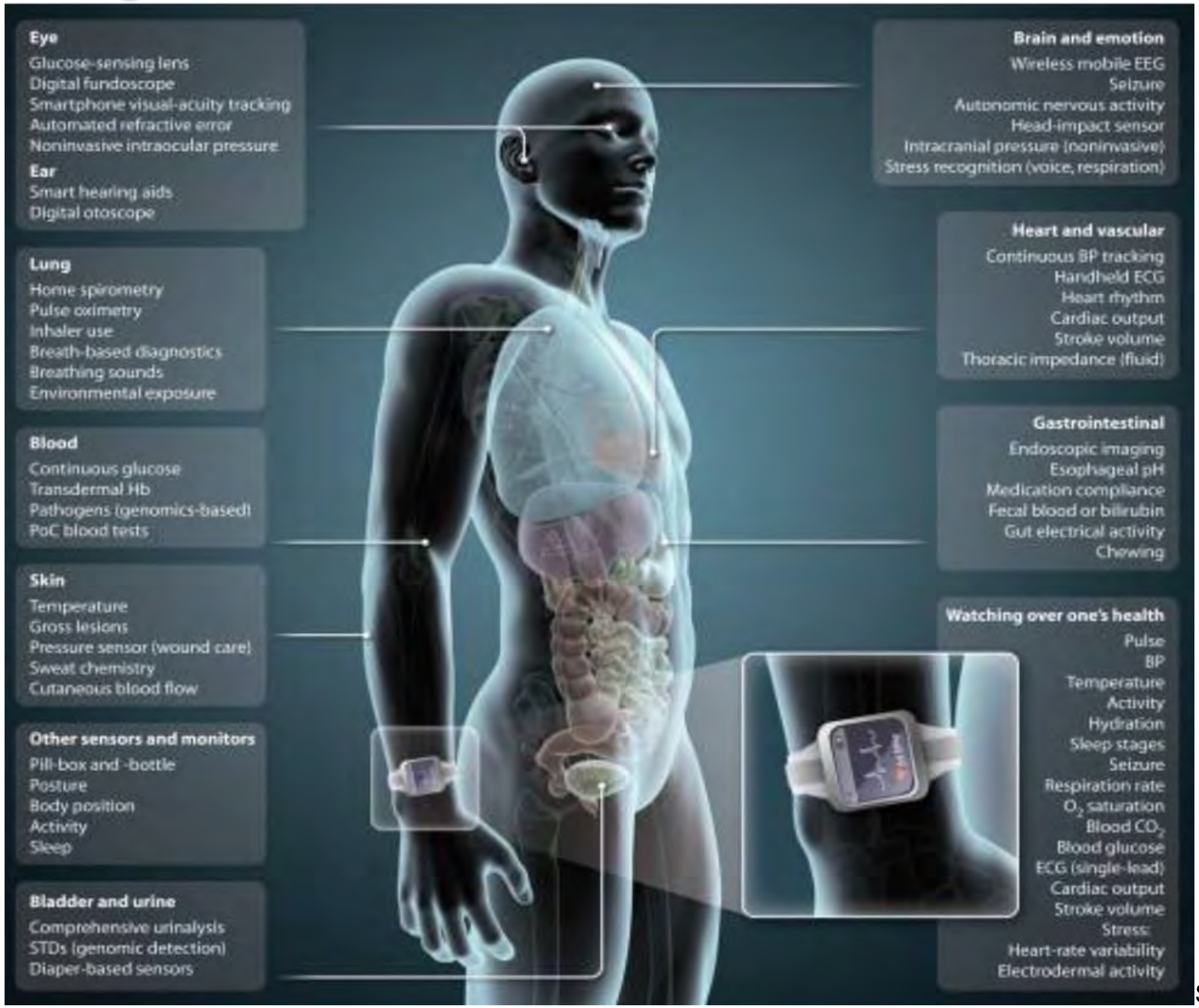


- Electroencephalogram (EEG)
- Electrocardiogram (ECG)
- Smart Pill
- Oximeter
- Electrodermograph
- Electromyography (EMG)
- Photoplethysmography (PPG)
- Glucose monitoring
- Thermal sensor
- Pulse sensor
- Accelerometer
- Gyroscope
- Magnetometer
- Altimeter

Types of Sensors

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

Bodywide Measurement in Mobile Health



Source: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4748838/

Photoplethysmograph (PPG)

Green LED - 540 nm wavelength
– Preferred for wearables

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

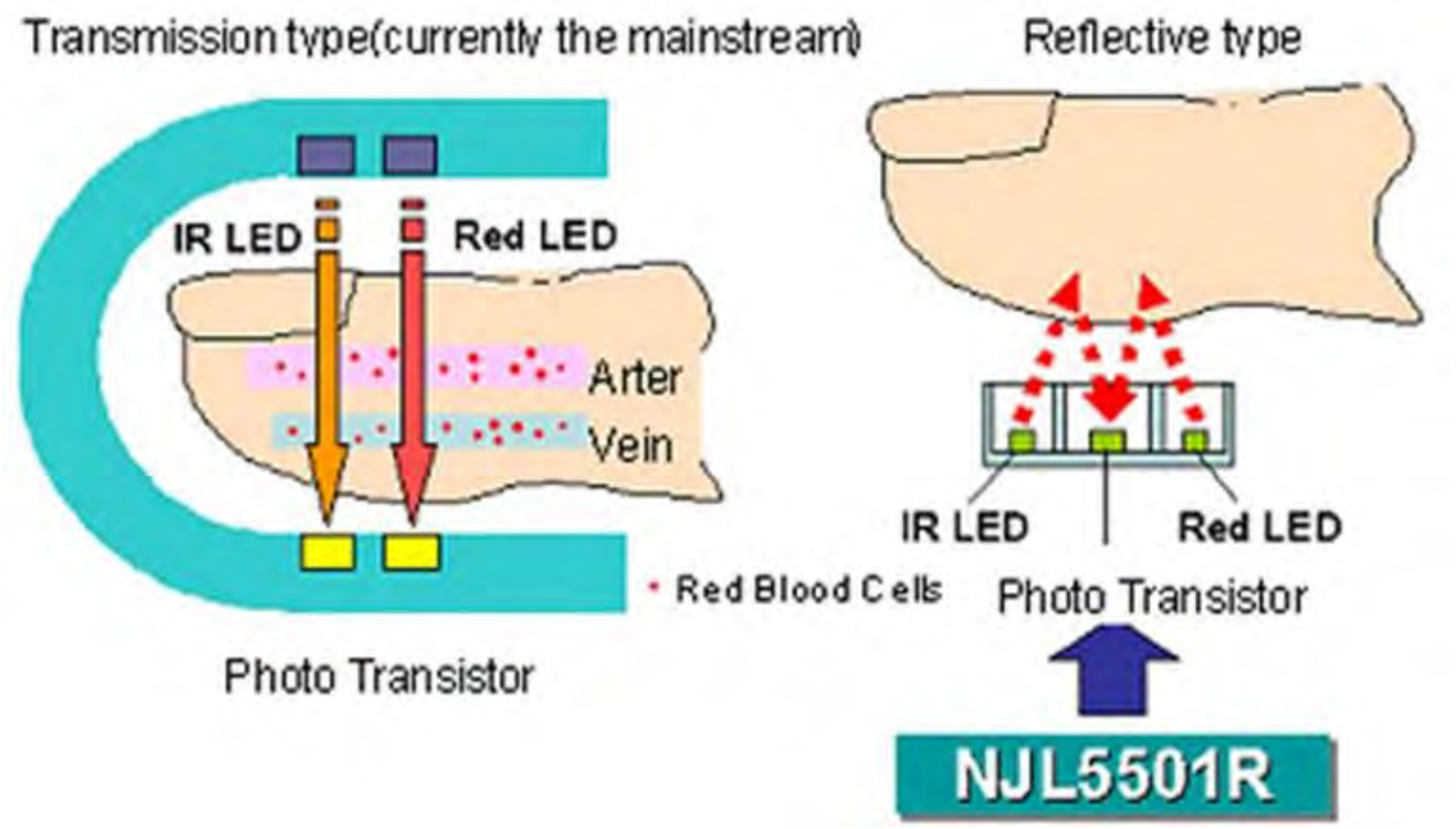
The body absorbs green really well, it's great for reducing signal distortion, but it doesn't penetrate deep. A lot of it is absorbed by your body so you don't get anything deeper than heart rate.

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

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

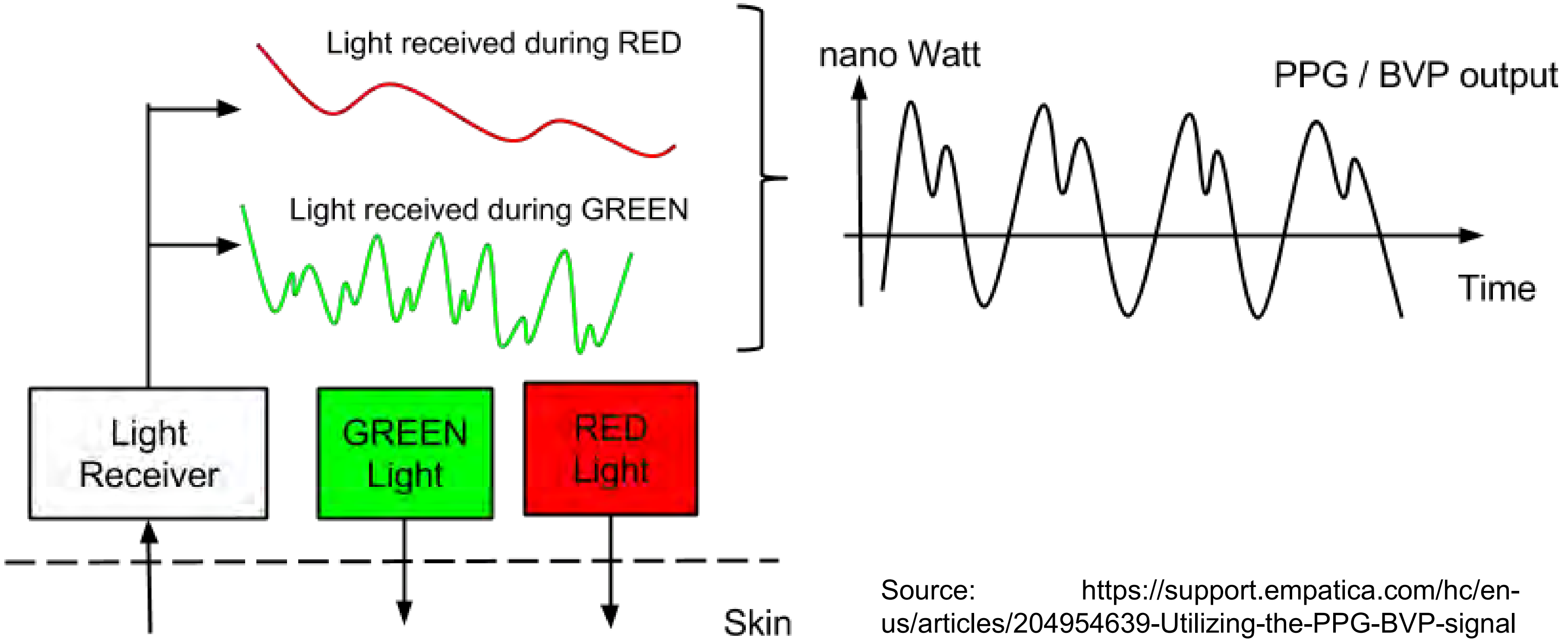
The body is a poor absorber of red light allowing the light to pass much deeper into the body and a larger volume of tissues to help provide more insightful data and could lead to improved accuracy with biometric data like heart rate.

Photoplethysmograph (PPG) …



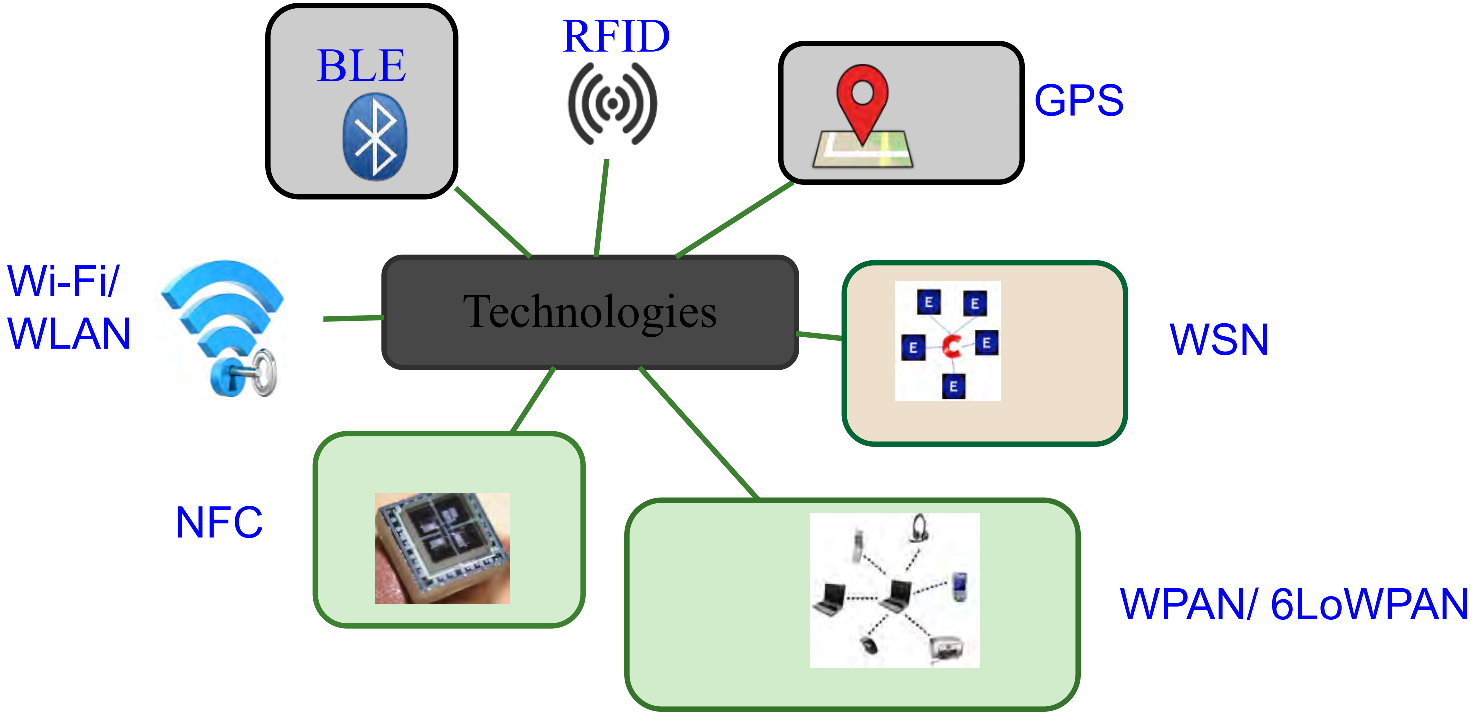
Source: http://www.ee.columbia.edu/~kinget/EE6350_S15/08_PPG1_Girish_Oliver/overview.html

Photoplethysmograph (PPG)



Source: https://support.empatica.com/hc/en-us/articles/204954639-Utilizing-the-PPG-BVP-signal

Smart Healthcare - Communications Technology



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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.

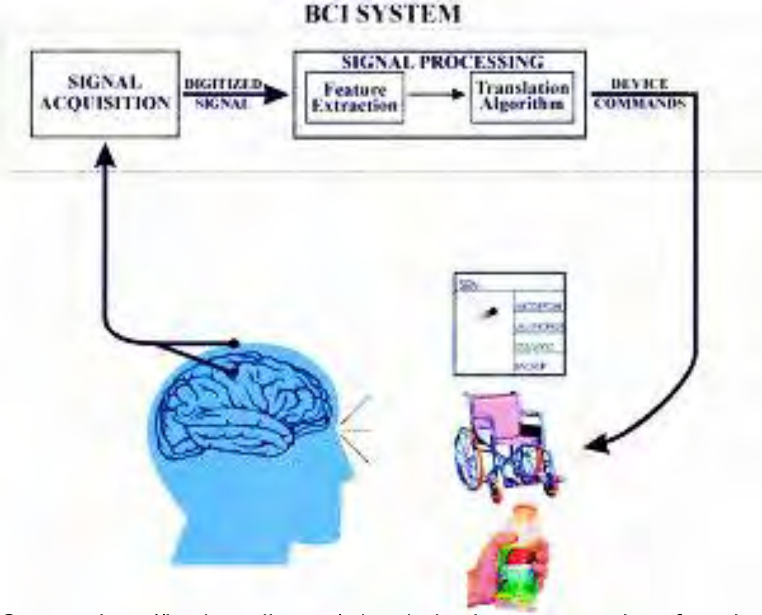
Brain Computer Interface (BCI)

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

-- Neuralink - neurotechnology company - Elon Musk.

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

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

Virtual Reality in Healthcare

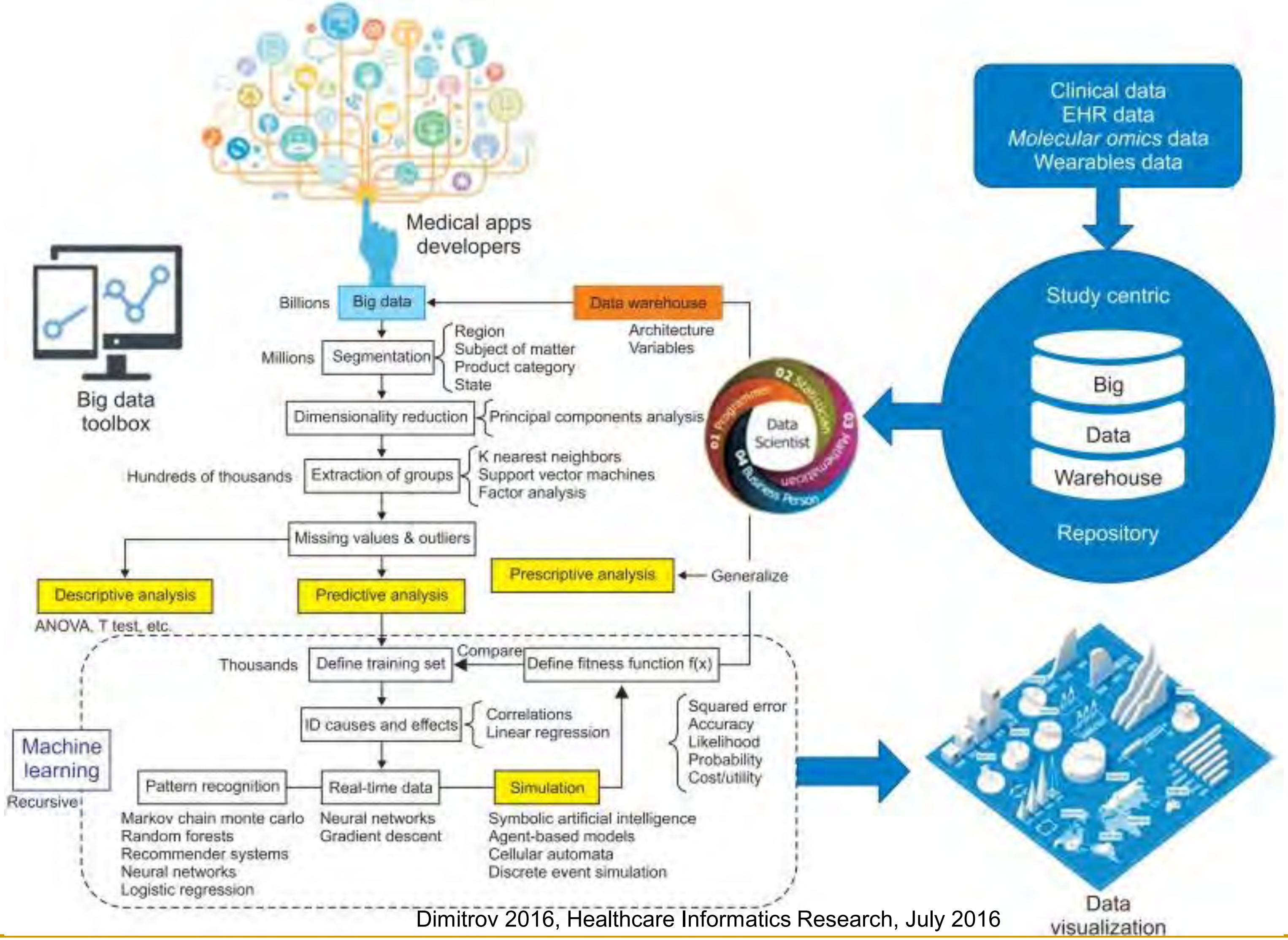
Source: https://touchstoneresearch.com/tag/applied-vr/

In Surgery

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

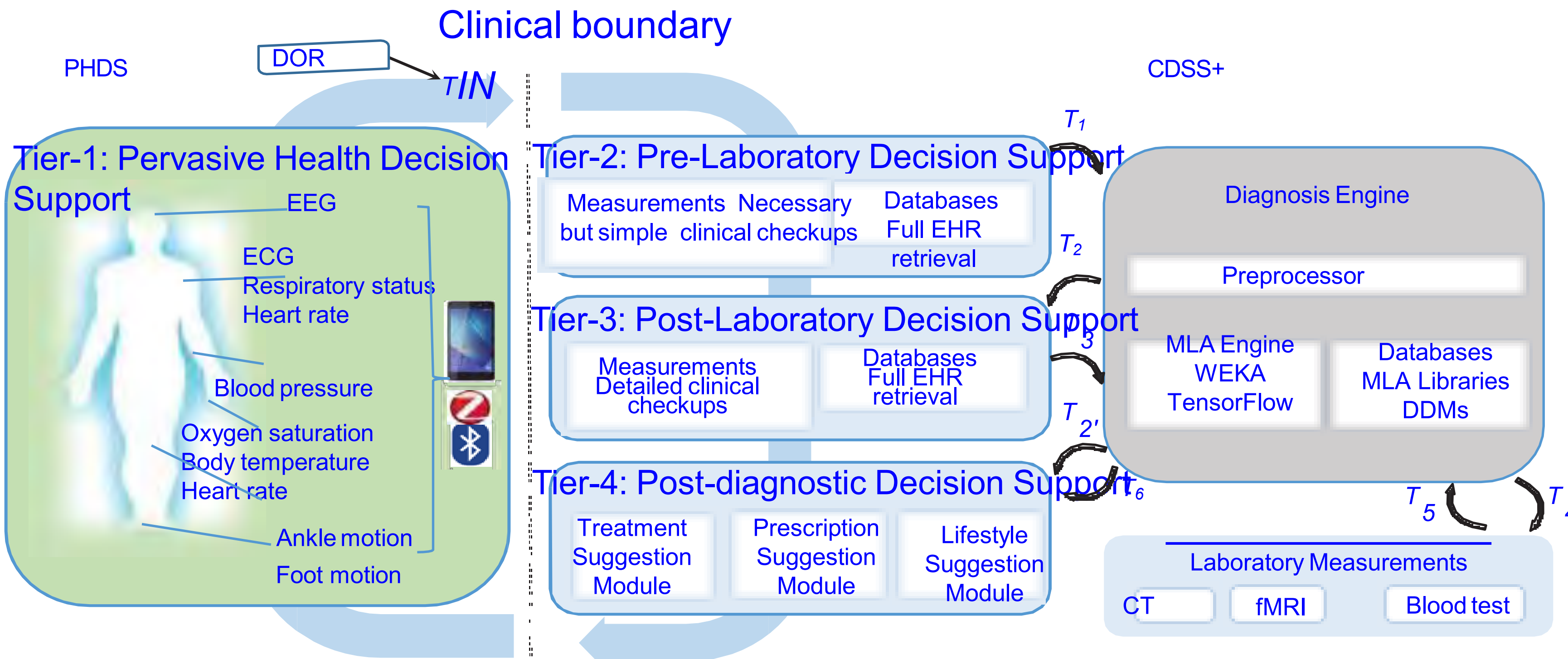
For Therapy

Healthcare CPS – Data



Dimitrov 2016, Healthcare Informatics Research, July 2016

Health Decision Support System (HDSS)



Pervasive Health Decision Support (PDHS)

PHDS-assisted Clinical Decision Support System (CDSS+)

Ti - Transition i, DDM - Disease Diagnosis Modules,
DOR - Disease-Onset Record, MLA - Machine Learning Algorithm

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 Framework

Smart Healthcare - System and Data Analytics : To Perform Tasks

Systems & Analytics

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

Machine Learning Engine

Data

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

Systems & Analytics

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

Machine Learning Engine

Data

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

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

Machine Learning (ML)

Supervised ML

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

Enhancement Techniques

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

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

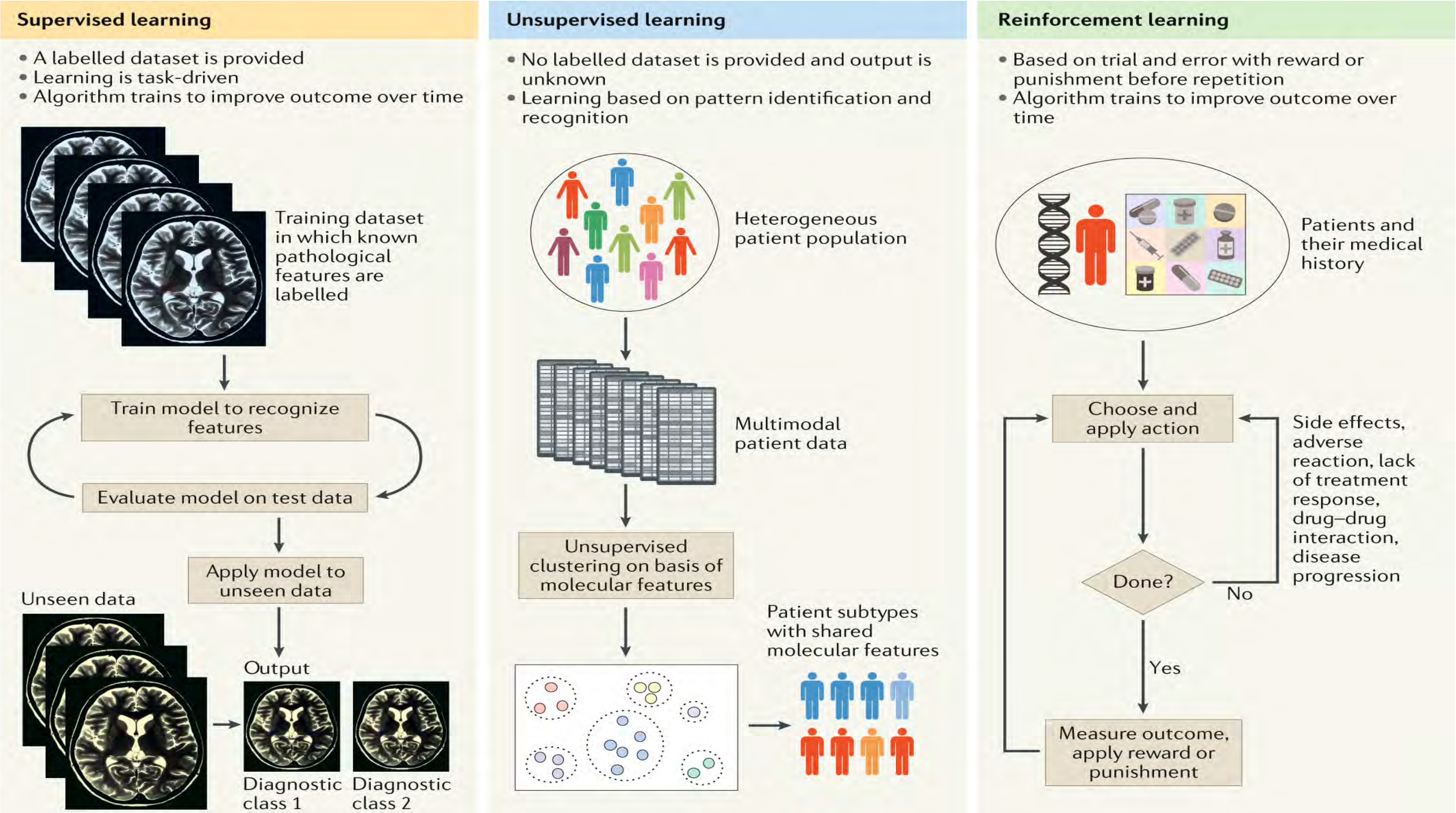
Smart Healthcare – AI/ML is Key

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 Electronic Systems Laboratory (SESL)

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

Crowdsourcing for Smart Cities

Smart Healthcare Data Gathering (Diet Dataset, Healthcare Dataset)

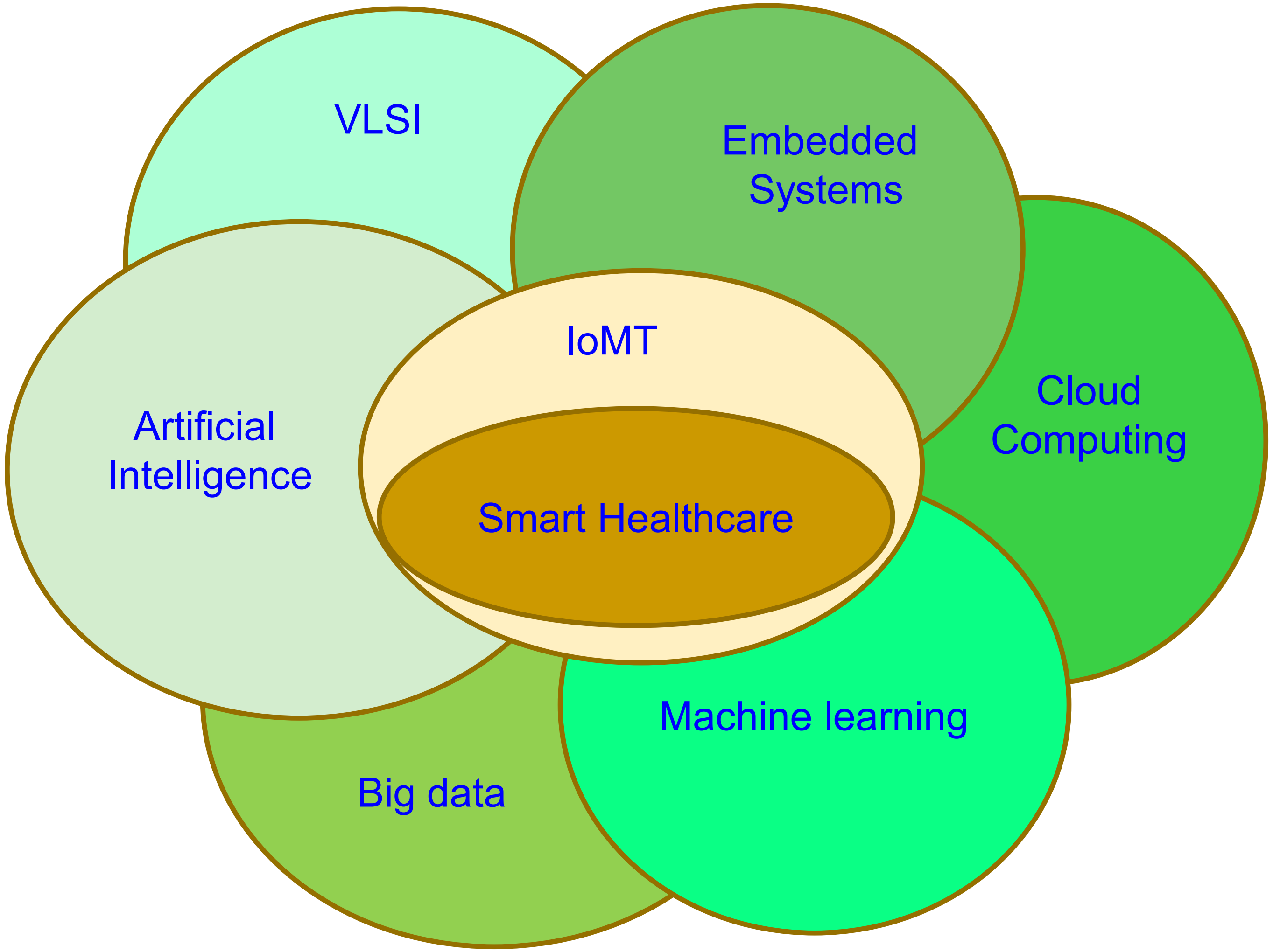
Last-Mile Logistics (Package Pickup Delivery)

Crowdsourcing for Smart Cities

Urban Data Gathering (Bike Data, Energy Usage Data)

City Service Monitoring (Park Maintenance, Waste Disposal)

Smart Healthcare - Verticals



Smart Healthcare – Specific Examples

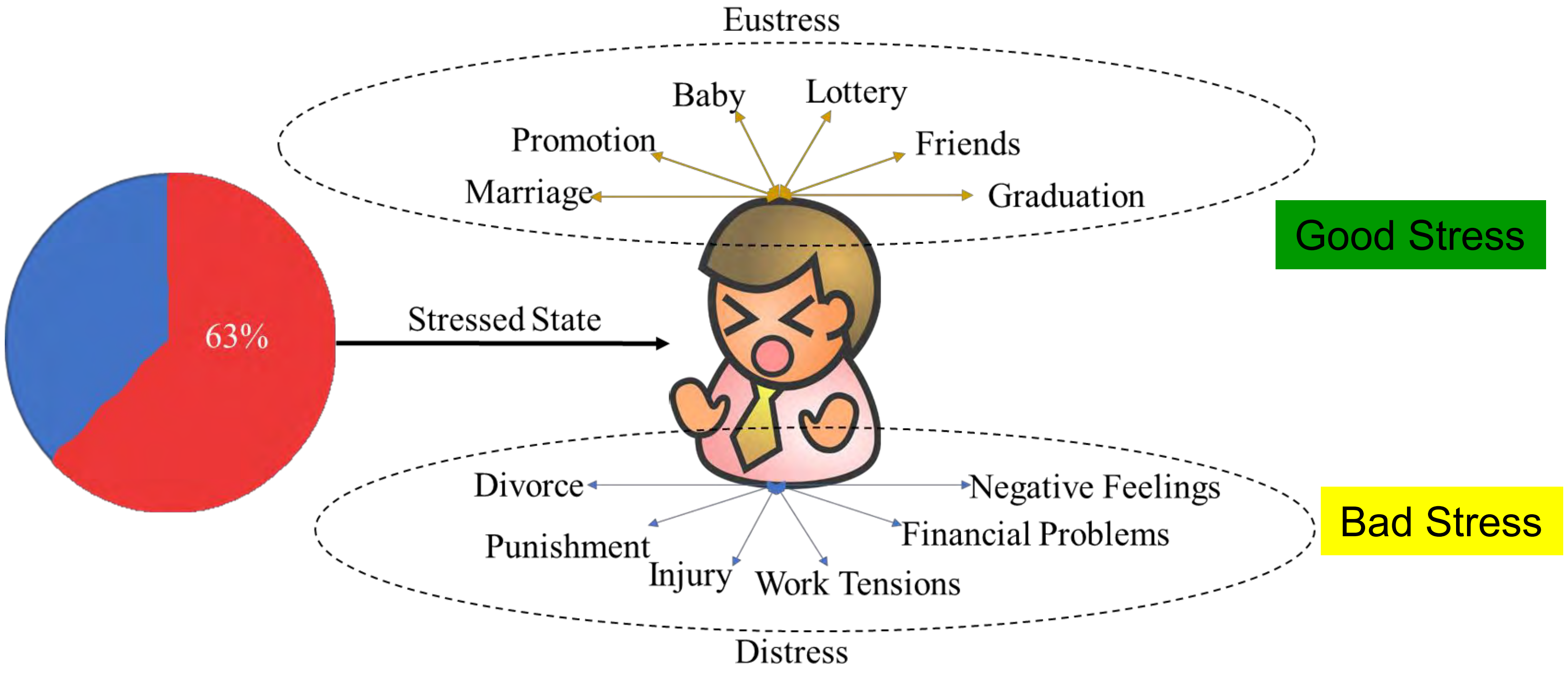
Symptoms of Stress

Stress is a Global Issue

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

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

What is Stress?



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

Why Stress Needs to be Resolved?

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

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

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

Distress

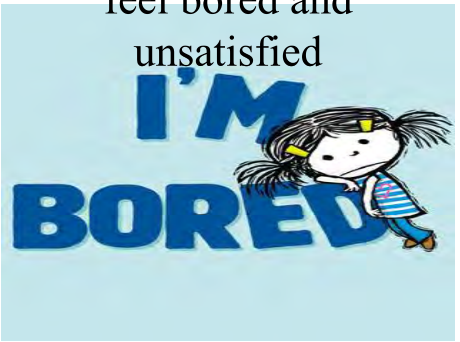
Eustress

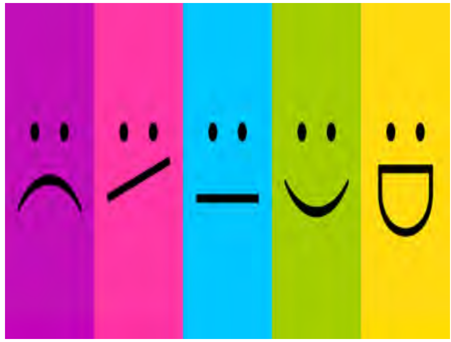
How is stress detected?
(techniques)

1. DETECTING EMOTIONAL AND COGNITIVE SIGNS OF STRESS

Recognize feeling overwhelmed

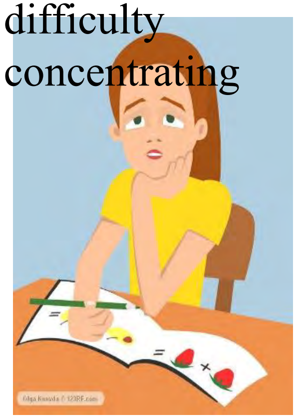
Consider whether you feel bored and unsatisfied





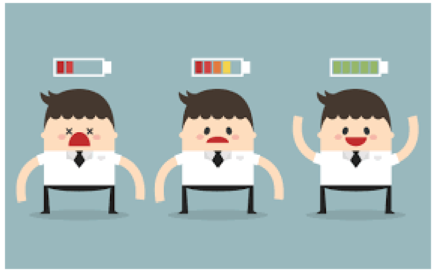
Look for mood changes

Recognize difficulty concentrating



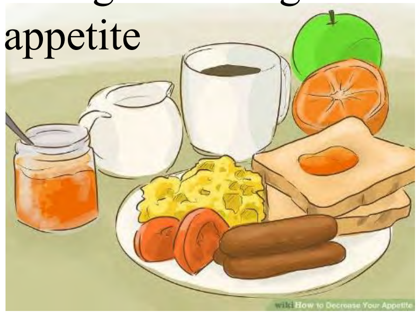
How is stress detected? (contd..)

2. Looking for Physical and Behavioral Signs of Stress



Notice your energy levels

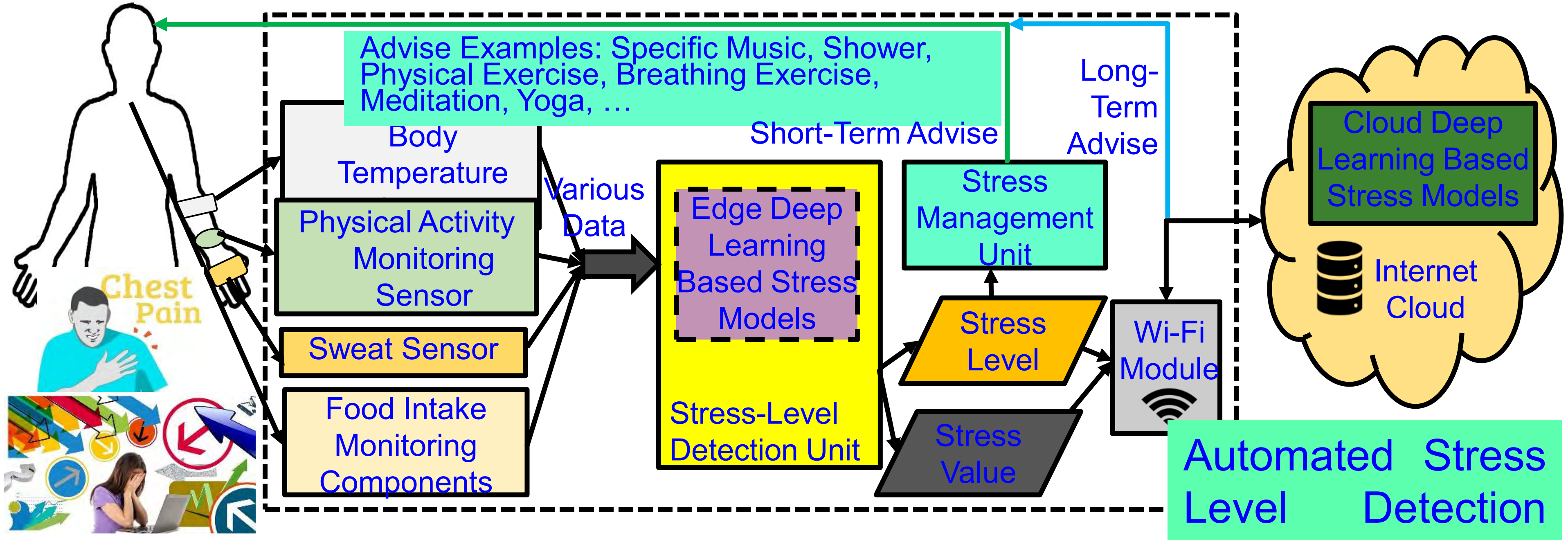
Recognize changes in appetite



Pay attention to aches and pains

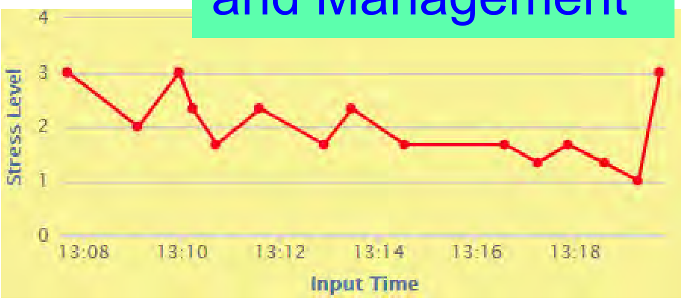
Look for sleep issues

Smart Healthcare - Stress Monitoring & Control



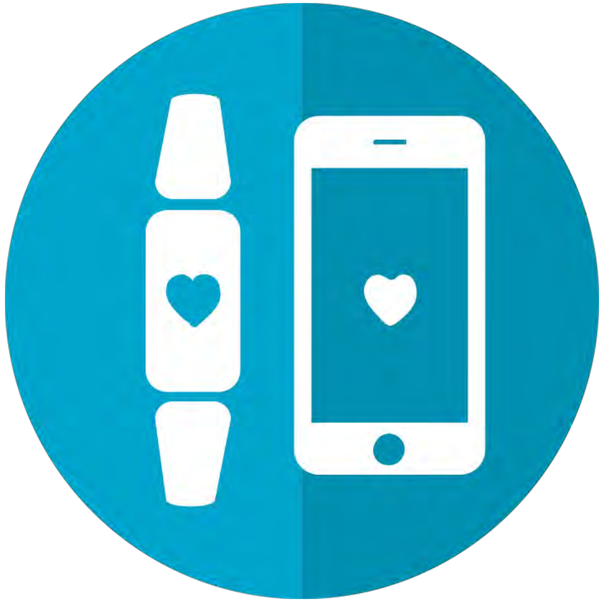
Automated Stress Level Detection and Management

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



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

Existing Products



Muse-EEG

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

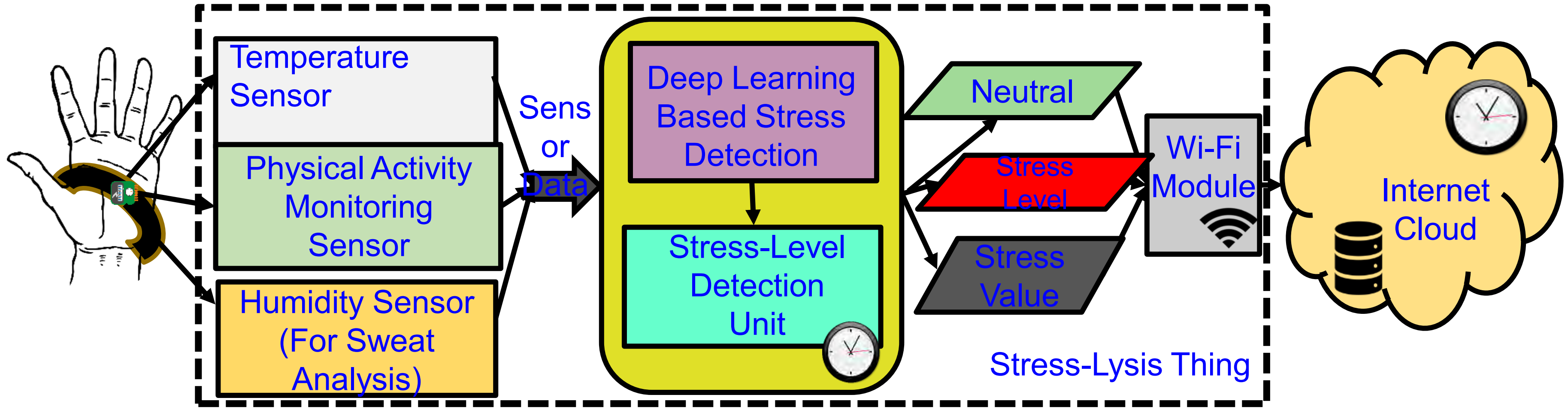
Source: R. K. Nath, H. Thapliyal, A. Caban-Holt, and S. P. Mohanty, "Machine Learning Based Solutions for Real-Time Stress Monitoring", *IEEE Consumer Electronics Magazine (MCE)*, Vol. 9, No. 5, September 2020, pp. 34--41.

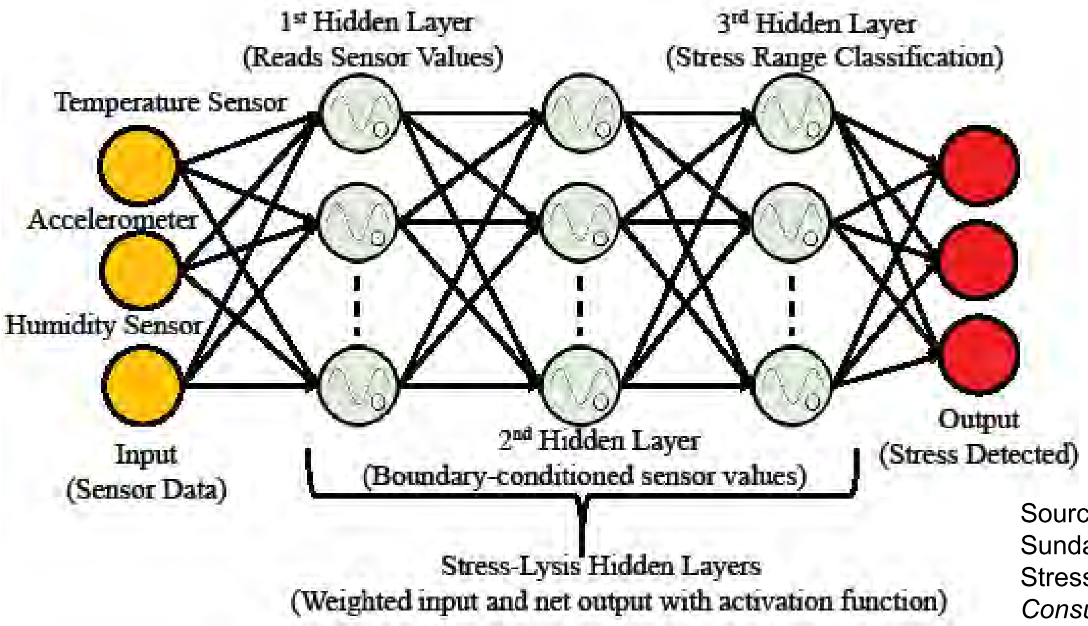
Stress-Lysis: Research Question

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

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

Stress-Lysis: From Physiological Signals



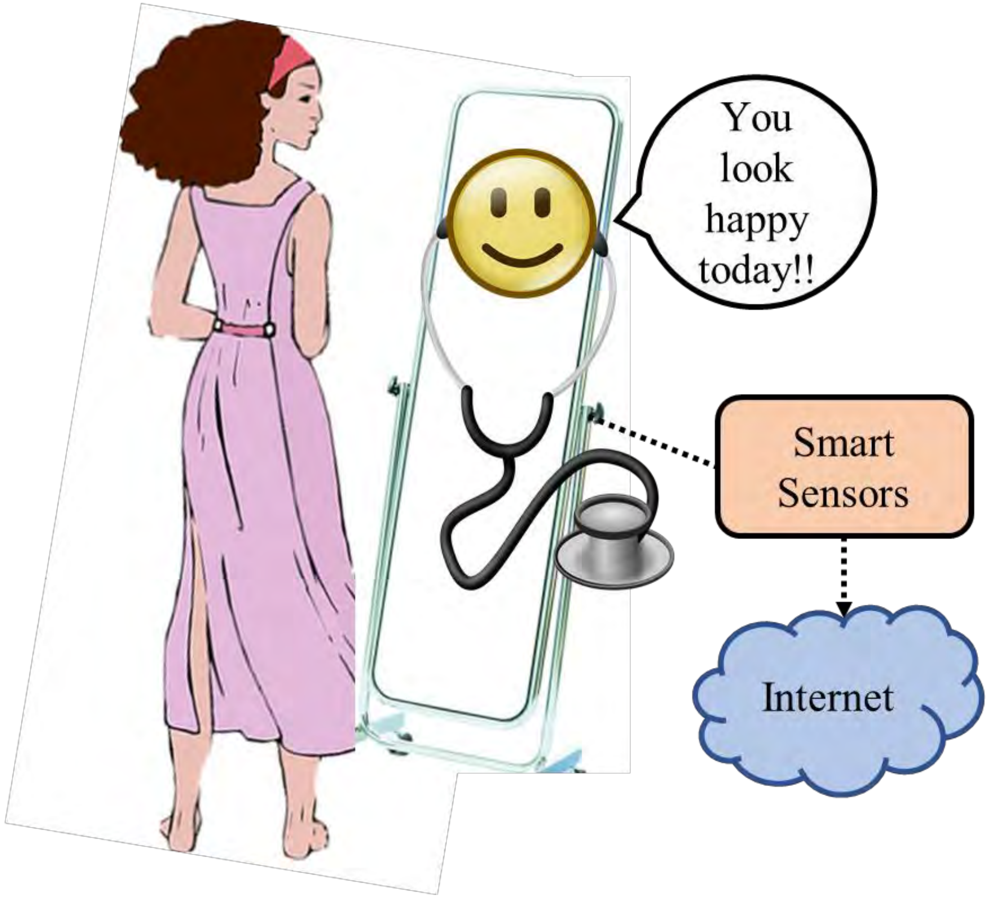


Stress-Lysis - DNN has been trained with a total of 26,000 samples per dataset and has accuracy upto 99.7%.

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.

Proposed Solution- iStress

✓ **Conceptual Overview of the iStress System.**



Novel Contributions

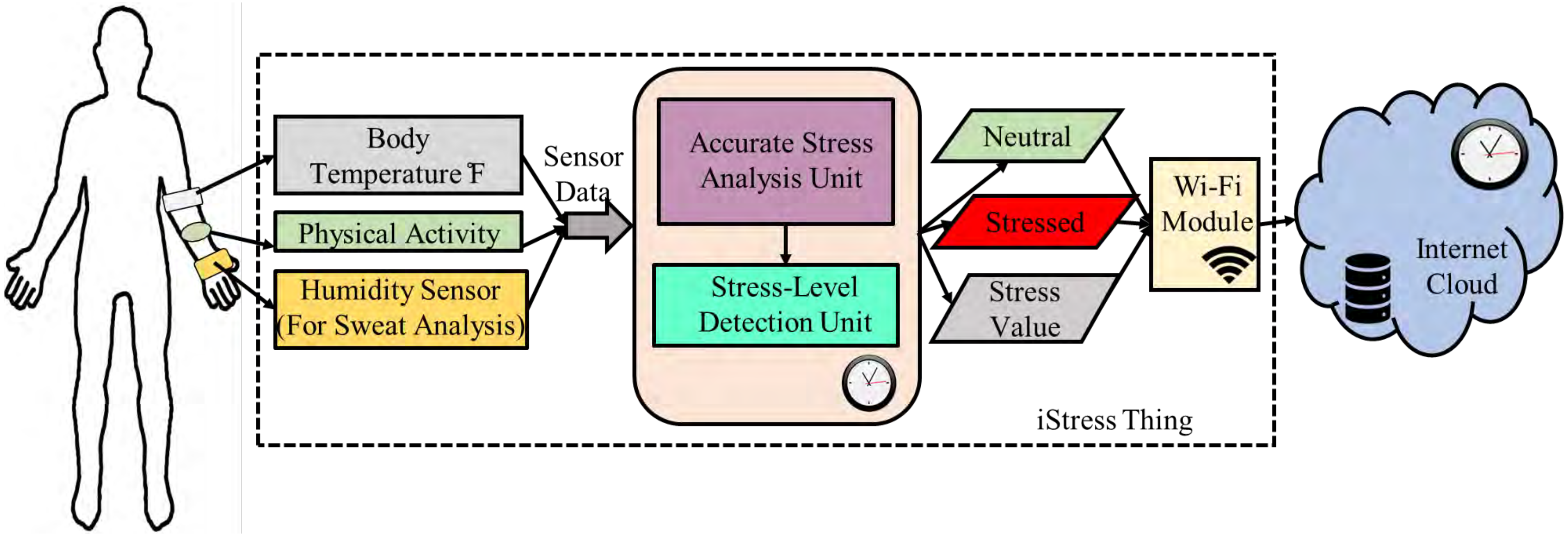
- Stressor – Physical Activity.
- A novel sensor that uniquely quantifies the body temperature, rate of motion, and body sweat accurately and quickly to detect stress level is presented.
- A novel IoMT-enabled system for stress analysis at the edge and not at the cloud is proposed, thus advancing the state-of-the-art in the IoMT.

Issues Addressed in this Research

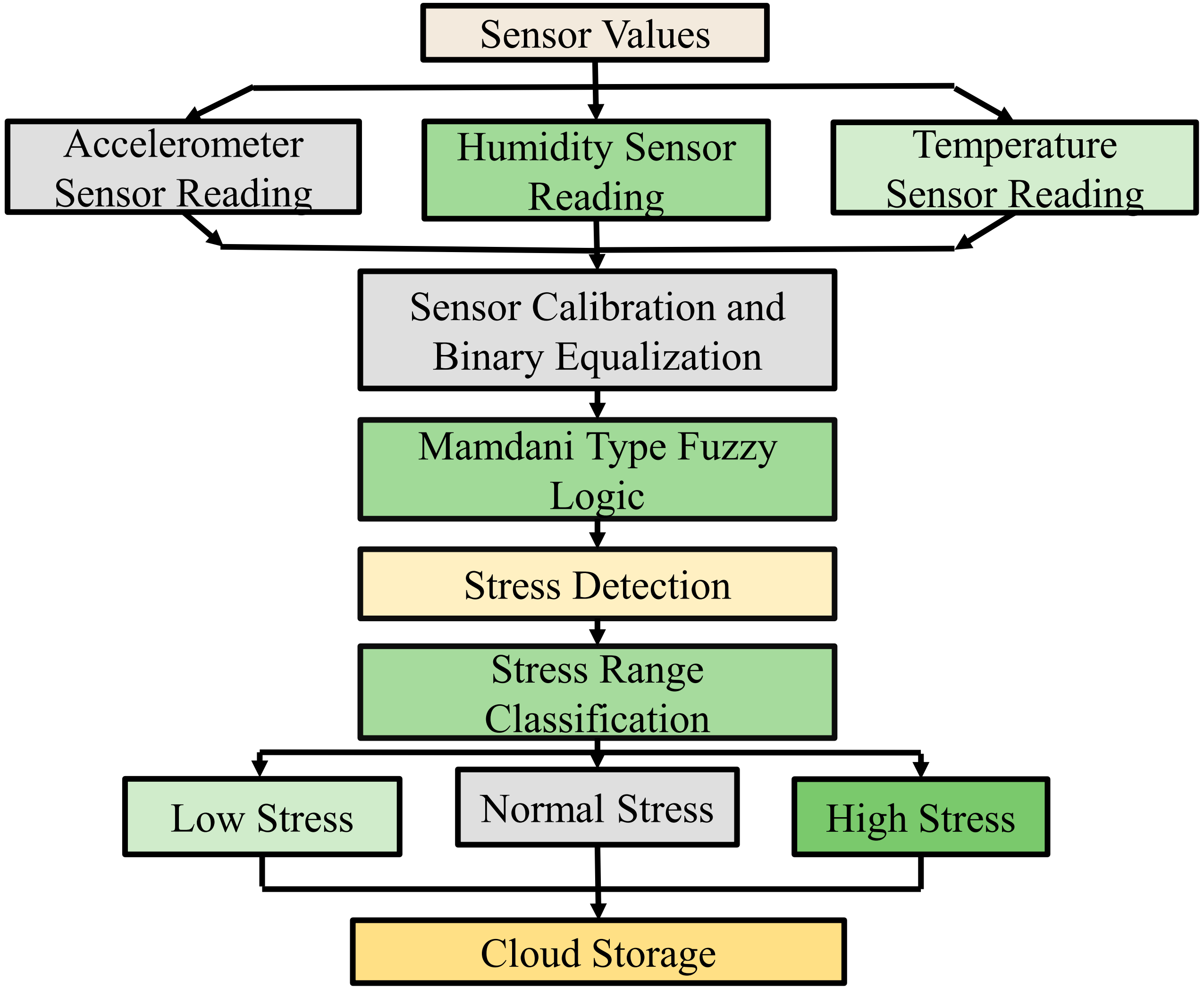
- Advancement through this paper in Electronics.
- Significant Improvement in the Accuracy of Stress Level Detected
- Considered Multiple Stressors for the detection.
- Provided cloud storage access for future purposes.
- Proposed a self-aware system which is intelligent enough to detect the stress levels.
- An edge level system is presented with which the performance, accuracy and stabilization of the system can be maintained.

The Proposed Novel iStress System

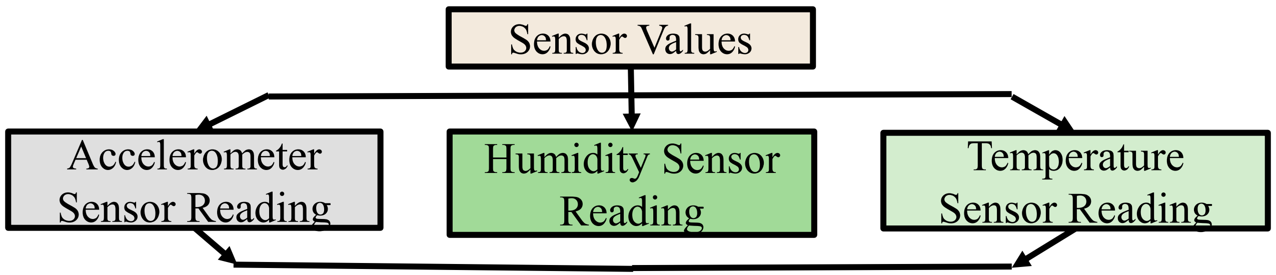
✓ **Proposed Architecture of the iStress System.**



The Proposed Novel iStress Flow



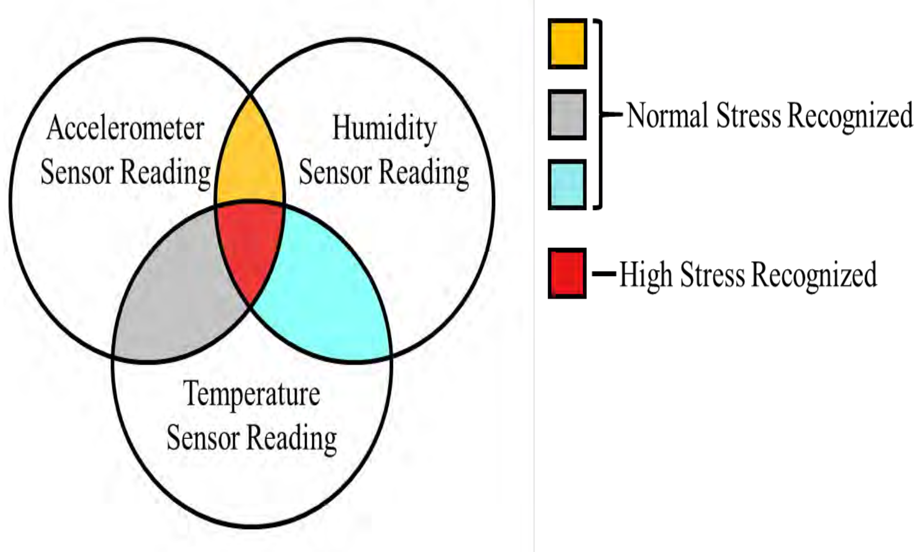
Flow of the iStress Model



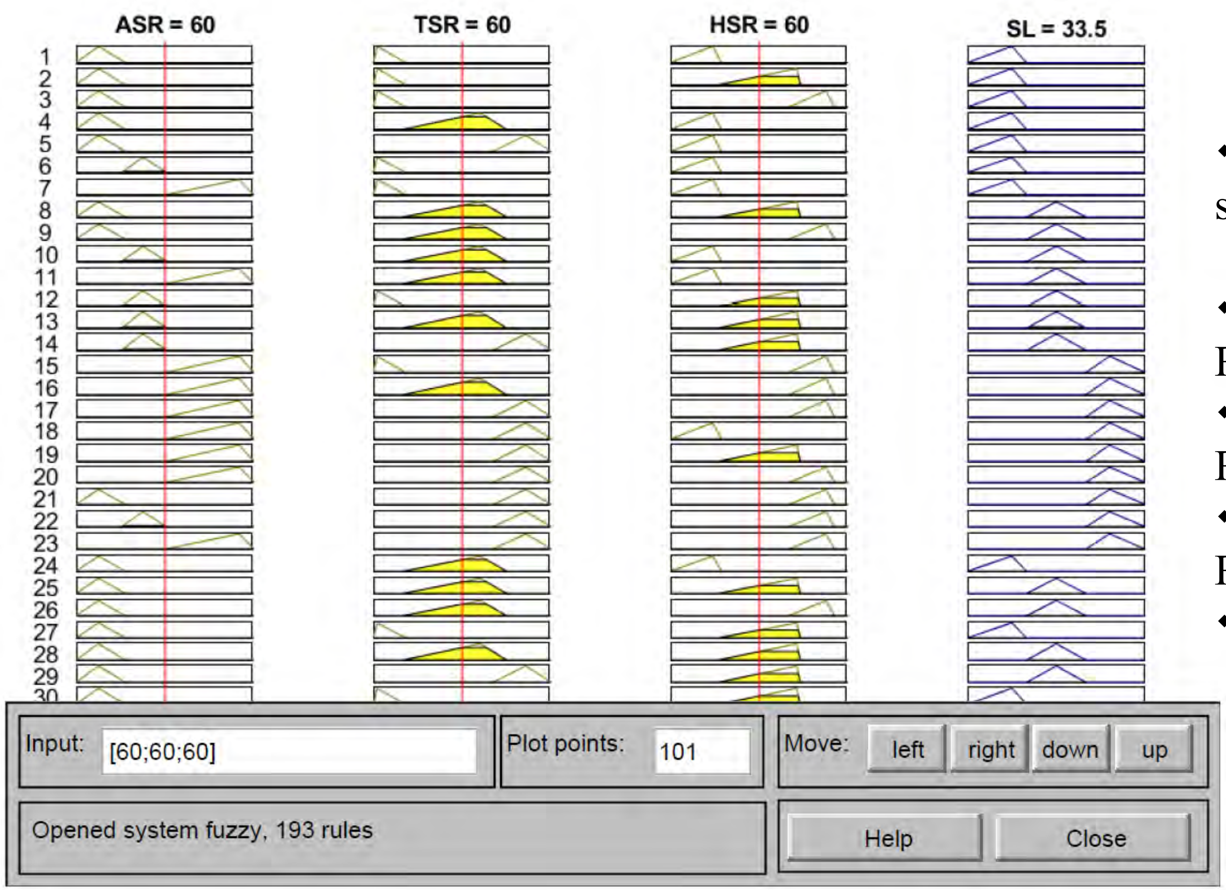
- The general step rate of a person in a strenuous physical workout is high if it is greater than 100 steps per minute.
- When a person is not stressed and is in normal condition the proposed accelerometer sensor value is reduced to 50 steps per minute.
- The lower the temperature of the human body, the palm portion of the hands becomes cold. Colder palms are a symptom of a person under stress.

Sensor Calibration

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

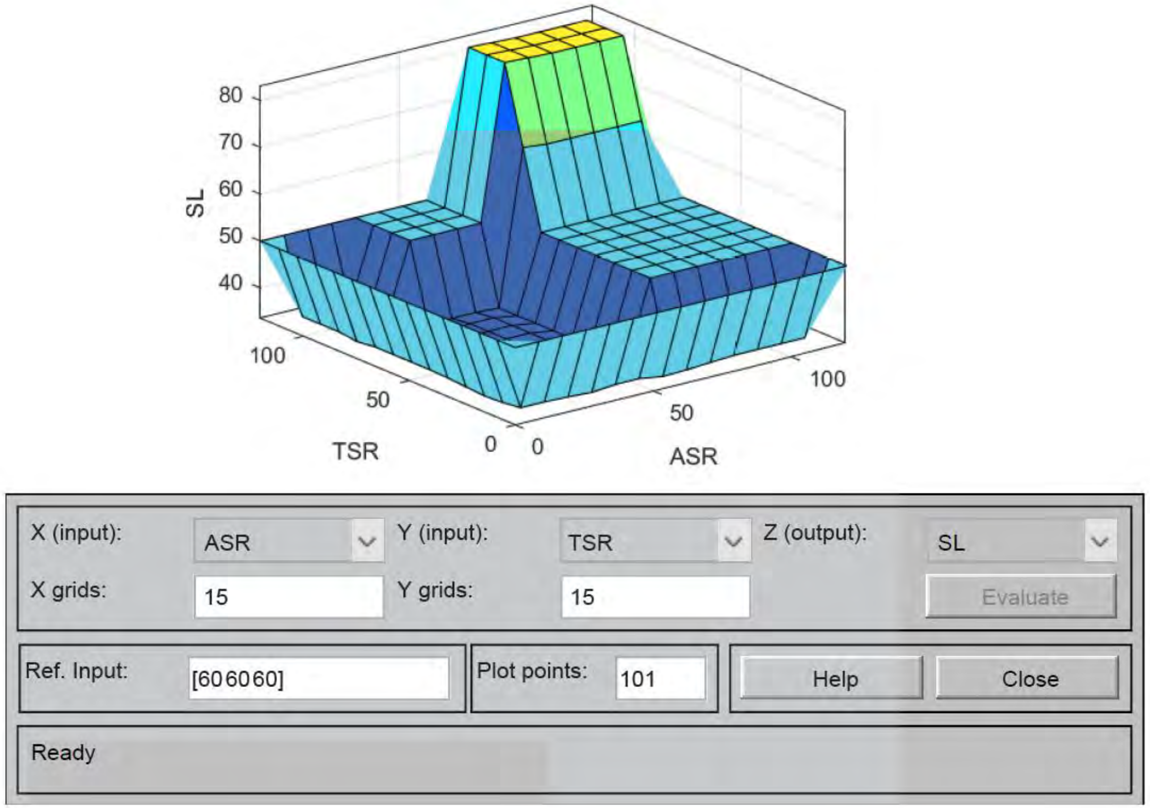


Grid Partitioned View of Rules

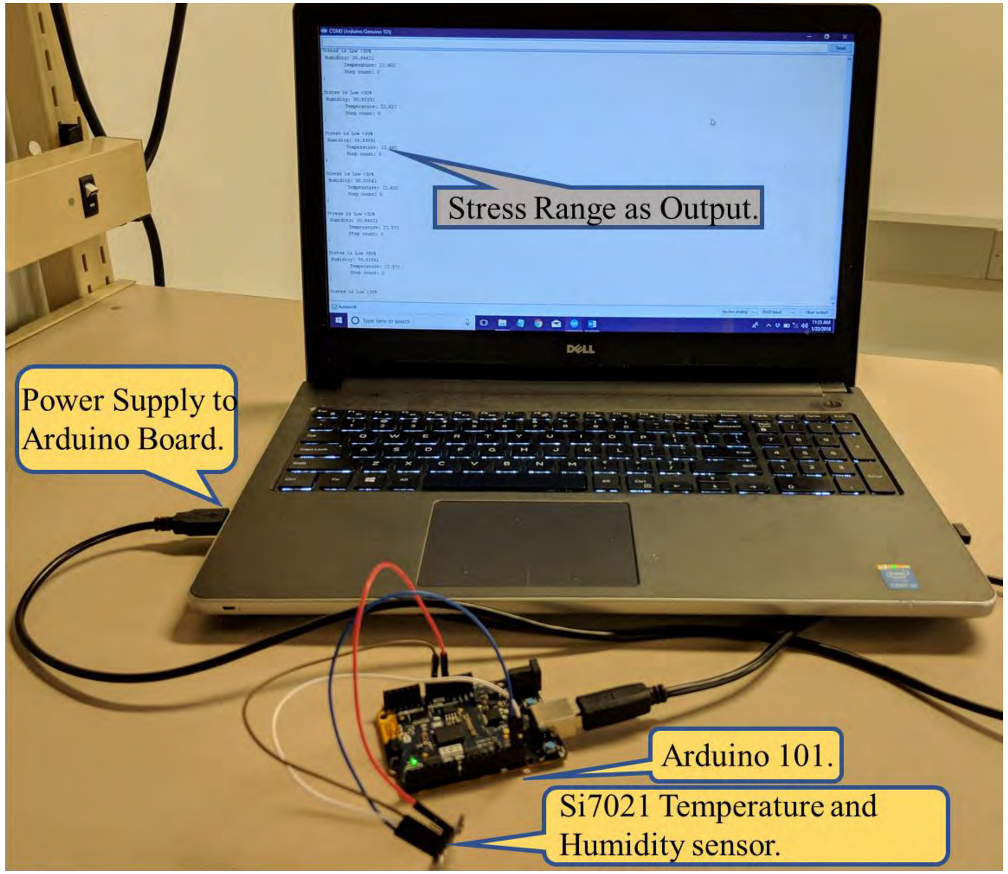


- ❖ The system is trained by a set of 150 rules
- ❖ ASR- Accelerometer Sensor Reading
- ❖ TSR- Temperature Sensor Reading
- ❖ HSR- Heart Rate Sensor Reading
- ❖ SL- Stress Level

Surface Plot of iStress



CE Implementation and Validation



❖ An Adafruit Si7021 Temperature and Humidity Sensor along with Arduino/Genuino 101 were used.

Stress Detection in iStress

COM3 (Arduino/Genuino 101)

Stress is High >60%-100%		
Humidity: 97.22953	Temperature: 32.433	Accelerometer: 101
Stress is High >60%-100%		
Humidity: 97.16853	Temperature: 32.373	Accelerometer: 109
Stress is High >60%-100%		
Humidity: 97.13803	Temperature: 32.393	Accelerometer: 119

High Stress Detection

COM3 (Arduino/Genuino 101)

Stress is Normal >30%-<60%		
Humidity: 92.93203	Temperature: 32.122	Accelerometer: 88
Stress is Normal >30%-<60%		
Humidity: 90.94203	Temperature: 32.002	Accelerometer: 98
Stress is Normal >30%-<60%		
Humidity: 89.98903	Temperature: 28.172	Accelerometer: 120

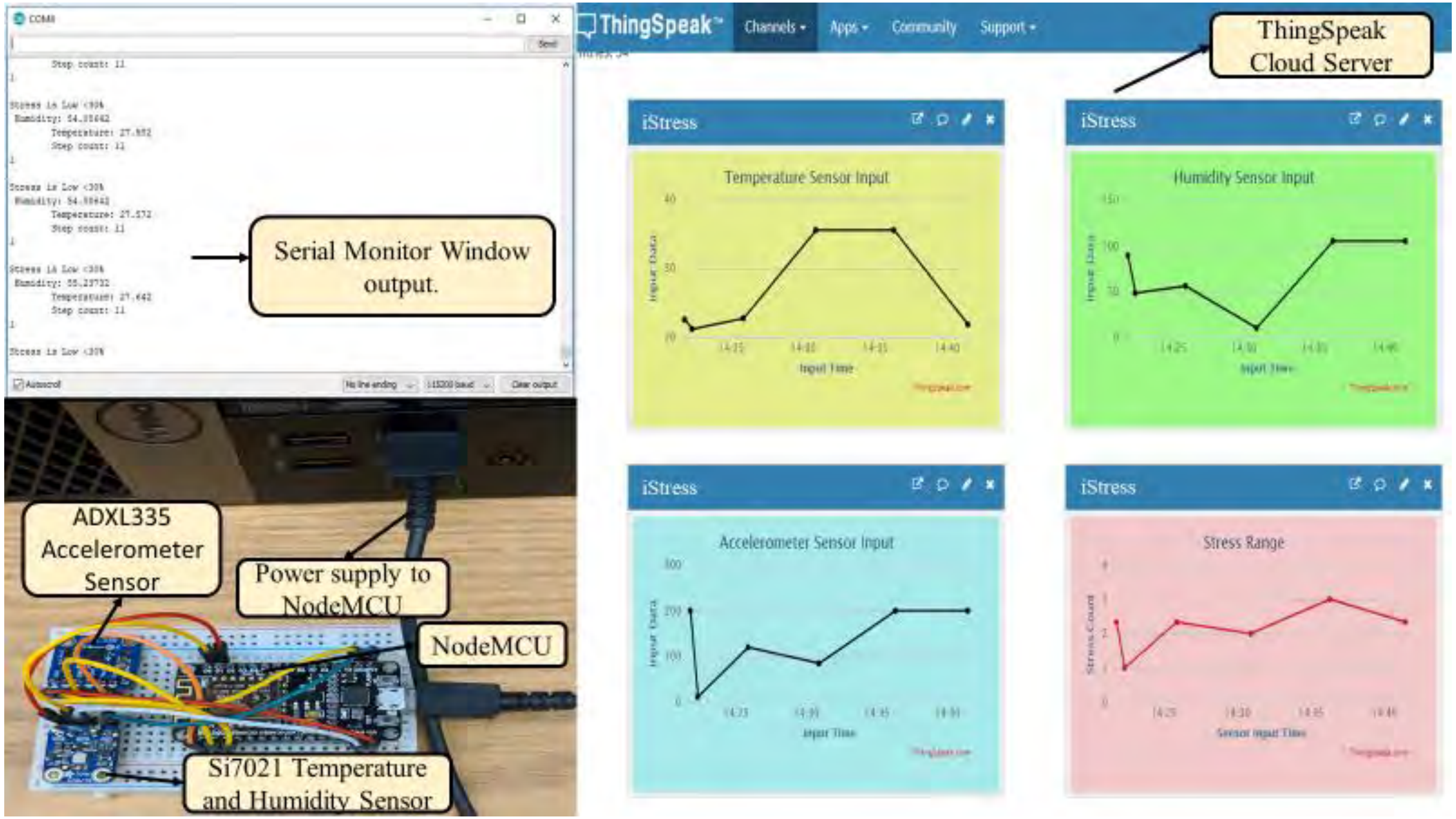
Medium Stress Detection

COM3 (Arduino/Genuino 101)

Stress is Low <30%		
Humidity: 36.25541	Temperature: 25.452	Accelerometer: 25
Stress is Low <30%		
Humidity: 44.21731	Temperature: 28.842	Accelerometer: 67
Stress is Low <30%		
Humidity: 78.98903	Temperature: 32.172	Accelerometer: 120

Low Stress Detection

Stress-Lysis: Experiments



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.

Conclusion and Future Research

- The detected stress value is classified to three levels: low, normal and high.
- This method helps in improving and controlling the overall stress levels of a person.
- Implementation of the system incorporating deep learning concepts are suggestions for future research.

Smart-Pillow: Research Question

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

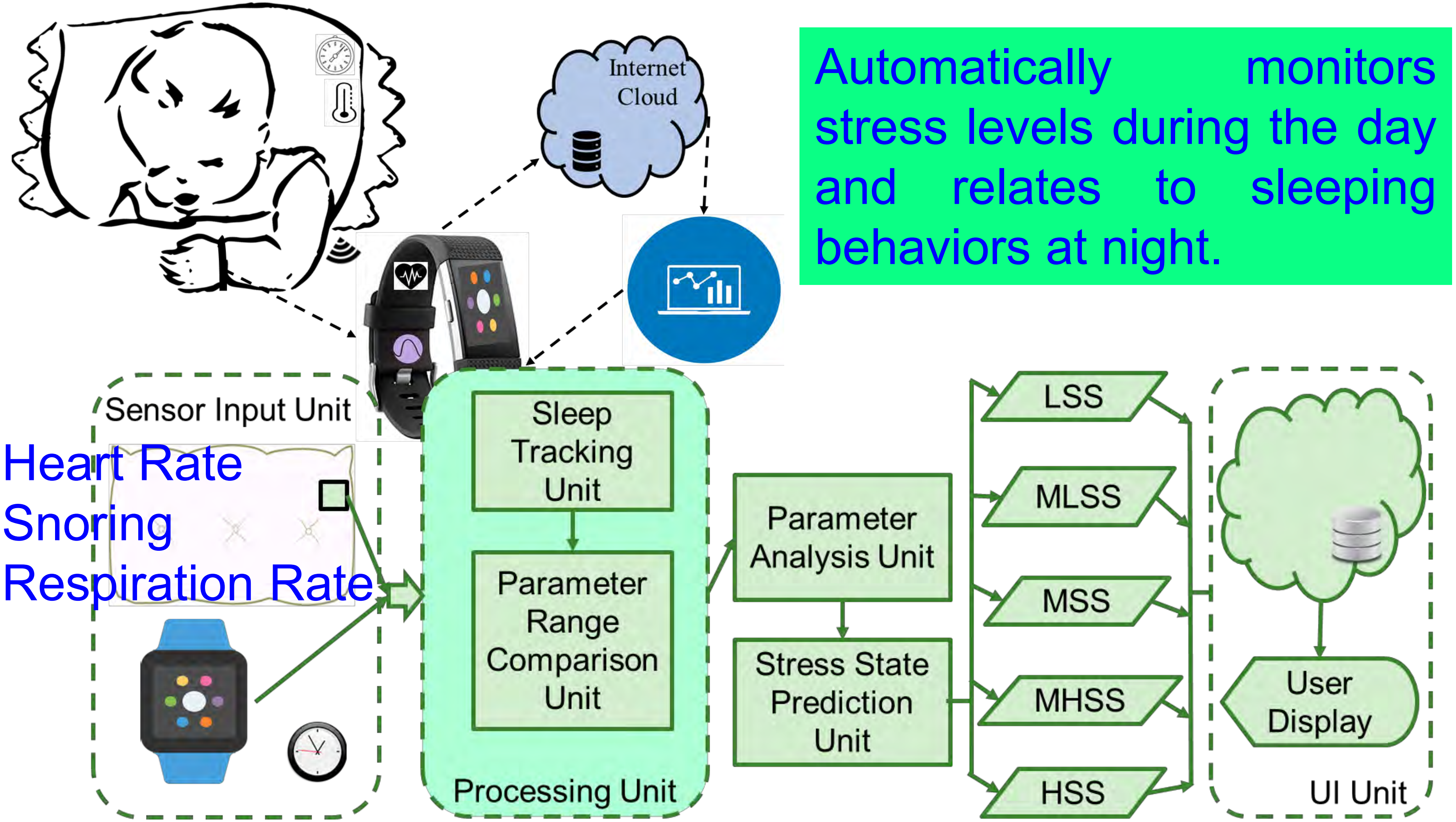
Source: Mohanty iSES 2018: "Smart-Pillow: An IoT based Device for Stress Detection Considering Sleeping Habits", in *Proc. of 4th IEEE International Symposium on Smart Electronic Systems (iSES)* 2018.

Consumer Electronics Sleep Trackers

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

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

Smart Healthcare – Smart-Pillow



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

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

Parameter Ranges

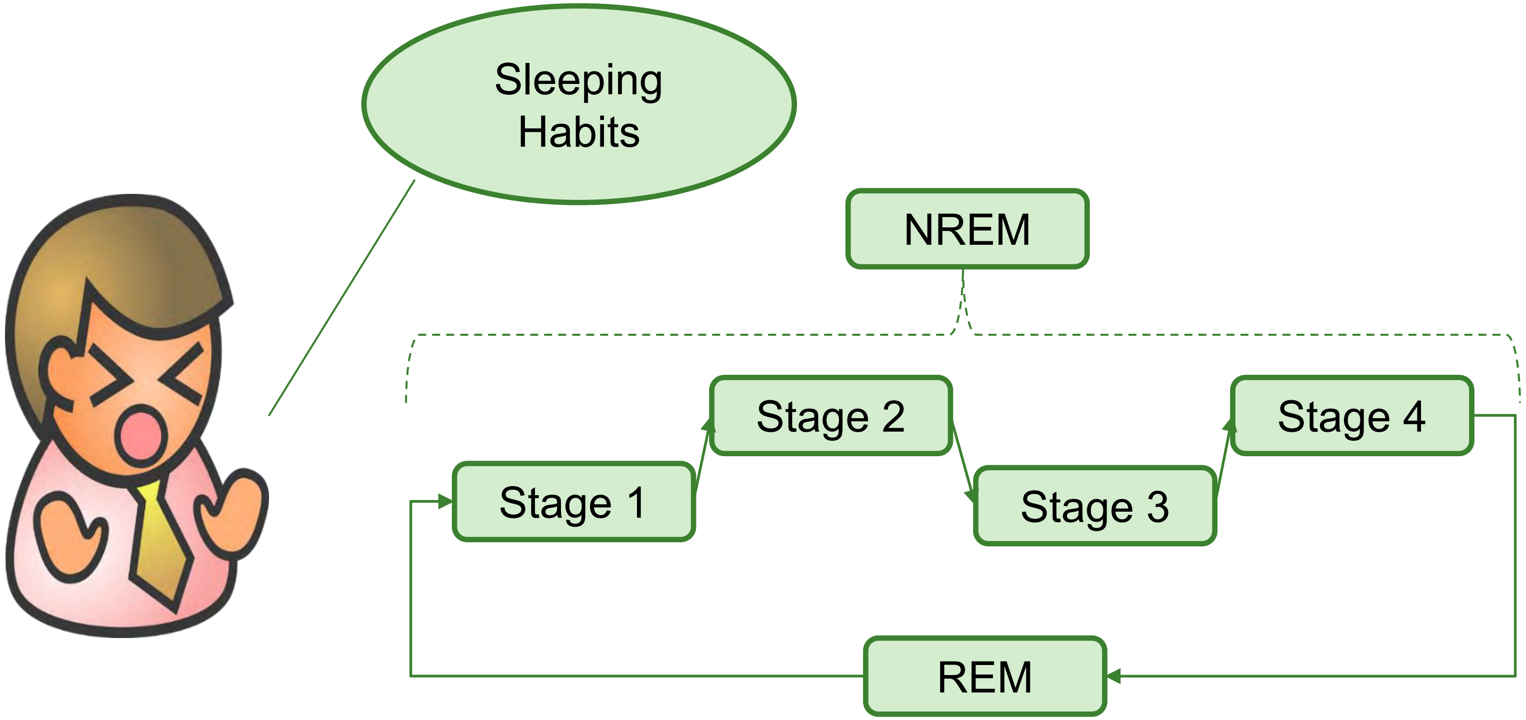
Snoring Range (dB)	Respiration Rate (bpm)	Heart Rate (bpm)	Stress State
50-60	17-19	54-57	LSS
60-70	19-21	57-60	MLSS
70-80	21-22	60-64	MSS
80-89	23-25	65-70	MHSS
90+	25+	70+	HSS

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

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

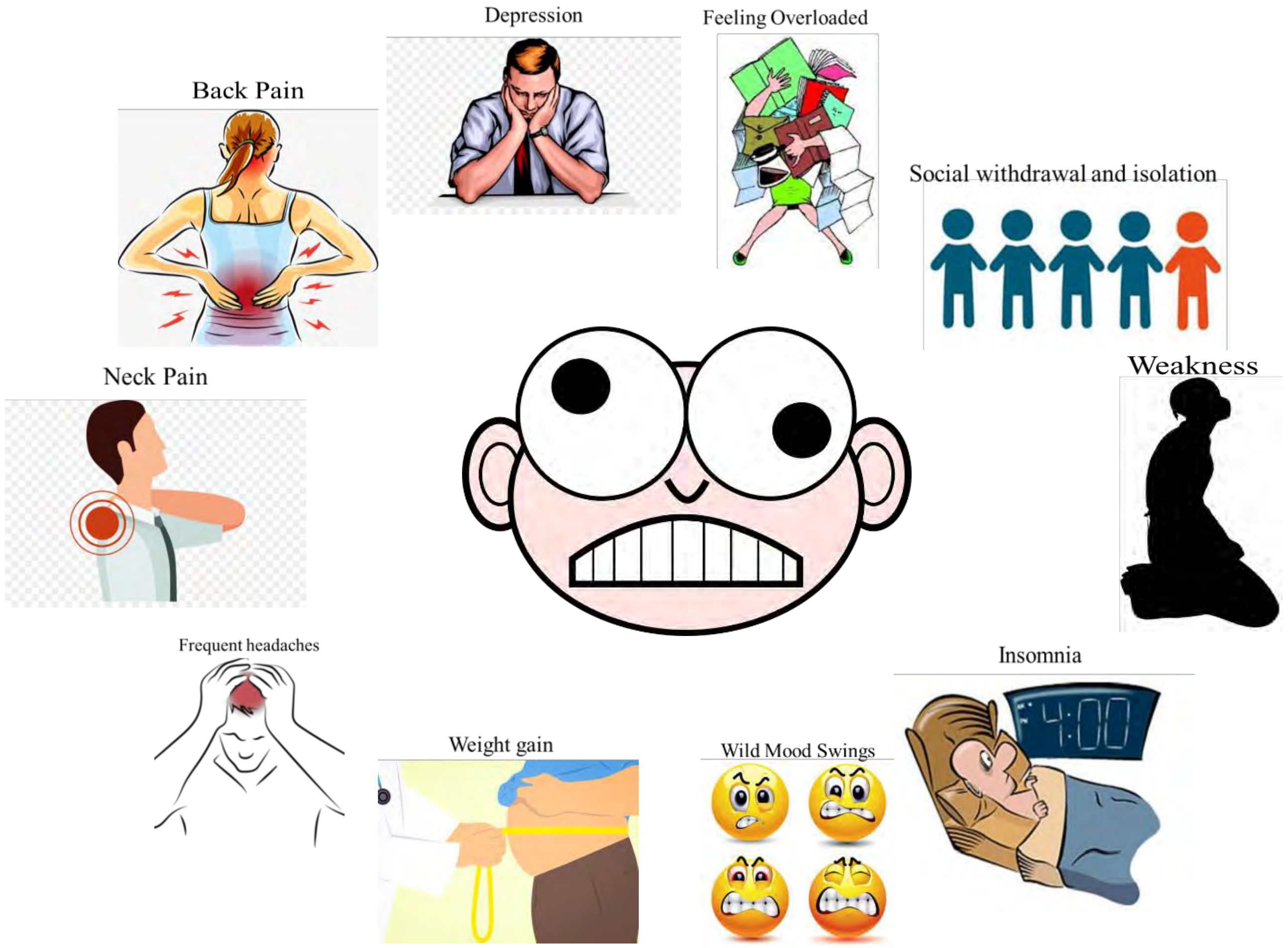
Research Motivation

✓**Is sleep an important factor of Stress?**

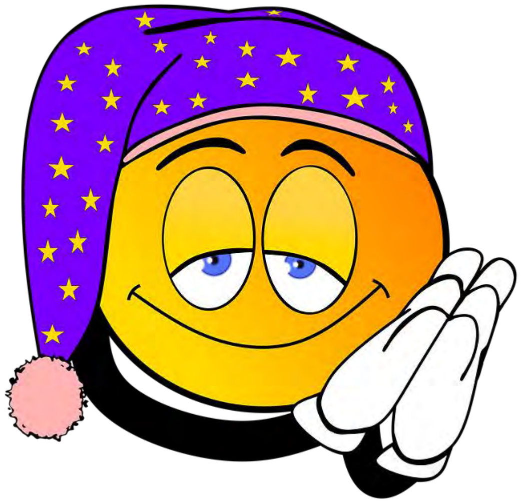


The quality of sleep during the night reflects on productivity during the day.

Symptoms of Improper Sleep



How to Monitor Sleep?



Existing Products

sleepscore labs

EverSleep

Related Research

Research	Method	Drawback
Choi et al [6]	Wearable	Importance of sleep to stress is missing.
J.-M. Lee et al [10]	Survey by Wearables	Study of sleep is mentioned but couldn't establish a relationship among stress and sleep.
Zhenyu Chen et al [11]	Mobile Application	The accuracy of the system cannot be trusted as the user will have to manually enter the data also the relationship with stress is missing.

Issues of Existing Solutions

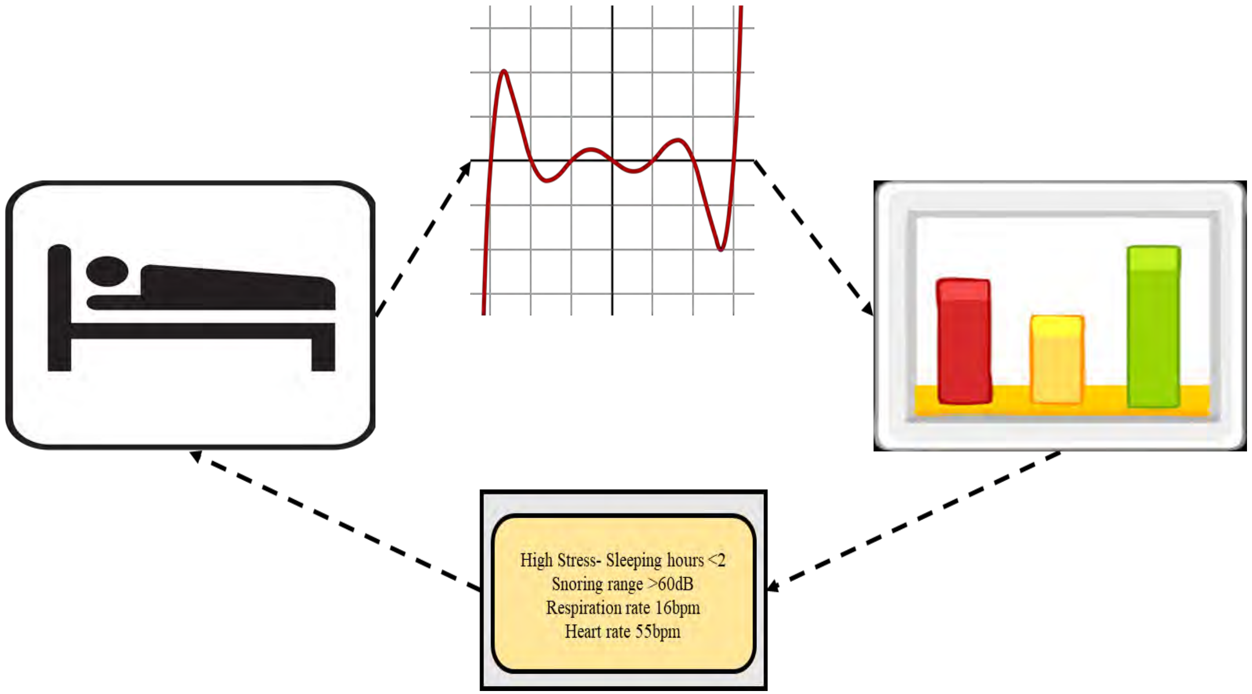
- ❖Lack of Detection Accuracy of Sleep.
- ❖Lack of having multiple stressors for effective sleep analysis.
- ❖No Unified detection of the problem.
- ❖Storage availability of the detected parameters for future usage.
- ❖Self-Aware systems.
- ❖Lack of knowledge on the relationship among stress and sleep.

The Research Question Addressed in this Paper

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

Proposed Solution: Smart-Pillow

✓ **Schematic Representation of Smart-Pillow.**



- This research proposes the idea of a Smart-Pillow connected to a wireless tracker as a device to help monitor sleeping habits and let the user know using a wearable.

Novel Contributions

- A continuously monitoring battery optimized device which gets activated only when a person is lying on a bed.
- A non-invasive technique which allows the person to analyze behavior considering sleeping habits.
- Determining the stress state of a person based on the sleeping pattern through out the night.
- Providing diagnostic results and home remedies in order to maintain or control the stress variations based on their characteristics for future improvement.
- Allowing the user to detect the exact level of stress variation by classifying stress states into five levels based on their sleeping habits.

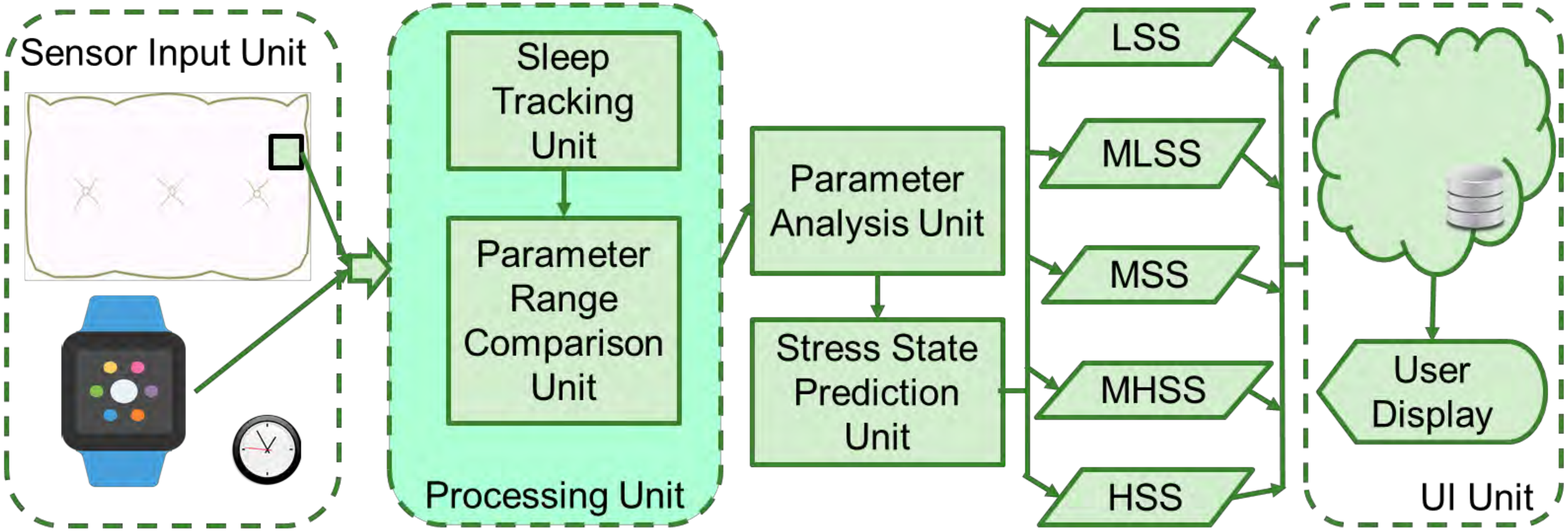
Issues Addressed in this Research

- ❖ Advancement through this paper in Electronics.
- ❖ Significant Improvement in the Accuracy of Sleep Analyses
- ❖ Considered Multiple Stressors for the assessment.
- ❖ Provided cloud storage access for future purposes.
- ❖ Proposed a self-aware system which is intelligent enough to establish a relationship between stress and the sleeping habits.
- ❖ An edge level system is presented with which the performance, accuracy and stabilization of the system can be maintained.

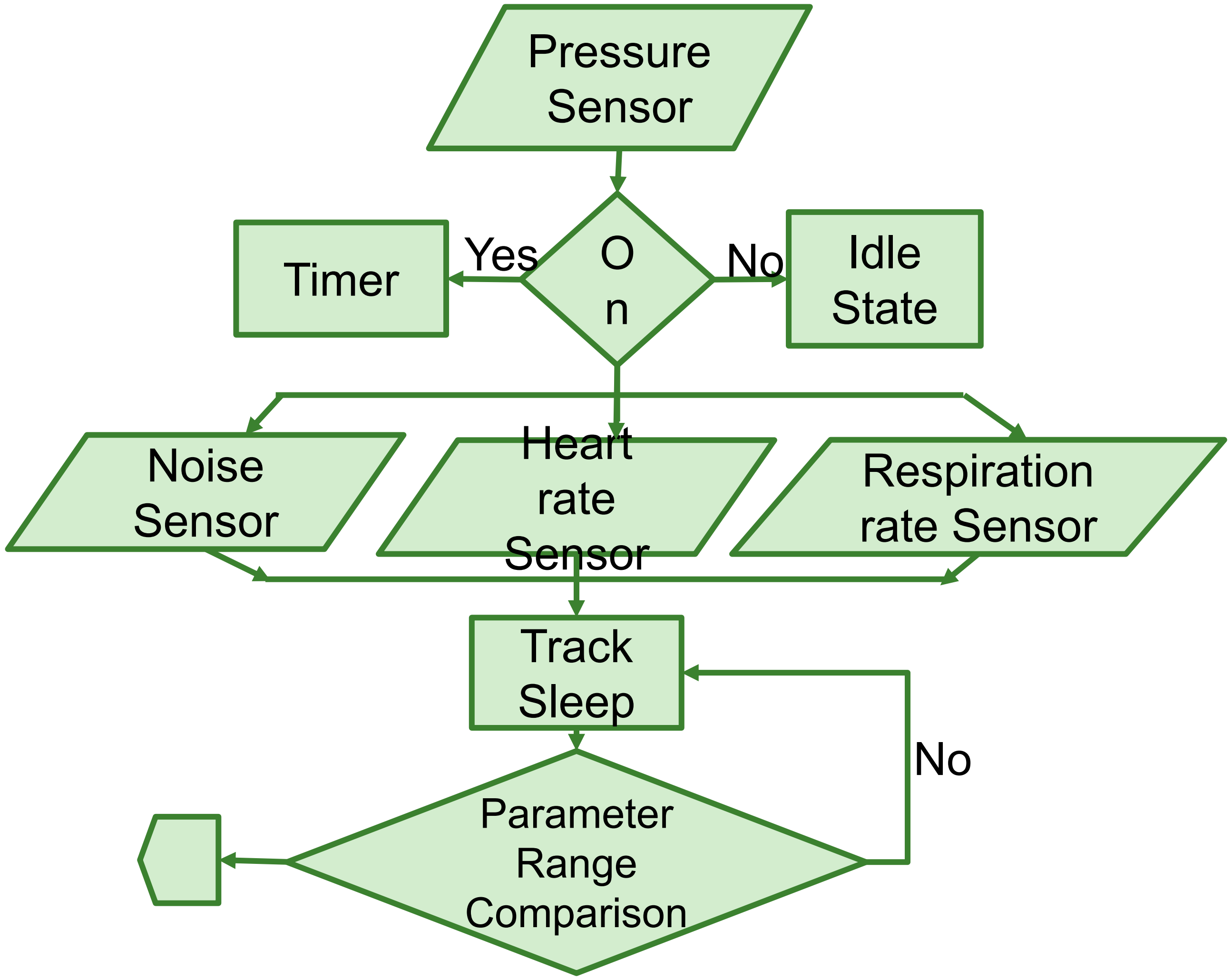
A Broad Perspective of Smart-Pillow

✓ **Broad Conceptual View of Smart-Pillow.**

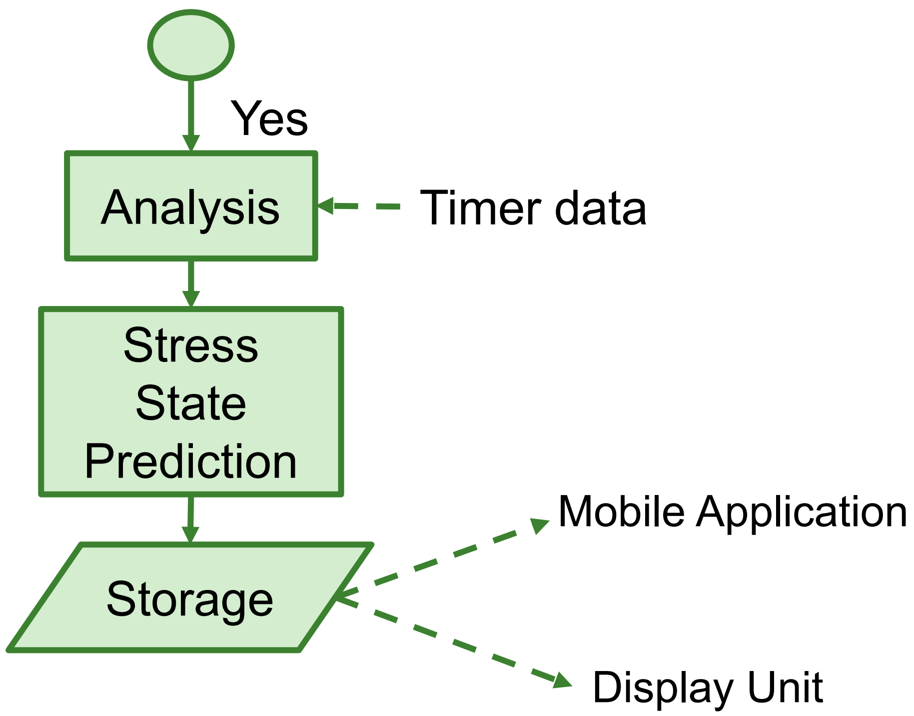
Architecture of Smart-Pillow



Flow of Smart-Pillow



Flow of Smart-Pillow



Dataset Acquisition

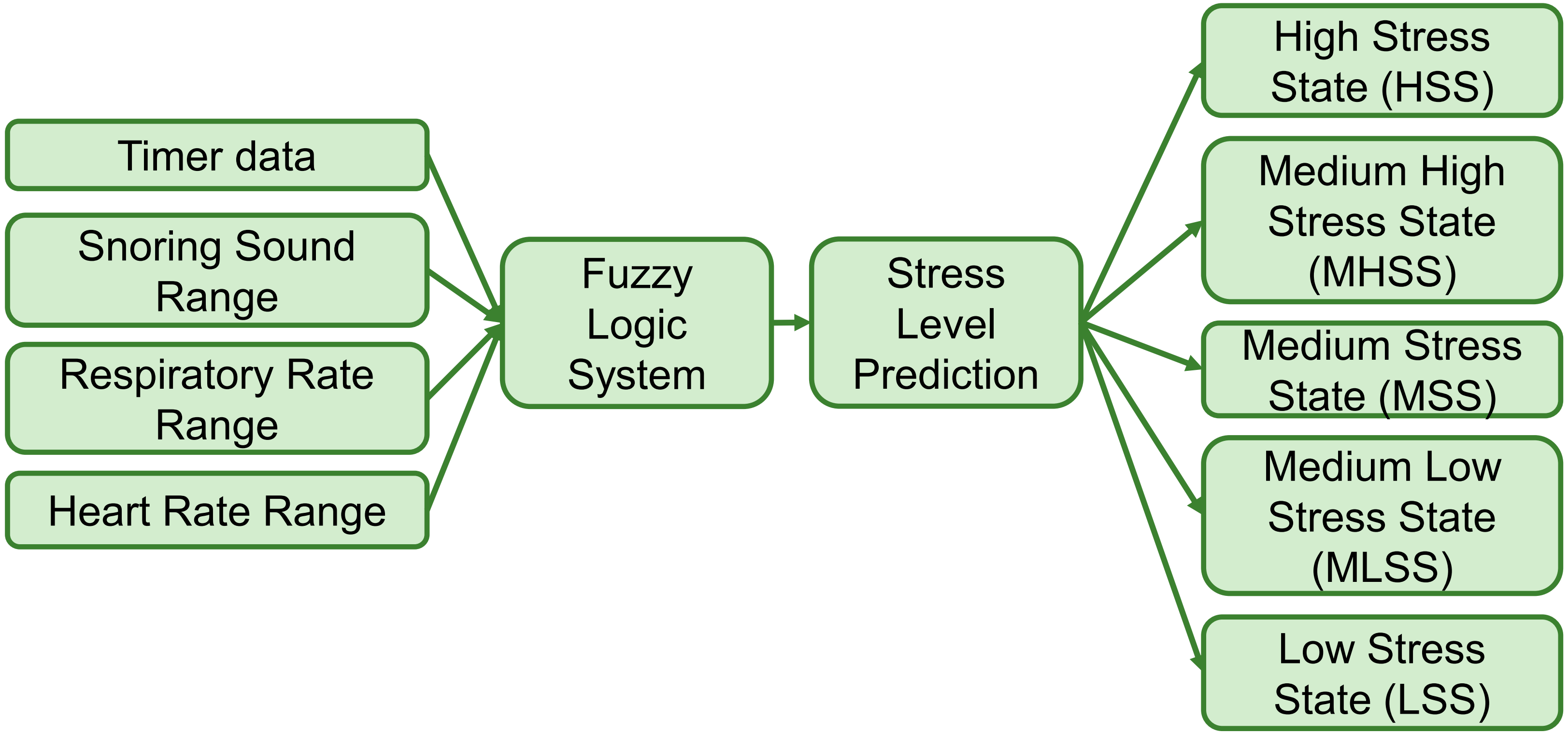
The Data at the sensor units are:

- ❖ Snoring Rate- When Snoring level exceeds 50dB, the chances of having stress is high
- ❖ Respiration Rate- Number of breathes per minute (bpm) when exceeds 15-17, can cause stress
- ❖ Heart Rate- If there is an observed heartrate more than 54-64 beats per minute (bpm), the chances of stress are high.
- ❖ Number of hours of Sleep- Minimum of 7 hours of sleep is required to maintain a healthy life.

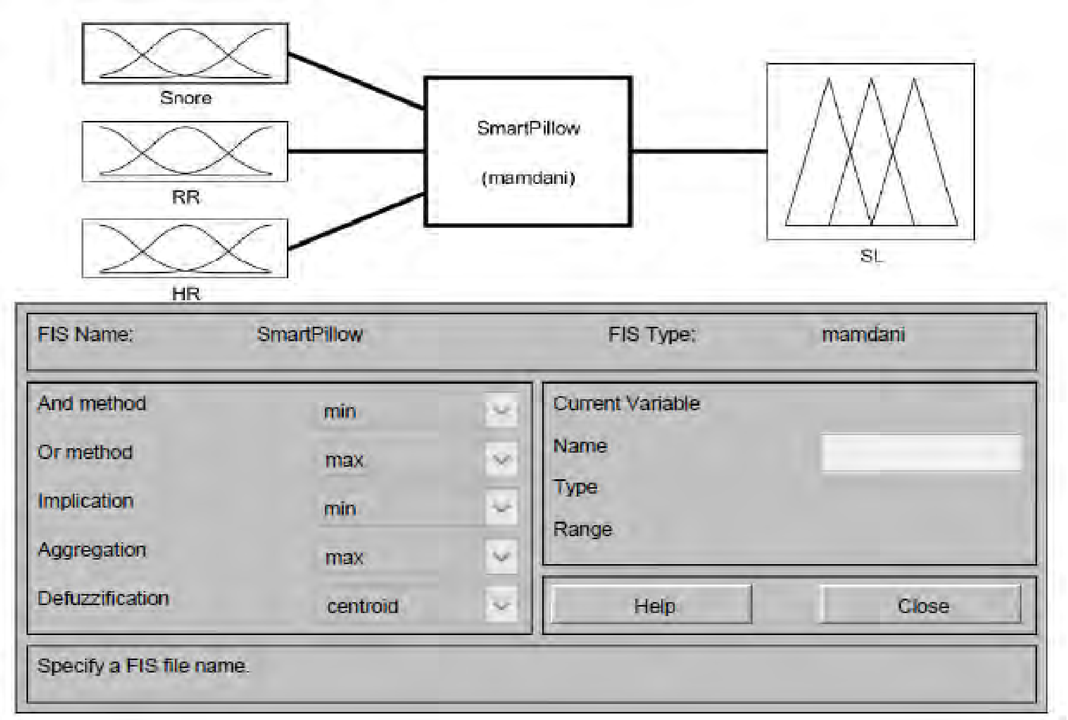
Parameter Ranges

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

Parameter Analysis



Fuzzy Logic-Designer's View

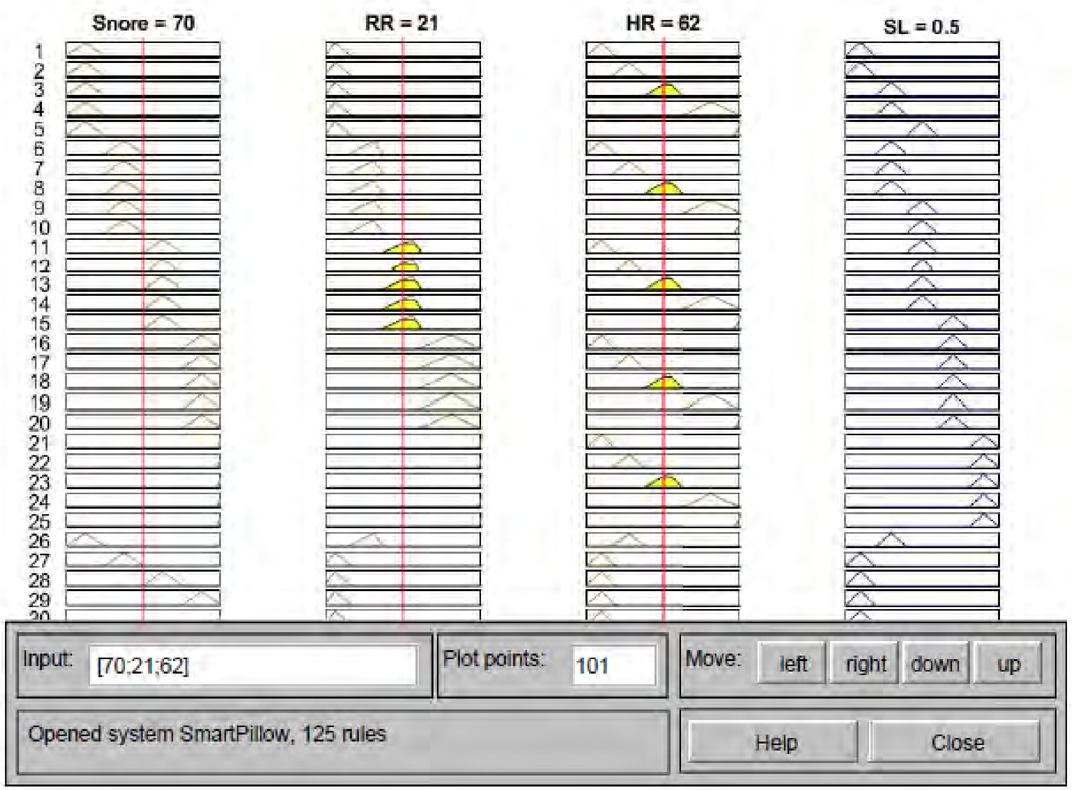


- A Mamdani Type Fuzzy Logic System is used.
- As there are 3 parameters and 5 sets of states, the total rules which can be generated are 5^3=125.

Fuzzy Output Range Specification

Stress State	Output Range
Low Stress State (LSS)	0.00-0.20
Medium Low Stress State (MLSS)	0.21-0.40
Medium Stress State (MSS)	0.41-0.60
Medium High Stress State (MHSS)	0.61-0.80
High Stress State (HSS)	0.81-1.00

Rules of Fuzzy Logic Design

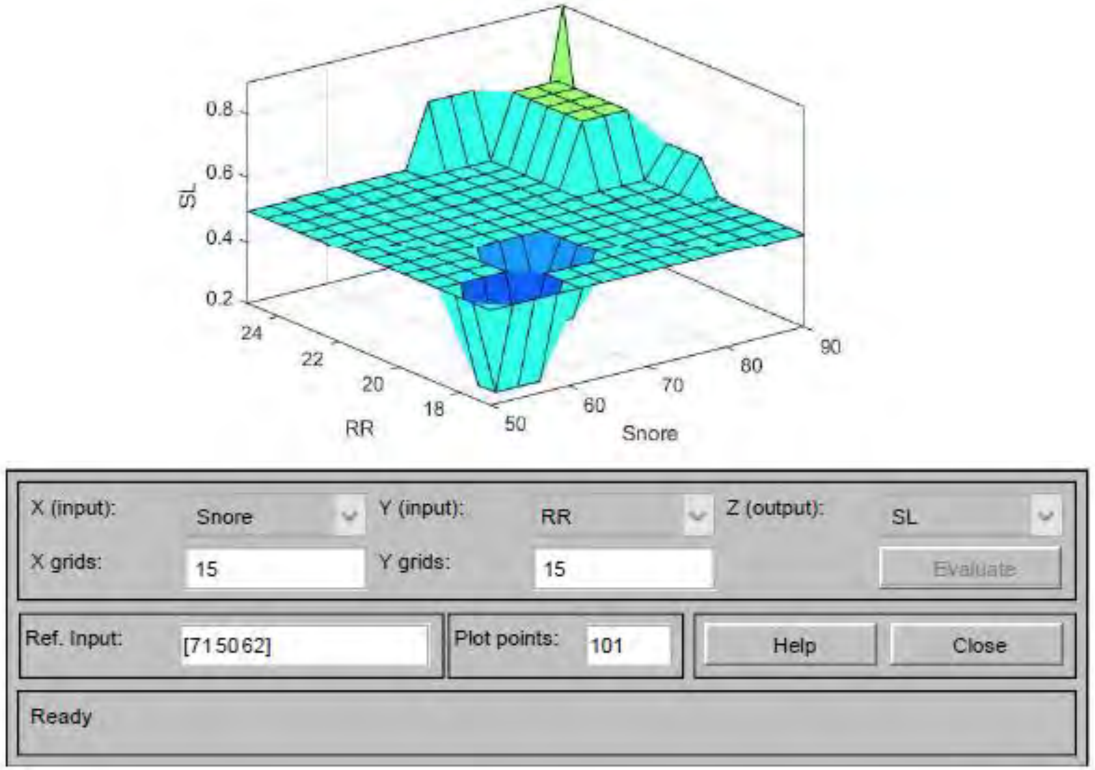


- The representation of rules and its implementation in the Fuzzy Designer is shown.

- The system is trained by a set of 125 rules and the output, i.e. the stress state, is defined in between the values 0 and 1.

Sleep Parameters-Surface Plot

✓ **Surface Plot of the Fuzzy System Response.**



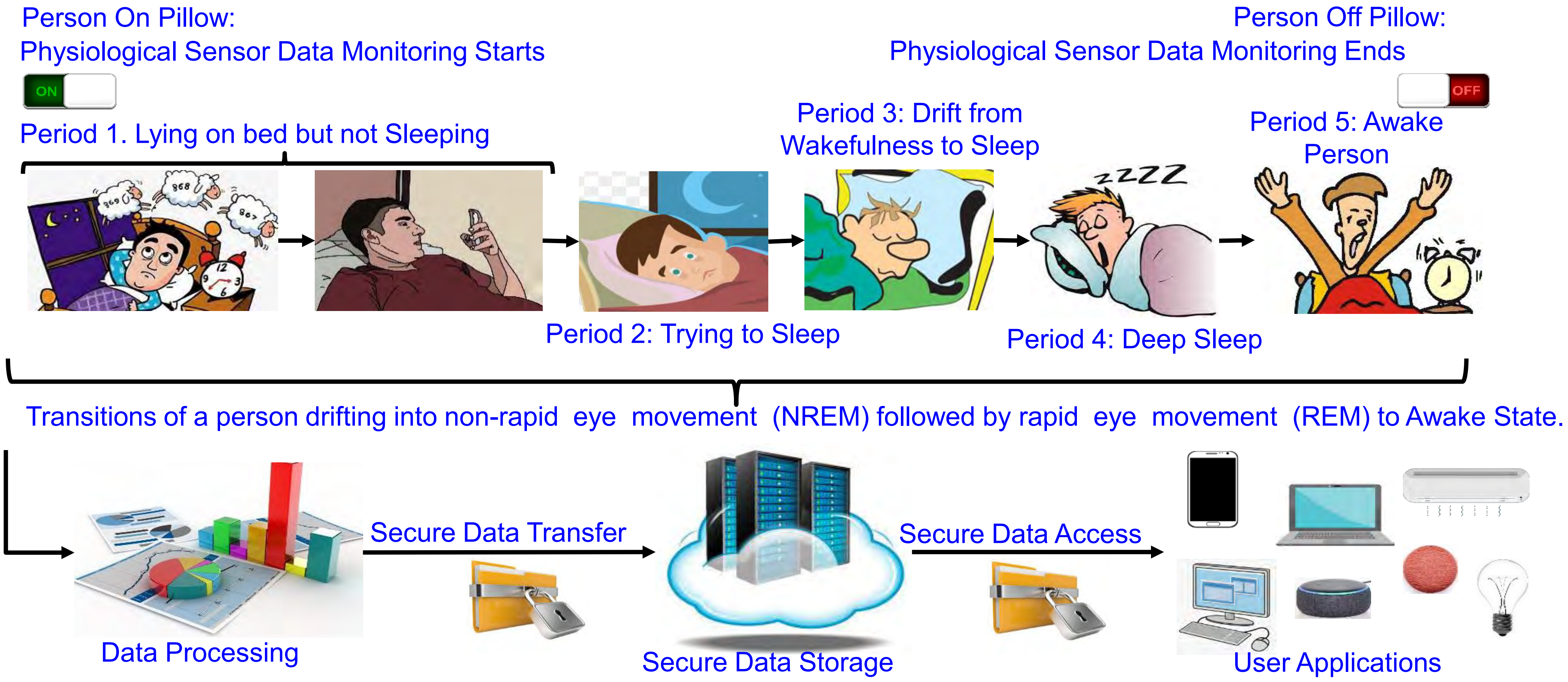
- The 3D plot of the system is Represented here.

- The values Stress Level (SL), Respiration Rate (RR) and Snoring rate are represented along with their boundaries as a validation of the system.

Comparison with Existing Research

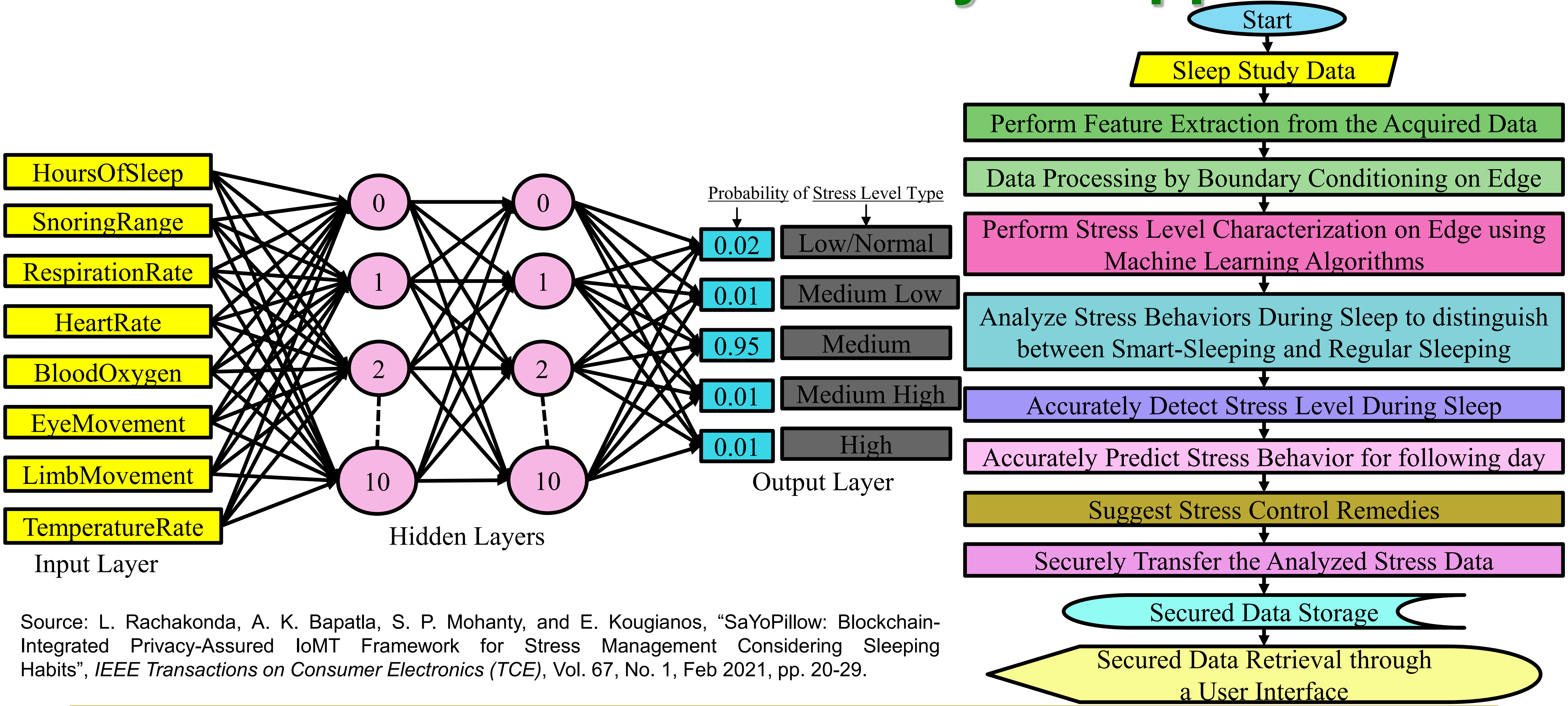
Name	Approach	Features	Drawback
Fitbit [14]	Wearable	Heart rate monitor, sleep stages monitor	Does not manage stress with sleep.
SleepScore Max [15]	Non-wearable	Invisible radio wave sleep tracking	Does not manage stress with sleep.
Xiaomi Mi Band 3 [16]	Wearable	Pulse Monitor	Does not manage stress with sleep.
Beddit [18]	Non-wearable	Monitors snoring	Does not manage stress with sleep.
This Paper	Wearable	Heart rate, Snoring, Respiration rate	Establishes a relationship between sleep and stress, allows the user to have a control over the stress level variations.

Smart-Yoga Pillow (SaYoPillow) - Sleeping Pattern



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



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.

Conclusion and Future Research

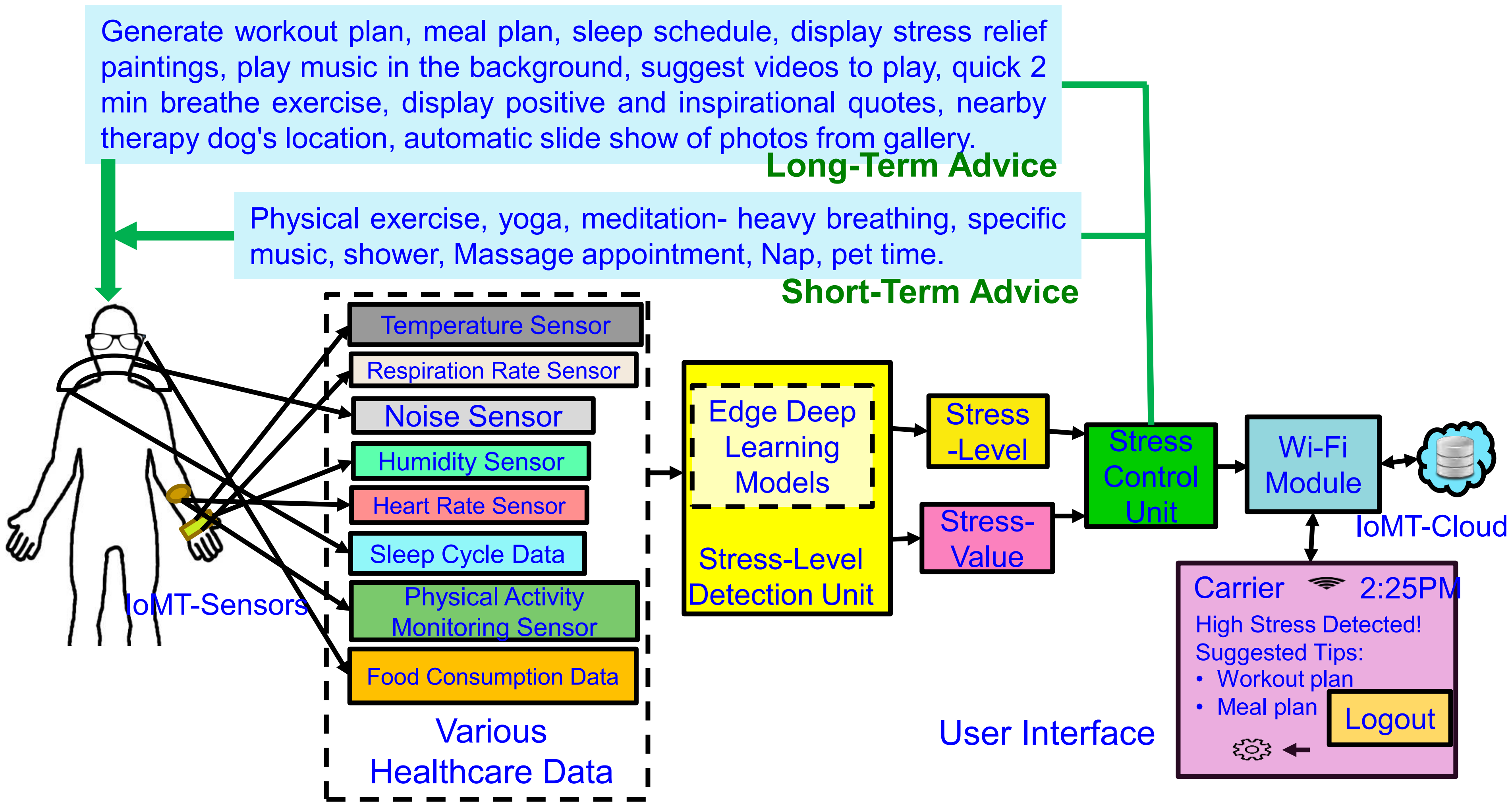
- Five different classifications of stress based on measurement of sleeping parameters is presented in this work.
- This method helps in improving and controlling the overall stress levels of a person.
- Implementation of the system incorporating machine learning or deep learning concepts are suggestions for future research.

iFeliz: Research Question

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

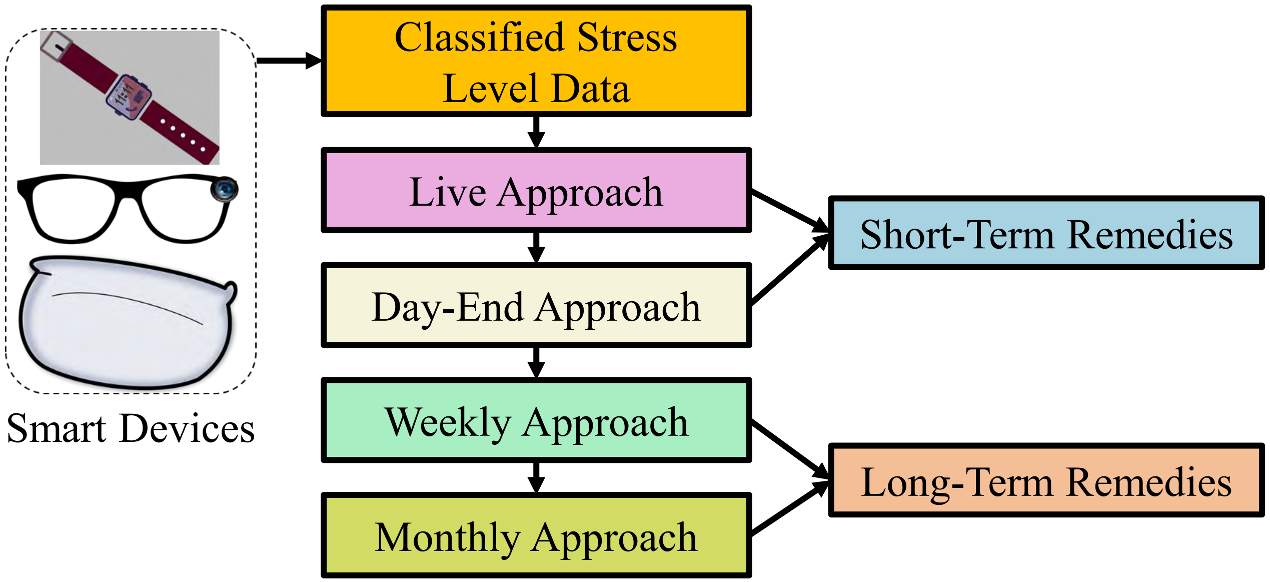
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference (ISC2)*, 2020.

iFeliz: Proposed System



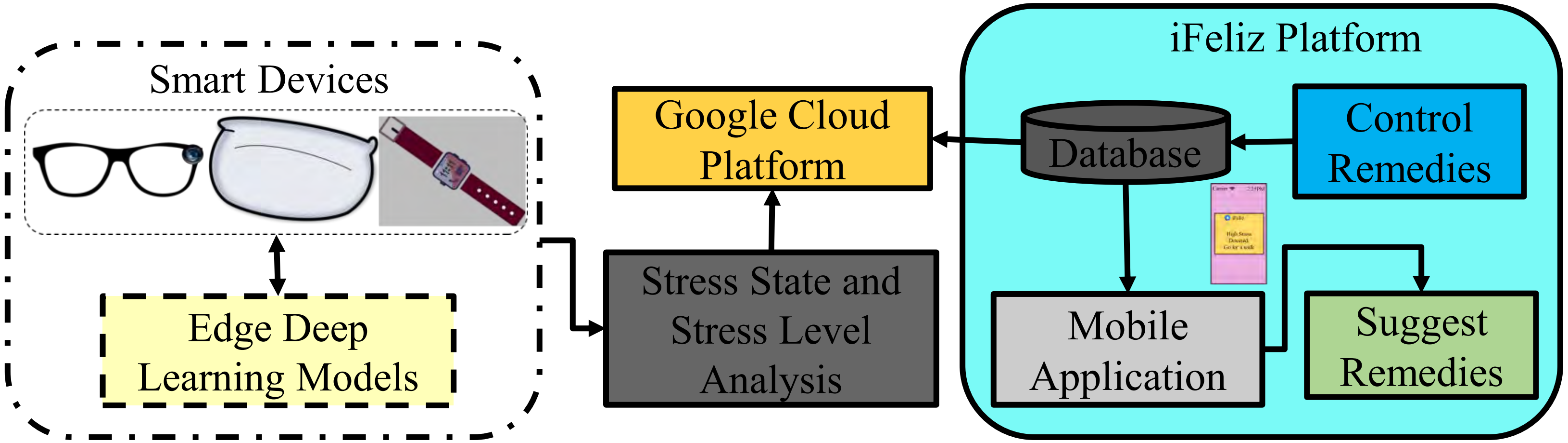
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference (ISC2)*, 2020.

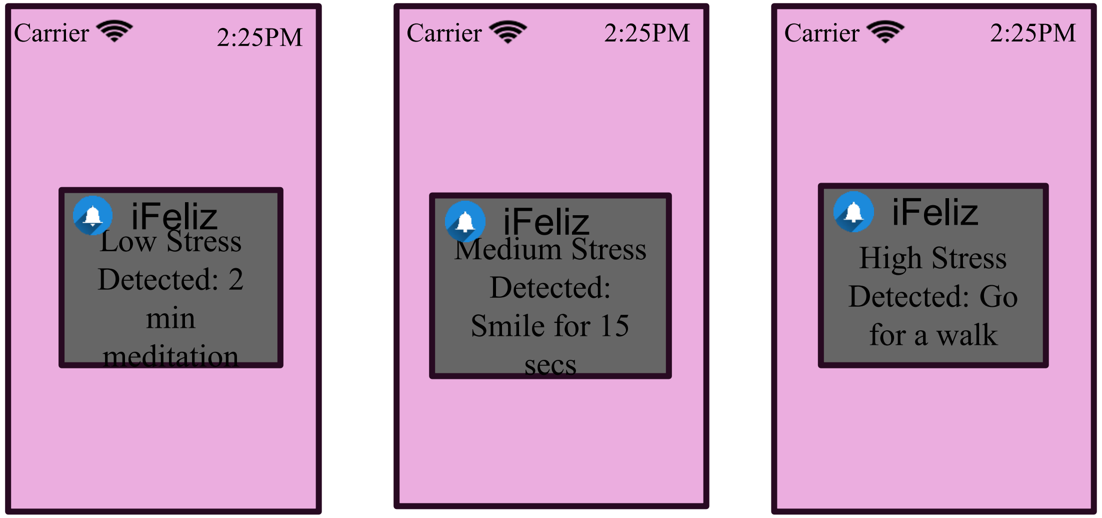
iFeliz: Stress Control Approaches



Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iFeliz: An Approach to Control Stress in the Midst of the Global Pandemic and Beyond for Smart Cities using the IoMT", in *Proc. of IEEE Smart Cities Conference (ISC2)*, 2020.

iFeliz: Prototyping

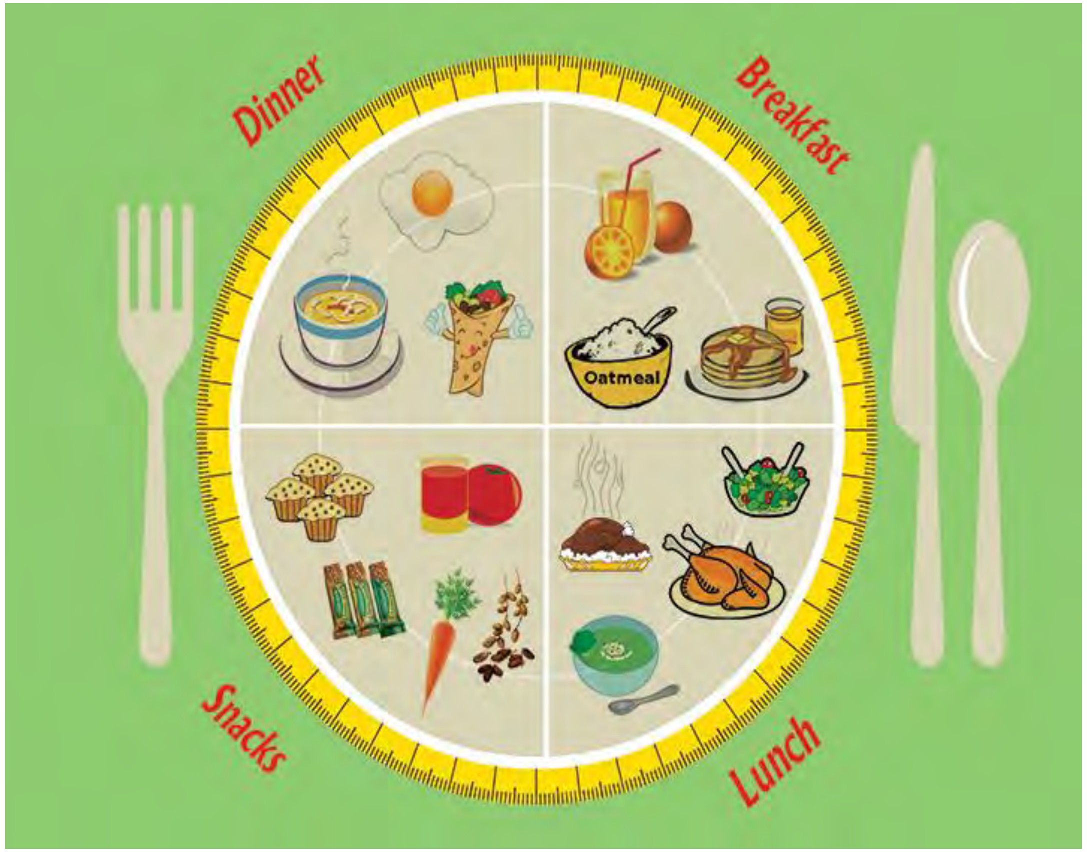




iFeliz - 15 Features, Stress Detection, Stress Control, Accuracy - 97%.

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.

Automatic Food Intake Monitoring and Diet Management is Important



Imbalance Diet is a Global Issue

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

➢ Psychiatric disorders ➢ Coronary heart disease ➢ High blood pressure	➢ Obesity ➢ Tooth decay ➢ Diabetes

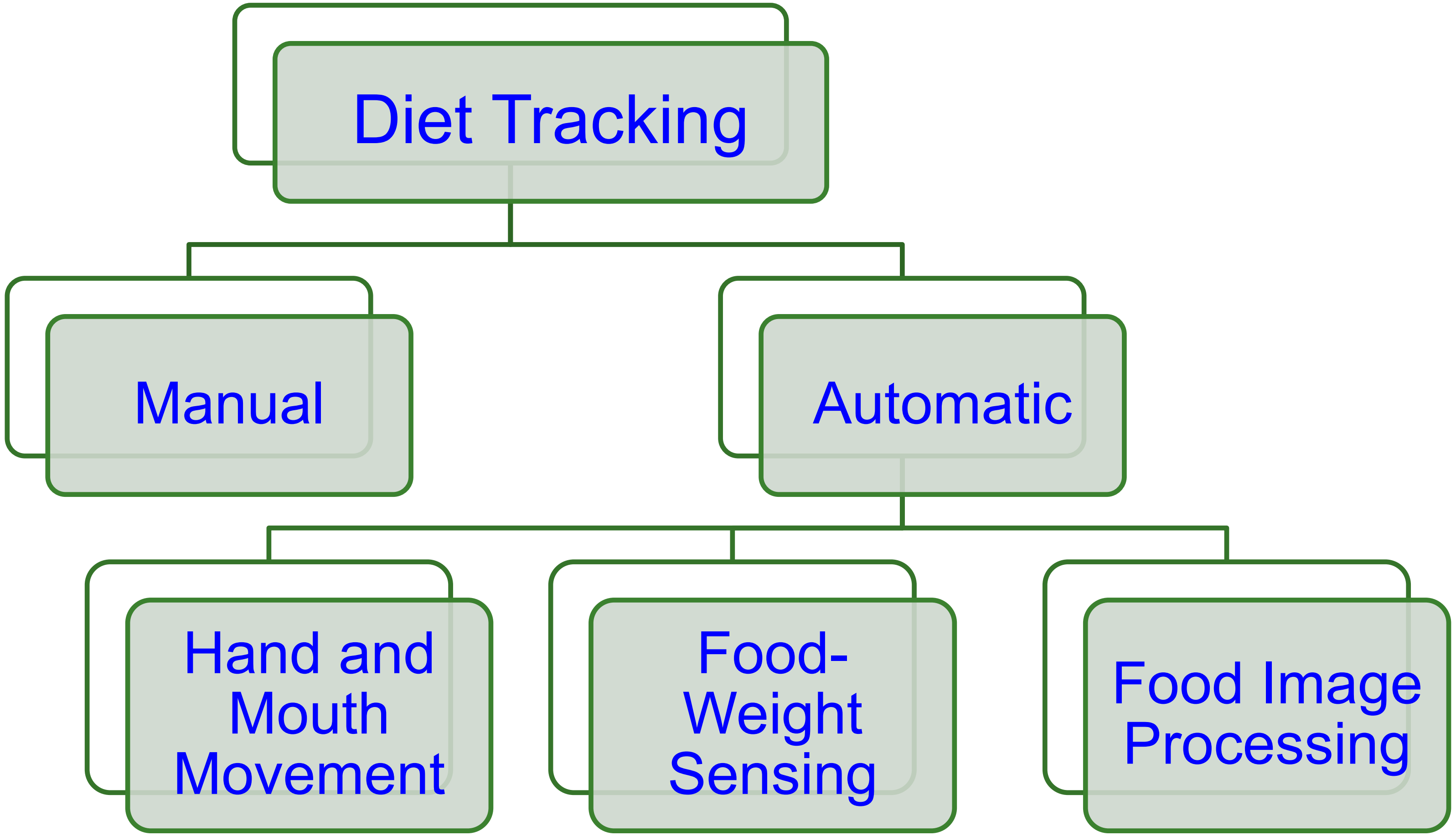
Source: https://obesity-diet.nutritionalconference.com/events-list/imbalanced-diet-effects-and-causes
https://www.thelancet.com/article/S0140-6736(19)30041-8/fulltext

Food Tracking Apps

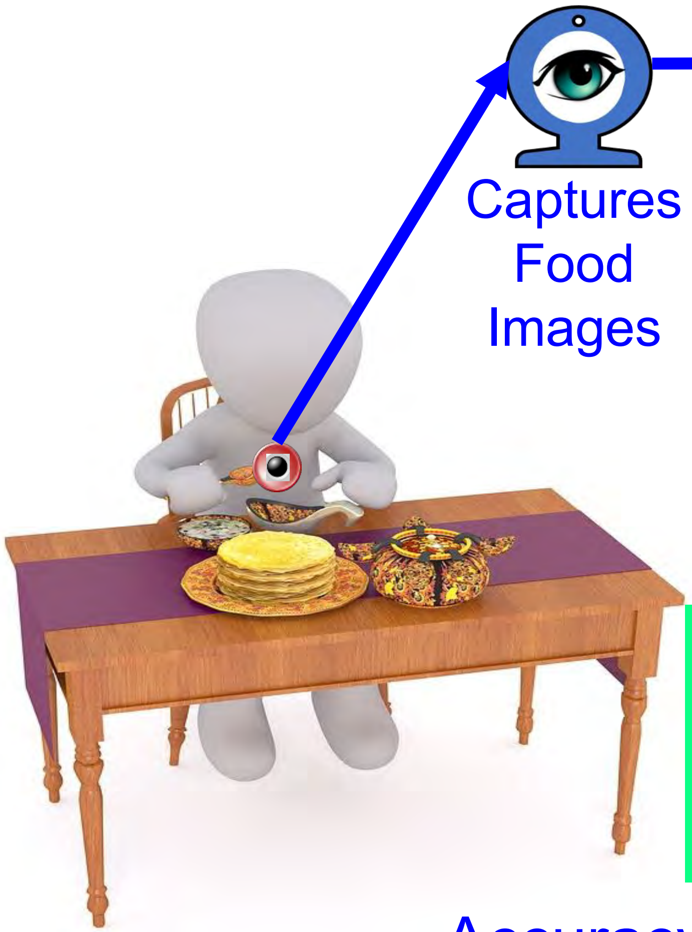
Table 1. Overview of popular food tracking approaches and their capabilities.

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

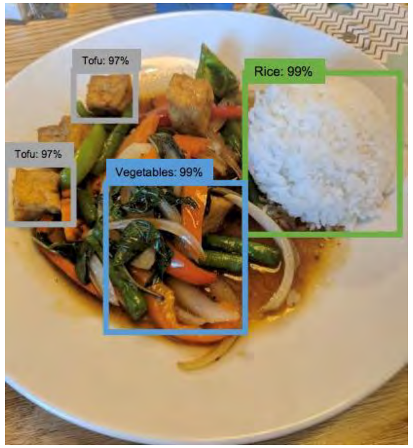
Diet Tracking Approaches

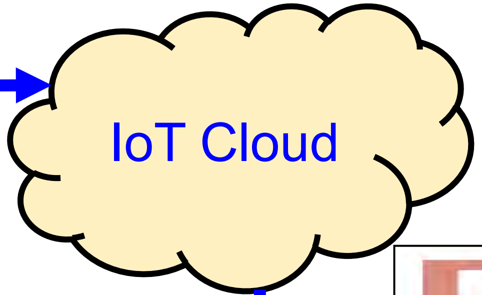


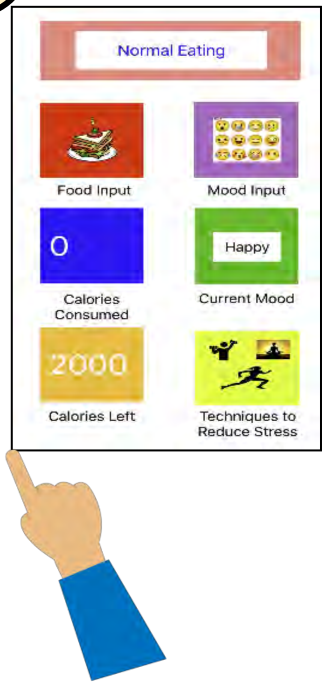
Smart Healthcare – Diet Monitoring



Automatic Food
Image Analysis







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

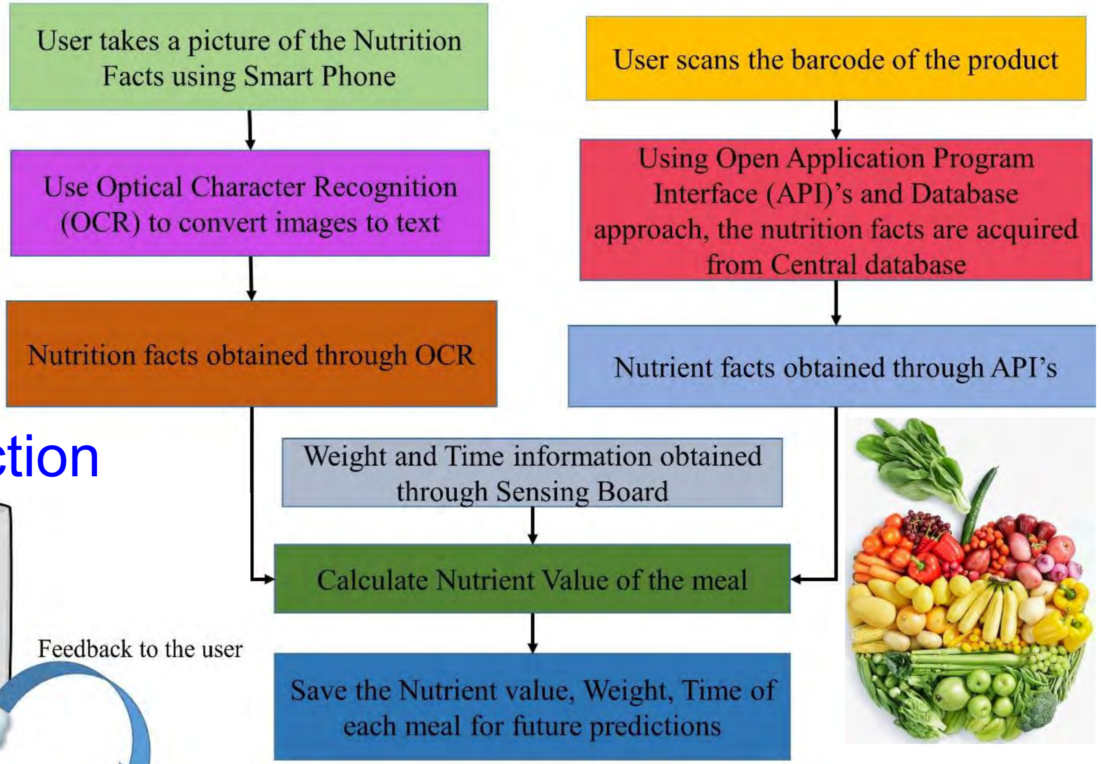
Accuracy of detecting food - 97%

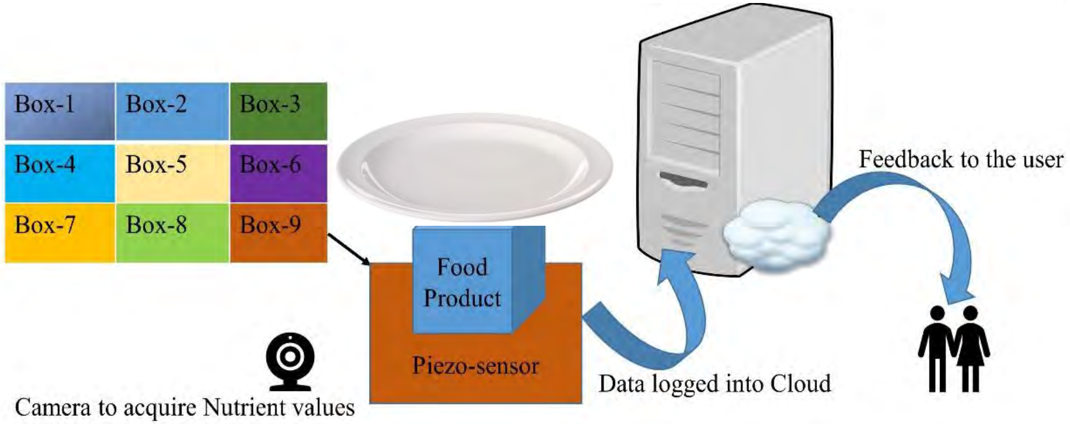
Source: L. Rachakonda, S. P. Mohanty, and E. Kougianos, "iLog: An Intelligent Device for Automatic Food Intake Monitoring and Stress Detection in the IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 66, No. 2, May 2020, pp. 115--124.

Smart Healthcare - Smart-Log

Automated Food intake Monitoring and Diet Prediction System

- Smart plate
- Data acquisition using mobile
- ML based Future Meal Prediction





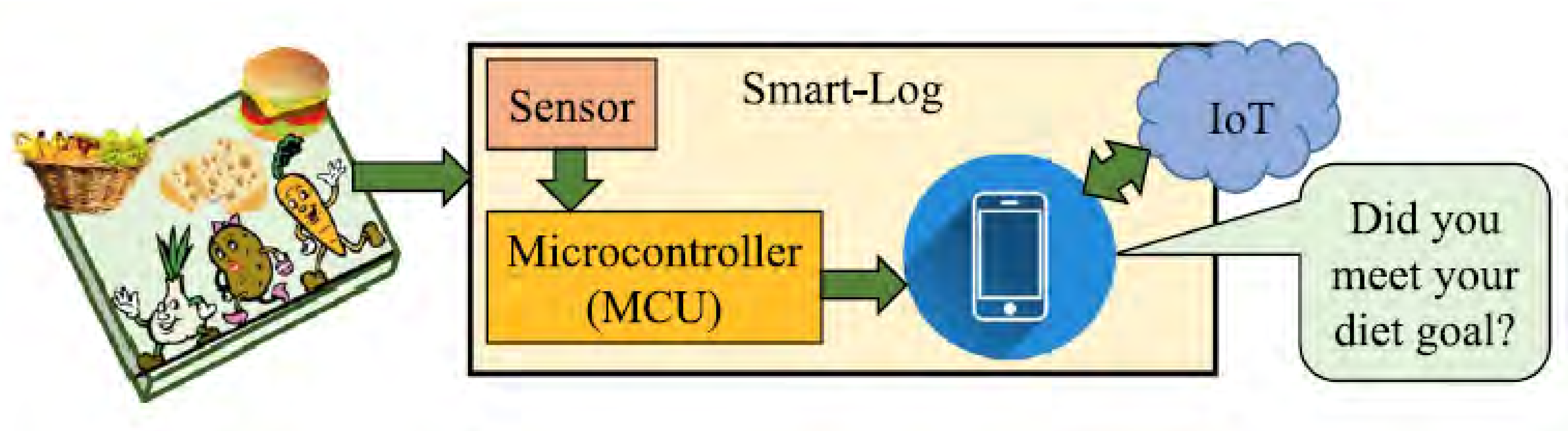
USDA National Nutrient Database for Standard Reference is used for nutrient values of 8791 items.

Research Works	Food Recognition Method	Efficiency (%)
This Work	Mapping nutrition facts to a database	98.4

8172 user instances were considered

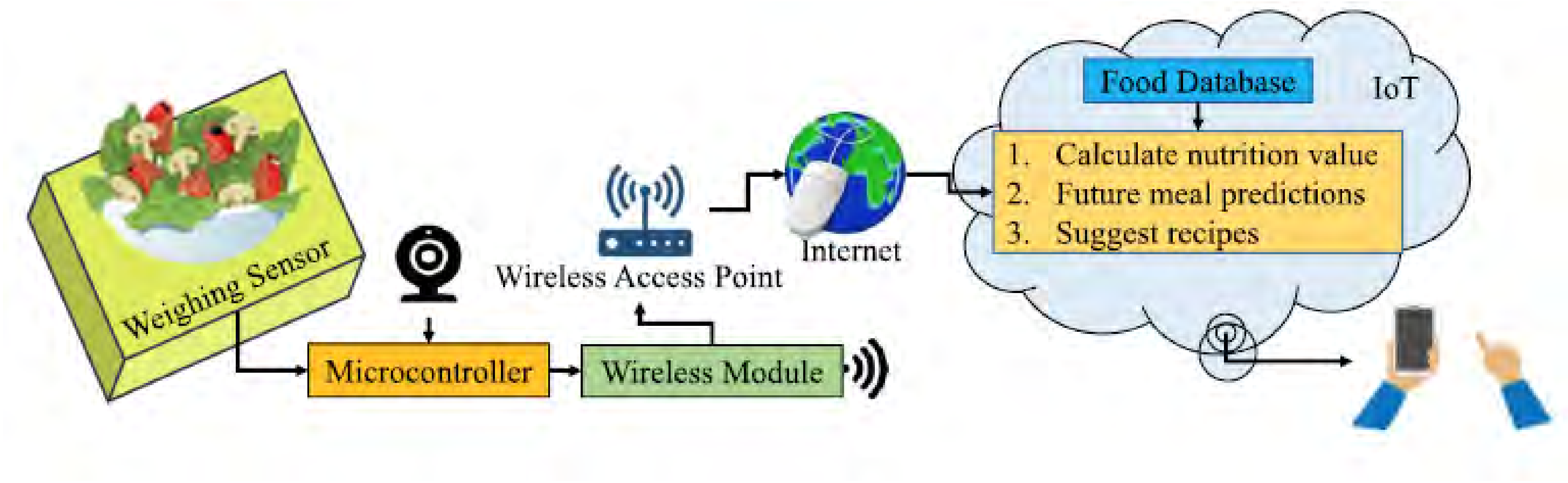
Source: Mohanty ICCE 2018

Conceptual view of the Smart-Log

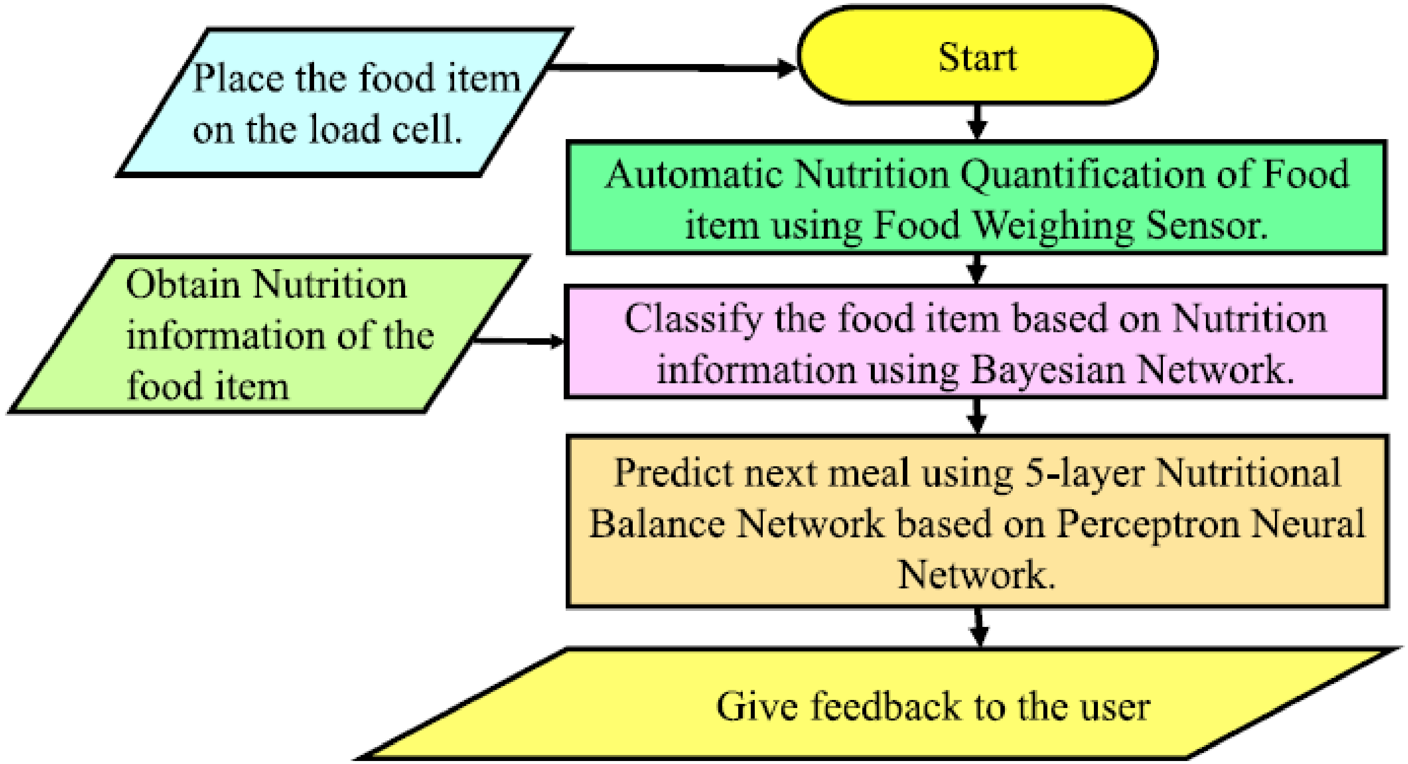


- A novel 5-layer deep learning model based on a perceptron neural network with densely connected hidden layers for determining the nutritional balance after each meal is proposed.
- A novel algorithm based on Bayesian networks for determining nutrient features from food materials and for suggesting future meals or recipes, accordingly.
- The proposed IoT based fully automated diet monitoring solution is the first solution to be built using Bayesian algorithms and 5 layer perceptron neural network method for diet monitoring.

Architecture of Smart-Log

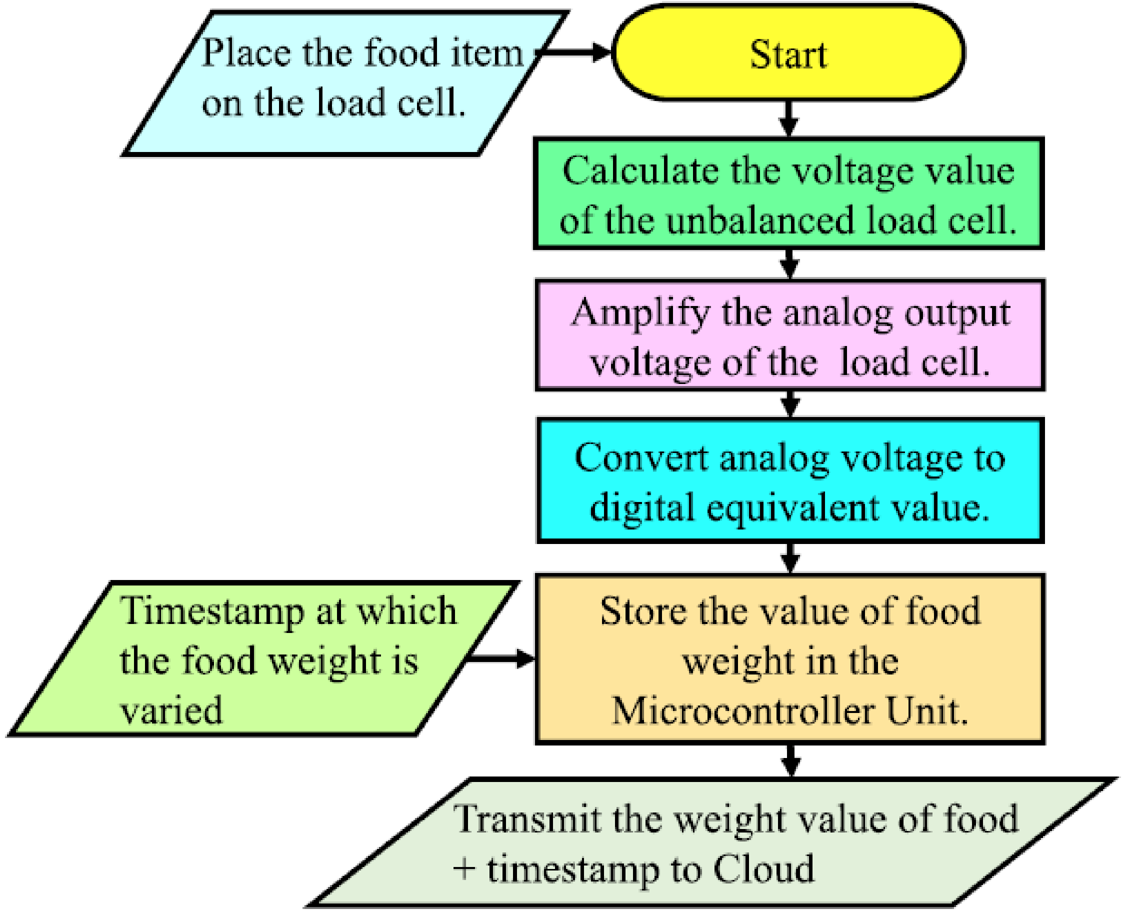


Data Flow of Smart-Log



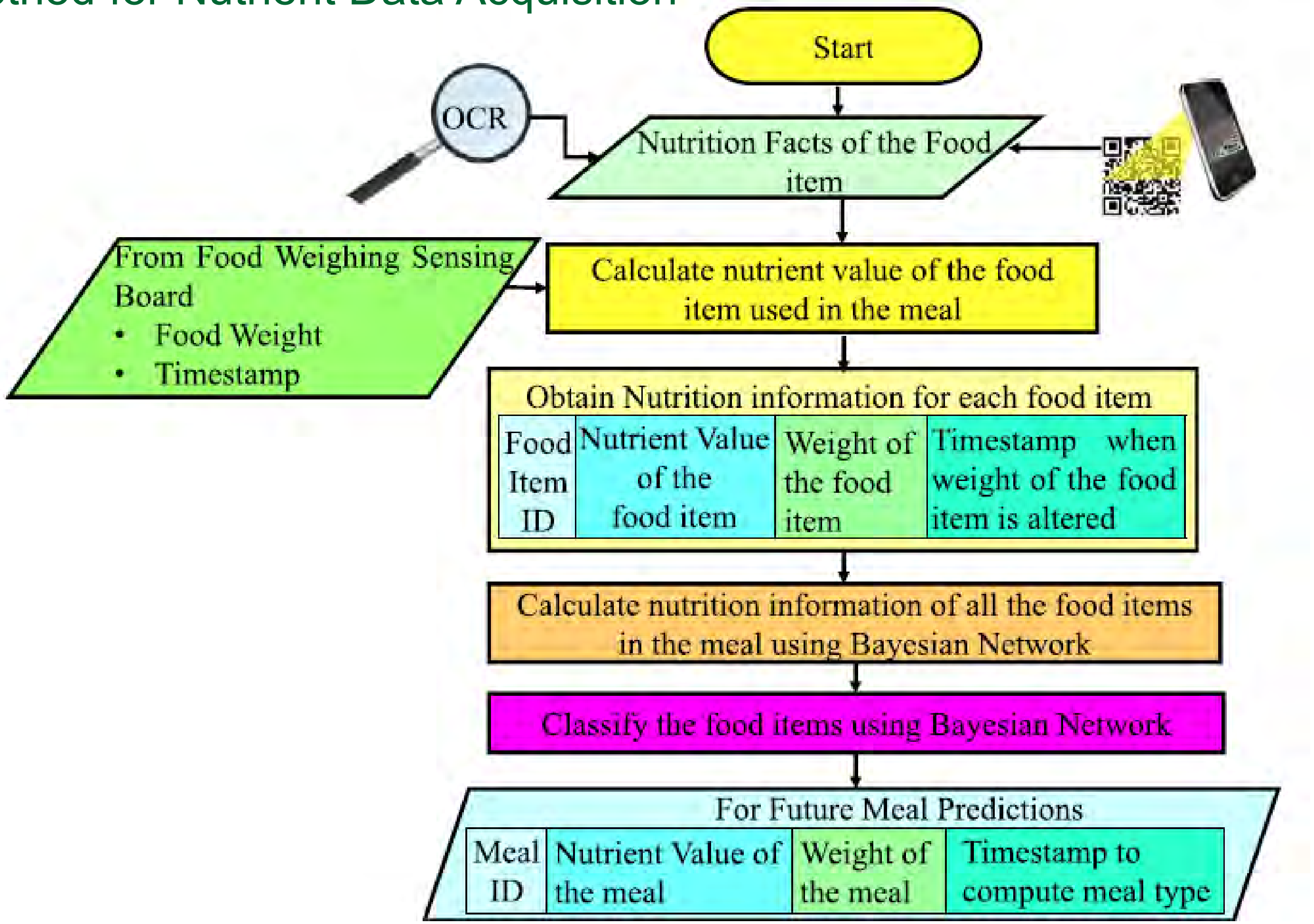
Proposed Methods

1. Method for Automatic Nutrition Quantification



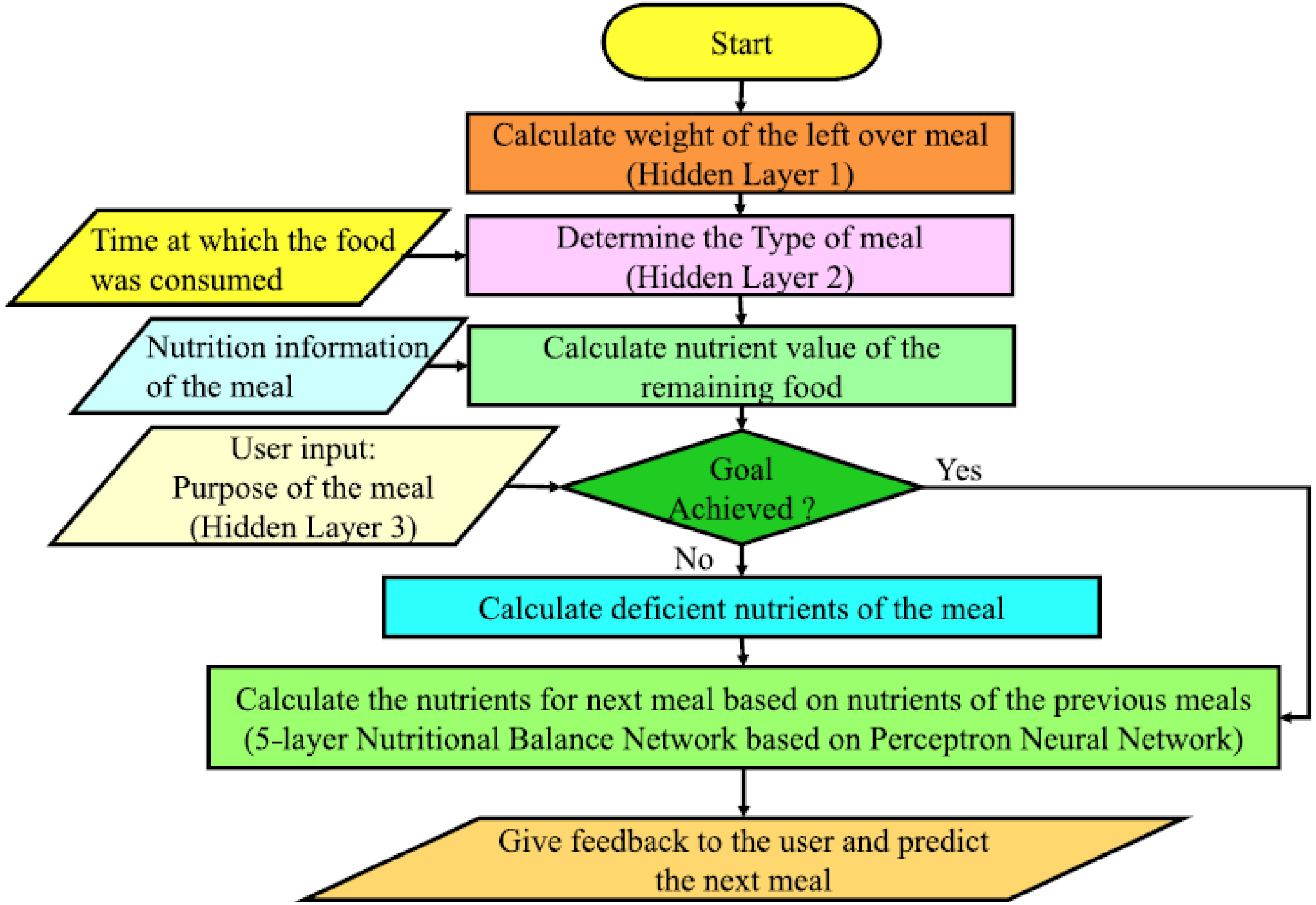
Proposed Methods

2. Method for Nutrient Data Acquisition



Proposed Methods

3. Proposed Method for Future Meal Predictions



Data Acquisition

a. Food Weighing Sensor System

- A load cell which has the capacity to weigh objects in the range of 0-5 Kg was considered. The output of the load cell was connected to a 24-bit Analog-to-Digital Converter (ADC), designed specifically for weighing applications.

Characteristics	Model 1	Model 2
Operating Voltage	5 Volt	3.3 - 5 Volt
Dimensions of the board	101.52×53.3 mm^2	49×24.5 mm^2
Clock Speed	16MHz	80 MHz
Built-in Wi-Fi module	No	Yes
Digital I/O pins	54	11

b. Nutrition Acquisition

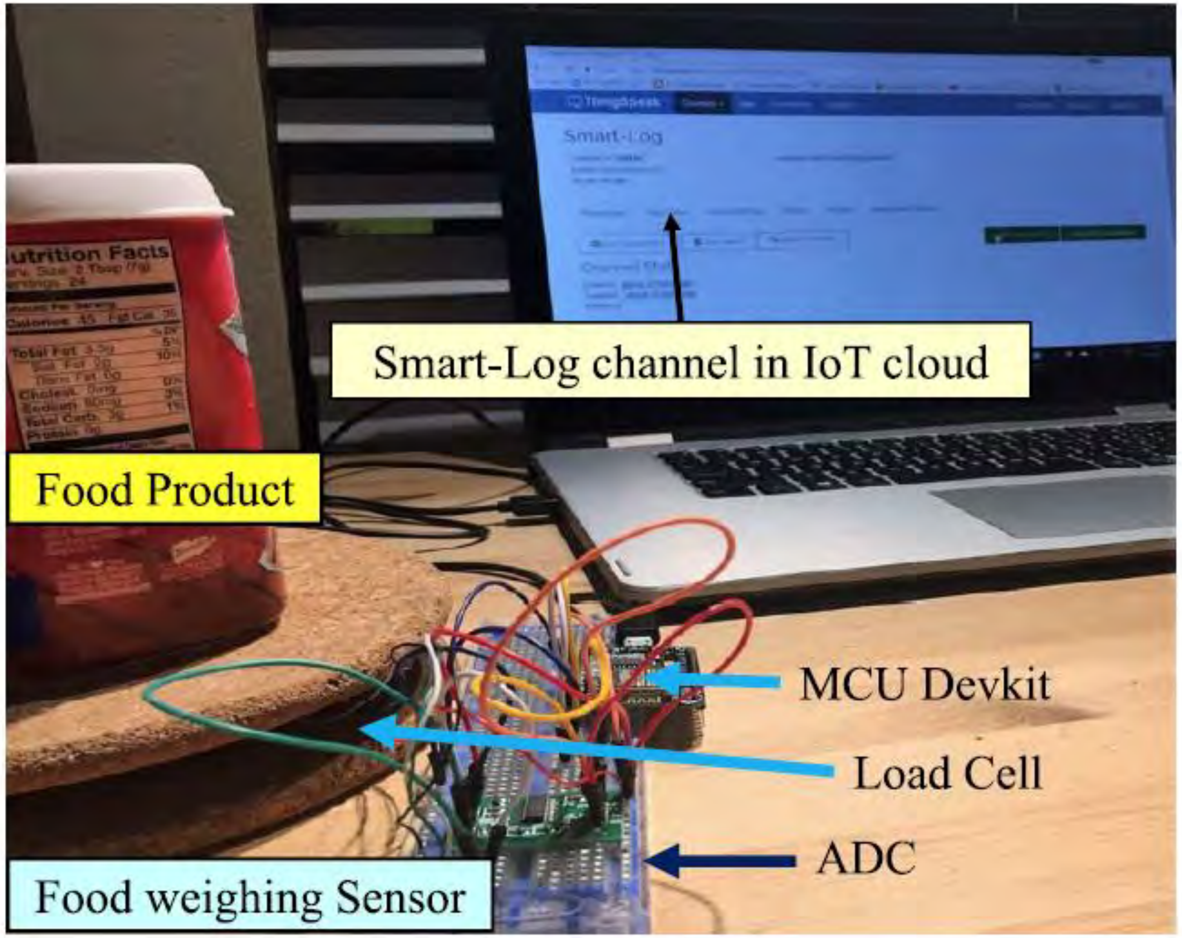
- The USDA provides a freely accessible database of 8791 food items and this was used for retrieving nutritional values.

Characterization

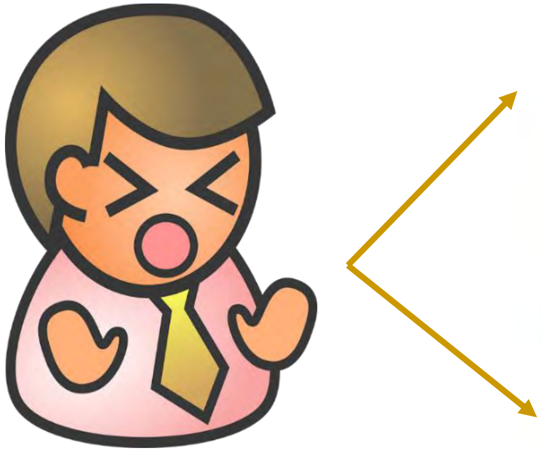
Characteristics	Specifics
Sensor system	Food Weighing Sensor
Data acquisition	API and Database approach
Data Analysis Tool	WEKA
Input Dataset	8791 instances
Classifier	Bayesian Network
Accuracy (worst case)	98.6 %

- The number of main classes to be predicted by the food classification algorithm are 4, i.e., protein-rich, carbohydrate-rich, fiber-rich and vitamin-rich.

Experimental setup



Stress-Eating?



Chronic stress releases a hormone called cortisol which increases the appetite of a person.

Existing Applications

YAZIO

MyNetDiary

myfitnesspal

MyPlate Calorie Tracker

My Diet Coach

Lose It!

Fooducate

fatsecret

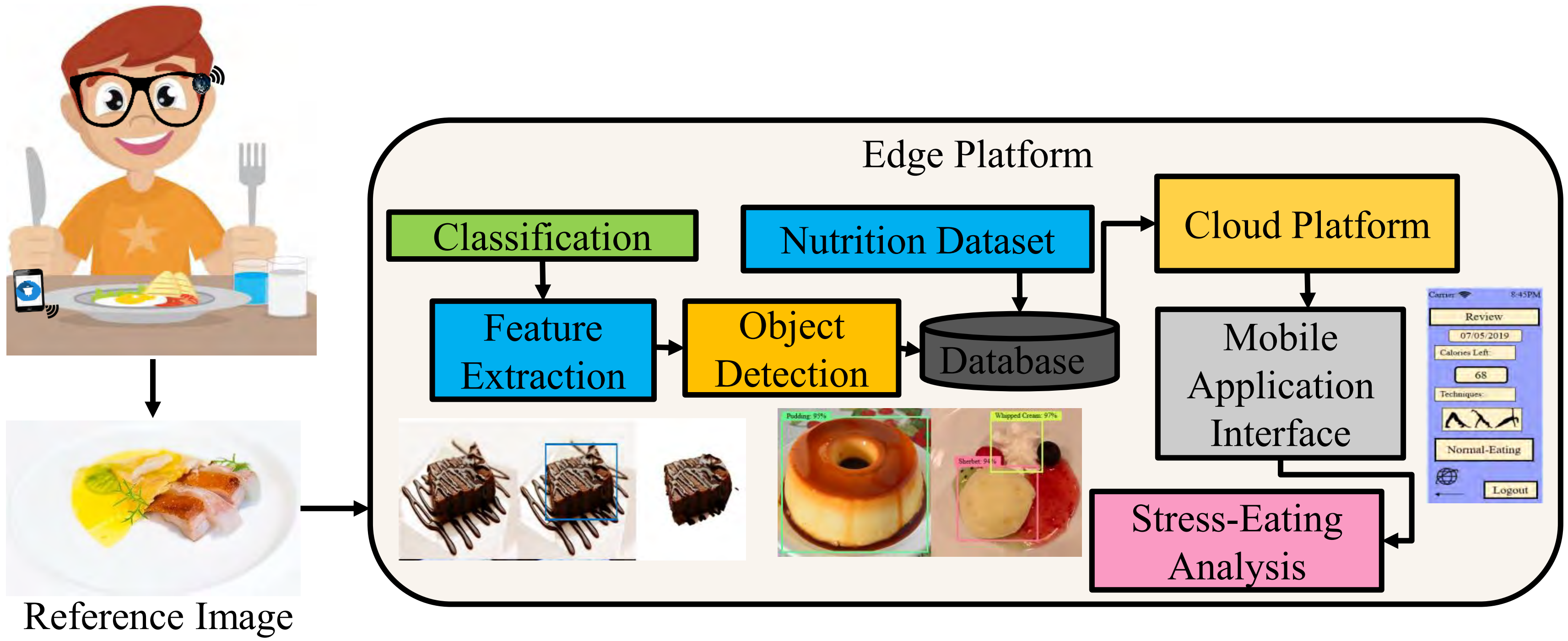
Issues of Existing Solutions

- Continuous Analysis of Food Monitoring is not provided.
- Manual Input of food consumed is a must.
- No Unified detection of the problem.
- Fully utilization of technology which can be a part of the product.
- Storage availability of the detected parameters for future usage.
- Self-Aware systems.

Issues Addressed in this Research

- Advancement through this paper in Electronics.
- Significant Improvement in the comfort of the user.
- Considered Non-Wearable for the detection.
- Provided cloud storage access for future purposes.
- Proposed a self-aware system which is intelligent enough to detect the stress-eating behavior.
- An edge level system is presented with which the performance, accuracy and stabilization of
  the system can be maintained.

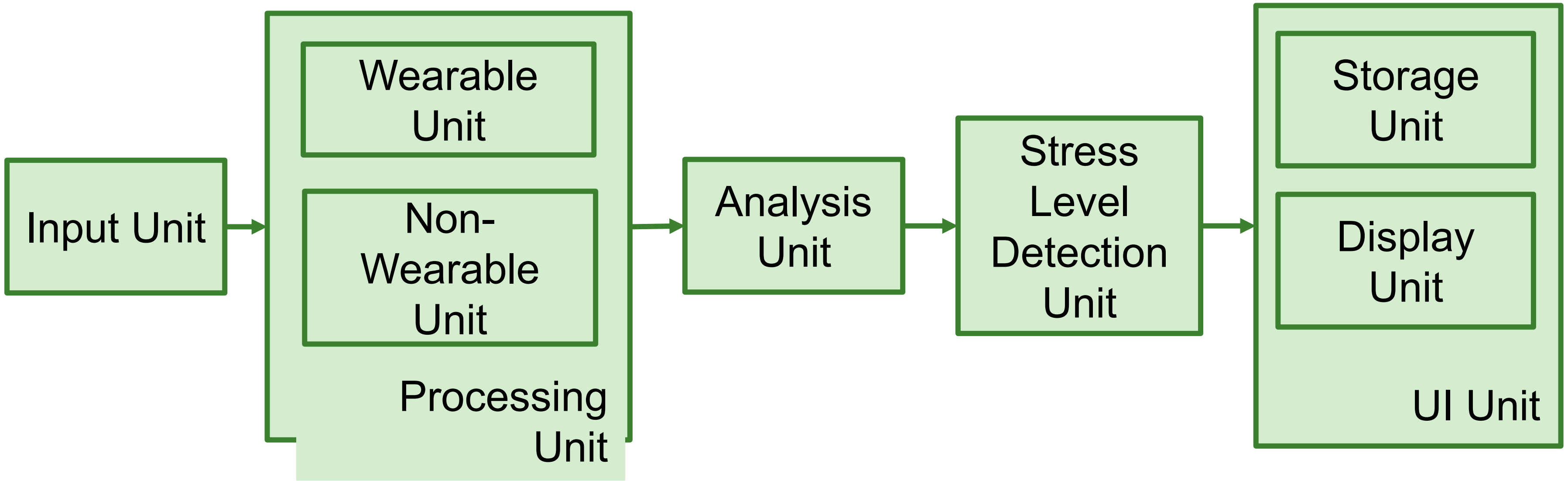
Smart Healthcare – iLog



iLog- Fully Automated Detection System with 98% accuracy.

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

Block Diagram Representation



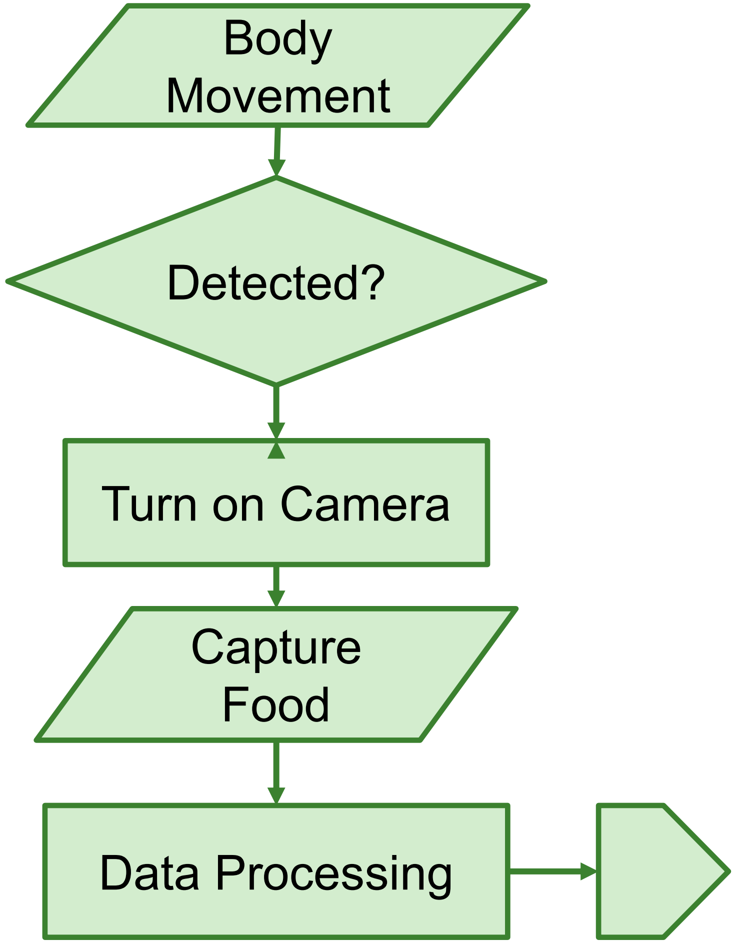
Factors Considered

✓ **Data Collection.**

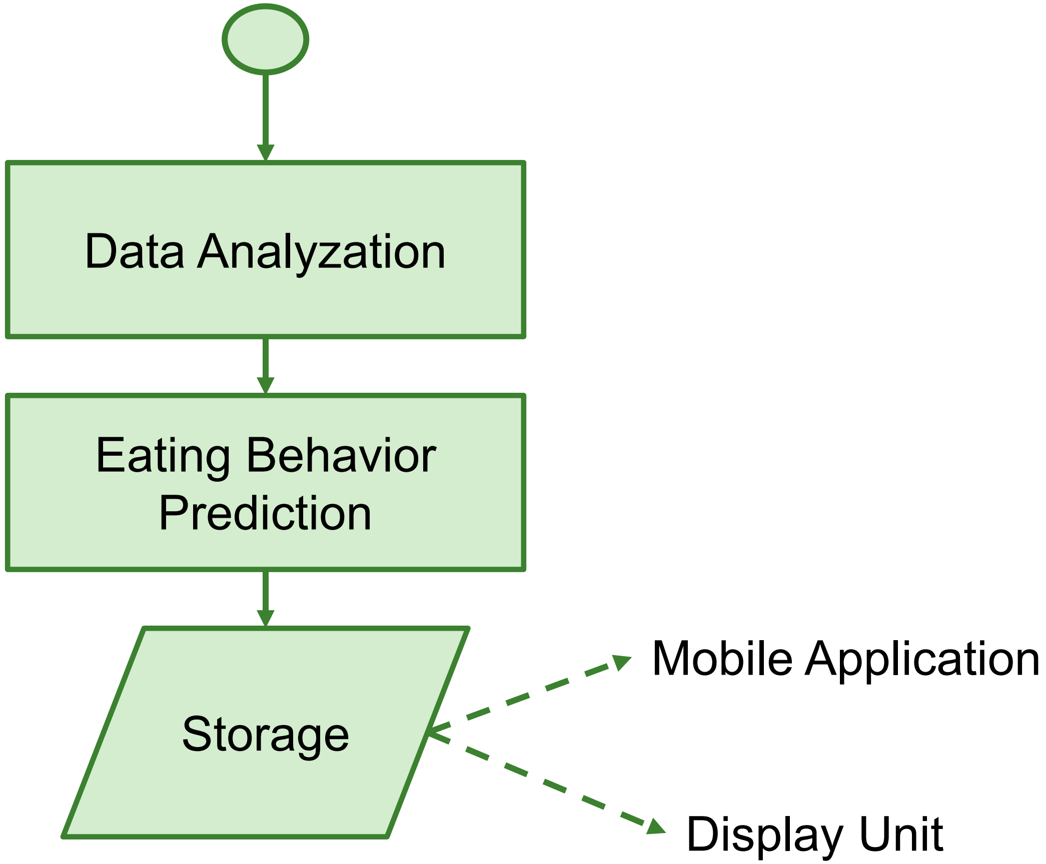
In order to analyze the eating behavior of the person, the following data are considered:

- The type and amount food consumed.
- The time at which the food is consumed.
- The gender of the person.
- The mood of the person after every meal.

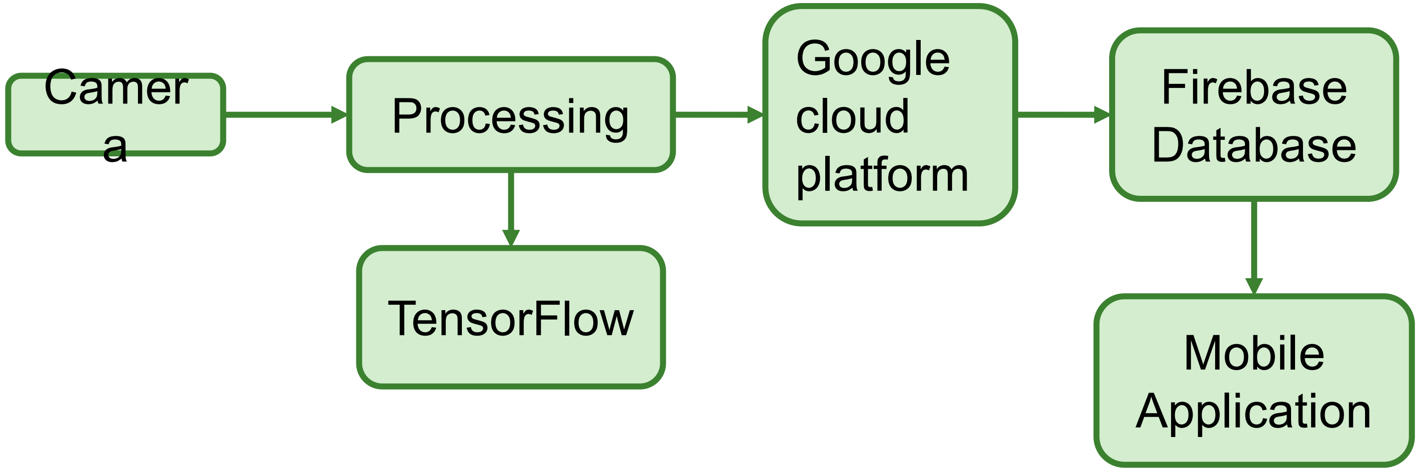
Flow of Stress-Log



Flow of Stress-Log



Wearable Approach



Wearable Approach

✓ Processing

❖ Tensorflow Object Detection API

- Creating accurate machine learning models capable of localizing and identifying multiple objects in a single image remains a core challenge in computer vision.

- The TensorFlow Object Detection API is an open source framework built on top of TensorFlow that makes it easy to construct, train and deploy object detection models.

Wearable Approach

❖ Google Cloud Platform

- ✓ Google Cloud Platform is a suite of public cloud computing services offered by Google. The platform includes a range of hosted services for compute, storage and application development that run on Google hardware.
- ✓ Google Cloud Platform offers services for compute, storage, networking, big data, machine learning and the internet of things (IoT), as well as cloud management, security and developer tools.

❖ Firebase Database

- ✓ The Firebase Realtime Database is a cloud-hosted database. Data is stored as JSON and synchronized in real-time to every connected client. All the clients share one Realtime Database instance and automatically receive updates with the newest data.

Wearable Approach

✓Methodology

❖ In order to analyze the data from the collected images to detect stress-eating behavior, the machine learning based smart system TensorFlow is used.

❖ We collected 1,000 images from the open access repository Pixabay by searching for images with food-specific keywords such as doughnuts, vegetables, noodles, rice, etc.

❖ The images are labeled manually using the TensorFlow application labelimg.exe, to mark the image regions with specific food items.

Wearable Approach

✓**Methodology**

❖ Overall, there were 130 varieties of food labeled in the images.

❖ Of these images, 800 were used for training and 200 were used for testing.

❖ We have used TensorFlow version 1.9.0 and have utilized the object detection application programming interface.

❖ The dataset which is used for training and testing is an opensource Food-a-pedia dataset with 2015 varieties of food along with their calorie count per serving, sugars and fats.

Non-Wearable Approach

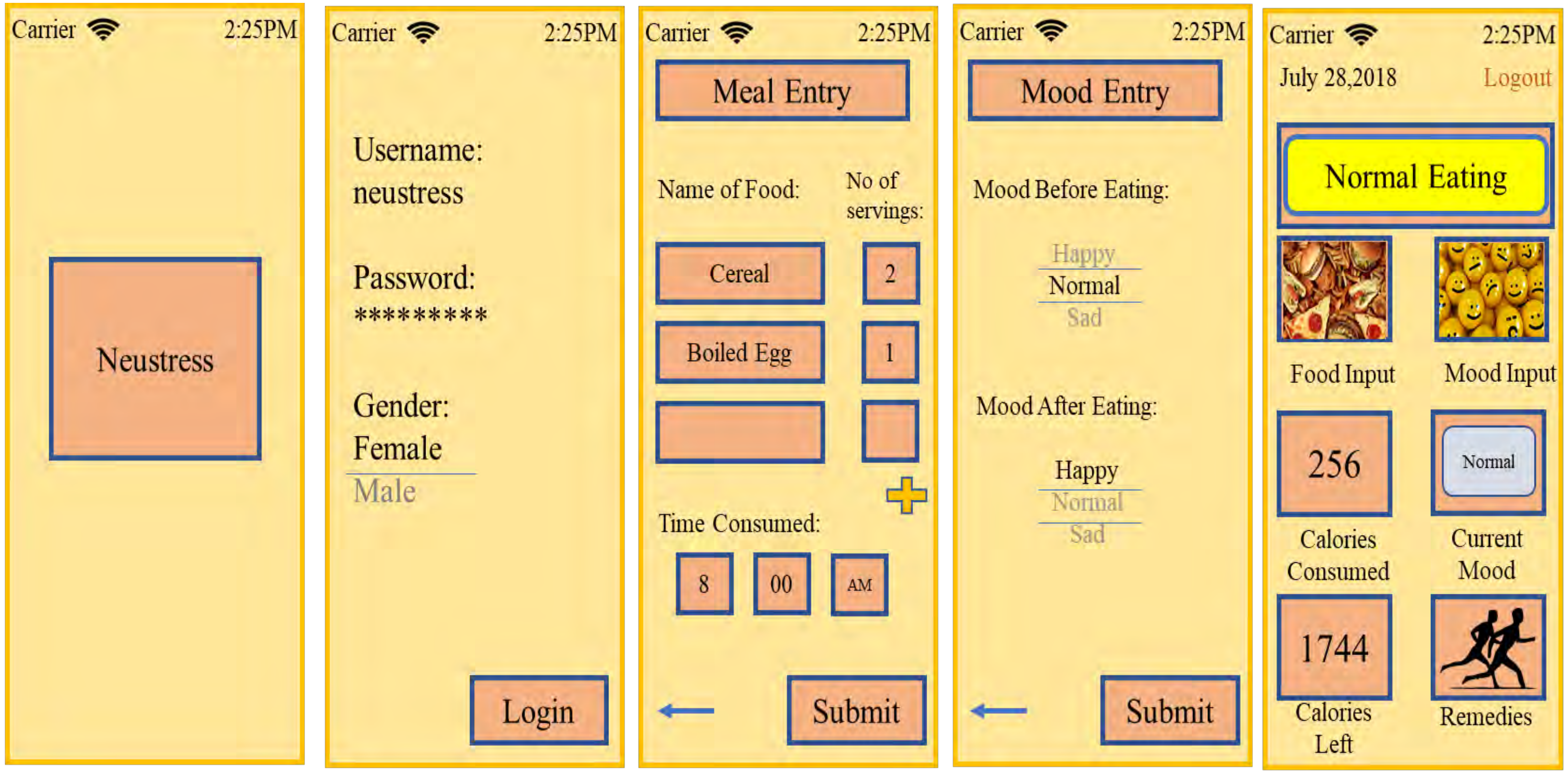
- The application was developed by using the Xcode 8.3 development platform and used the Swift 3.0 programming language.

Analyses of Stress-Eating

Recommended Calories/day	Sugars (gm/day)	Total calories	Time interval (hours)	Mood	Stress-Eating
Men: 2330	37.5gms of sugar or 150 calories	2500	6	Happy	Stress-Eating
Women: 1830	37.5gms of sugar or 150 calories	2000	5	Happy	Stress-Eating

Implementation- Normal Eating

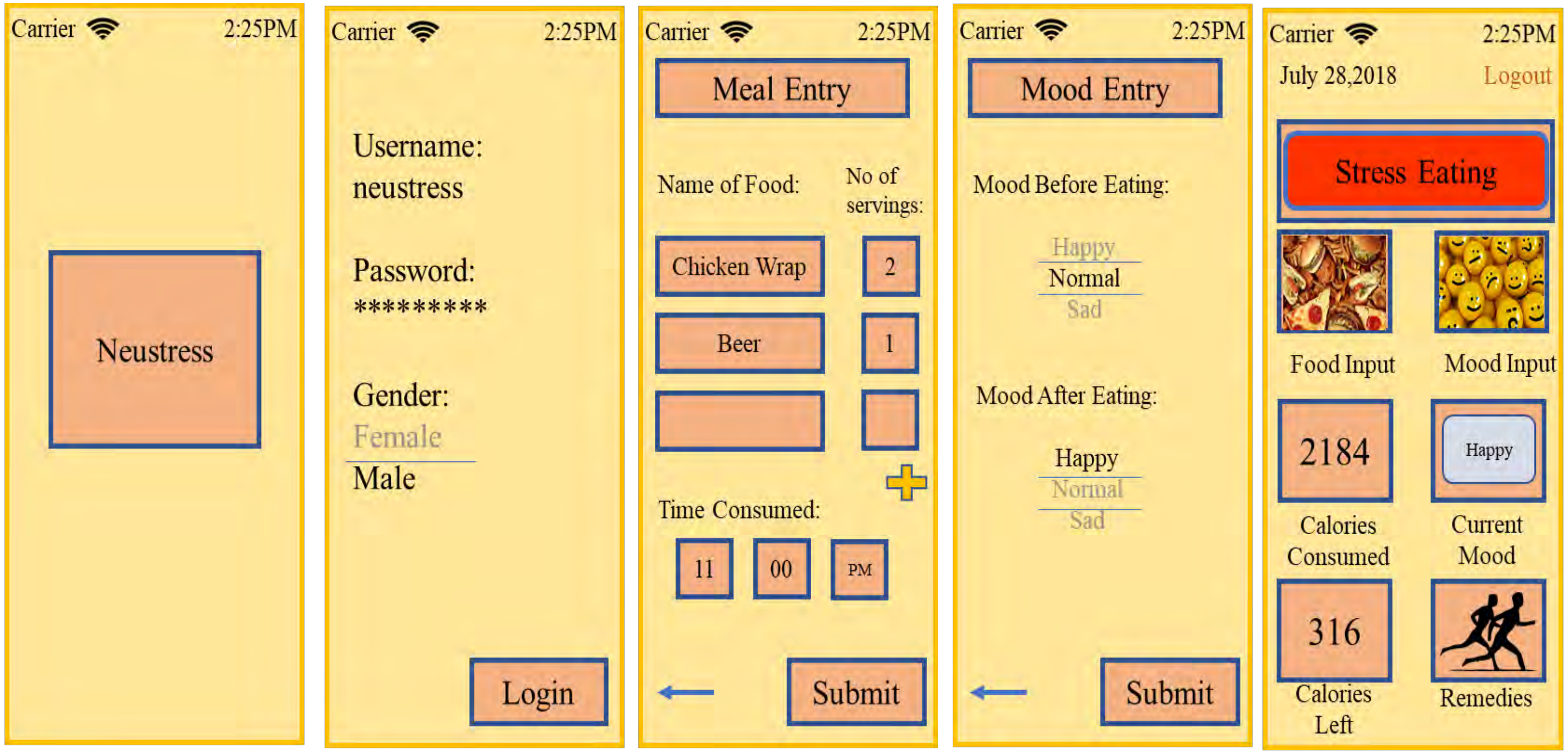
✓ Non-Wearable Approach



Non-wearable Normal Eating Result

Implementation: Stress-Eating

✓ **Non-Wearable Approach**



Non-wearable Stress Eating Result

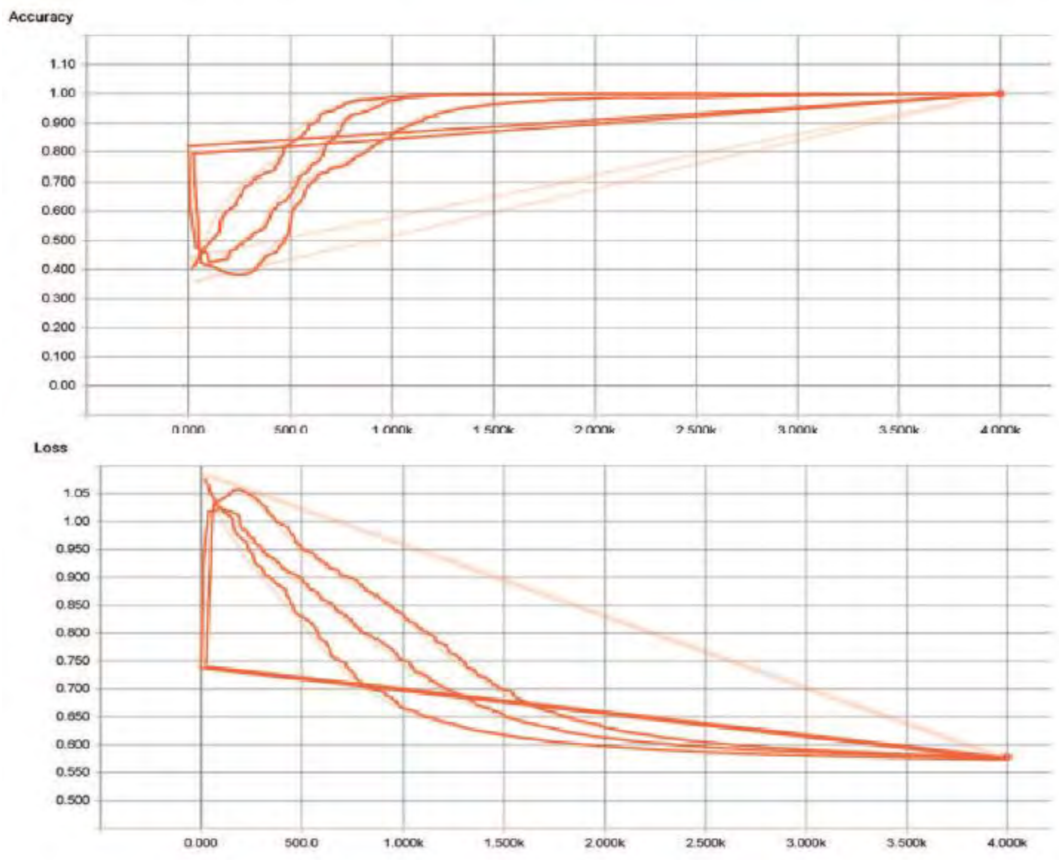
Smart Healthcare – iLog

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.

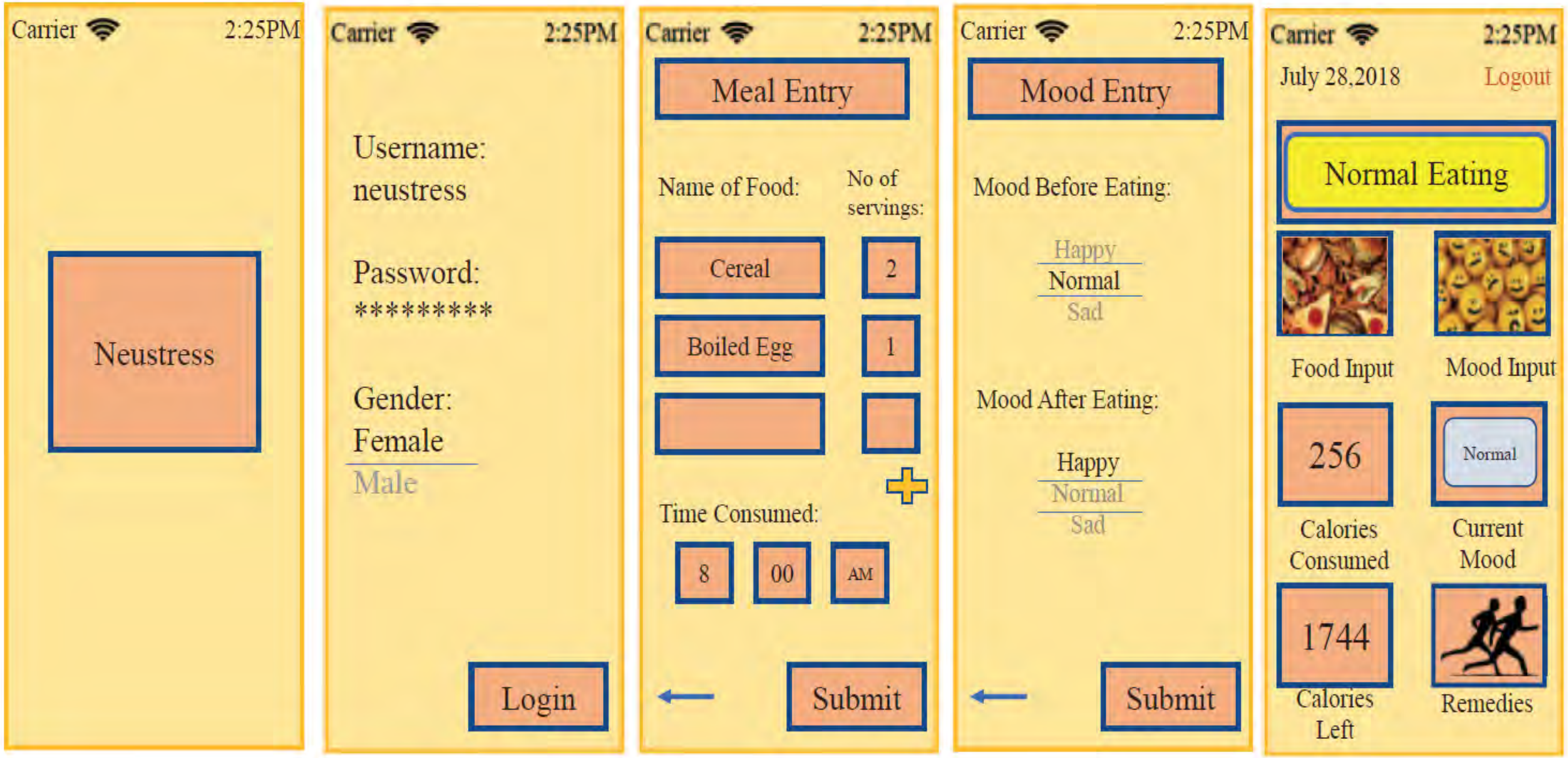
Implementation: Loss & Accuracy

✓ **Loss and Accuracy of Object Detection**



Implementation- Normal Eating

✓ **Wearable Approach**



Wearable Vs Non-Wearable

✓ Brief of the Proposed Approaches

Wearable Approach	Non-Wearable Approach
Expensive when compared to the non-wearable approach as it doesn't deal with much hardware.	Cheaper when compared to the wearable approach.
User should feel comfortable to have the hardware on them.	User will not face any discomfort as it is the mobile application.
Smart, Intelligent system which helps in producing results with better accuracy.	Manual input systems where the accuracy will be questionable.
Establishes the relationship between the food consumed and the stress levels of the person with minimum manual input.	Establishes the relationship between food consumed and stress with only manual inputs.

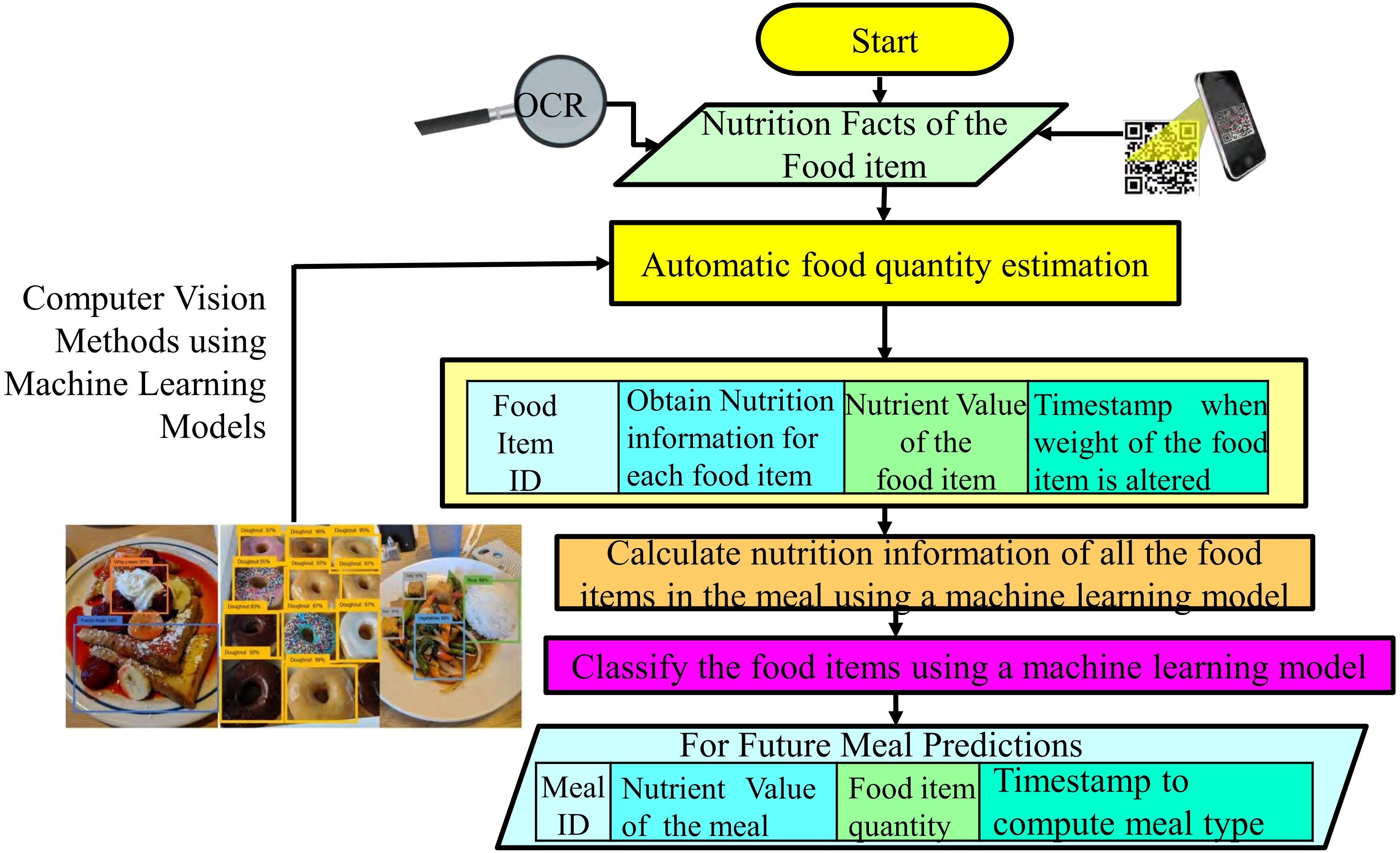
Comparison with Existing Research

Research	Stressors	Device Prototype	Self-analysis	Cost
Vanstrien, et.al [38]	Sad and Joy news	No	Not possible	Moderately High
Vanstrien, et.al [39]	Statistics and Meditation	No	Not possible	Moderately High
Adam, et.al [40]	Challenge and Fear conditions	No	Not possible	Moderately High
Harrison, et.al [41]	Pictorial stroop task, emotion recognition in images	No	Not possible	Moderately High
Ariga, et.al [42]	Structured interviews, self-rate questionnaire, statistical analysis	No	Not possible	Moderately High
Stress-Log (Current Paper)	Daily activity, human time isn't required	Yes, a mobile phone application and a wearable for instance a camera are presented	No need of heavy equipment; self monitoring is allowed	Moderately low

Conclusion and Future Research

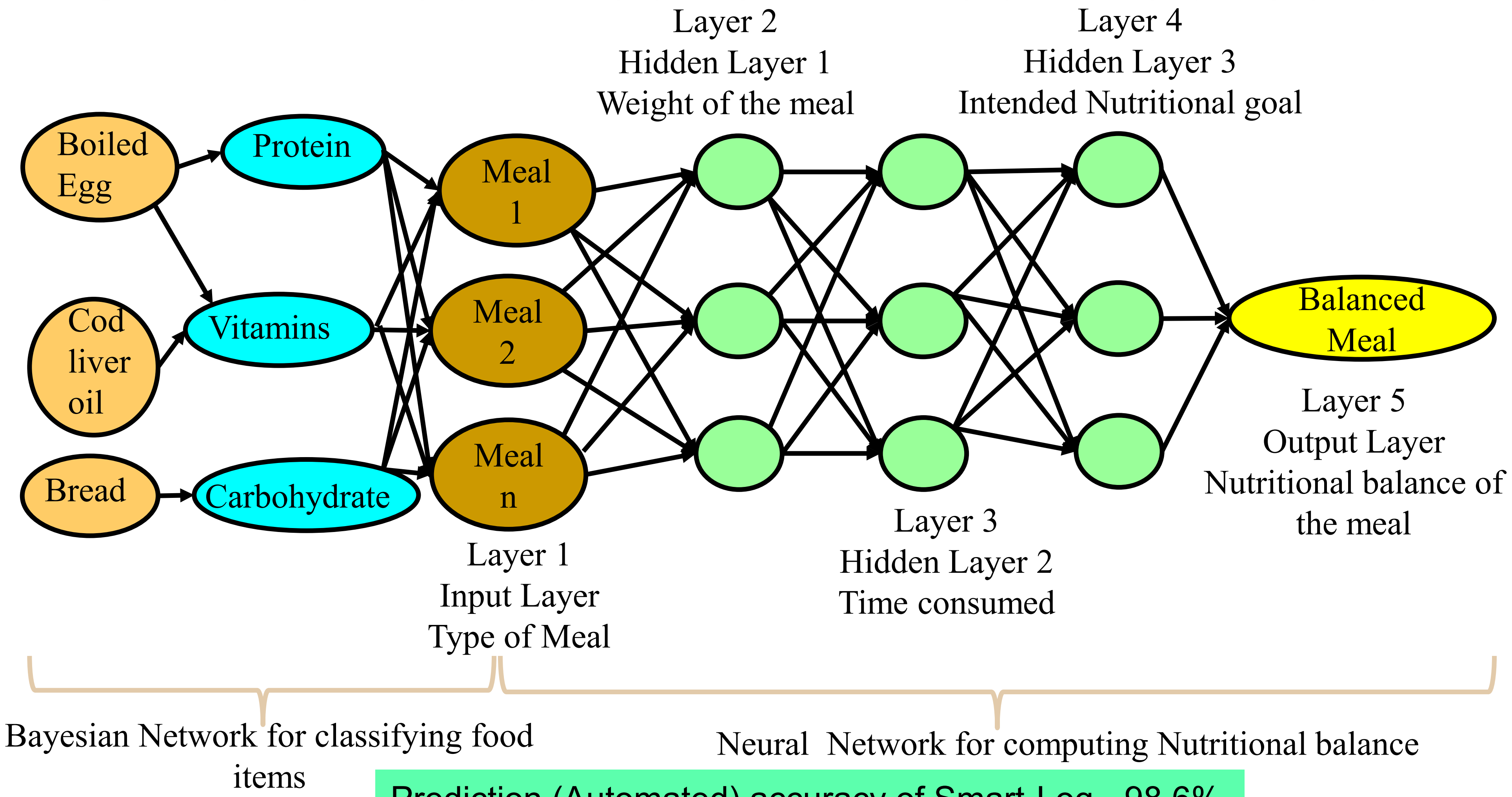
- The approach presented here provides an extension to the monitoring systems by focusing on the eating behaviors of the users and analyzing if the eating is stressed eating or normal eating.
- The accuracy of detecting food composition is found to be 97%, which strongly suggests this approach is suitable for effectively logging nutritional and calorific value of daily food intake.
- The approach could be an answer to a long-time sought-after need for watching the food behaviors and their impact on overall physical and mental health.

Smart Healthcare – Diet Prediction



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

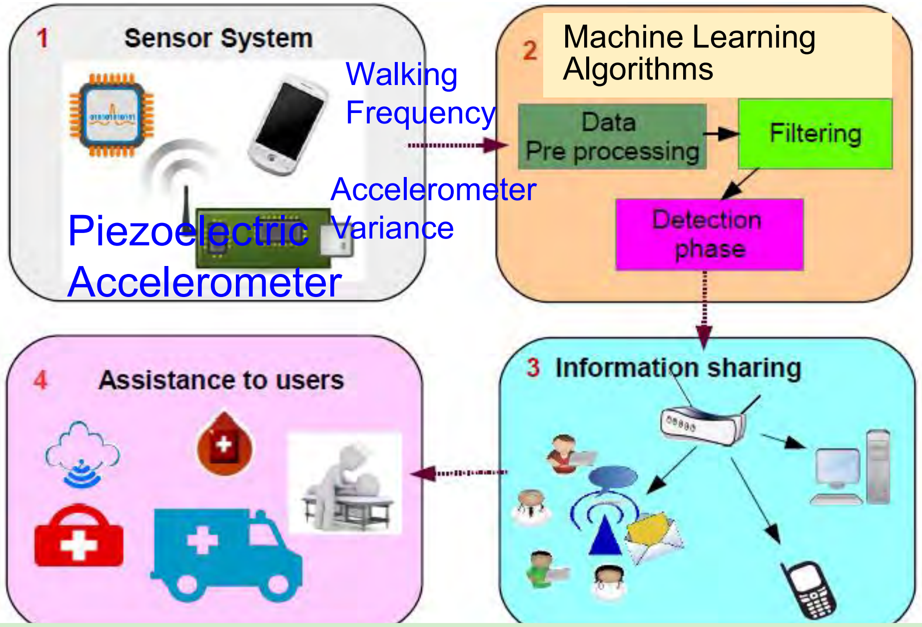
Smart Healthcare – Diet Prediction



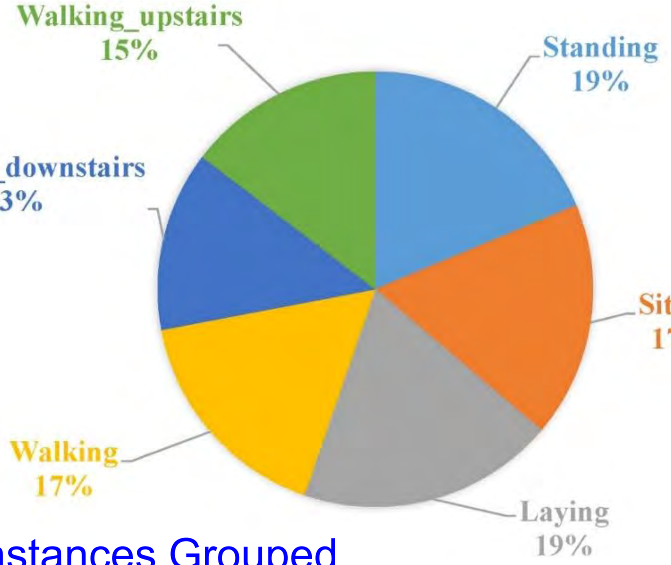
Prediction (Automated) accuracy of Smart-Log - 98.6%

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

Smart Healthcare - Smart-Walk



Automated Physiological Monitoring System



10291 Instances Grouped Under 6 Activities - Kaggle

Research Works	Method	Features considered	Activities	Accuracy (%)
This Work	Adaptive algorithm based on feature extraction (WEKA)	Step detection and Step length estimation	Walking, sitting, standing, etc.	97.9

Source: Mohanty ICCE 2018

Novel Contributions of This Paper

1. An architecture is proposed for vital sign monitoring in families.

2. A dynamic calibration module to improve the accuracy of the sensor design is proposed.

3. A feature based framework for human step-detection based on the learning parameters is proposed.

4. The algorithm is validated using a classifier which analyzes different learning parameters and dynamically calibrates the sensor system.

Framework of the Smart Walk System

✓ **Ideal Components**

- Sensor/transducer for data acquisition.
- Algorithms
- Information sharing
- Assistance to users

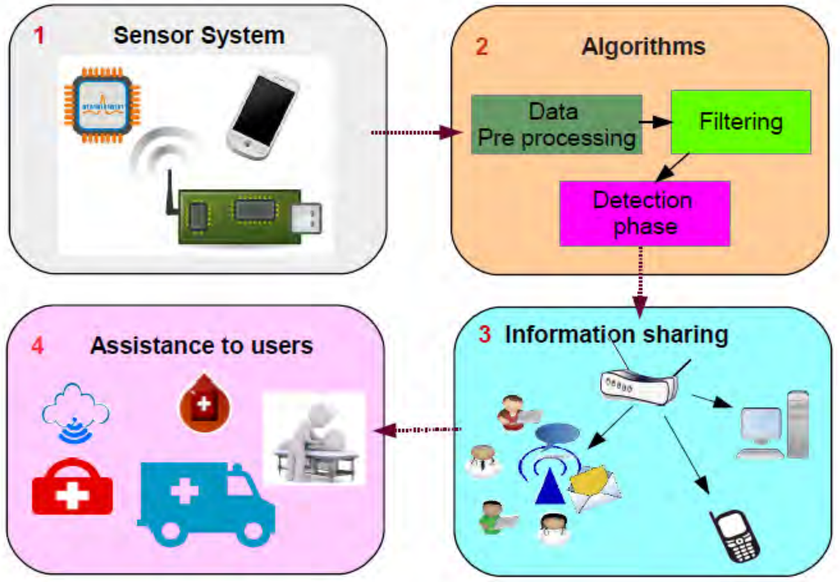
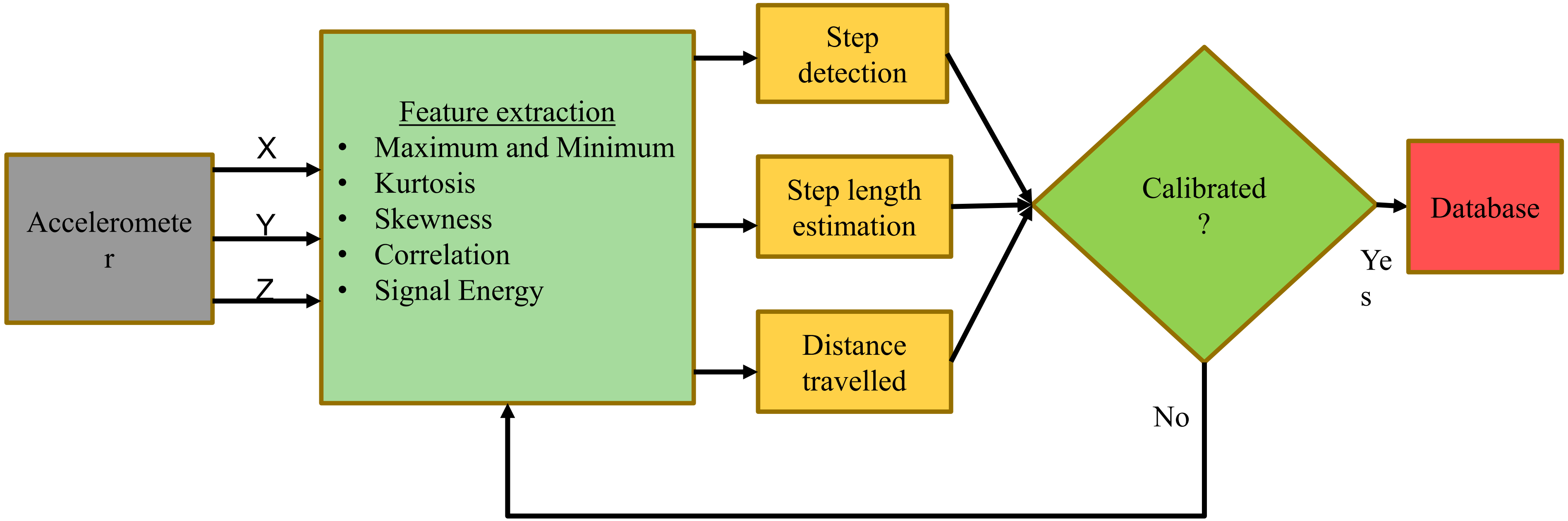


Fig. 2. Framework of the Smart walk system

Proposed method for Efficient Parameter Estimation



Feature extraction

✓ Accelerometer data

- X-axis → twisting or turning
- Y axis → leaning backward or forward
- Z-axis → movement against gravity

✓ Features

- Kurtosis
- Mean
- Standard deviation
- Maxima and Minima
- Skewness

Human Activity Monitoring Algorithm

Step detection

Step length estimation

Human Activity Monitoring Algorithm

- Step length is measured from heel to heel

- Human step length estimation varies linearly in accordance to the walking frequency and accelerometer variance

$$\text{Step length} = \alpha.f + \beta.v + \gamma$$

- f → walking frequency
- v → Variance of the accelerometer
- α β and γ → pre-learned parameters

Data for the Sensor System

- A public database consisting of 10291 instances of smartphone based human activity data was considered from Kaggle.

- These instances were grouped into six categories of activity: sitting, standing, walking, climbing downstairs, climbing upstairs, and laying.

Classifier evaluation using WEKA

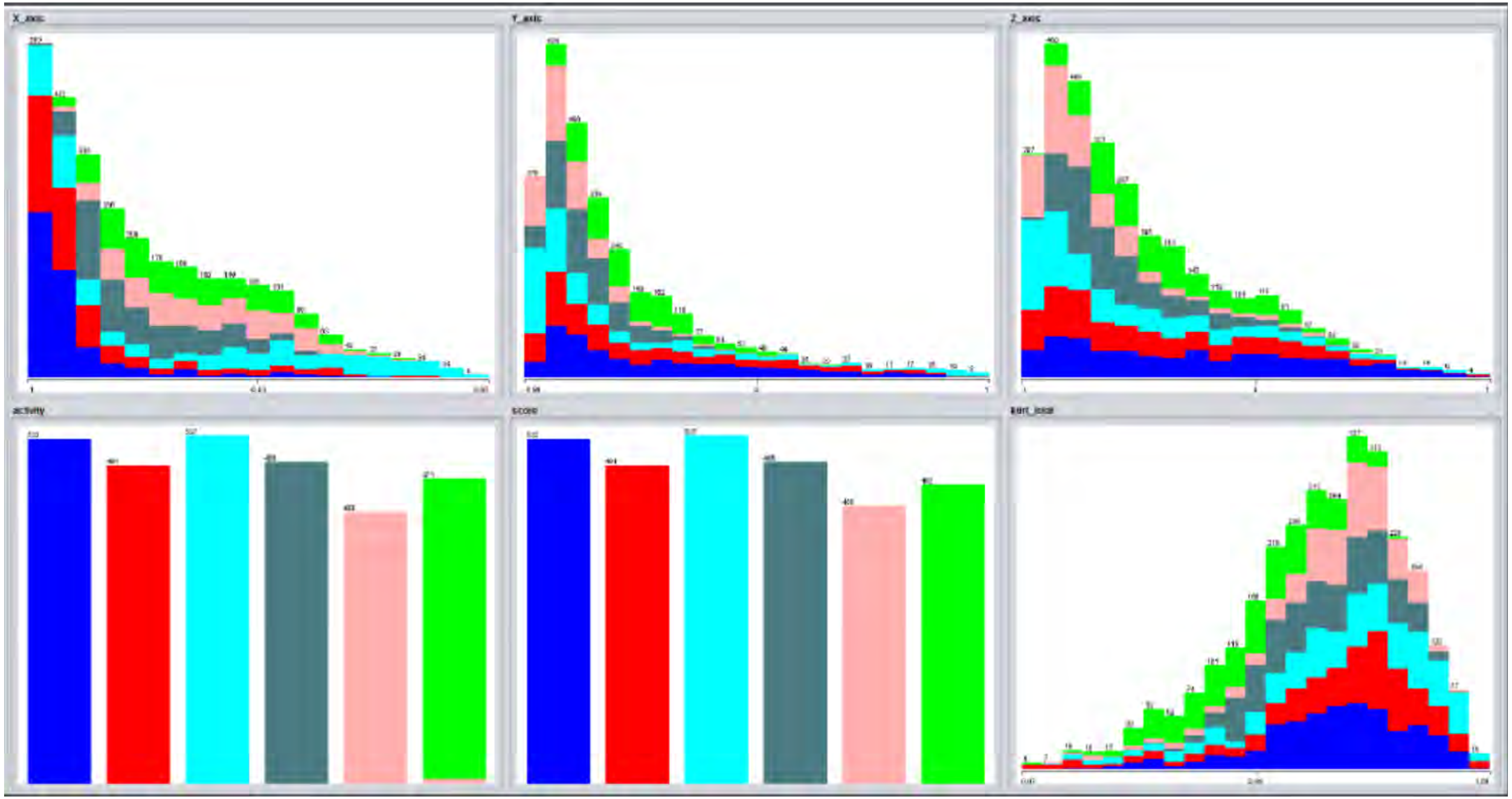
- Waikato Environment for Knowledge Analysis (WEKA) helps in evaluating system using numerous algorithms.

- Whenever a user makes a data entry, an Attribute-Relation File Format (.arff) is created, which serves as input for WEKA.

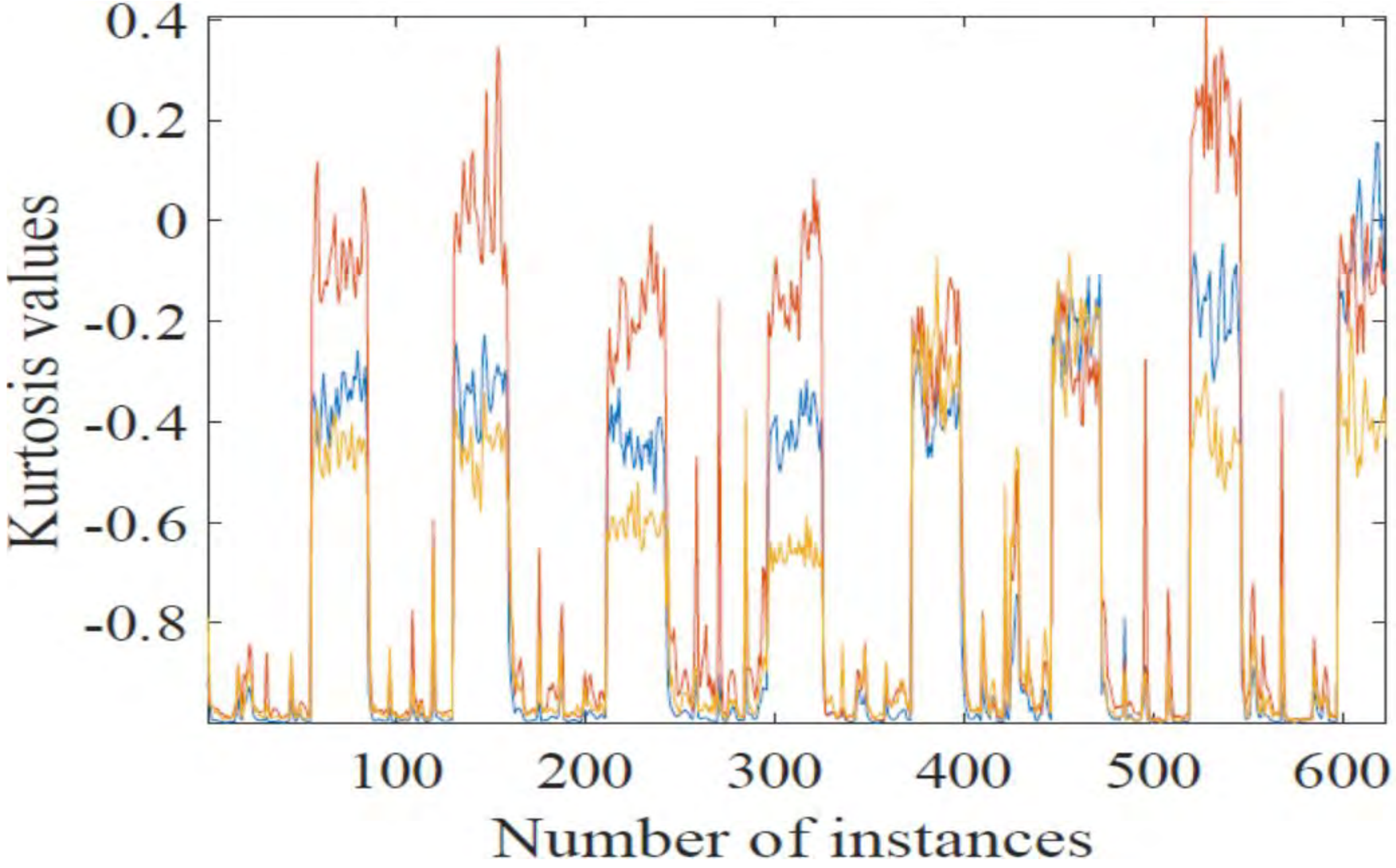
Classifier evaluation for Kurtosis values using WEKA

Classifiers	Correlation Coefficient	Mean absolute error	Root Mean Squared error	Relative absolute error(%)	Root Relative Squared error (%)
SMO Regression	0.7795	0.1029	0.1956	44.8049	67.68
Gaussian Process	0.7979	0.1146	0.1742	49.90	60.28
M5 Rules	0.9741	0.0409	0.0657	17.82	22.72
Decision Table	0.9263	0.0619	0.11	26.94	38.07
Linear Regression	0.7979	0.1142	0.1741	49.71	60.27
Multilayer Perceptron	0.9645	0.0597	0.0868	26.00	30.03
Additive Regression	0.9273	0.0856	0.111	37.26	38.41

Kurtosis Analysis in WEKA



Kurtosis values in different postures from 3 different subjects



Classifier evaluation for Minimum and Maximum Accelerometer values using WEKA

Classifiers	Mean Absolute error	RMS error
Input Mapped Classifier	0.0014	0.0018
SMO	0.222	0.3089
Decision Stump	0.2234	0.3342
Simple Logistic	0.0437	0.0587
Decision Table	0.0015	0.0002
Bayes Net	0.0009	0.3309
Multilayer Perceptron	0.0012	0.0016

Performance Comparison with Existing Research

Research Works	Method	Features considered	Activities	Accuracy (%)
Shin et al [21]	Awareness algorithm of movement status	Step length and total walking distance	Walk and run	96
Chien et al. [20]	Dynamic algorithm	Number of steps taken	Walking, jumping and jogging	95
This paper	Adaptive algorithm based on feature extraction	Step detection and Step length estimation	Walking, sitting, standing	97.9

Characterization Table for the Proposed System

Characteristics	
Sensor System	TIMSP432 launchpad integrated with Educational Booster Pack MKII
Operating Frequency	48 MHz
Sensor data acquisition tool	Energia and MATLAB
Data Analysis Tool	WEKA
Sample Dataset	10291 instances for analysis and 623 instances for validation
Classifier	Decision Table
Accuracy (Worst Case)	97.9%

Conclusion and Future Research

- A framework based on features, for human activity monitoring system to keep track of physiological health of friends and family.

- This method helps in improving the overall calibration of the activity monitoring system.

- The decision table classifier using the data acquired from the sensing module yields 97.9% accuracy.

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

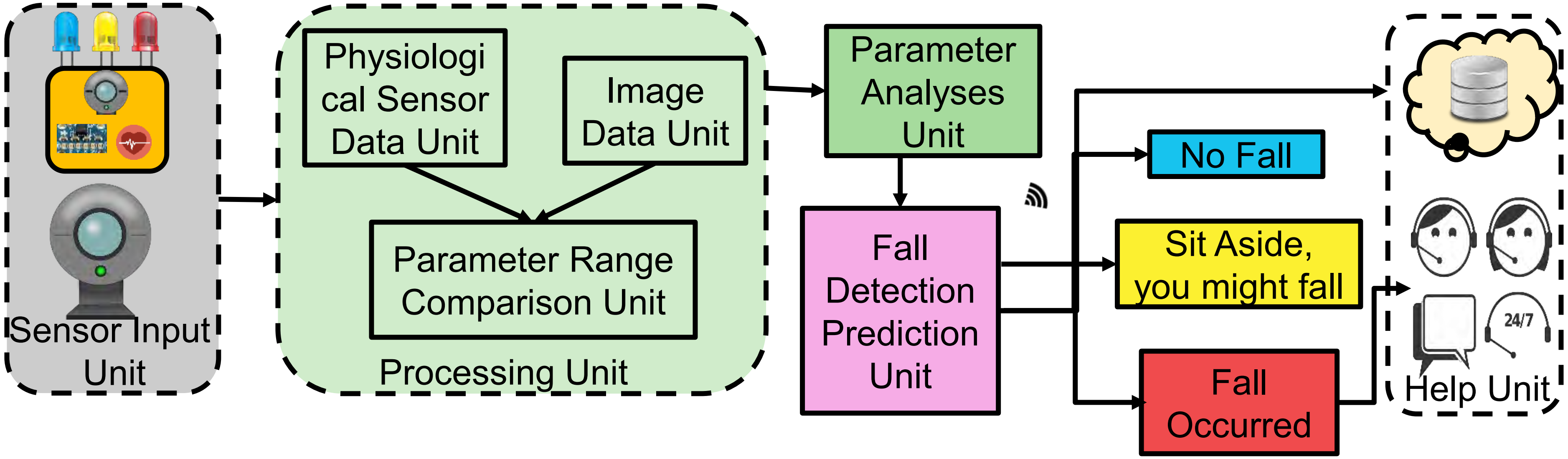
- Decisions of fall are dependent on the changes in accelerometer axes only.
- Some applications have user to give response after the fall and that can be time consuming as the user might not be conscious.
- Some applications are limited to a certain location and certain type of surroundings which add 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: Research Question

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

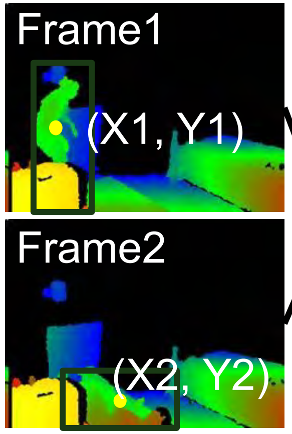
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019,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

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



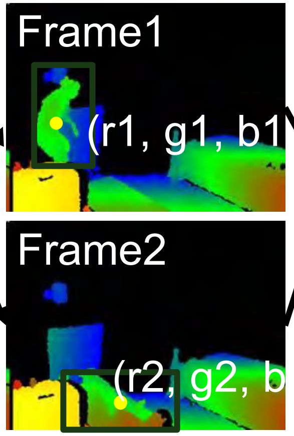
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019,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

Good-Eye: Elderly Fall Detection



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; }
```



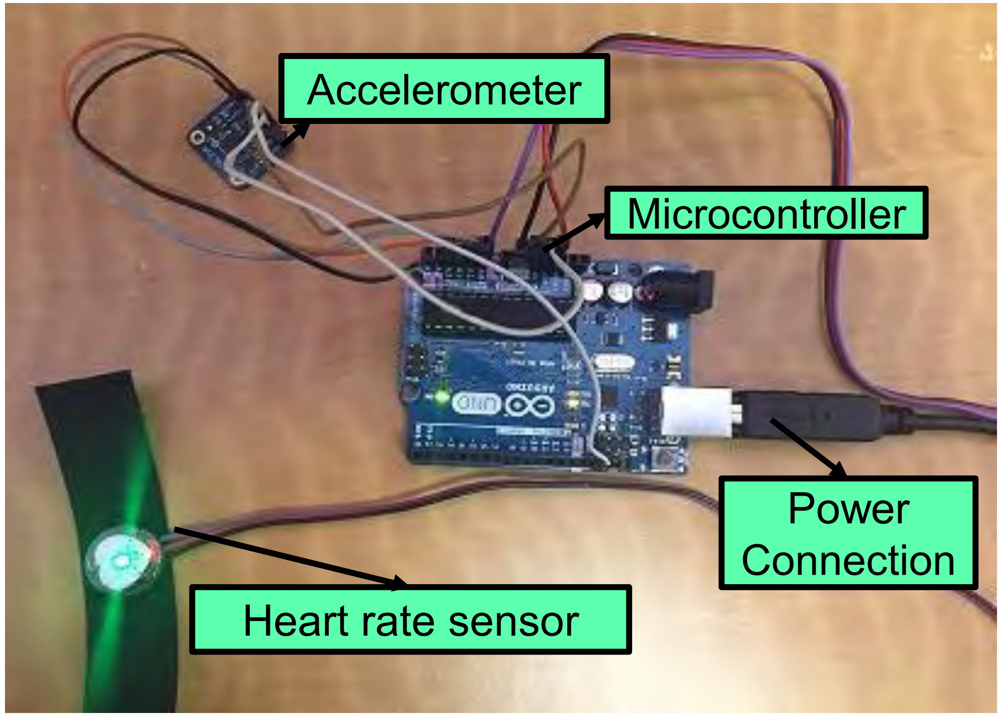
Distance Formula for r,g,b

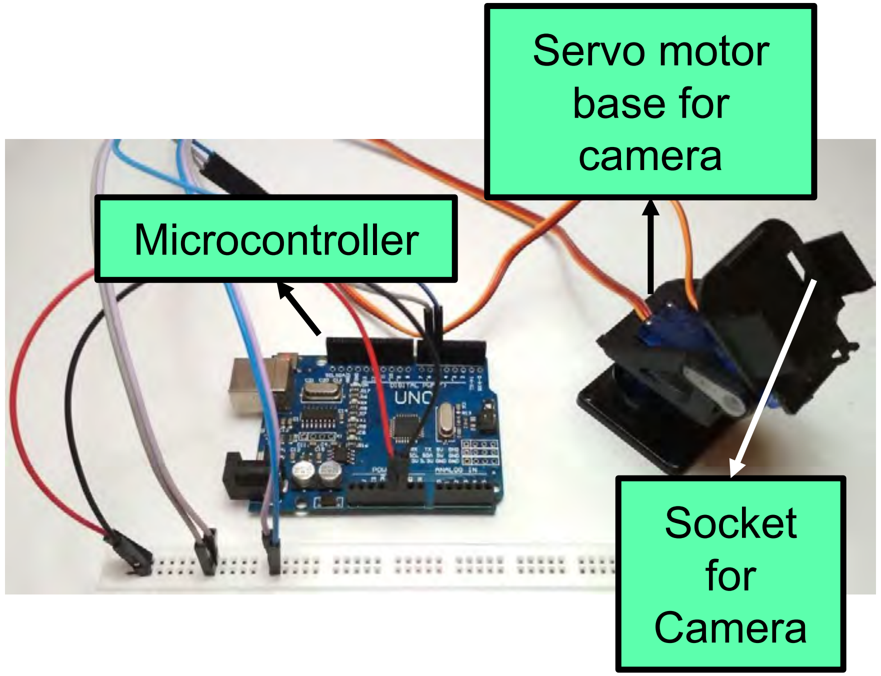
Check if the d is above the threshold

Decision of fall

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

Good-Eye: Prototyping

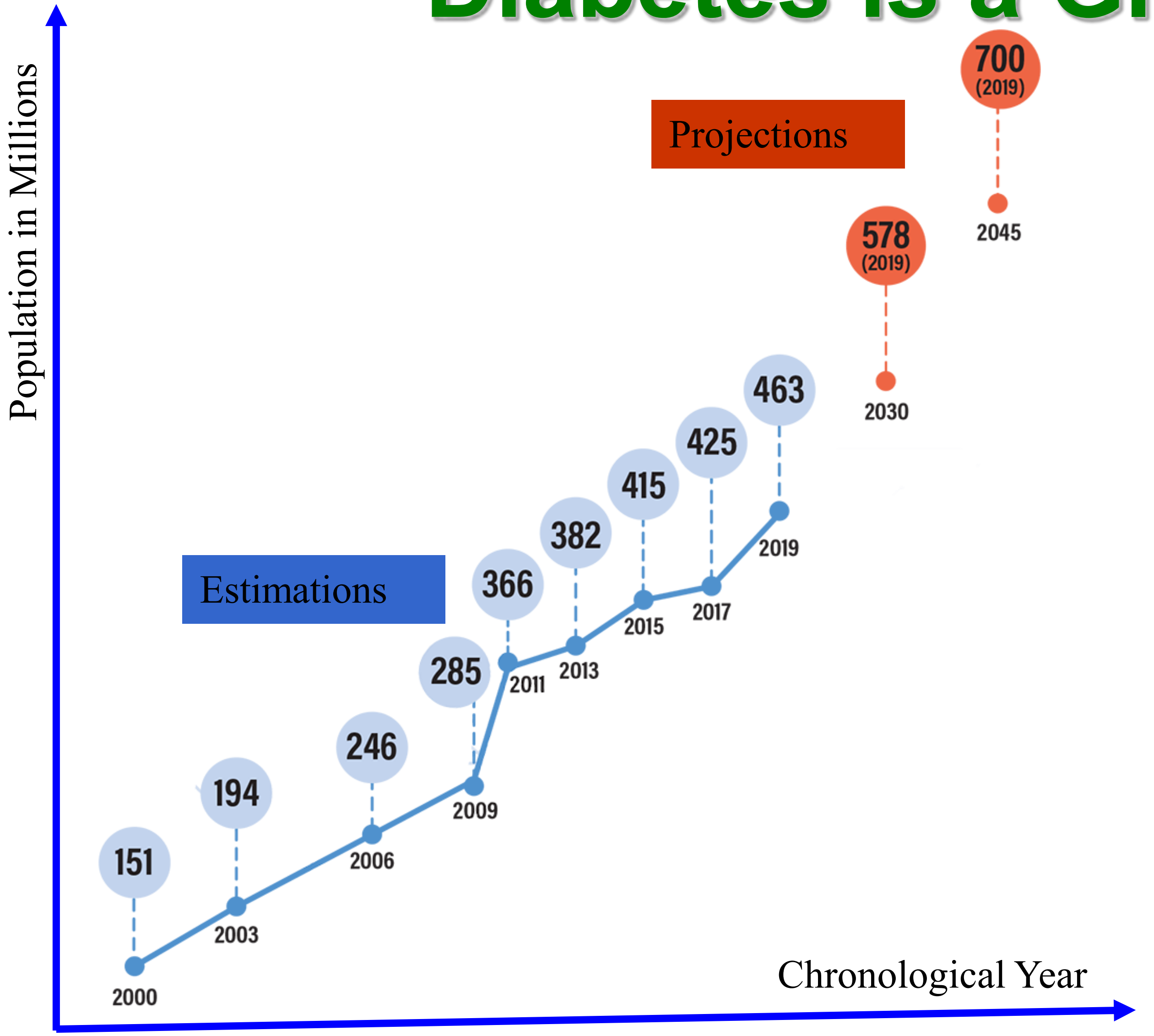




Good-Eye: Fall detection and prediction Accuracy - 95%.

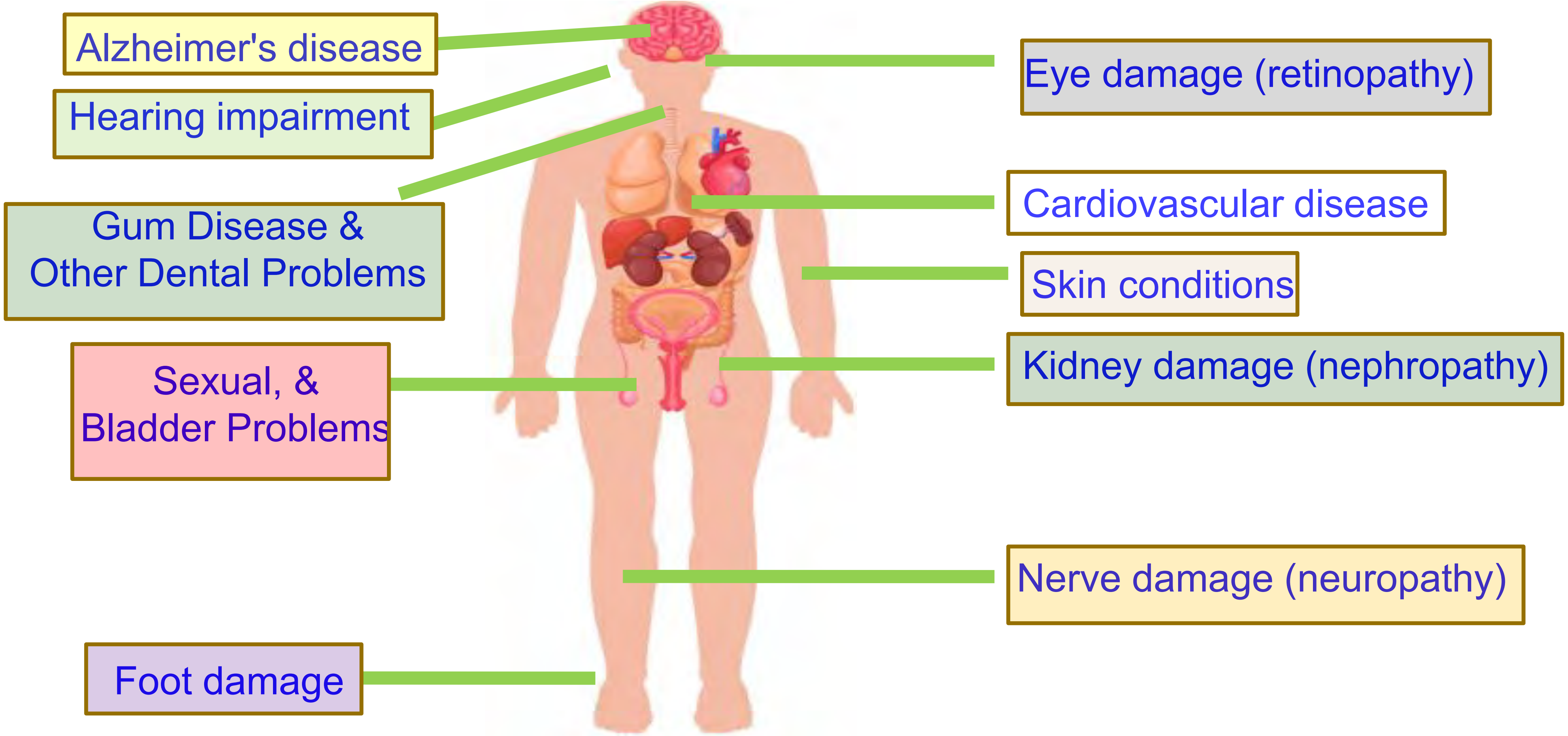
Source: L. Rachakonda, A. Sharma, S. P. Mohanty, and E. Kougianos, "Good-Eye: A Combined Computer-Vision and Physiological-Sensor based Device for Full-Proof Prediction and Detection of Fall of Adults", in *Proceedings of the 2nd IFIP International Internet of Things (IoT) Conference (IFIP-IoT)*, 2019,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

Diabetes is a Global Crisis



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: 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 - Types

Diabetes

Type 1 Diabetes

Body doesn’t generate sufficient insulin for glucose regulation

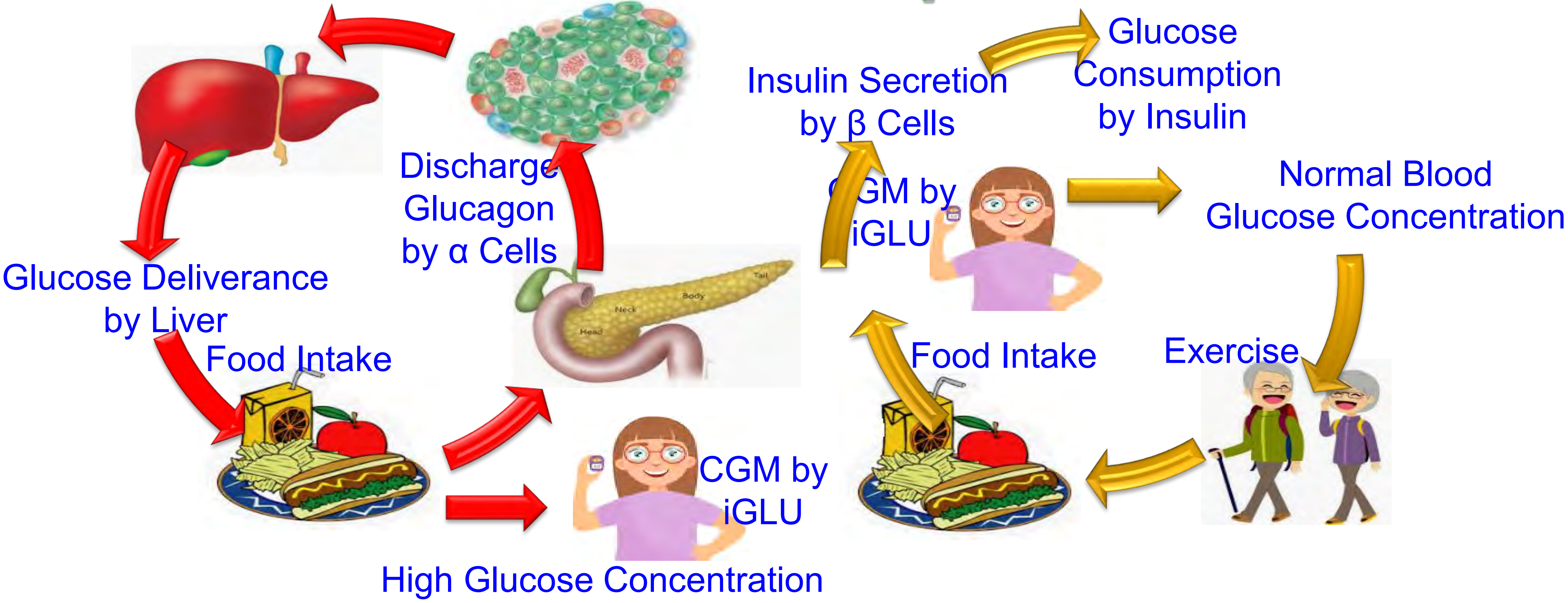
Type 2 Diabetes

Insufficient insulin secretion for blood glucose regulation

Gestational Diabetes

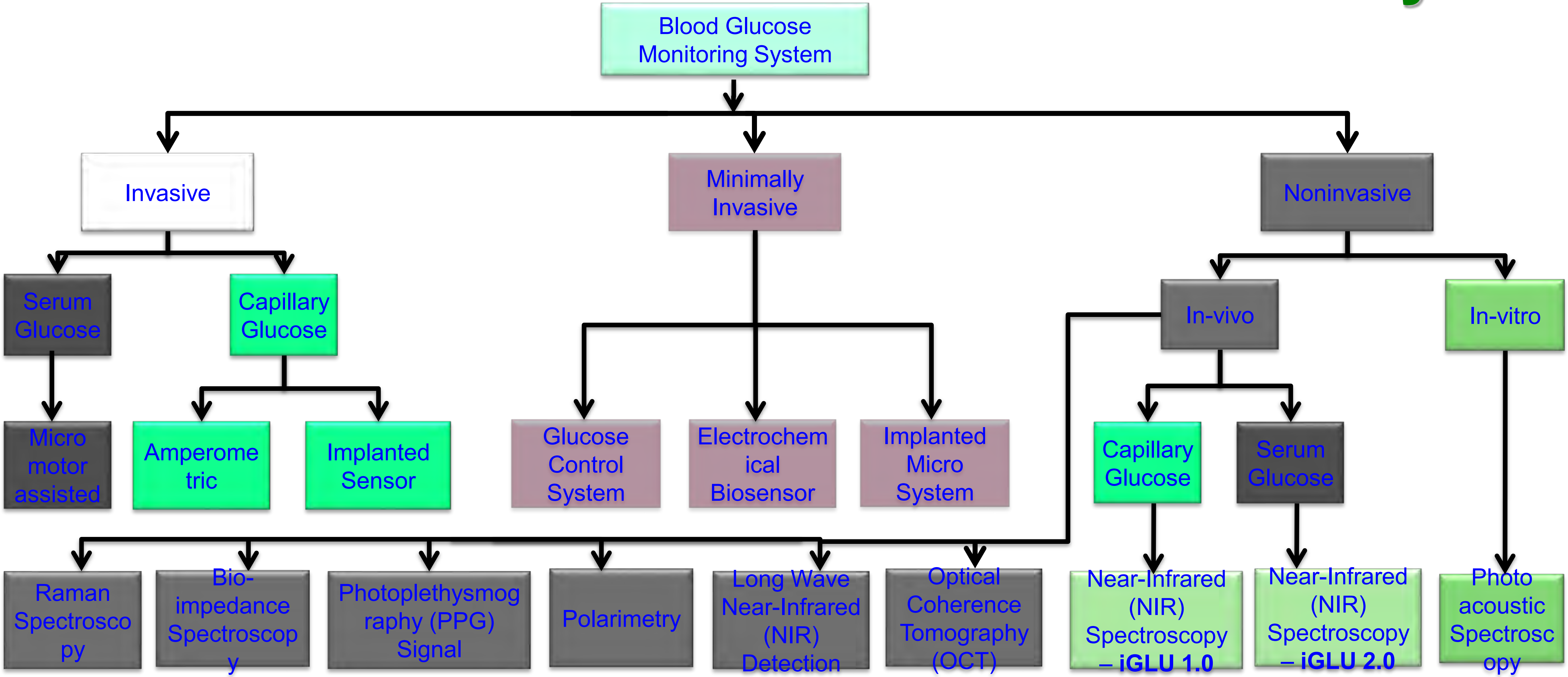
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

Glucose Generation and Consumption – Close Loop



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.

Glucose-Level Measurement - Taxonomy



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.

Invasive and Noninvasive Glucose Measurement

Invasive Glucose Measurement

- Conventional Method for Glucose Measurement
- Device, Strips and Lancets are easily available
- The Cost of each Test is Less

- Irritating Process for Glucose Measurement
- Not Recommended for Continuous Monitoring
- Probability of being Blood related infections

Non-invasive Glucose Measurement

LED

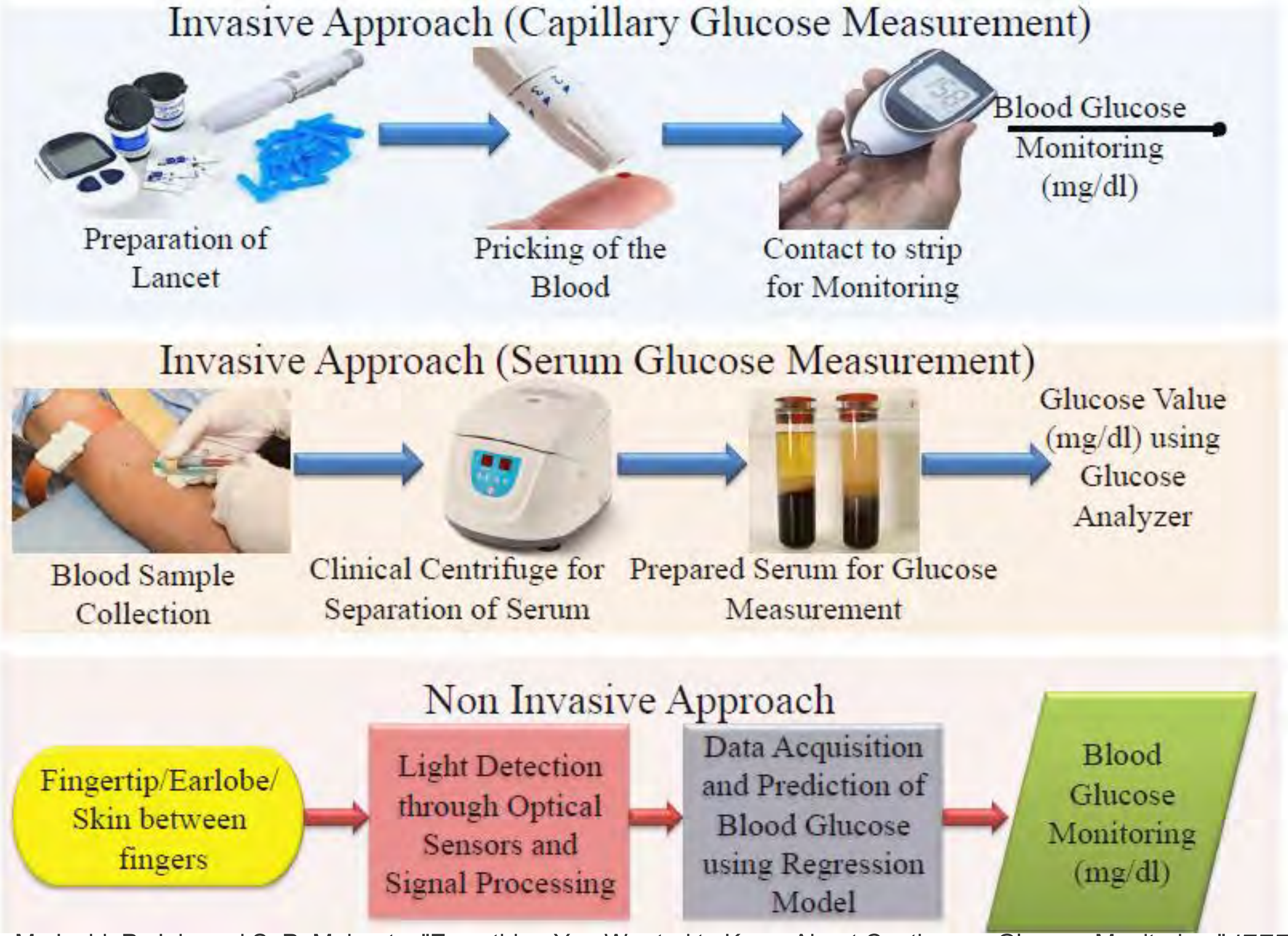
Detector

- Recent Advances in Glucose Measurement
- Measurement is Possible without Pricking Blood
- Suitable Device for Continuous Monitoring

- Accuracy in Measurement is yet to achieve
- The Device is not yet available for use
- Not Suitable for Glucose Measurement of Hypoglycemic Patients

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.

Blood Glucose Monitoring –
Invasive Vs Noninvasive



Traditional – Finger Pricking

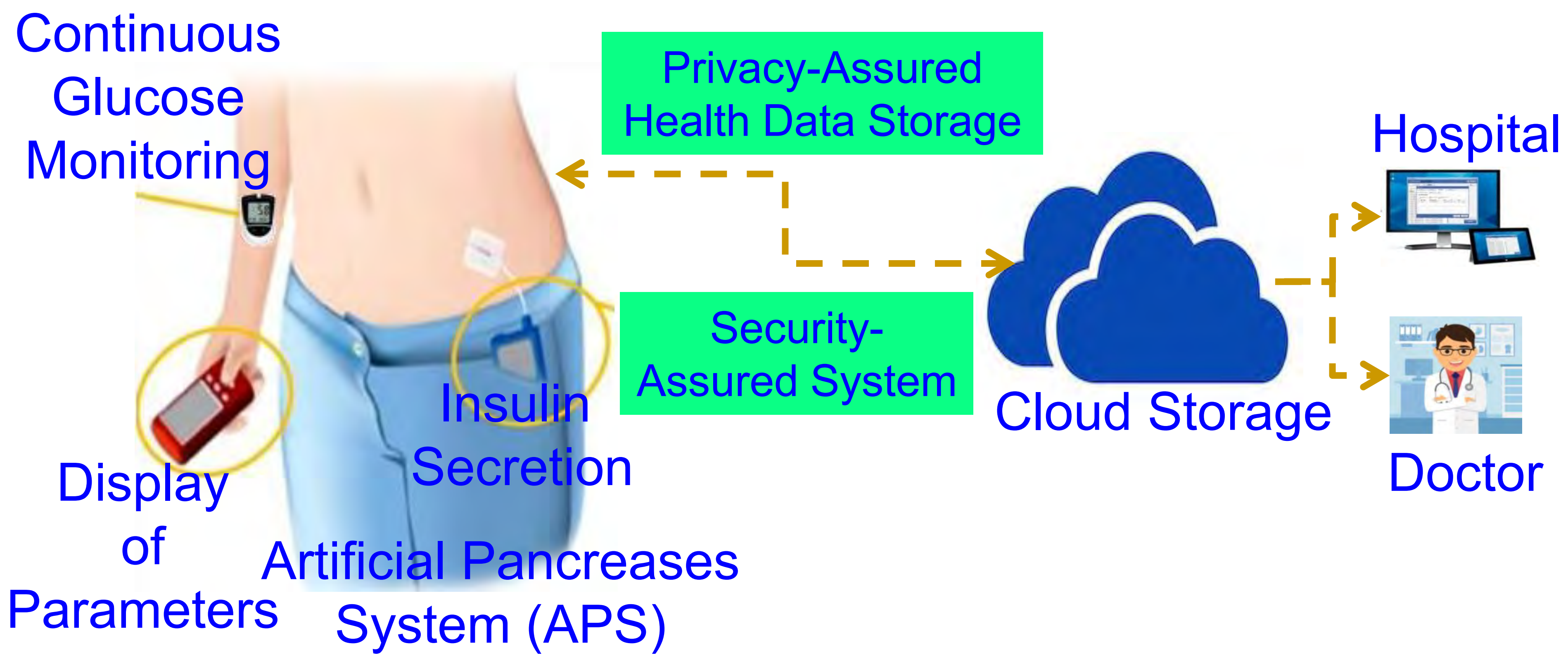
Invasive Approach – Processing Blood/Serum

Noninvasive – Wearable

Noninvasive Approach – Processing Light

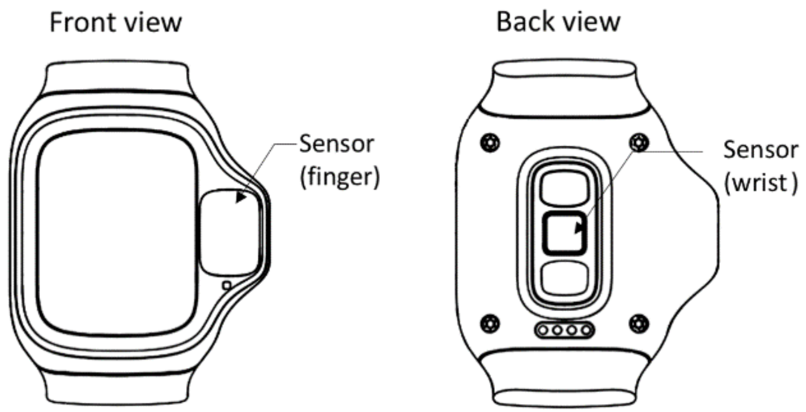
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

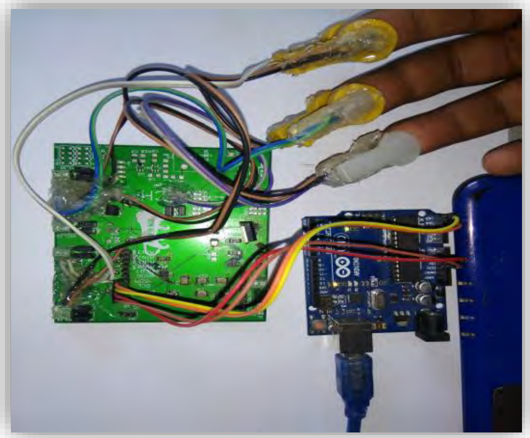
Our Vision – iGLU (Intelligent Noninvasive Monitoring and Control)



Source: A. M. Joshi, P. Jain, and **S. P. Mohanty**, "iGLU 3.0: A Secure Noninvasive Glucometer and Automatic Insulin Delivery System in IoMT", *IEEE Transactions on Consumer Electronics (TCE)*, Vol. 68, No. 1, February 2022, pp. 14--22, DOI: https://doi.org/10.1109/TCE.2022.3145055.

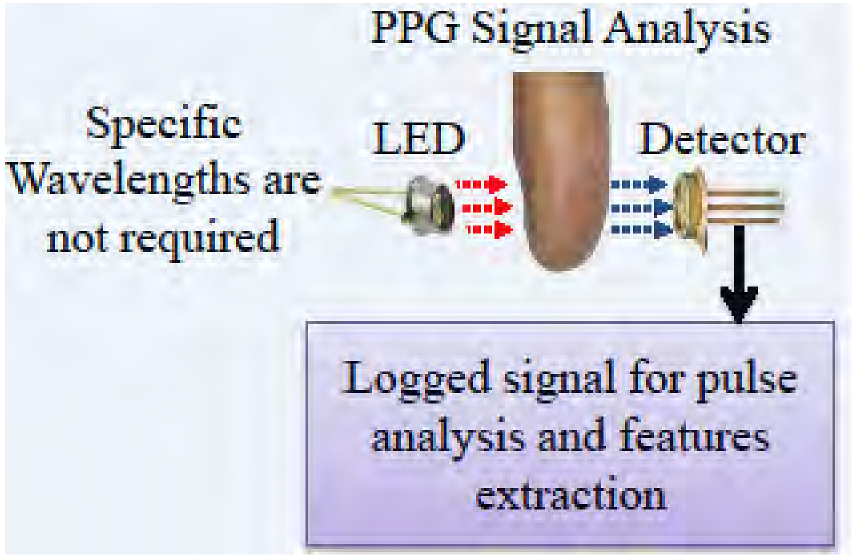
Noninvasive Glucose-Level Monitoring

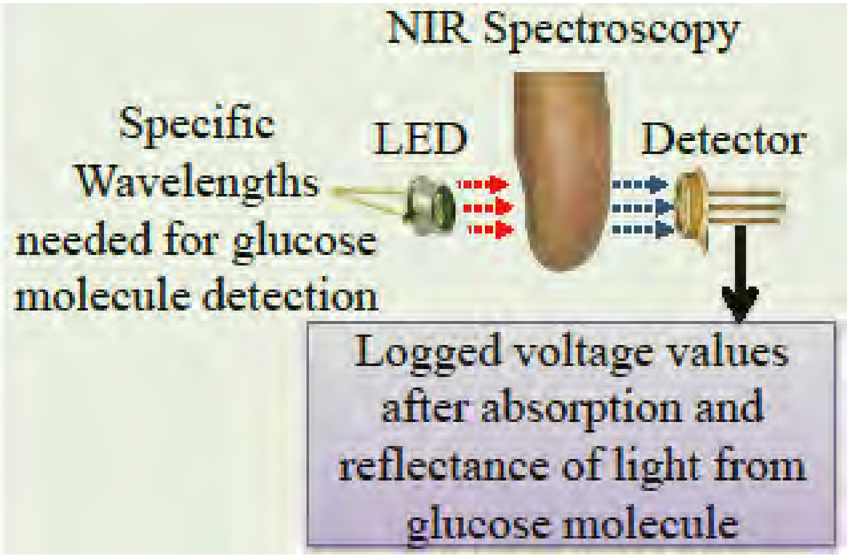




Photoplethysmogram (PPG)

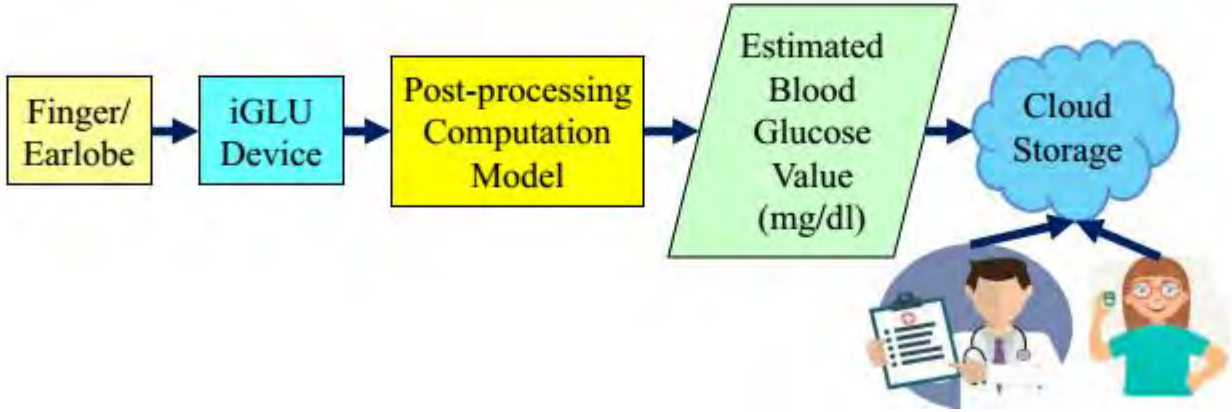
Near Infrared (NIR)





Design of iGLU

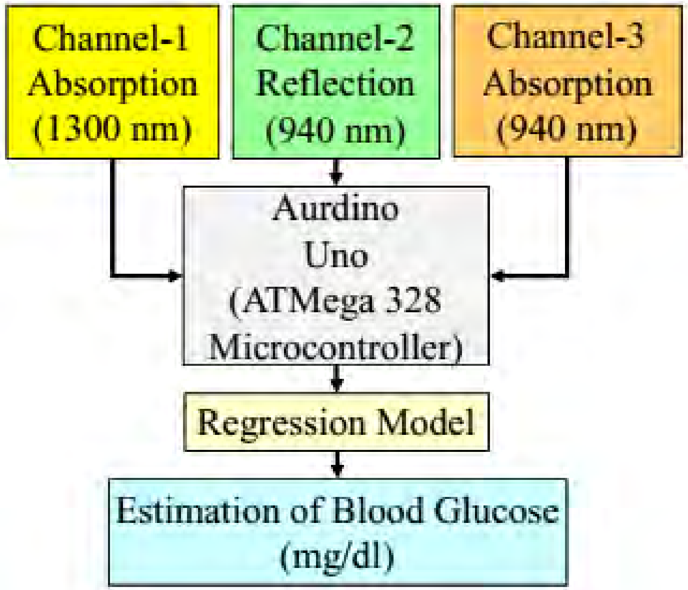
- iGLU is low cost and high accuracy solution to measure the blood glucose of any type of patients at any time.
- The device is user-friendly, fast operated and effective for smart healthcare [5].
- A novel non-invasive intelligent device is proposed using NIR light with specific wavelengths for instant glucose measurement.



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.

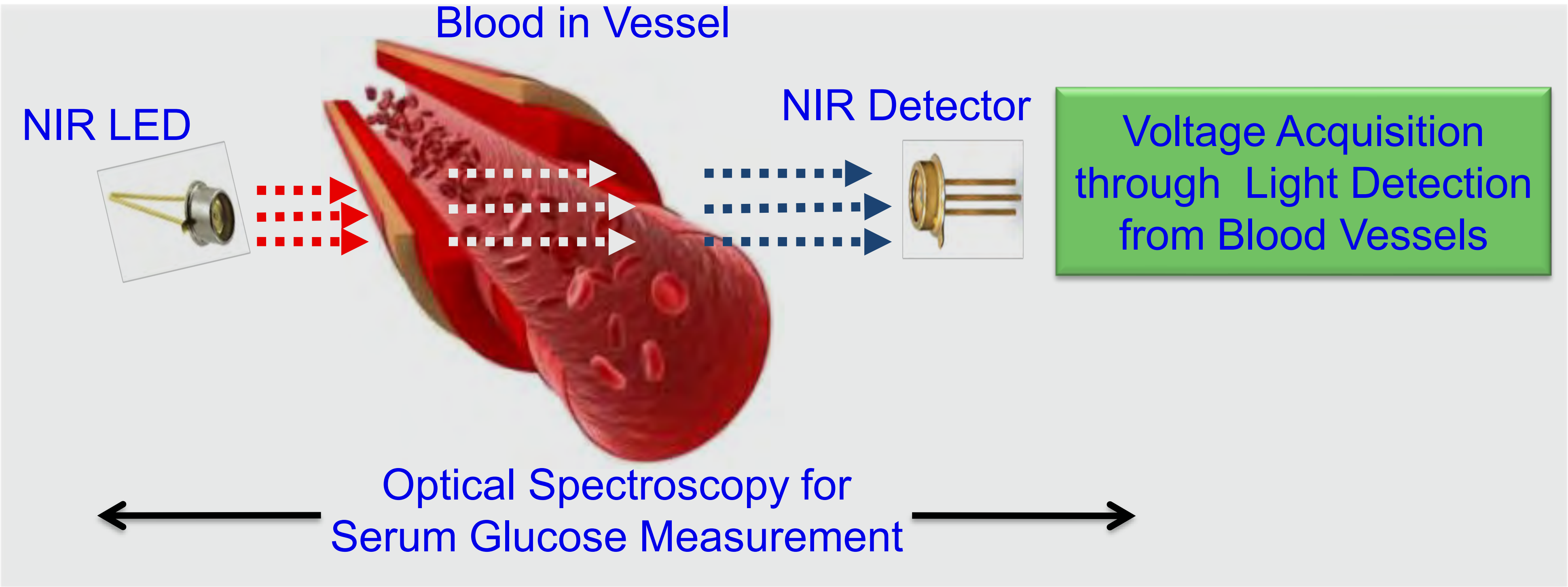
Proposed iGLU

- Proposed iGLU device uses the concept of NIR spectroscopy with multiple short wavelengths.
- The device is implemented with three channels where each channel is embedded for particular wavelength with emitter and detector.



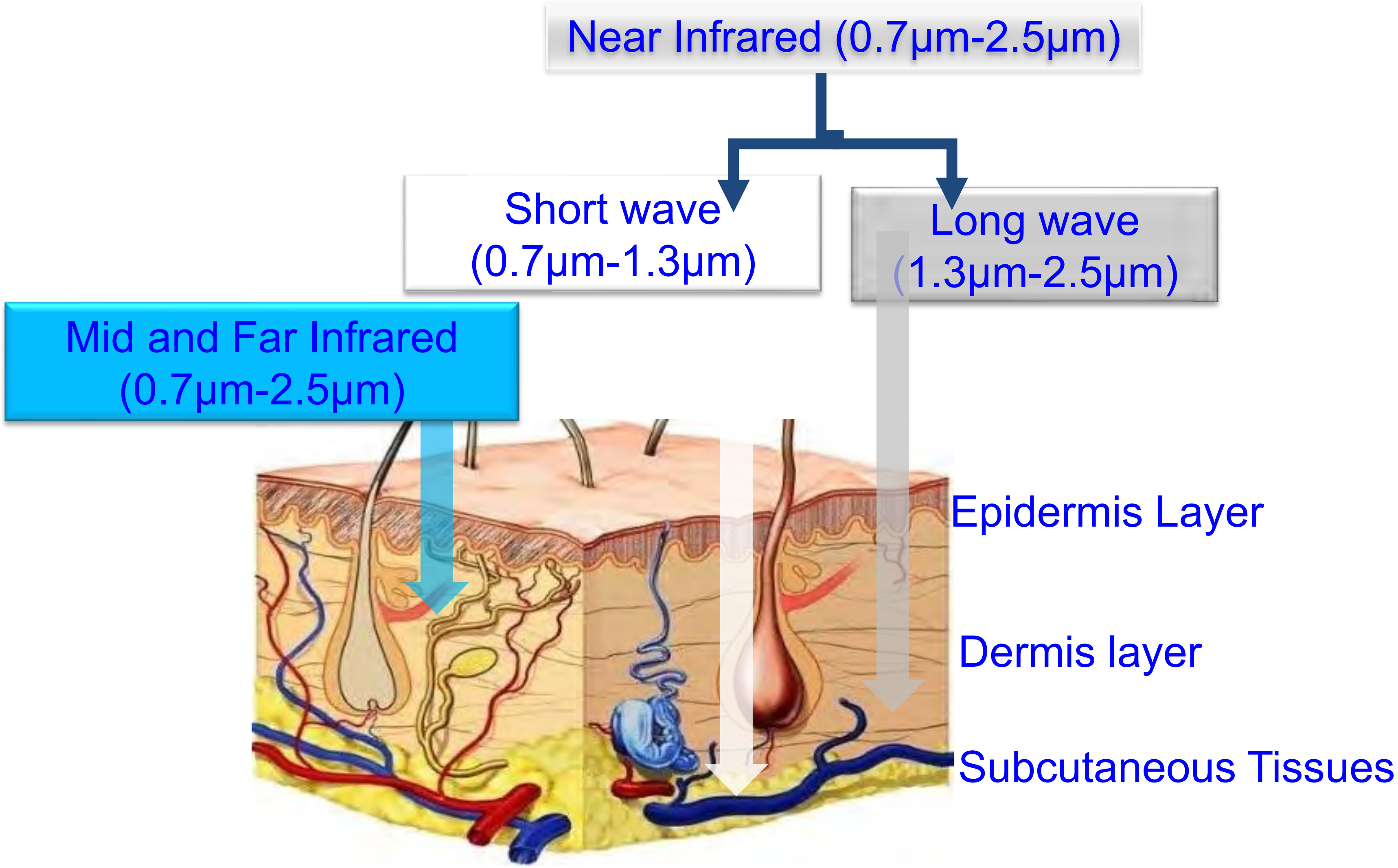
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

NIR Spectroscopy Mechanism of Blood Glucose Measurement



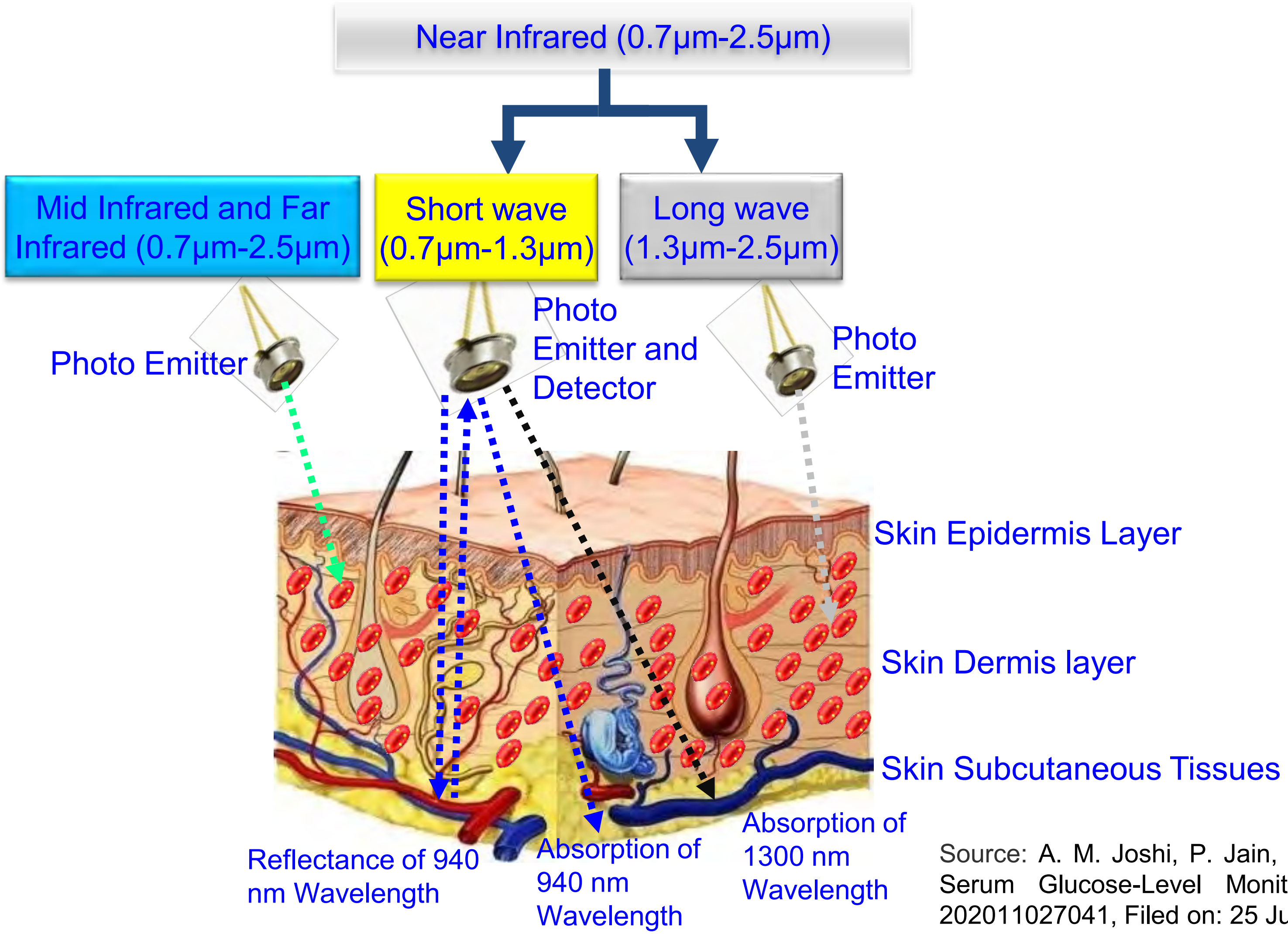
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

IR Signals in Human Skin – Penetration Depth



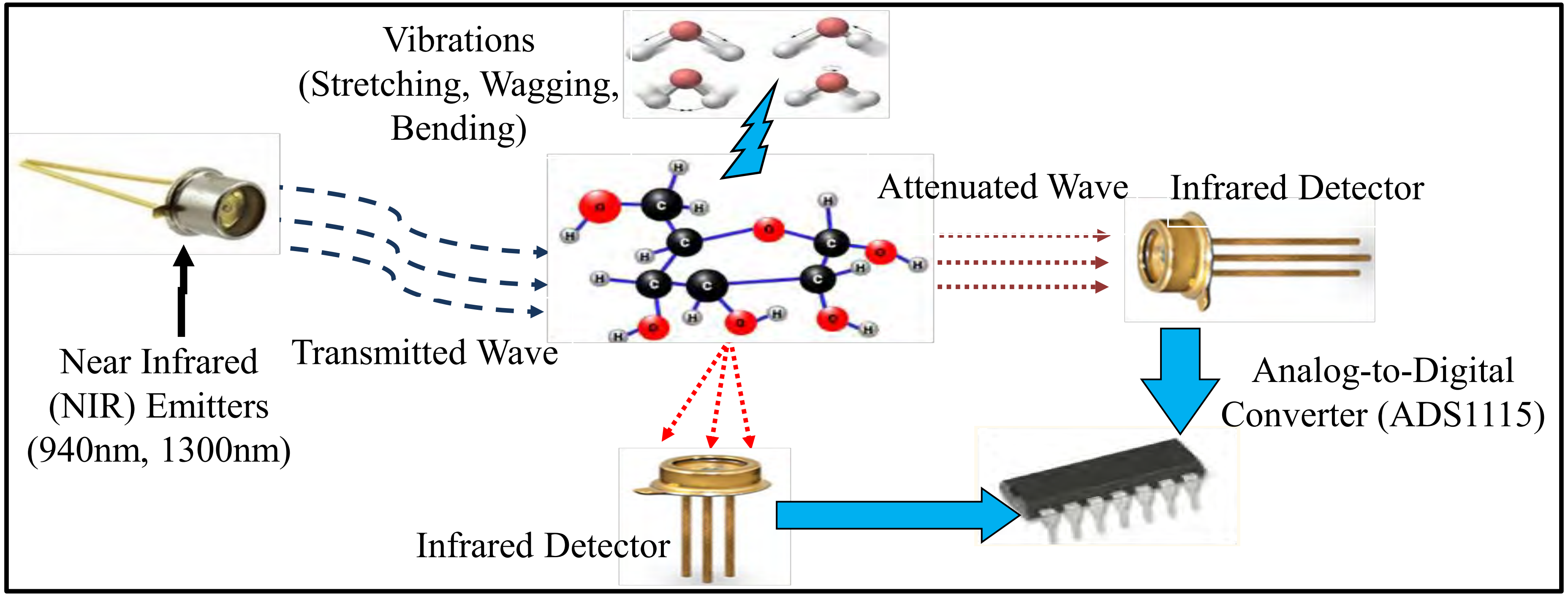
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

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

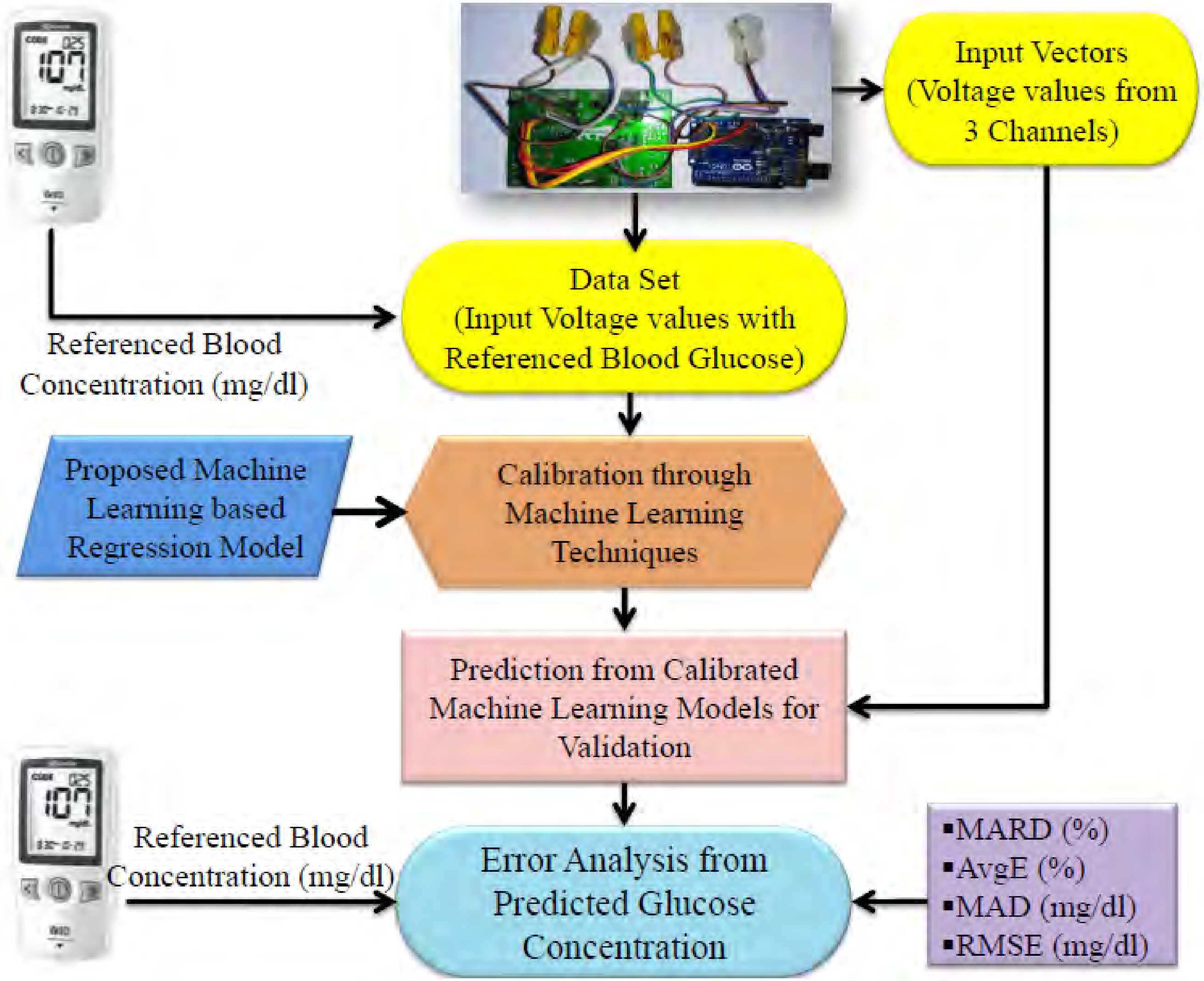


Clinically tested in an hospital.

Cost - US$ 20
Accuracy - 100%

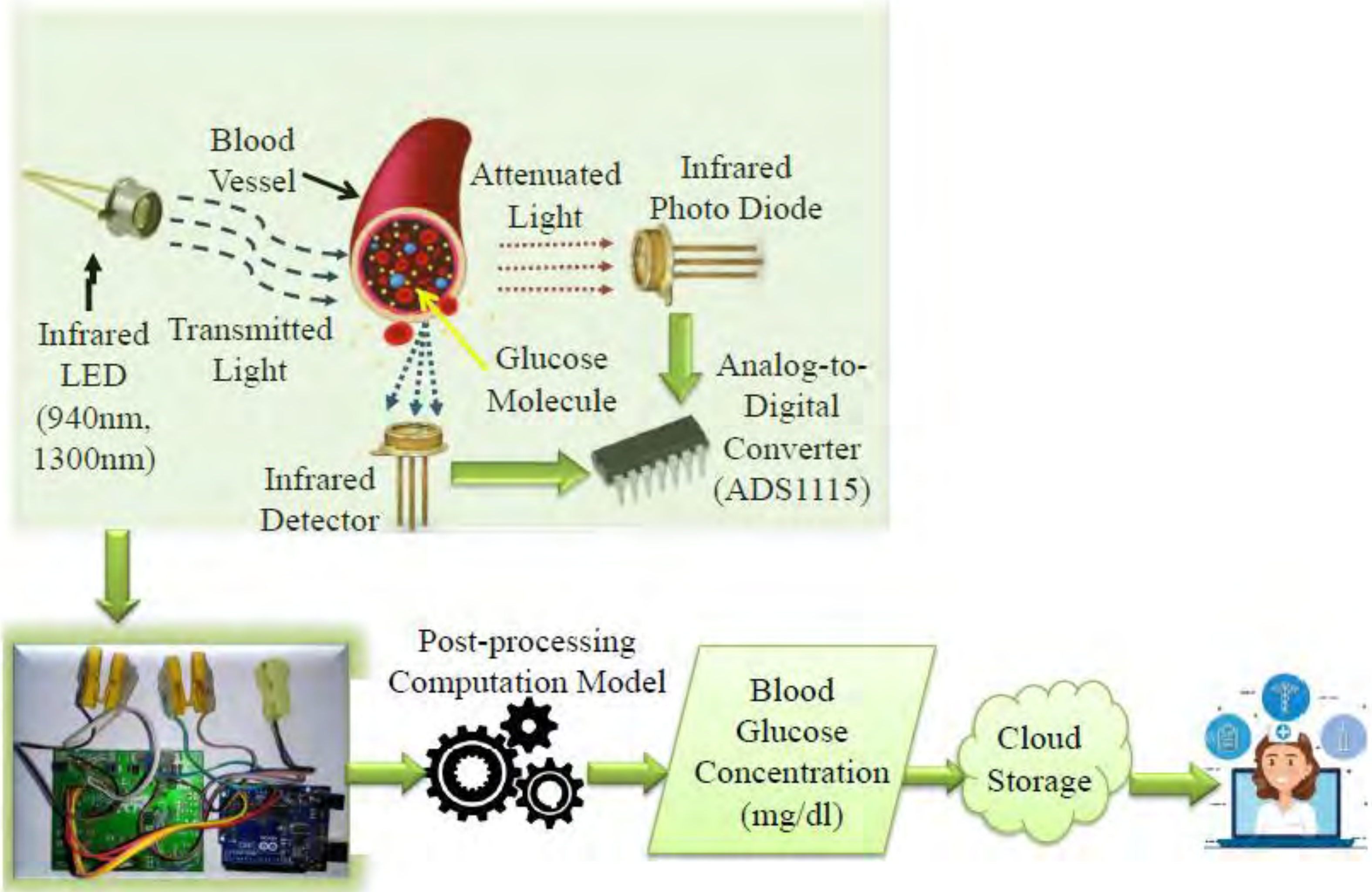
Source: P. Jain, A. M. Joshi, and S. P. Mohanty, "iGLU: An Intelligent Device for Accurate Non-Invasive Blood Glucose-Level Monitoring in Smart Healthcare", *IEEE Consumer Electronics Magazine (MCE),* Vol. 9, No. 1, January 2020, pp. 35-42.

iGLU 1.0: Modeling Flow



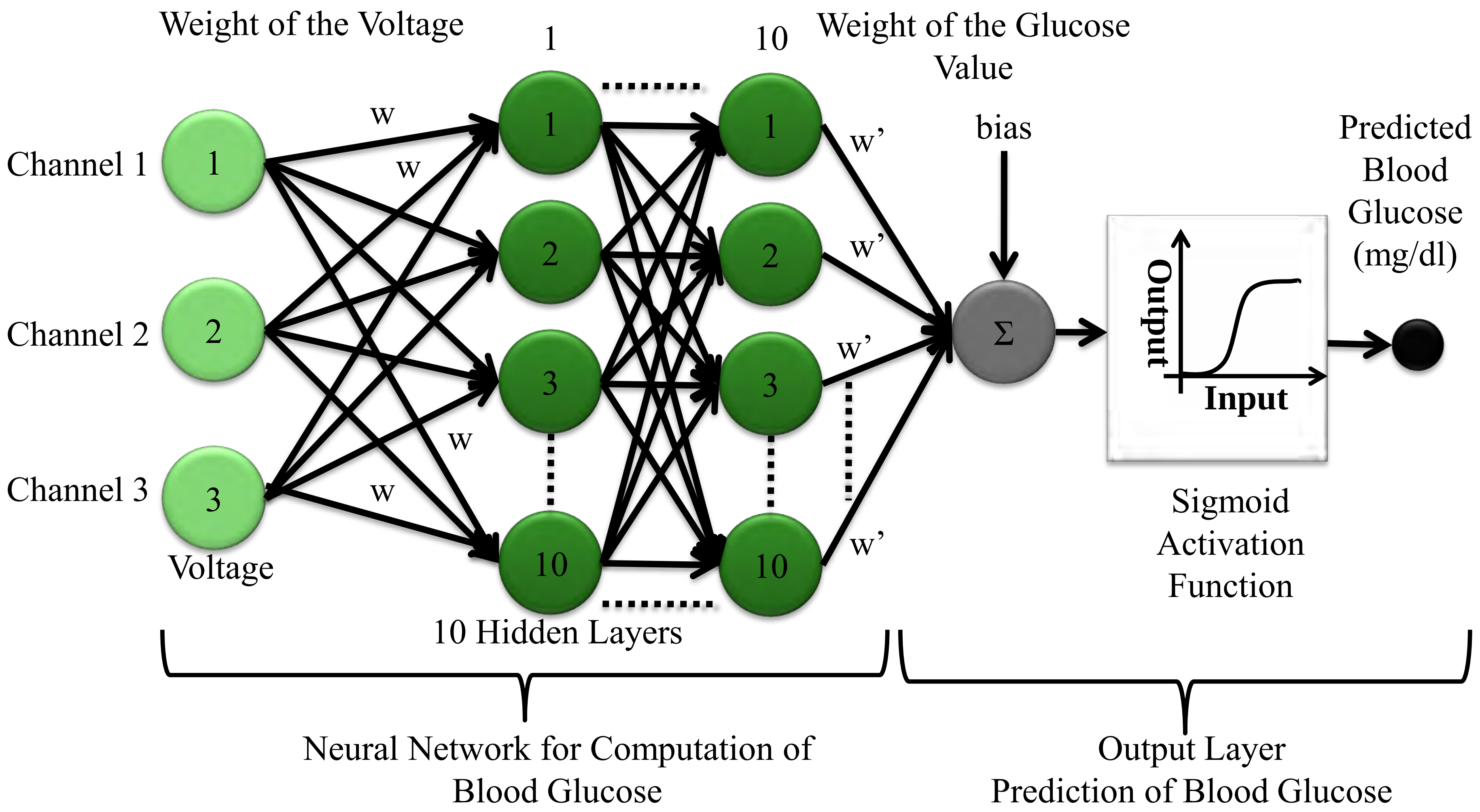
Source: A. M. Joshi, P. Jain and S. P. Mohanty, "Everything You Wanted to Know About Continuous Glucose Monitoring," *IEEE Consumer Electronics Magazine*, doi: 10.1109/MCE.2021.3073498.

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, November 2020, pp. 327--335.

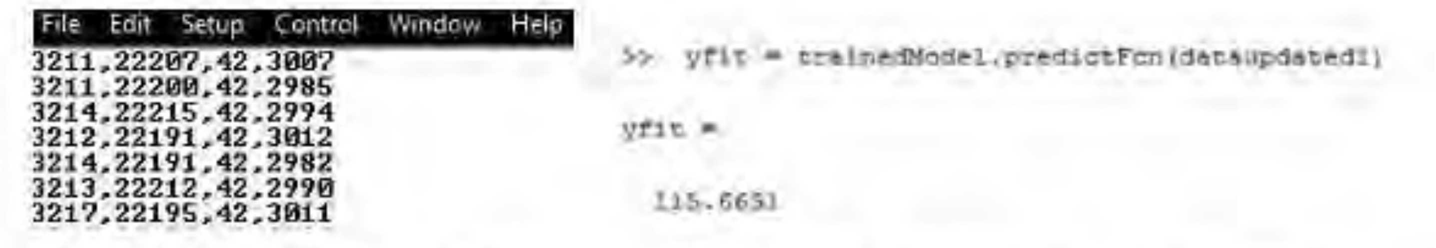
DNN Based Glucose Prediction



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.

DNN Based Glucose Prediction

- The coherent averaging has been applied on these collected data to stabilize the value.
- The Deep Neural Network (DNN) is applied to predict the blood glucose values.
- The output from one neuron of a hidden layer is the input the next layer neuron. The overall structure would provide the prediction output value of blood glucose (in mg/dl).



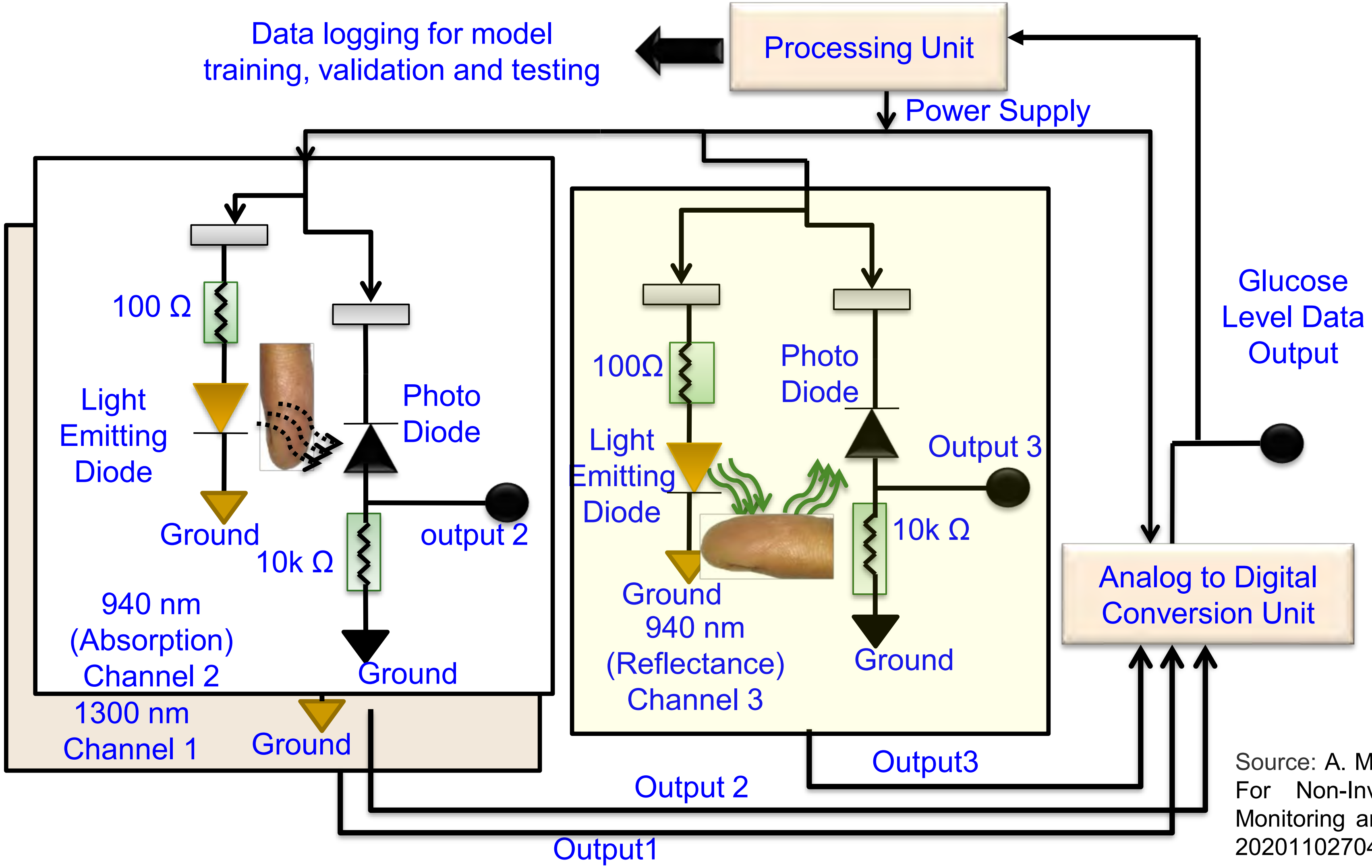
(a) Three channel Data (b) Time interval of 60 minutes

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 – Proof of Concept Prototyping

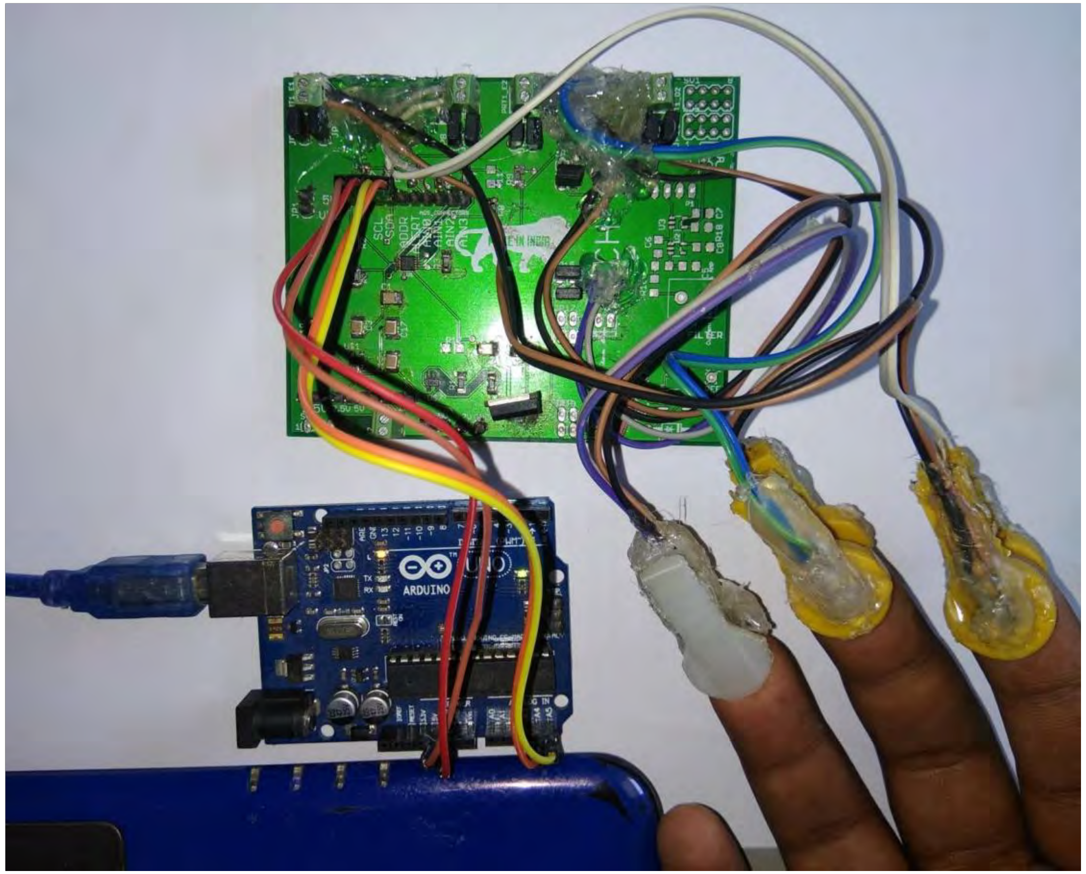
- The proof of concept of iGLU is prototyped using system on chip (SoC) with components like LEDs, detectors, ADC with noise filtering capability and frame acquisition controllability.
- These components are embedded on single 2 layer PCB to have portable continuous glucose measurement device.
- The data is collected and is further processed with help of 16 bit ADC at sampling rate of 128 samples per second. The efficient model for regression is analyzed to have accurate blood glucose estimation.

iGLU – Design Implementation



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 – Real-Life Testing



Clinically tested in an hospital.

Cost - US$ 20
Accuracy - 100%

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.

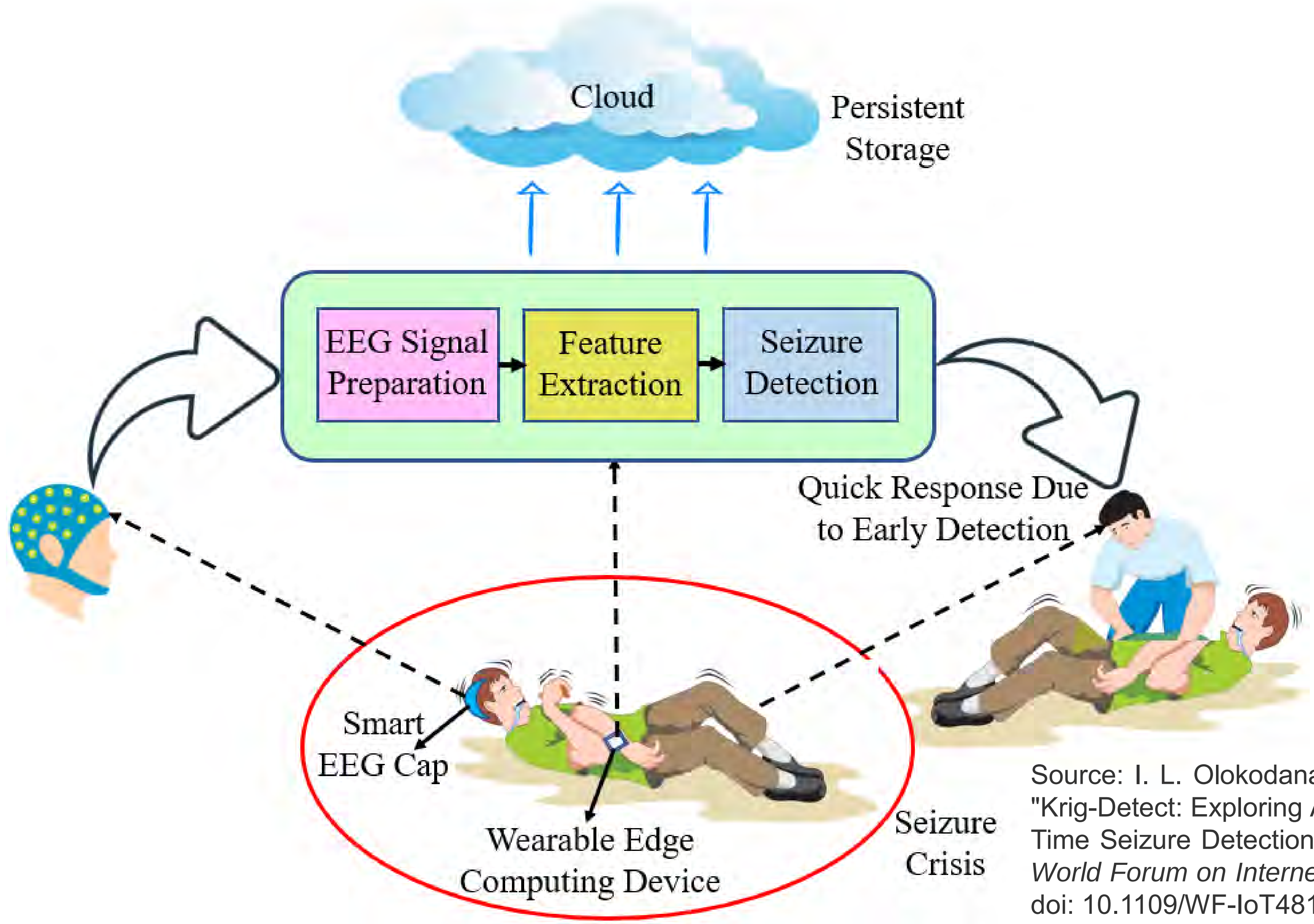
Conclusion

- This work presents a novel non-invasive device for the continuous glucose measurement for smart healthcare.
- NIR lights of specific wavelengths are used for the device prototyping for glucose molecule detection.
- The developed device has been calibrated and validated through all kinds of subjects.
- The estimation of glucose values are done using DNN.
- The device has been integrated with IoMT framework for patient monitoring, storage of glucose values and cloud access by caregiver for further treatment.

Epileptic Seizure

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

Epileptic Seizure - Research Vision



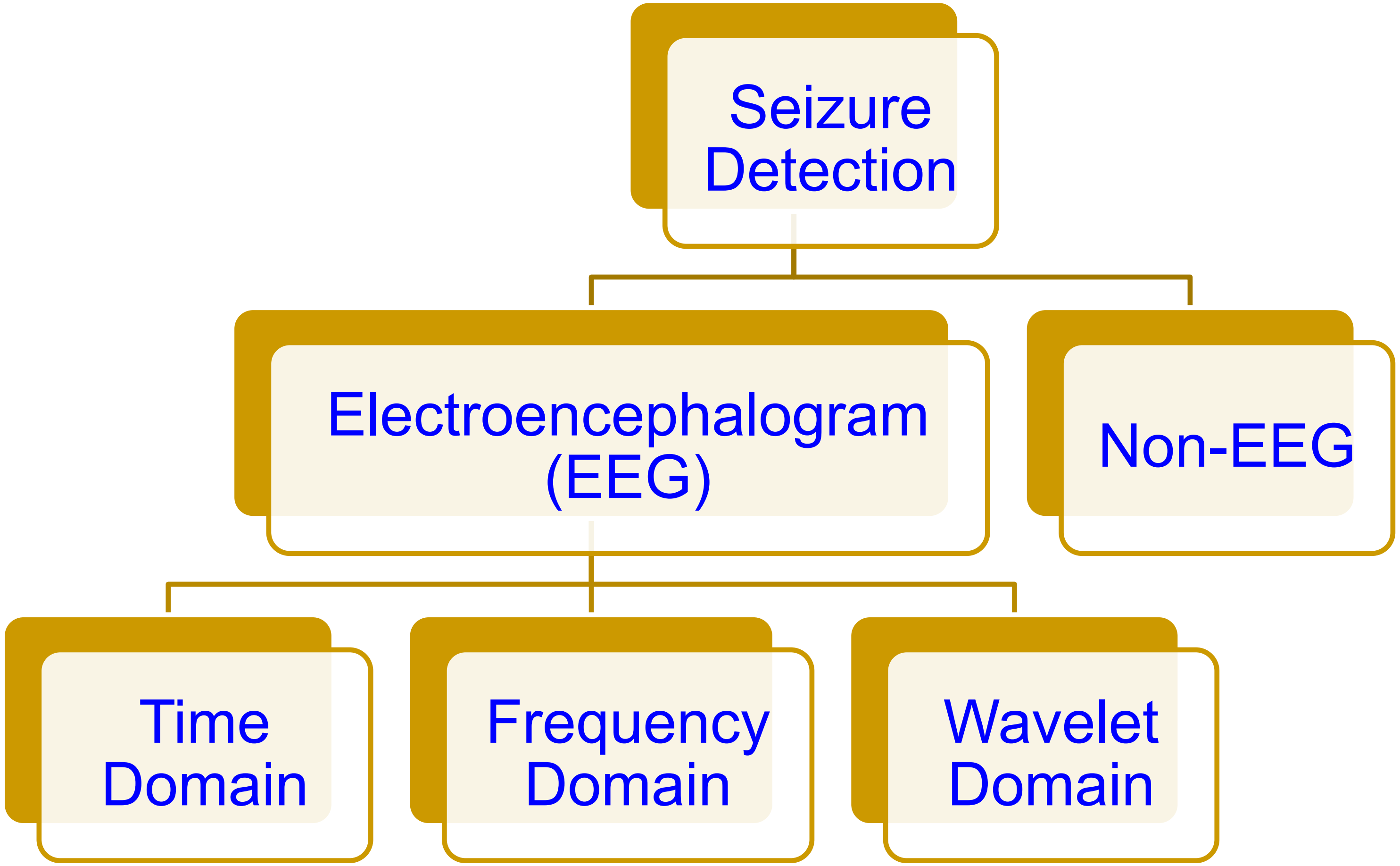
Source: I. L. Olokodana, S. P. Mohanty and E. Kougianos, "Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signals," *2020 IEEE 6th World Forum on Internet of Things (WF-IoT)*, 2020, pp. 1-6, doi: 10.1109/WF-IoT48130.2020.9221260.

Epileptic Seizure Has Global Impact

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

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

Seizure Detection Methods



Seizure Detection Methods – Non-EEG

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

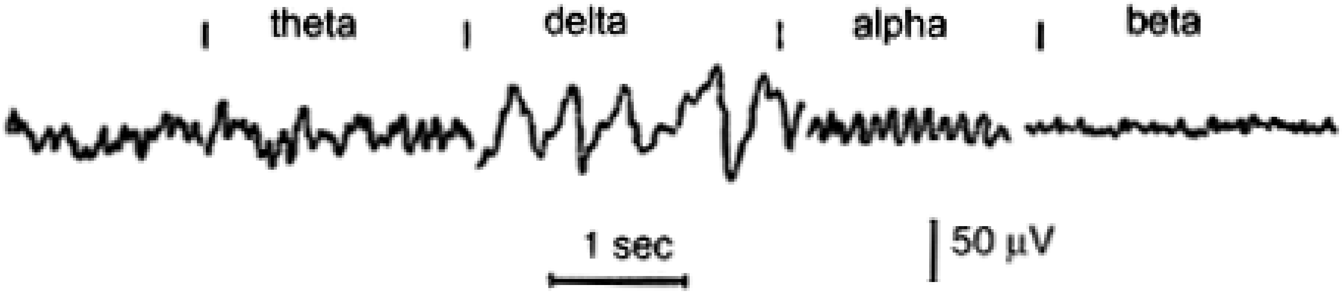
Source: https://www.seizure-journal.com/article/S1059-1311(16)30114-5/fulltext

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

Smart Electronic Systems Laboratory (SESL)
UNT EST. 1890

Brain Electroencephalogram (EEG) Signal

Source: https://www.medicine.mcgill.ca/physio/vlab/biomed_signals/eeg_n.htm

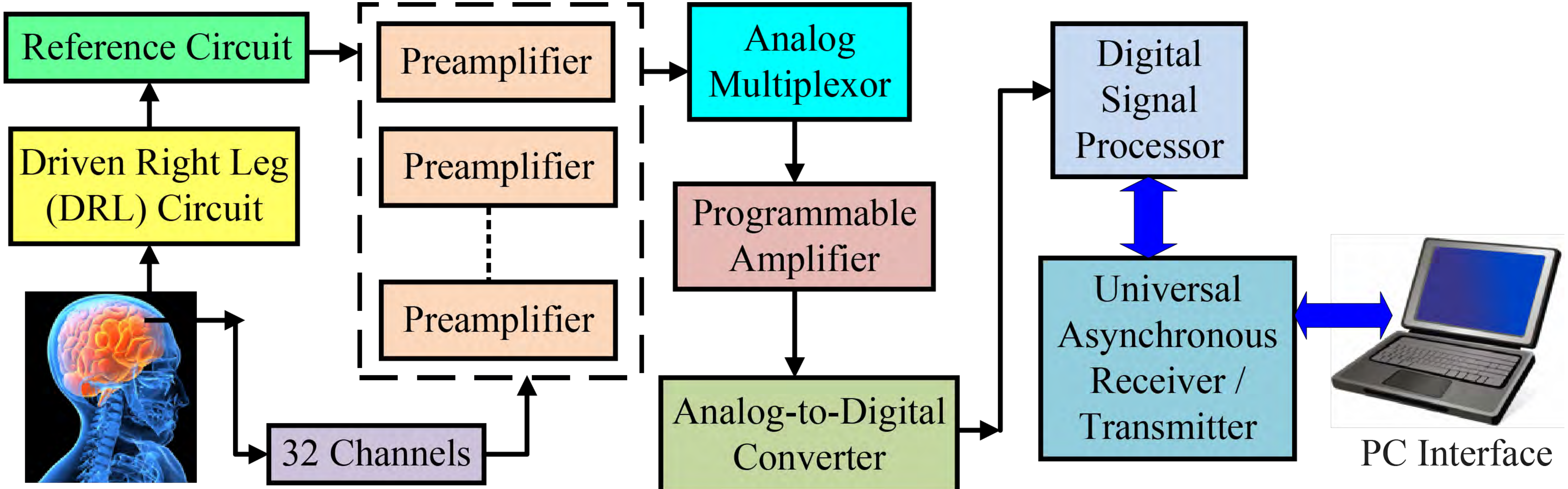


- ❖ Signal Intensity: EEG activity is quite small, measured in microvolts (µV).
- ❖ Signal Frequency: Main frequencies of the human EEG waves are:
  1. Delta (<3 Hz)
  2. Theta (3.5 to 7.5 Hz)
  3. Alpha (7.5 and 13 Hz)
  4. Beta (>14 Hz)

Electroencephalogram (EEG) System

- EEG is a non invasive method for measuring brain waves of a person.
- In EEG special electrodes are attached to the head and hooked by wires to the computer.
- Computer records electrical activity of the brain.
- An EEG can detect certain conditions such as seizures in the brain.

Inside an EEG System



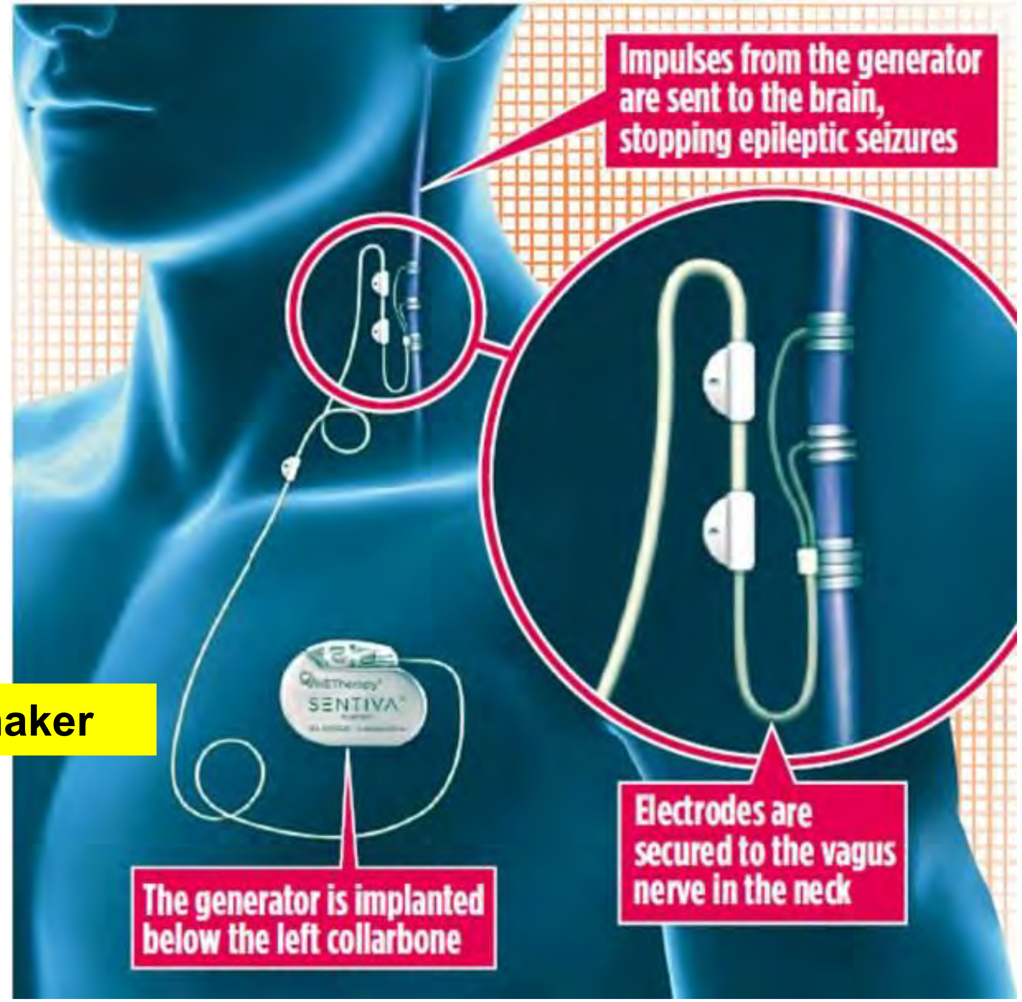
Source: Mohanty McGraw-Hill 2015

Figure 2.16 Block diagram of a EEG [151].

Inside an EEG System

- In the system, 32 channels with single or dual-pole measurements are included.
- Driven right leg (DRL) circuit is connected to the reference (REF) circuit to provide desired common-mode gain.
- Preamplifier is used to measure the EEG signals.
- EEG signals are of different frequencies that need adjustable amplifier and filter.
- An ADC provides DC voltages for further processing.

Seizure Control Devices



Brain Pacemaker

Source: https://www.dailymail.co.uk/health/article-5851595/Game-changer-brain-pacemaker-stops-epileptic-fits-tracks.html

IBM's Implantable Seizure Detector

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

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

Consumer Electronics for Seizure Detection

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

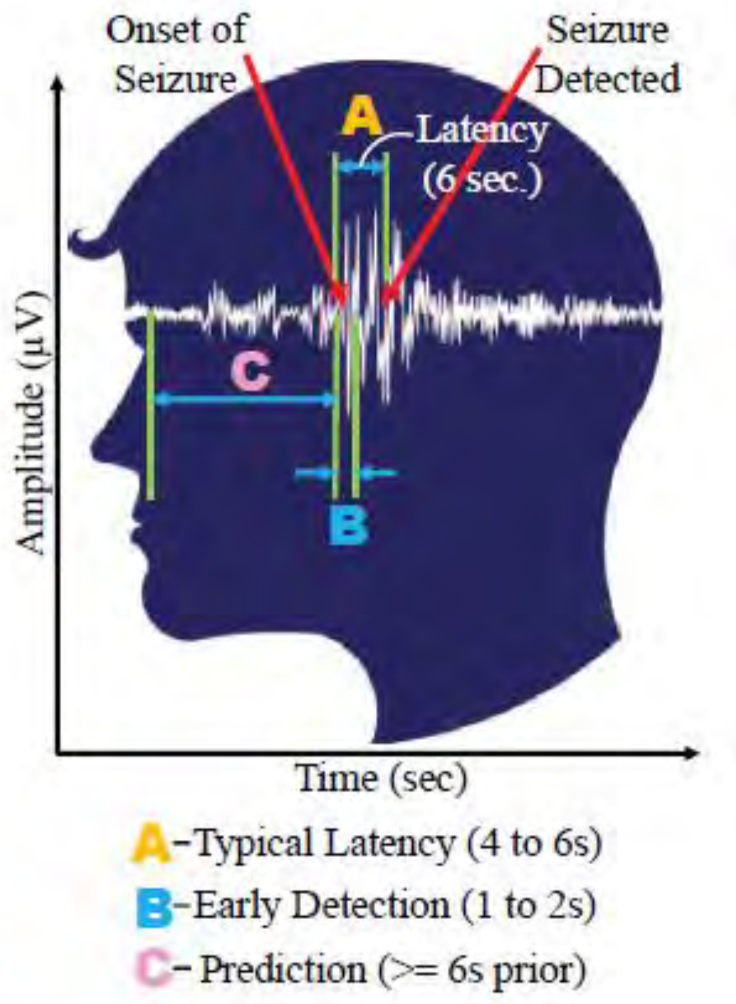
- Embrace2: Smart-band which uses machine learning to detect convulsive Seizures and notifies caregivers.

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

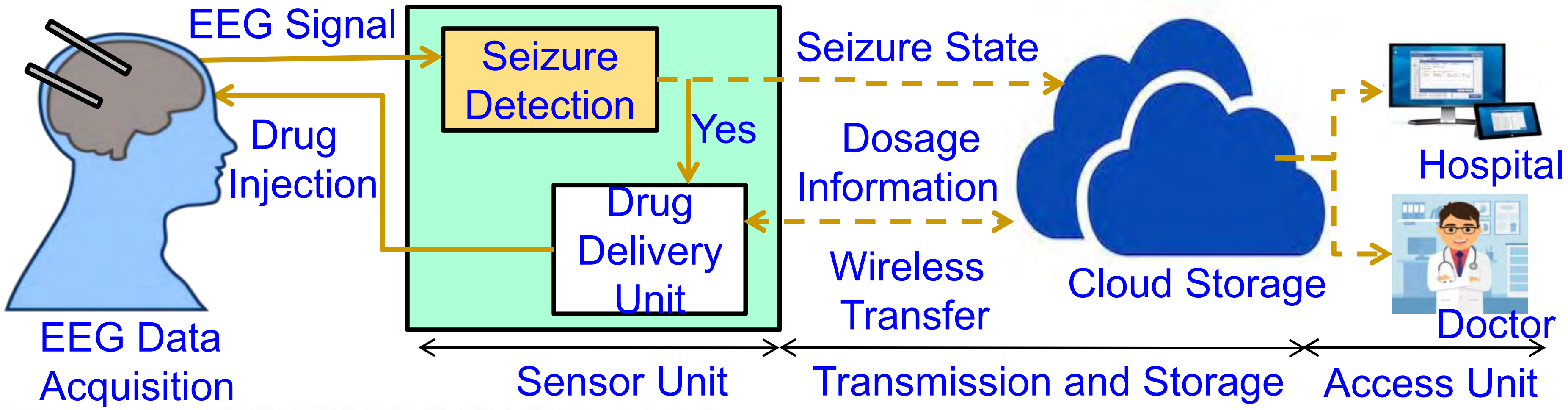
- Medical grade smart watch: It detects generalized clonic-tonic Seizures and notifies physicians.

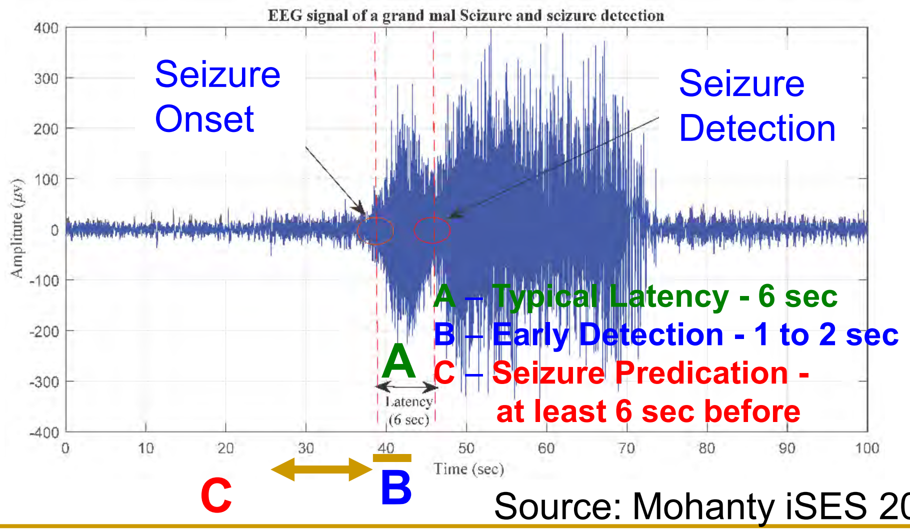
Drawbacks of Existing Works?

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



Smart Healthcare – Seizure Detection and Control



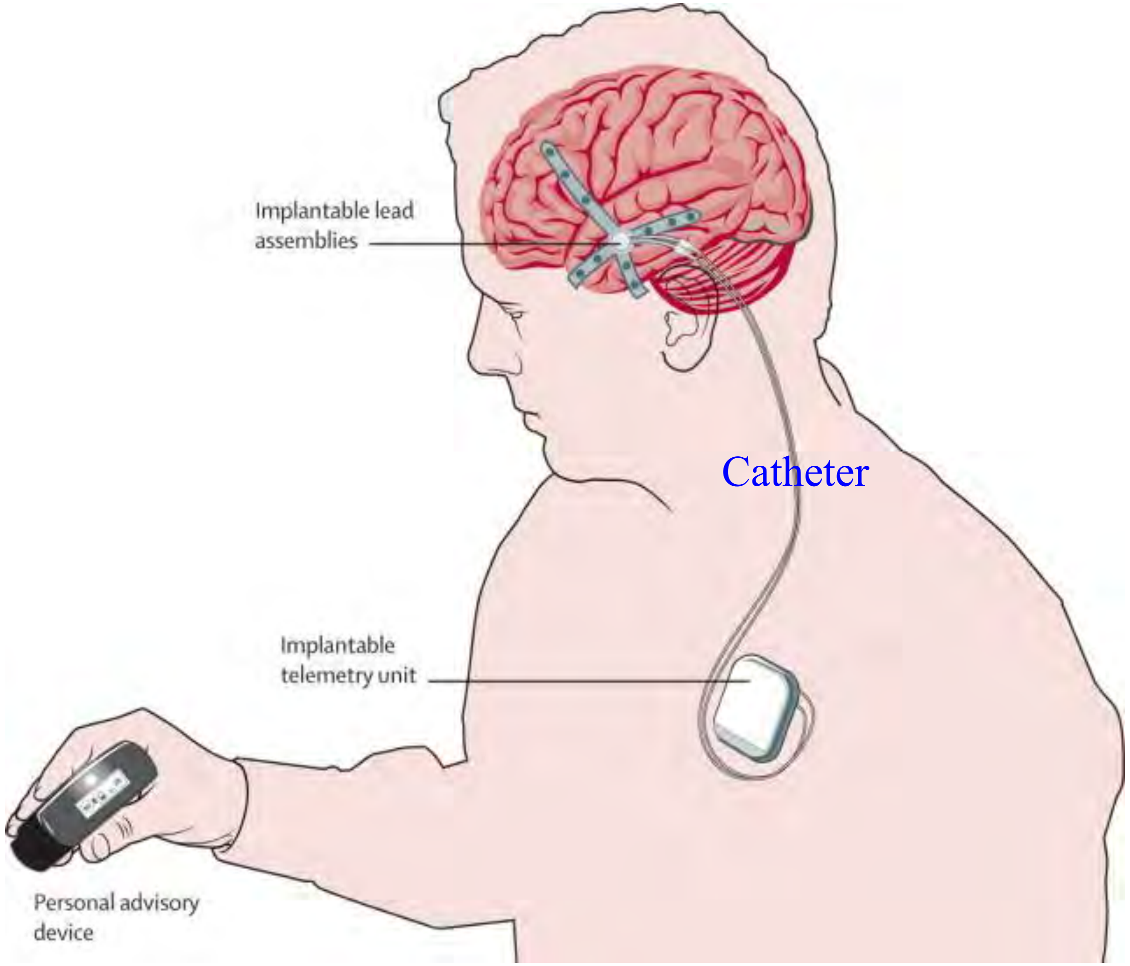


Automated Epileptic Seizure Detection and Control System

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

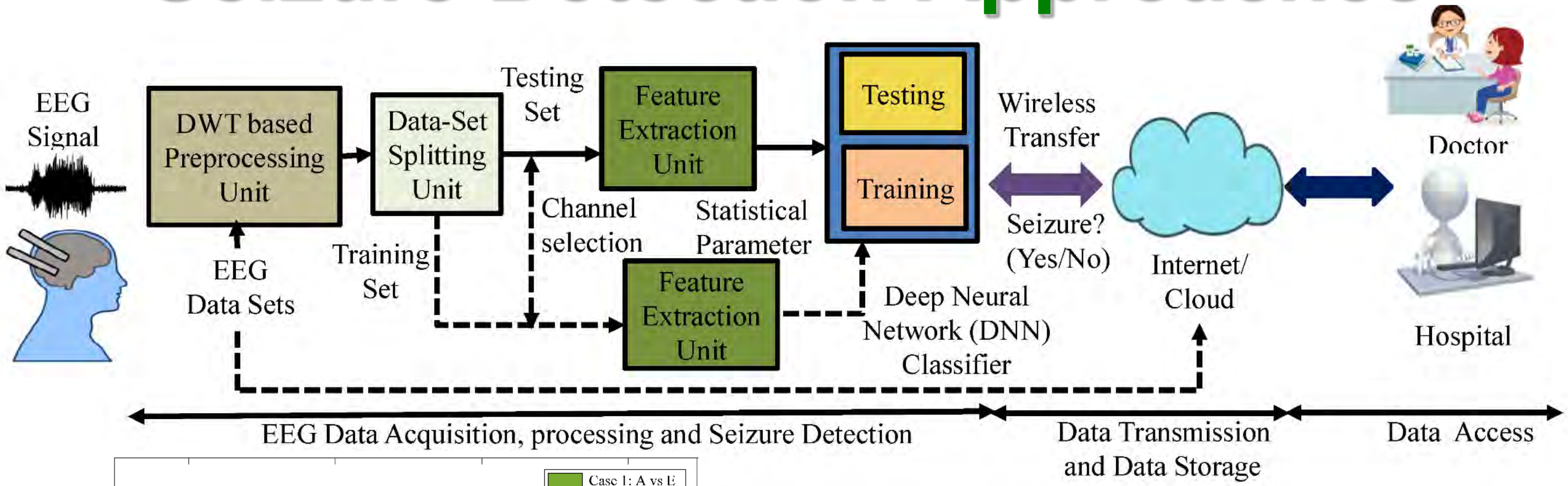
Source: Mohanty iSES 2018, IEEE Smart Cities 2018, and Mohanty ICCE 2019

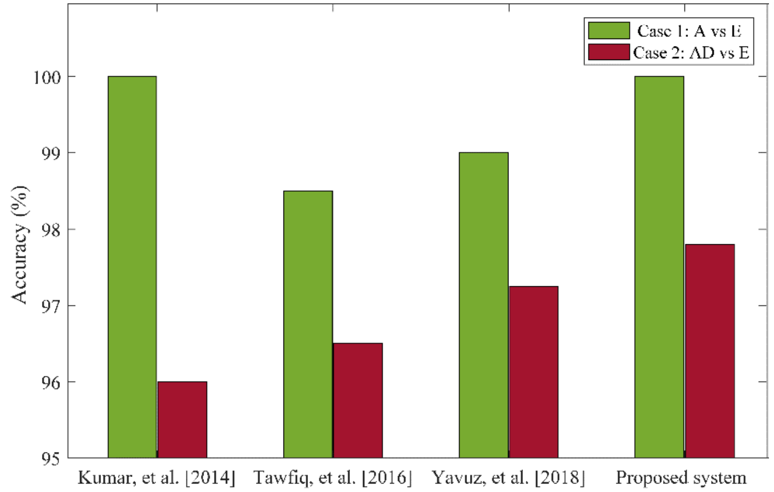
Implantable for Seizure Detection and Control



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

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%

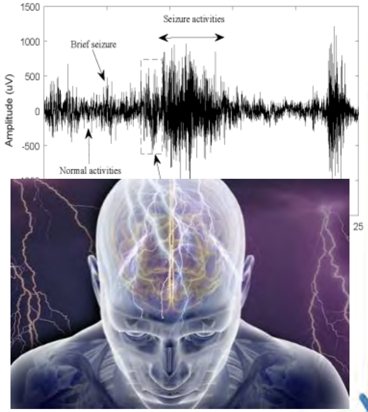
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, “Neuro-Detect: A Machine Learning Based Fast and Accurate Seizure Detection System in the IoMT”, *IEEE Transactions on Consumer Electronics (TCE)*, Vol 65, No 3, Aug 2019, pp. 359--368.

eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare

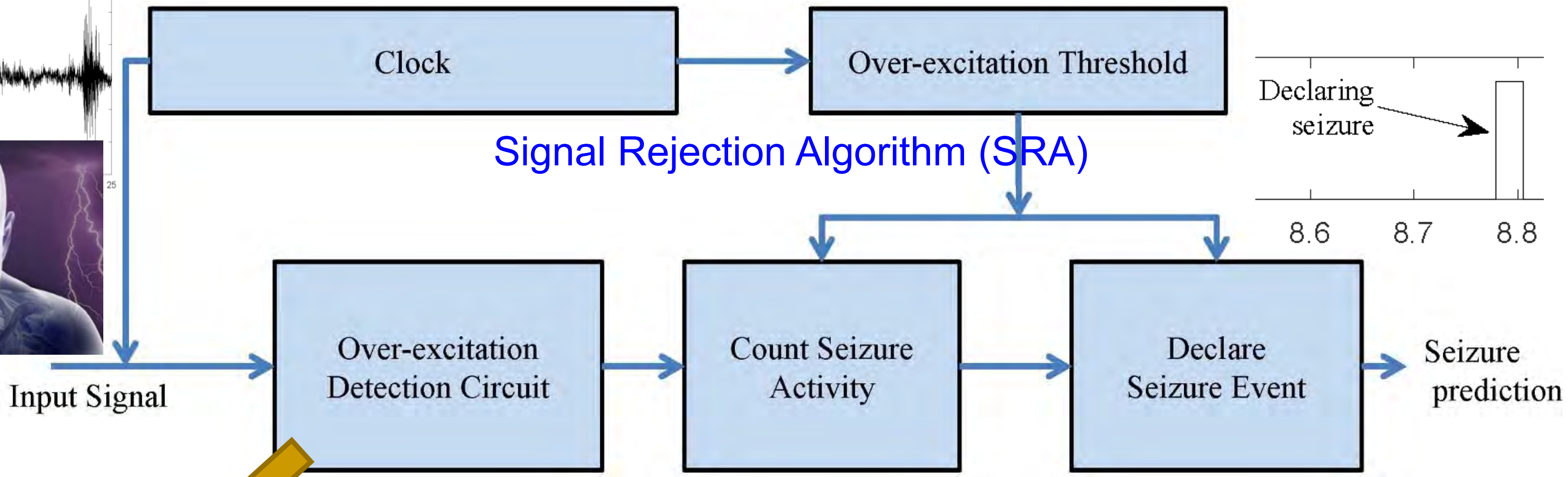
- A novel and highly effective algorithm (SRA) is introduced to remove unwanted signal and noise, which considerably enhances the performance of the detector.
- There is a considerable reduction in power consumption (12 %-18%) compared to existing methods.
- A Simulink® based prototype of the architecture is implemented

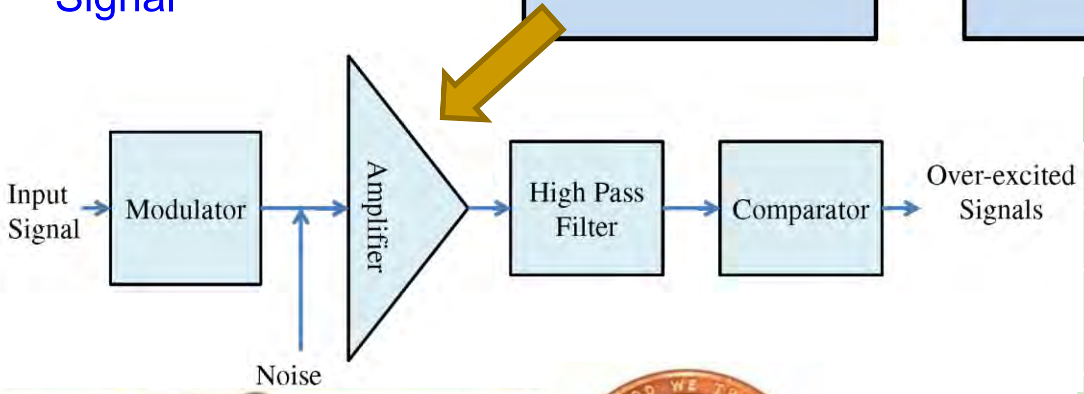
Source: M. A. Sayeed, S. P. Mohanty, E. Kougianos, and H. Zaveri, “eSeiz: An Edge-Device for Accurate Seizure Detection for Smart Healthcare”, *IEEE Transactions on Consumer Electronics (TCE)*, Volume 65, Issue 3, August 2019, pp. 379--387.

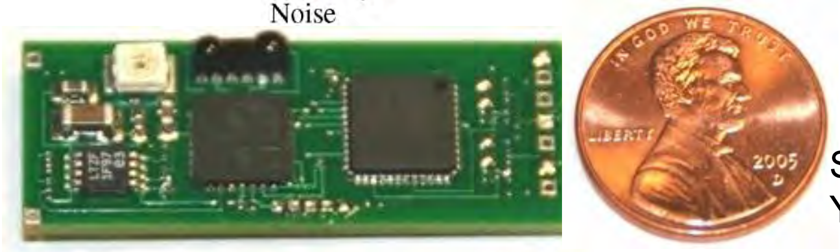
Smart Healthcare – Efficient Epileptic Seizure Detector



EEG Signal







Source: Zaveri, Yale University

Parameter	Value
Seizure Frequency (Minimum)	5 Hz
Seizure Frequency (Minimum)	25 HZ
Voltage Level Detector (Avg. Lower Threshold)	210 mV
Voltage Level Detector (Avg. Upper Threshold)	380 mV
Total power consumption	6.18 μW

Source: Mohanty ICCE 2018

Seizure Activity Characterization

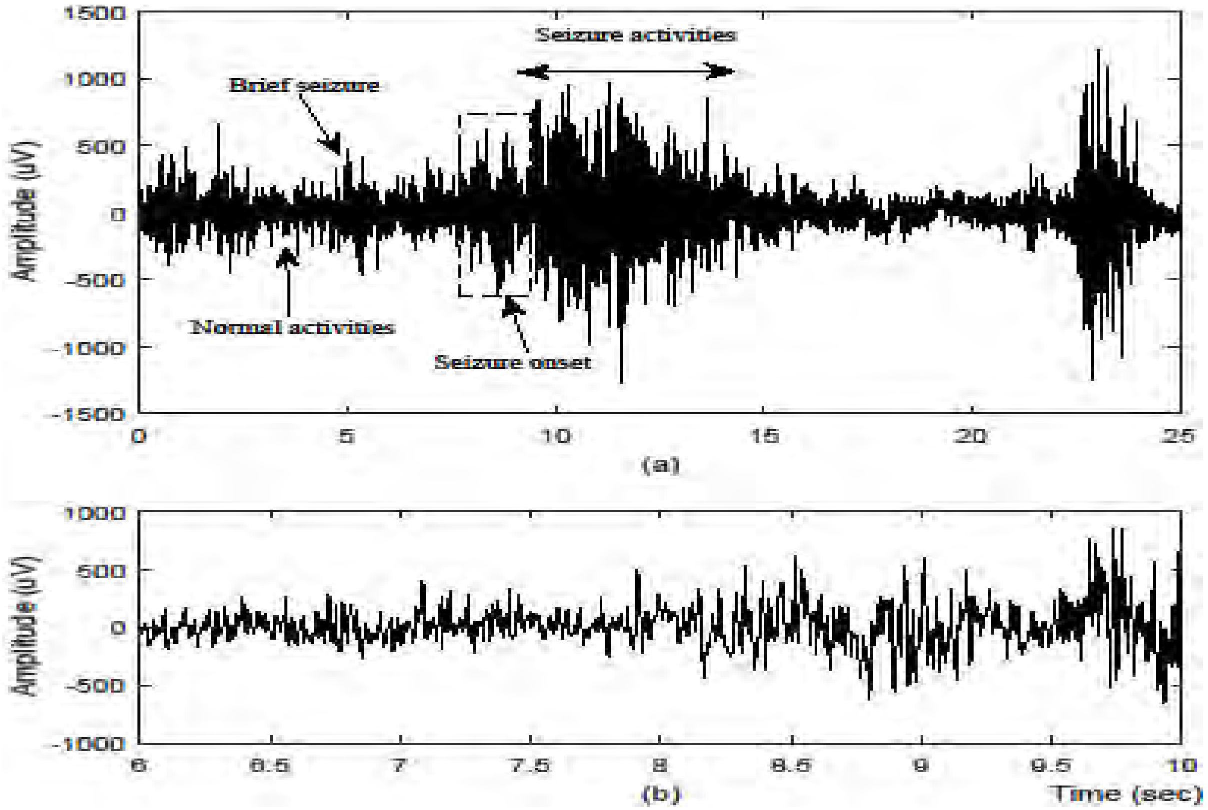


Fig.1 Seizure activity characterization (a) Invasive Electroencephalography (EEG) of an epileptic seizure (b) zoom inset 6-10 seconds

Proposed Architecture

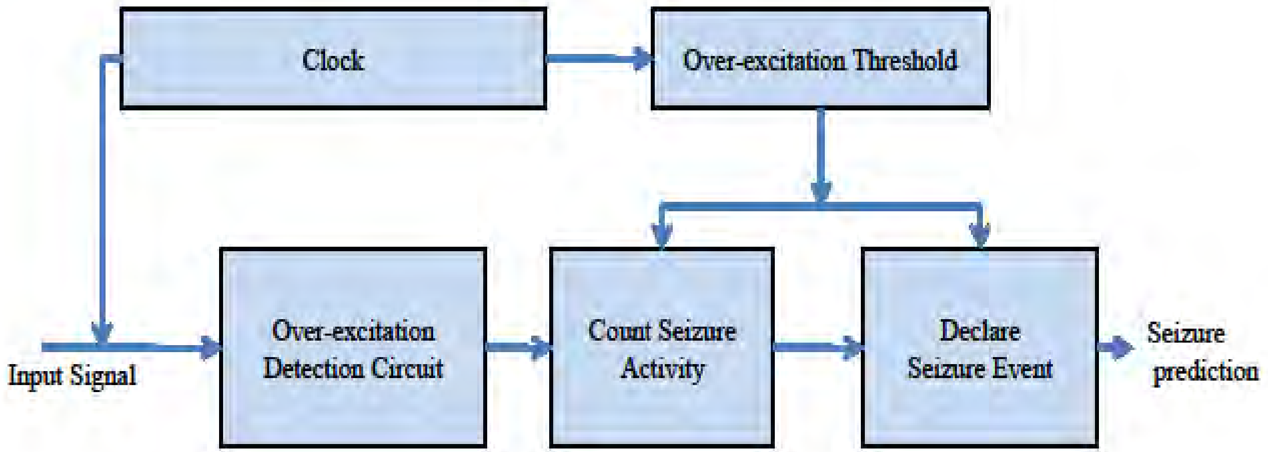


Fig. 2. Proposed architecture of the seizure detector

Design Flow

- Modulator
- Adjustable Gain Amplifier
- Filter
- Voltage Level Detector
- Signal Rejection Algorithm

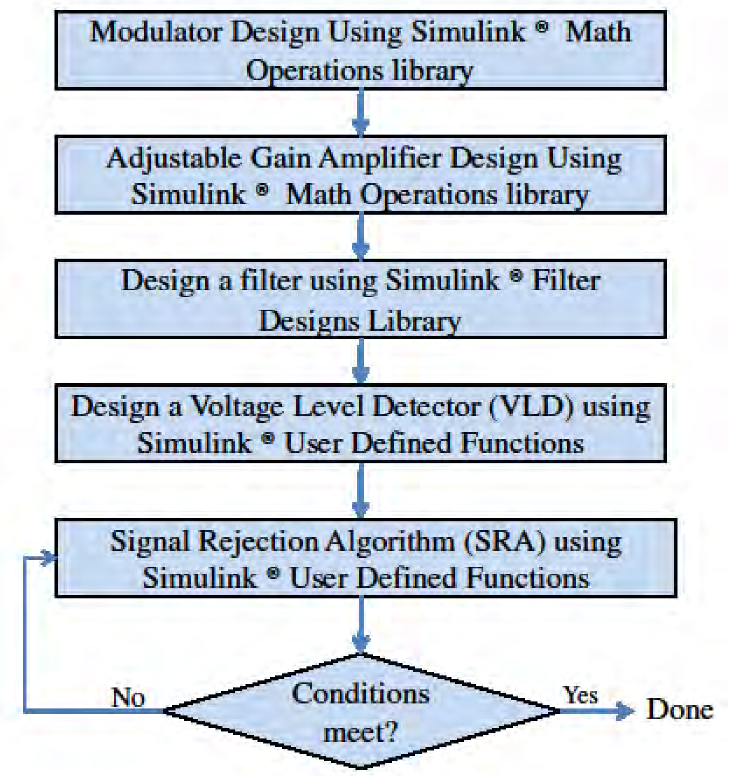


Fig. 3 Proposed design flow of the of the seizure detector

Hyper-synchronous Signal Detection Circuit

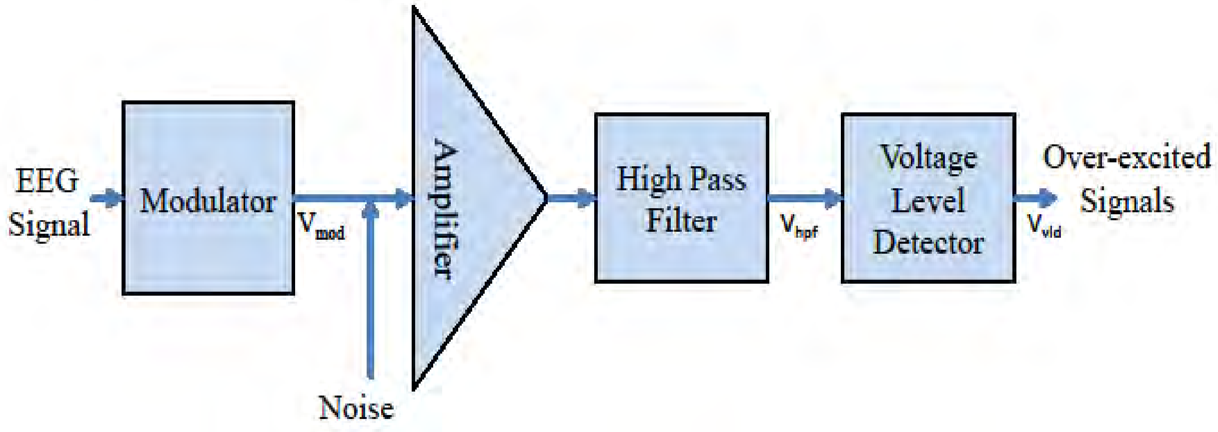


Fig. 4 Proposed hypersynchronous signal detection circuit

- Due to low amplitude range of neural signals, they need to amplified prior to analysis
- High pass filter attenuates low frequency signal and noise.

Signal Rejection Algorithm (SRA)

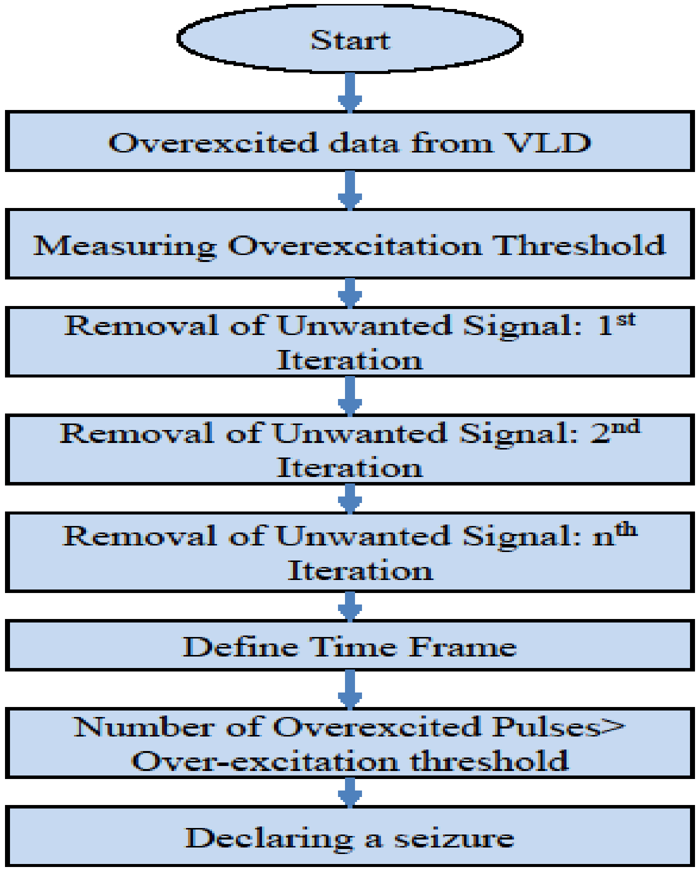


Fig. 5 Flowchart showing the detection of seizure from overexcited signal

Signal Rejection Algorithm (SRA)

- The SRA algorithm is highly effective in removing unwanted pulses and noise.
- In a time frame, this algorithm eliminates spurious pulses if they fall below the defined threshold.
- If the number of hyper-synchronous pulses exceeds the threshold number, seizure detector locks its VSE to 1, indicating a seizure

Modelling and Implementation of the Proposed Detector

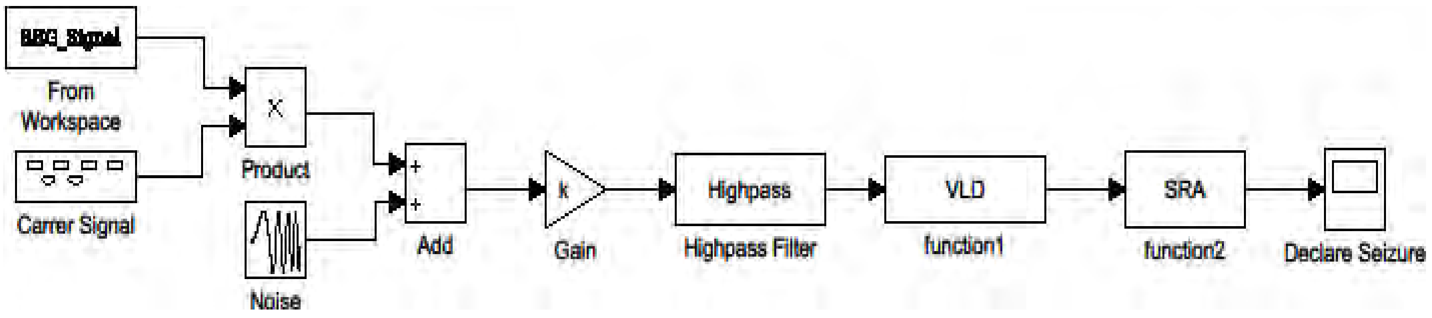


Fig. 6 Simulink model for the proposed seizure detector

- VLD uses a Simulink user defined function, has a maximum and minimum value.
- A threshold number of hyper-synchronous pulses define a seizure onset.

Power Measurement Set-up

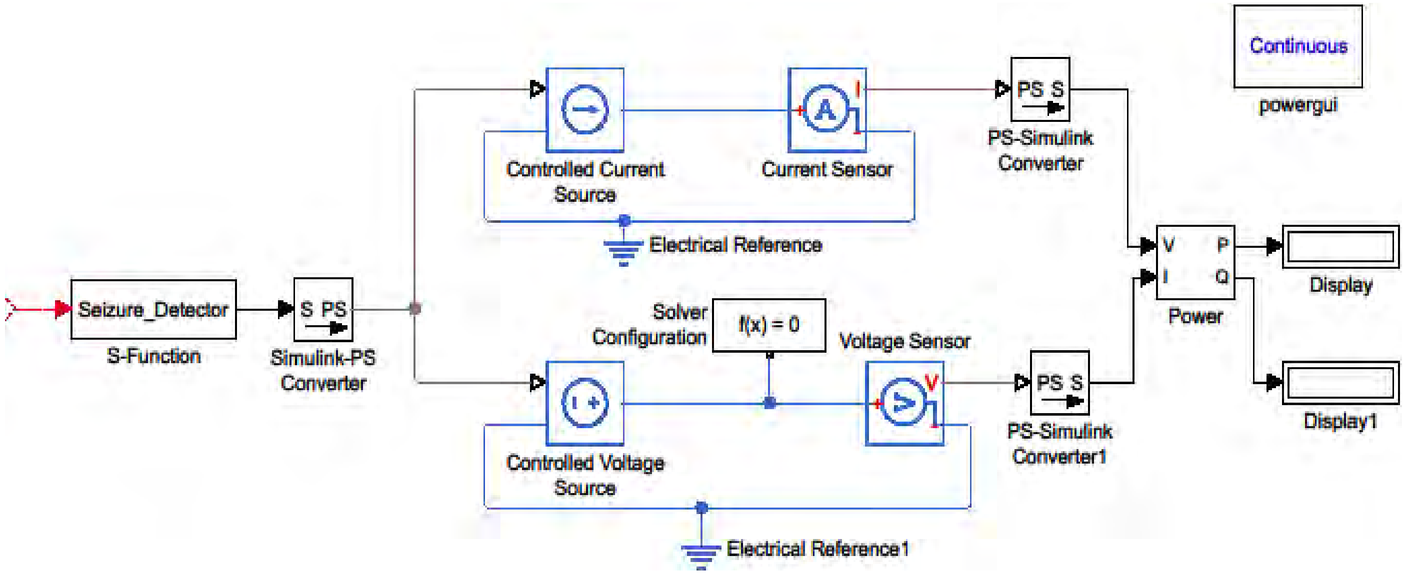


Fig. 7 Power measurement of the seizure detector

- In this design, the pattern independent method has been adopted.
- The design is considered a black box and current and voltage values are considered from the design, in order to calculate power.

Experimental Results

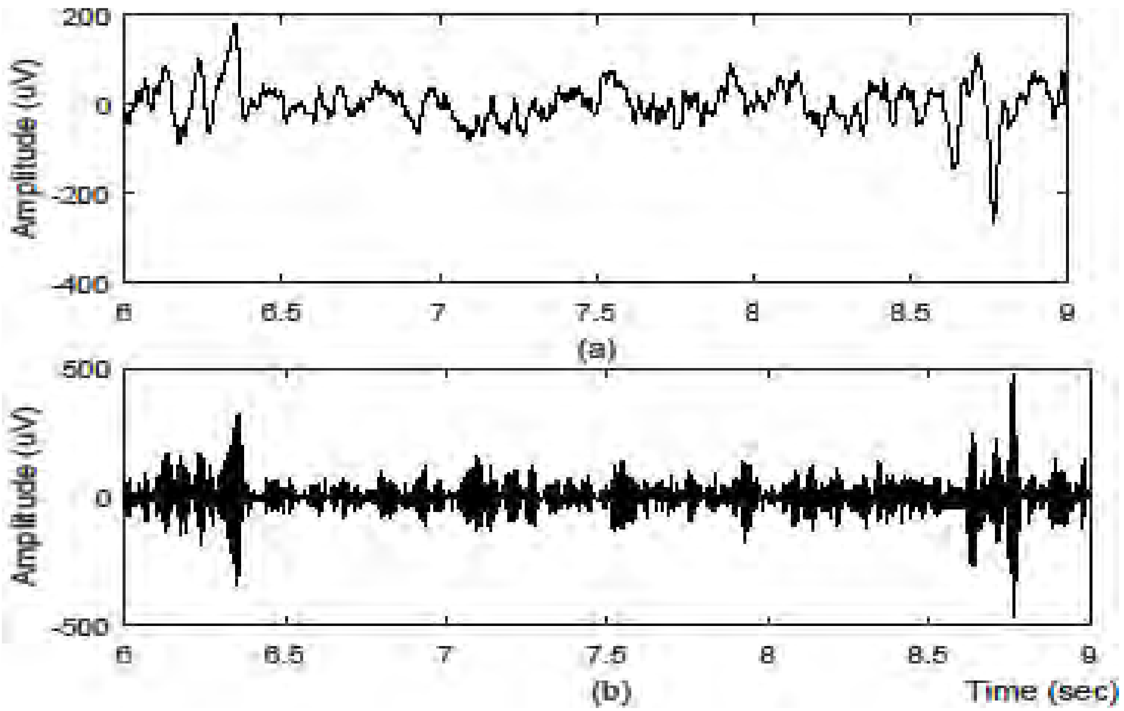


Fig. 9. Transient analysis (a) Zoom inset 6-9 seconds of input EEG signal (b) Modulated Signals

Experimental Results

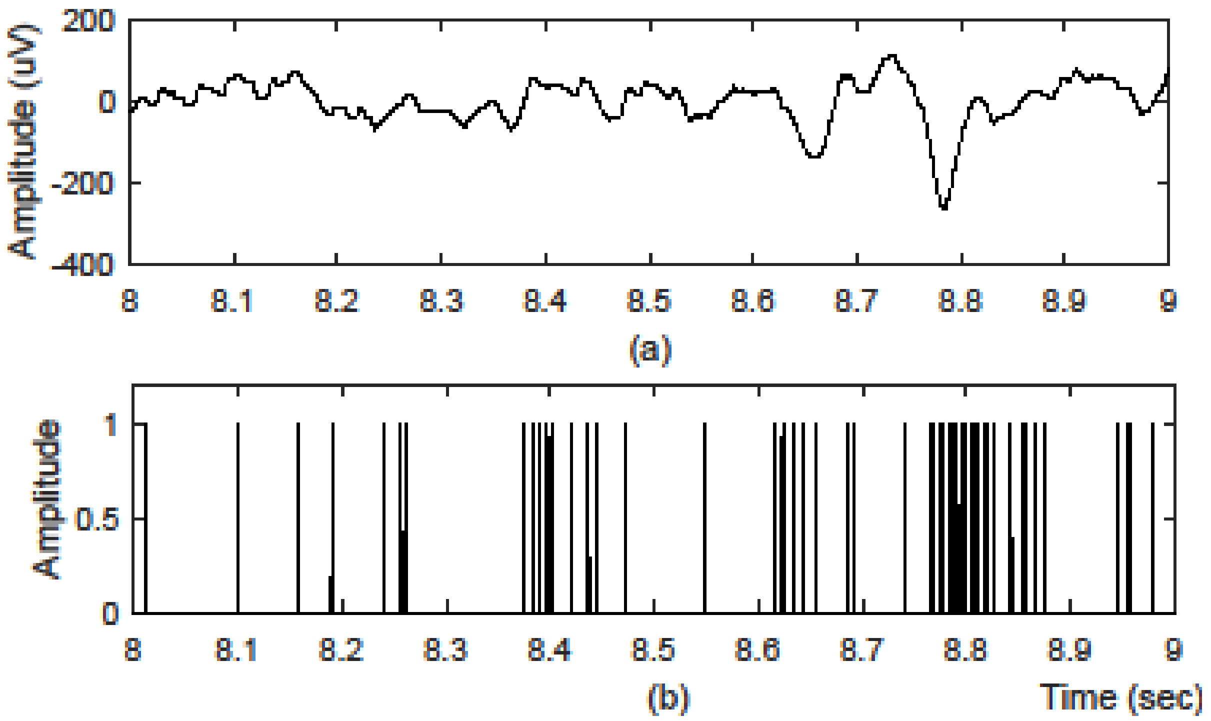


Fig. 10. Transient analysis (a) Zoom inset 8-9 seconds of input EEG signal (b) Output of VLD

Experimental Results

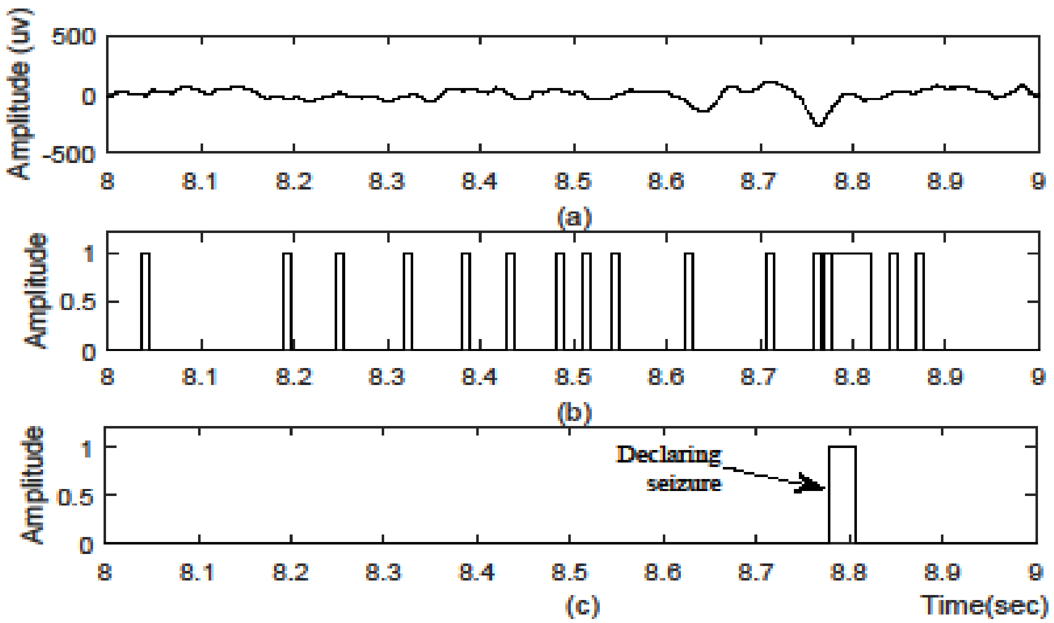


Fig. 11. Transient analysis (a) Zoom inset 8-9 seconds of input EEG signal (b) Output of SRA after first iteration (b) Output of SRA after nth iteration and detection of seizure onset

Experimental Results

Parameter	Value
Seizure Frequency (Minimum)	5 Hz
Seizure Frequency (Minimum)	25 HZ
VLD (Average Lower Threshold)	210 mV
VLD (Average Upper Threshold)	380 mV
Total power consumption	6.18 μW

Table 1. Simulation Data of the Proposed Seizure Detector

Conclusion and Future Research

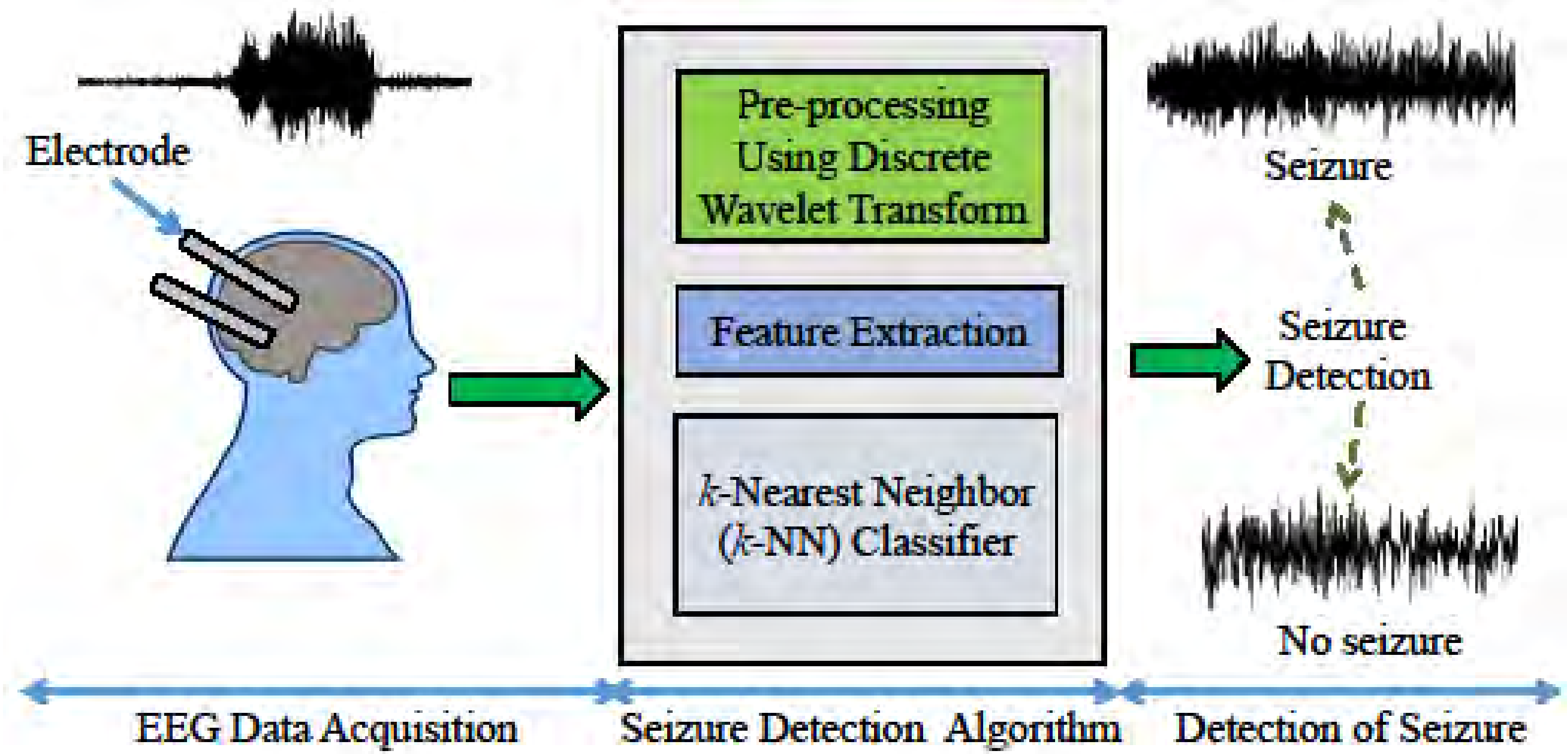
- The rejection algorithm employed by SRA minimizes false detection, improves the seizure detection accuracy.
- There is a considerable reduction in power consumption (12 %-18%) compared to existing methods.
- Future research involves generating a probabilistic pattern of EEG abnormalities and combining it with proposed architecture for the seizure onset detector.

Neuro-Detect: Machine Learning Based Fast and Accurate Seizure Detection

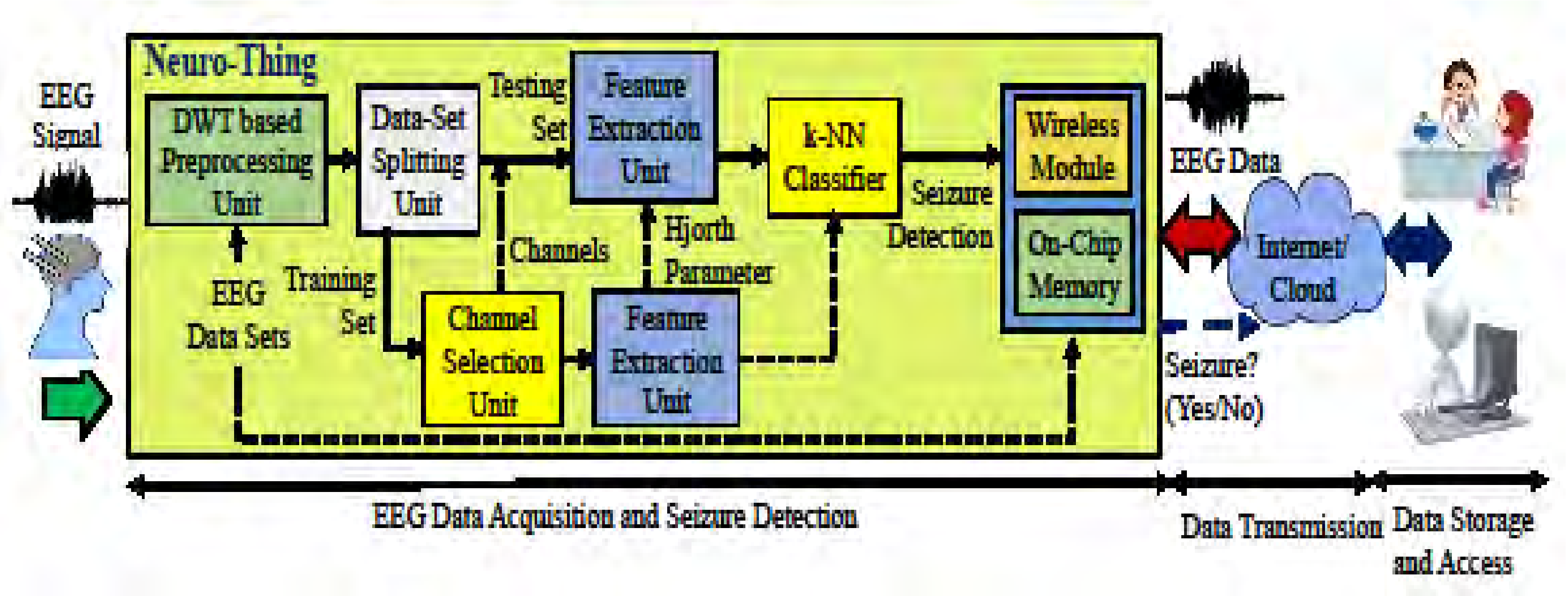
- An accurate seizure detection approach has been proposed.
- This is the first study to propose DWT based Hjorth parameters (HPs) for seizure detection.
- The inclusion of IoT with the proposed system provides universal connectivity with other healthcare applications.

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)*, Volume 65, Issue 3, August 2019, pp. 359--368.

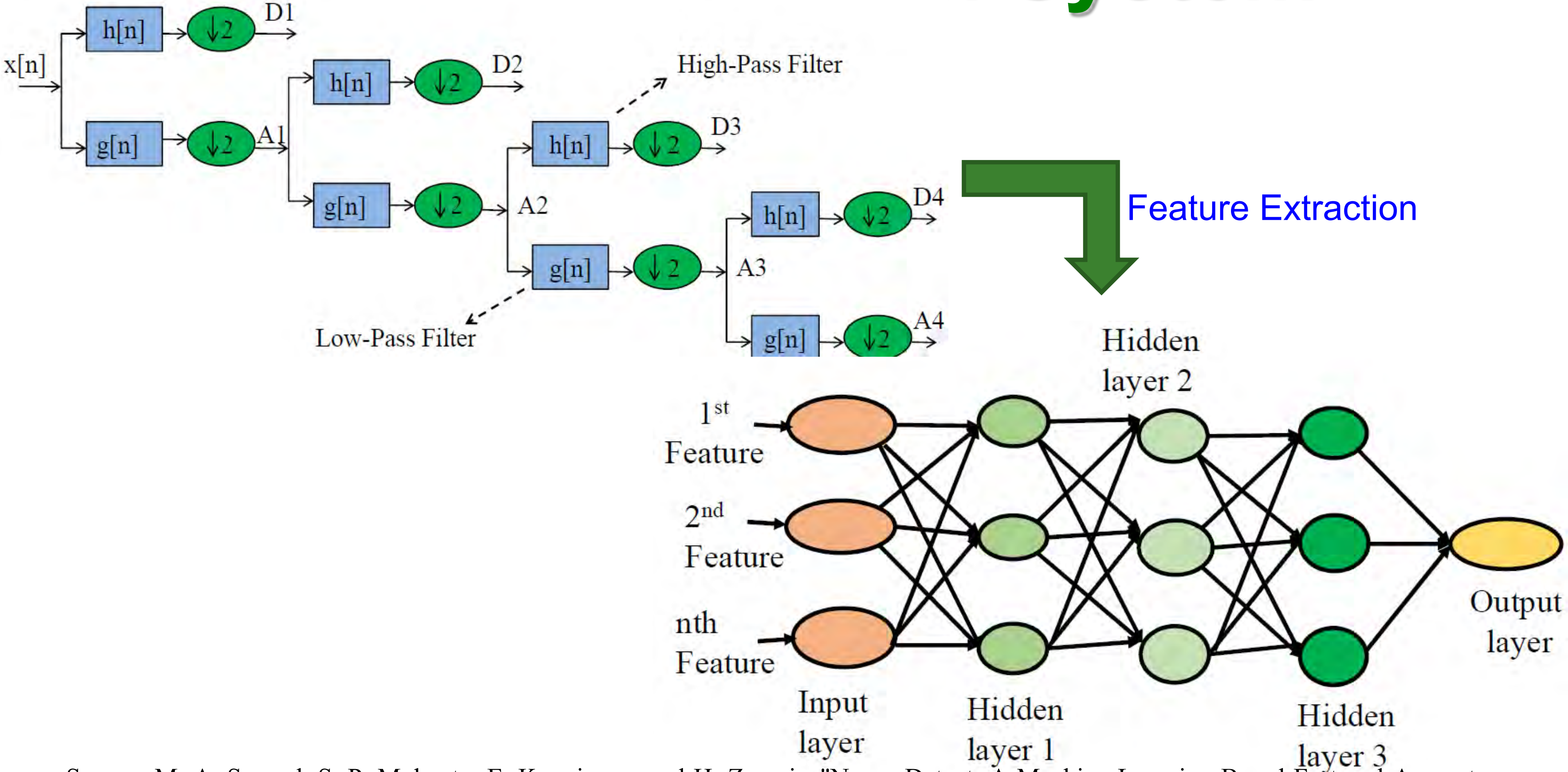
Epileptic Seizure Detection



Overview of the Proposed Architecture

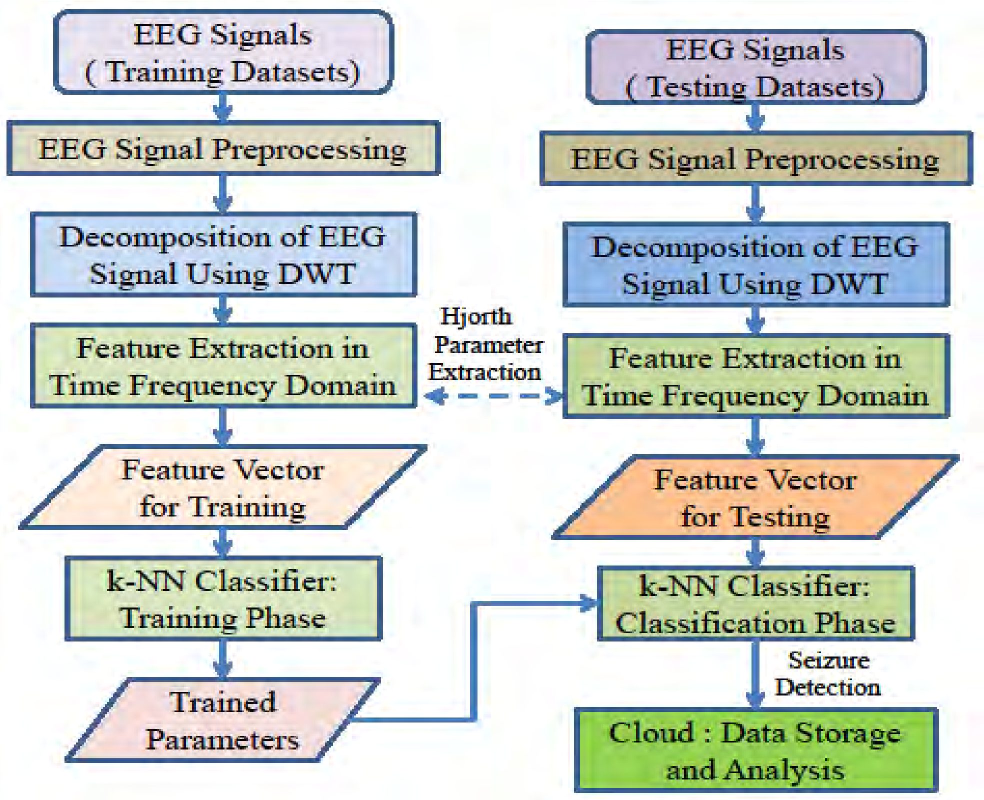


Our Neuro-Detect : A ML Based Seizure Detection System



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.

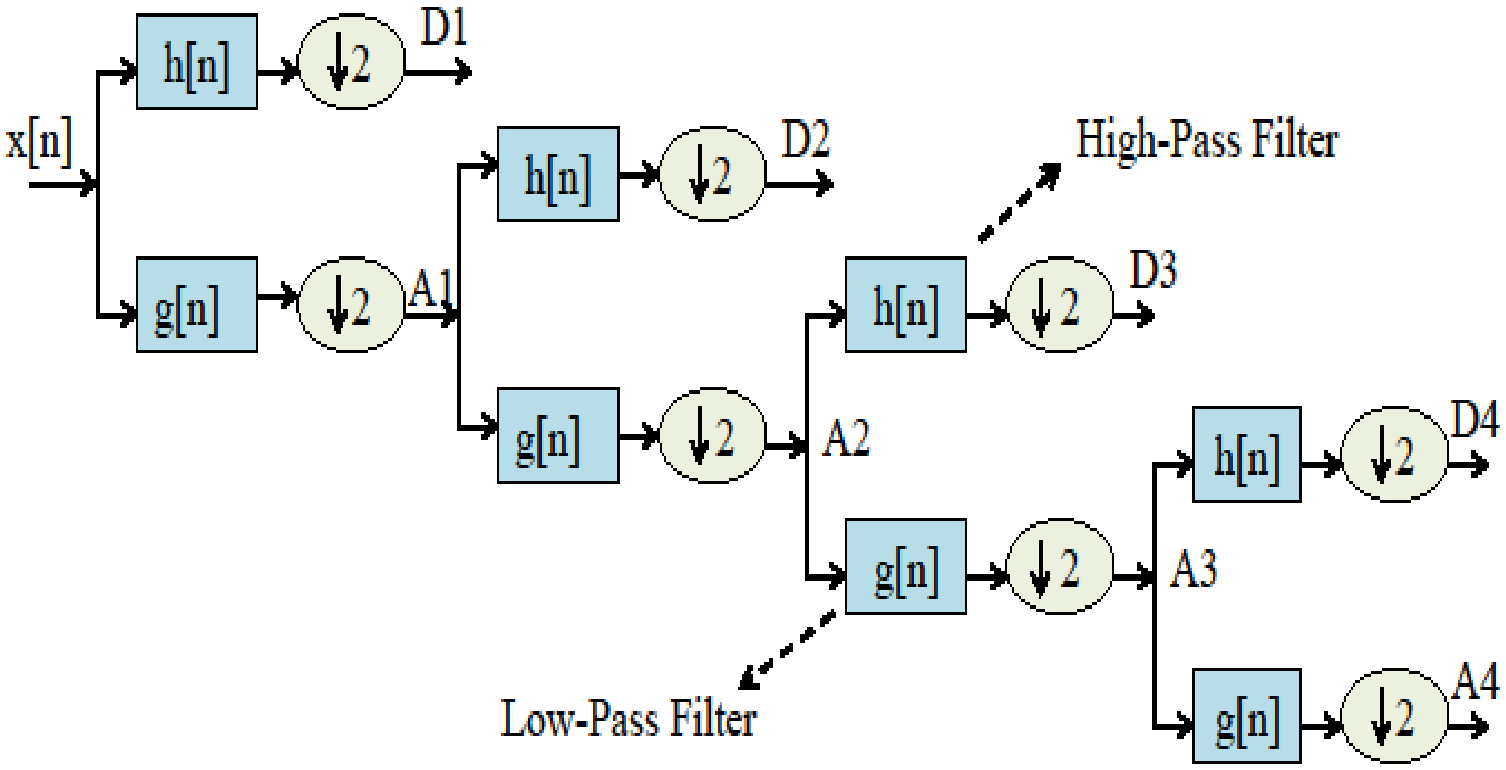
Flowchart of the Proposed System



Flowchart of the Proposed System

- The EEG is acquired and decomposed into several sub-bands using DWT.
- HP values are extracted from the different subbands to form a feature vector..
- The feature vectors are submitted to the k-NN classifier.
- The wireless module enables data to be transferred to clinical Care staff through the internet.

Discrete Wavelet Transform (DWT) Processing Unit



Hjorth Parameter Extraction

- Hjorth Parameters are: Signal complexity, signal mobility and signal activity.
- Signal complexity and signal mobility quantify the level of variations along the signal.
- Hjorth parameters are highly effective for capturing complex dynamics of brain signals.

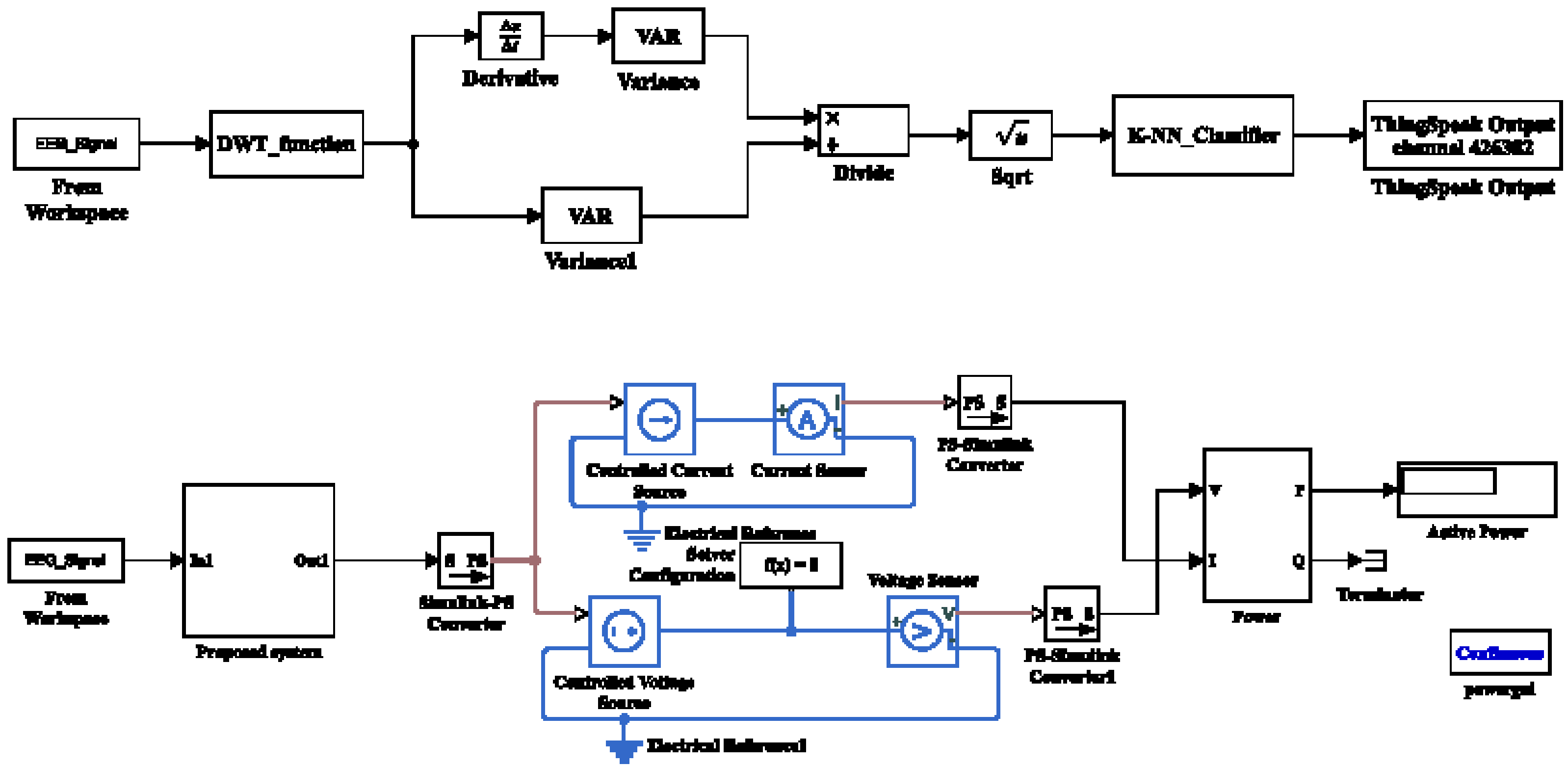
K-Nearest Neighbour Classifier

The nearness of the datasets has been calculated using the Euclidean distance metric:

$$\left\|\vec{x}-\vec{y}\right\| = \sqrt{\sum_{i=1}^{d}(x_i - y_i)^2}$$

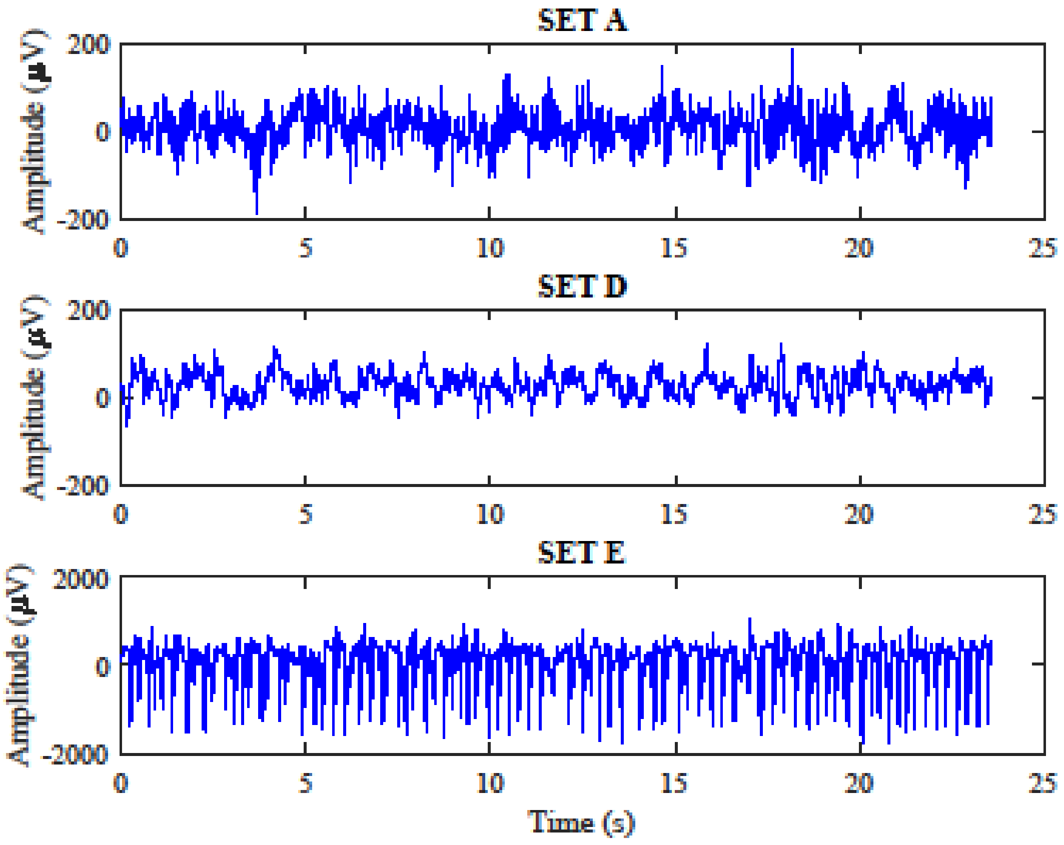
The classification accuracy depends on distance metric and the value of k.

Implementation of the Proposed System



Simulink Implementation (Top) System (Bottom) Power measurement set up

Results



Example of (Top) Normal EEG (Middle) Inter-ictal EEG (Bottom) Ictal EEG

Results

TABLE I
EXTRACTED FEATURE COEFFICIENTS OF SET A AND E

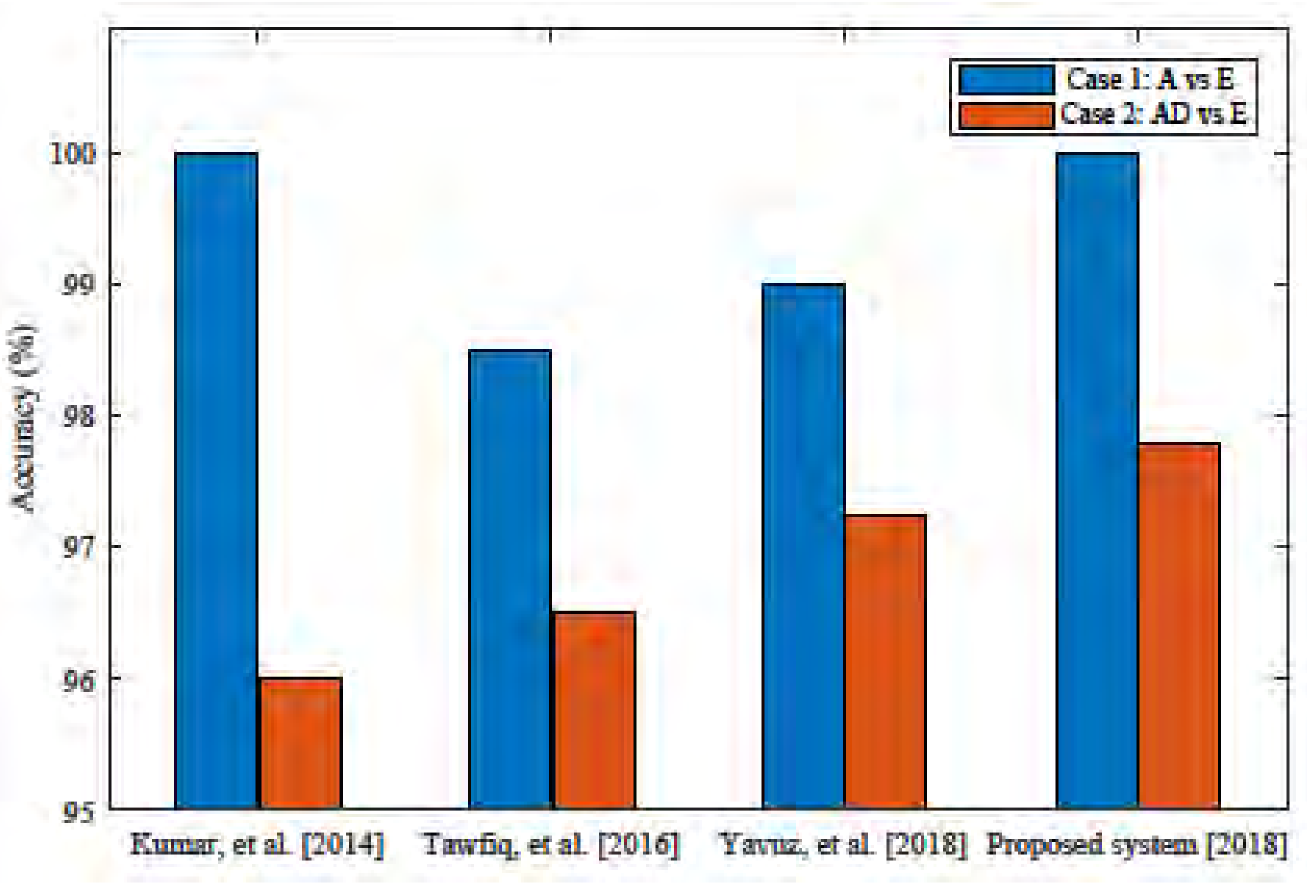
Dataset	Features	D1	D2	D3	D4	A4
A	Activity	18.44	362.5	3.88e+03	7.33e+03	1.91e+04
	Signal Complexity	0.9371	0.4688	0.7145	1.2315	1.4909
	Signal Mobility	1.4586	1.8296	1.7259	1.1894	0.7691
E	Activity	1.4e+03	5.82e+05	5.45e+05	3.07e+05	6.33e+05
	Signal Complexity	0.7797	0.3881	0.5904	0.6281	0.7126
	Signal Mobility	1.5579	1.8398	1.7613	1.8007	1.7968

Results – HP and k-NN

TABLE II
PERFORMANCE OF THE PROPOSED SYSTEM

Normal VS Seizure	
Accuracy	100%
Sensitivity	100%
Specificity	100%
Inter-ictal VS Seizure	
Accuracy	97.85%
Sensitivity	94.6%
Specificity	98.14%

Results - Comparison



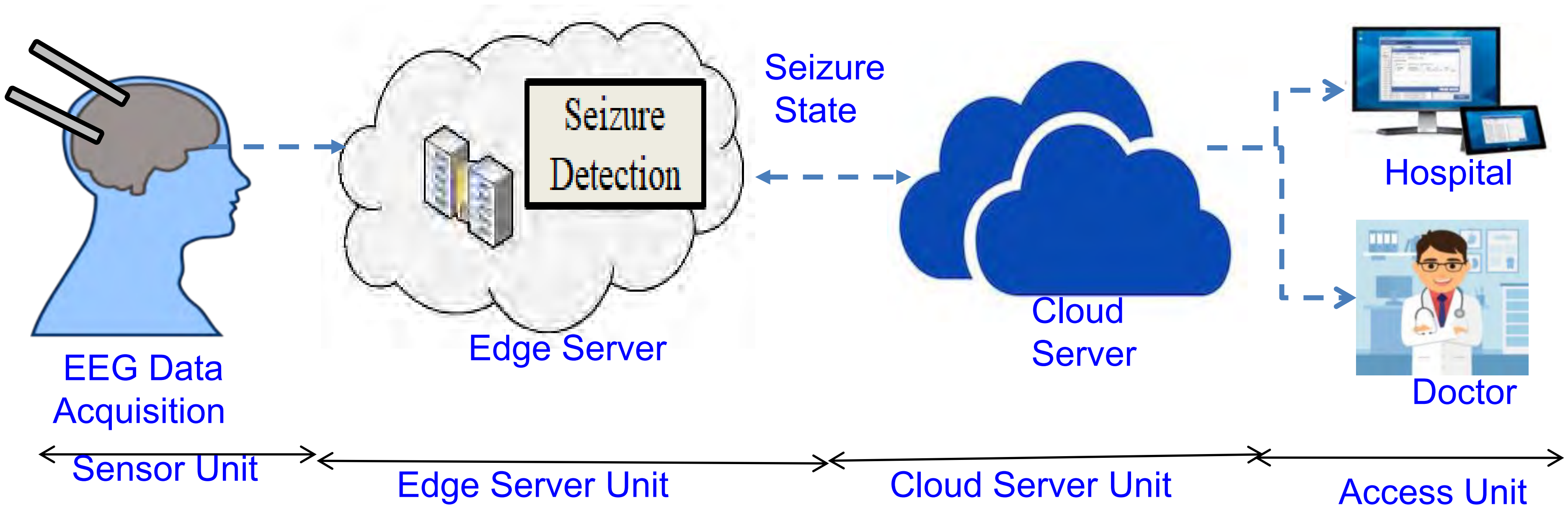
Results

- It is evident that signal complexity is higher in normal EEG compared to ictal EEG. On the otherhand, activity and signal mobility is higher for dataset E recorded during seizure.
- For case 1 (A-E): the classification accuracy was 100% for combined and individual features.
- For case 2 (AD-E): the highest accuracy obtained was 97.85% for individual feature AC (signal activity).

Conclusion and Future Research

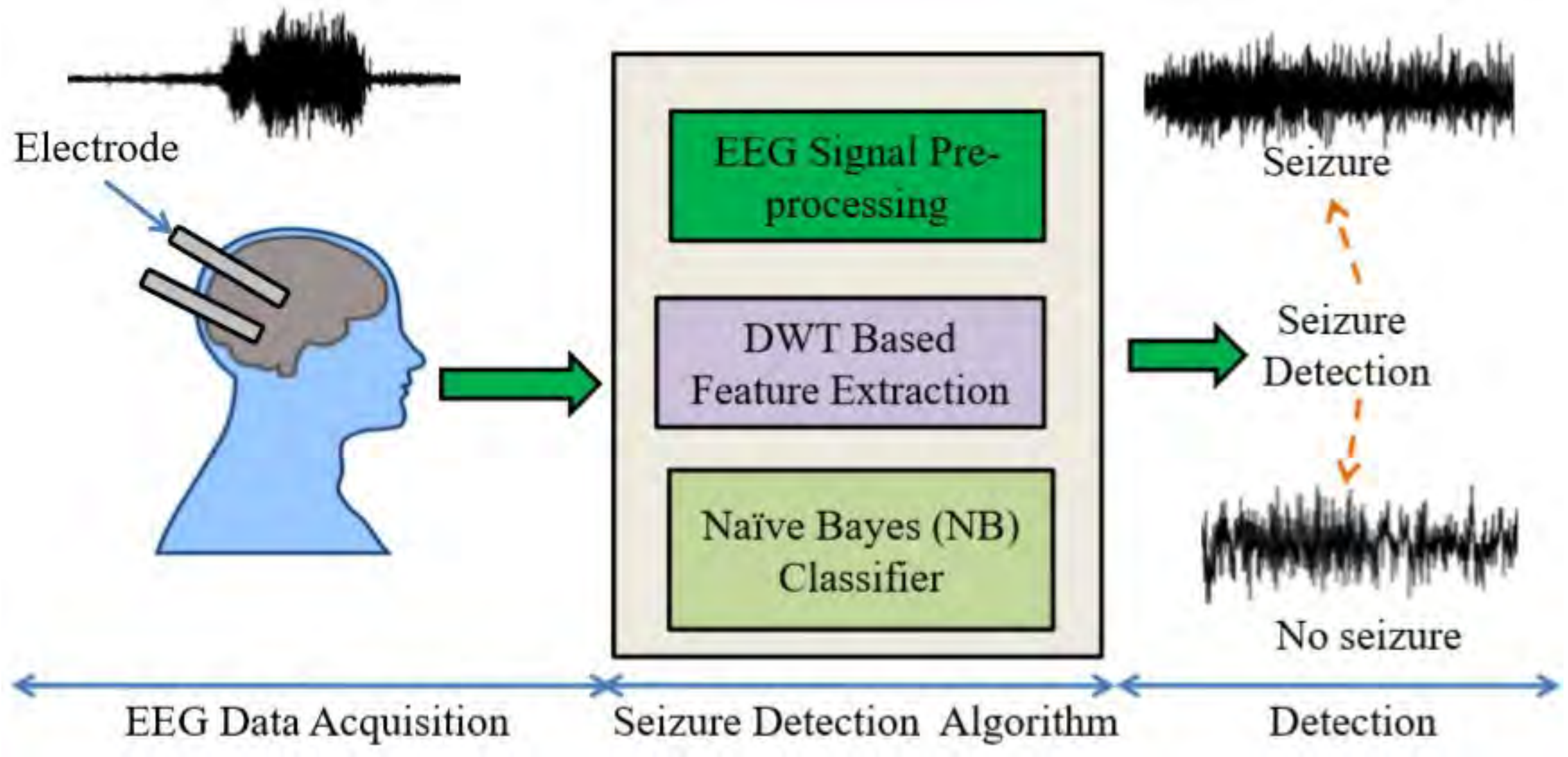
- The experimental results show that the DWT based Hjorth parameters are highly effective in distinguishing EEG signals, leading to an improved classification accuracy.
- The proposed IoT framework can be expanded to include wireless wearable icEEG sensors to detect patients' seizure activities.

Seizure Detection – IoT-Edge Computing

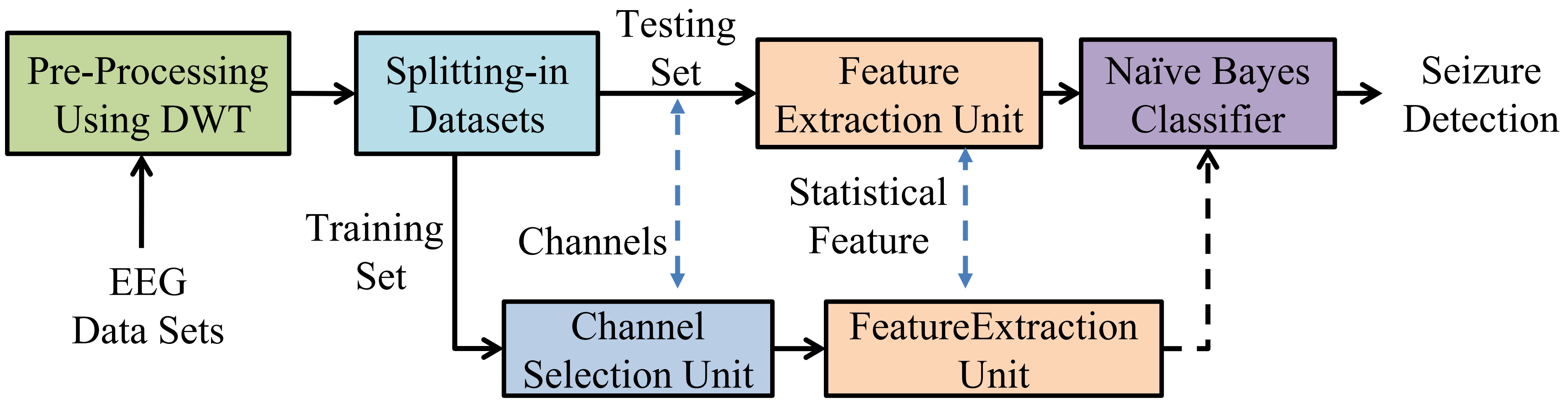


Source: A. Sayeed, S. P. Mohanty, E. Kougianos, V. P. Yanambaka and H. Zaveri, "A Robust and Fast Seizure Detector for IoT Edge," in *Proc. IEEE International Symposium on Smart Electronic Systems (iSES) (Formerly iNiS)*, 2018, pp. 156-160, doi: 10.1109/iSES.2018.00042.

Seizure Detection Paradigm



Architecture: Epileptic Seizure Detection



Feature Extraction From Discrete Wavelet Transform (DWT)

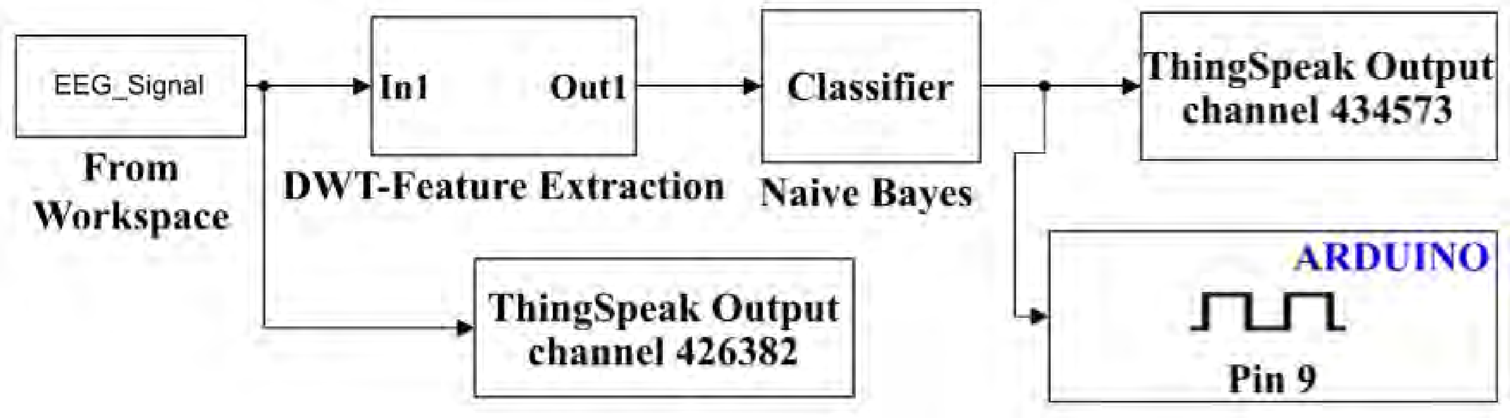
- Analysis of the EEG signals requires time-frequency (TF) decomposition to capture both low and high frequency information.
- The sub-band frequency ranges are: D1 (43.486.8Hz), D2 (21.7-43.4Hz), D3 (10.85-21.7Hz), D4 (5.4310.85Hz), and A4 (0-5.43Hz).
- The following statistical parameters are extracted from the decomposed EEG signals: variance, standard deviation, and energy.

Naïve Bayes Classifier

- A naïve Bayes classifier is based on Bayesian theory and requires fewer data for training.

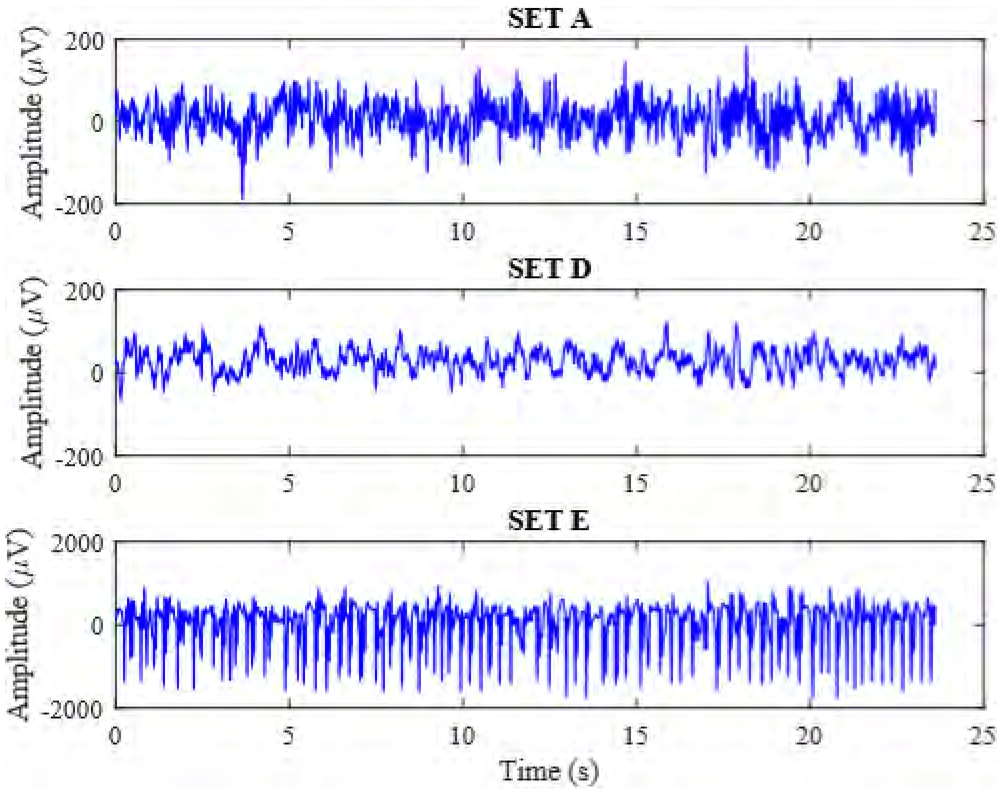
- A class label is given to the attribute based on the highest posterior probability.

Implementation of the Proposed System..



- The proposed system was implemented using Simulink and the Arduino UNO R3 microcontroller board.
- ThingSpeak, an open data platform, was utilized to gather data in the cloud.

Results-EEG Waveforms



Results…

Extracted feature coefficients for dataset A

Coefficients	Variance	Standard Deviation	Energy
D1	25.21	5.02	2.85e+04
D2	587.55	24.23	3.04e+05
D3	5.39e+03	73.45	1.44e+06
D4	9.90e+03	99.52	1.98e+06
A4	1.54e+04	124.25	4.05e+06

Results…

Extracted feature coefficients for dataset E

Coefficients	Variance	Standard Deviation	Energy
D1	1.42e+03	37.98	1.89e+06
D2	6.43e+04	253.73	4.87e+07
D3	7.01e+05	837.56	3.06e+08
D4	6.96e+05	834.76	1.88e+08
A4	1.71e+06	1.31e+03	4.08e+08

Results: Cloud-IoT VS Edge-IoT

System Details	Latency
Clod-IoT Framework	2.5 sec
Edge-IoT Framework	1.4 sec

- Latency includes both computation time as well transmission delay.
- Edge-based IoT provides 44% reduction in latency which is highly important for critical biomedical applications.

Results- Comparison

Author	Methods	Accuracy (%)
Shoeb et al. [2009]	Support Vector Machines	78.74
Kumar et al. [2014]	Neural Network	95
Tawfiq et al. [2016]	Weighted Permutation Entropy	96.5
Sharmila et al. [2016]	Feature Extraction and k-NN classifier	97.08
Proposed System [2018]	DWT and naïve Bayes Classifier	98.65

Conclusion and Future Research

- The proposed edge-IoT framework reduces latency significantly while maintaining high classification accuracy.

- Future research includes implementing a drug delivery system with the proposed system for seizure detection and simultaneous drug injection.

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

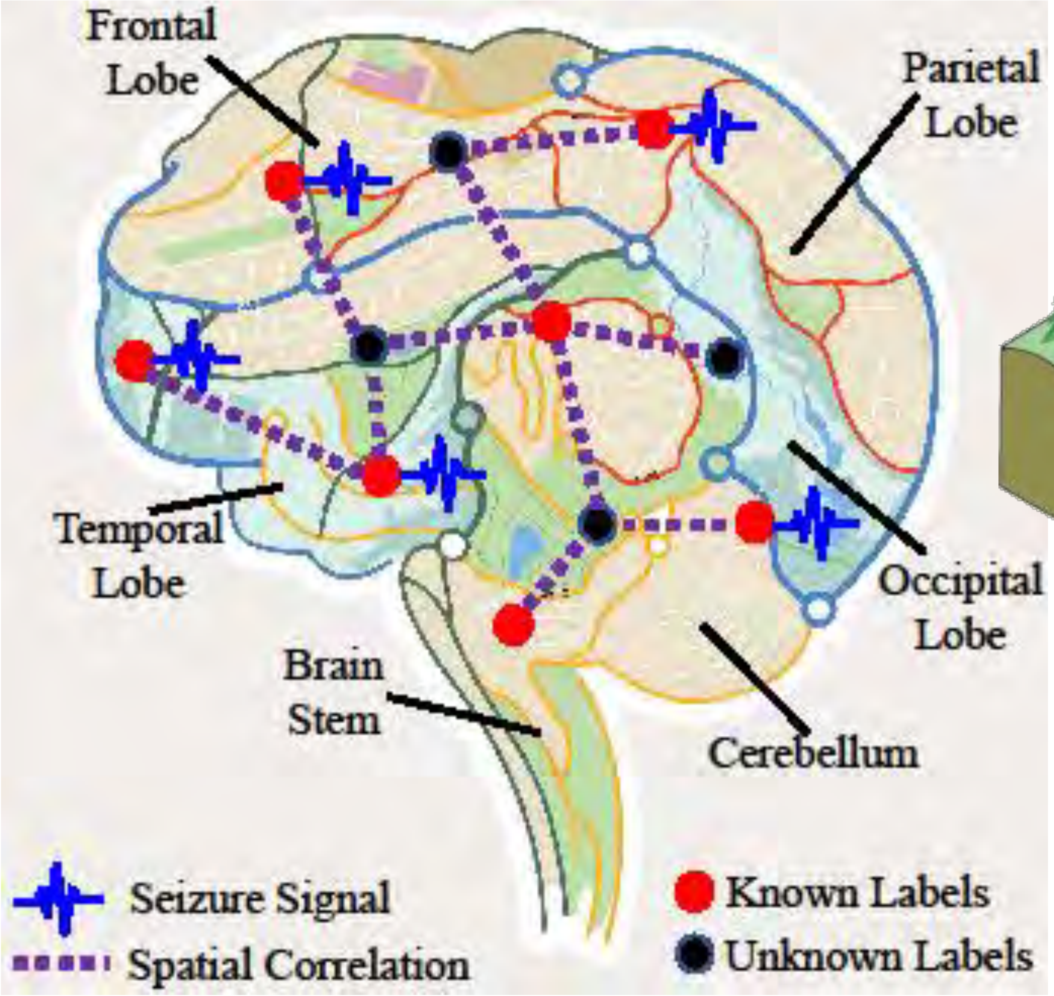
- To the best of the authors' knowledge, this is the first work where multiple Kriging methods have been used for real-time seizure detection in an edge computing paradigm.
- A novel achievement of an epileptic seizure detection latency of less than 1 second while maintaining a comparable accuracy with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

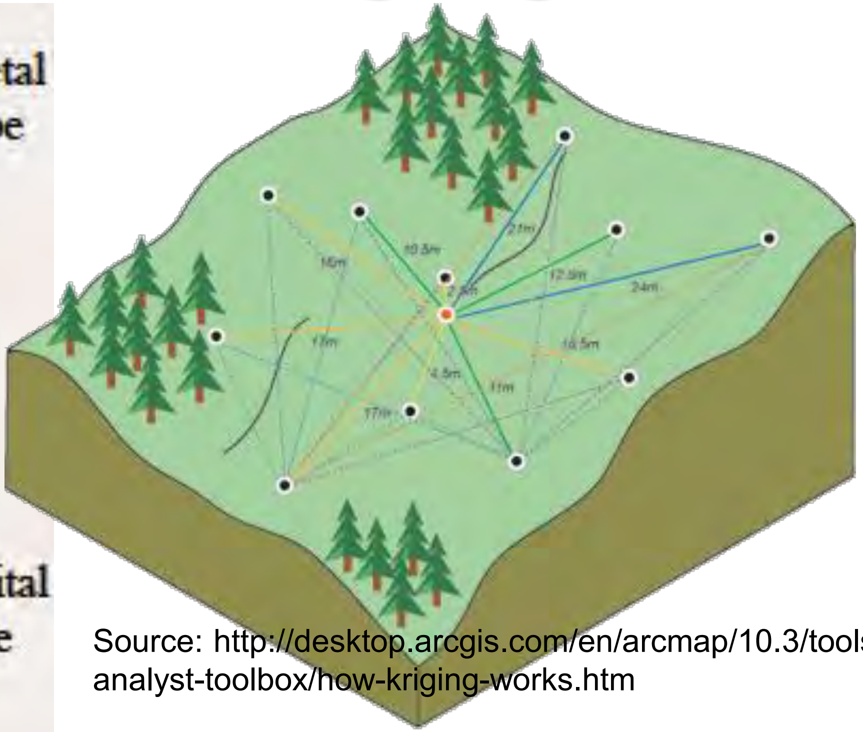
Source: I. L. Olokodana, S. P. Mohanty and E. Kougianos, "Krig-Detect: Exploring Alternative Kriging Methods for Real-Time Seizure Detection from EEG Signals," in *Proc. IEEE 6th World Forum on Internet of Things (WF-IoT)*, 2020, pp. 1-6, doi: 10.1109/WF-IoT48130.2020.9221260.

Research Question and Hypothesis

- How effective will Kriging Methods perform on a seizure detection problem given that the brain is structured like a geo map?
- Which Kriging method is best-suited for seizure detection?
- Is it possible to run a seizure detection algorithm on the edge rather than the cloud to achieve a better latency, without significant compromise on accuracy?

Smart Healthcare – Brain as a Spatial Map → Kriging Methods





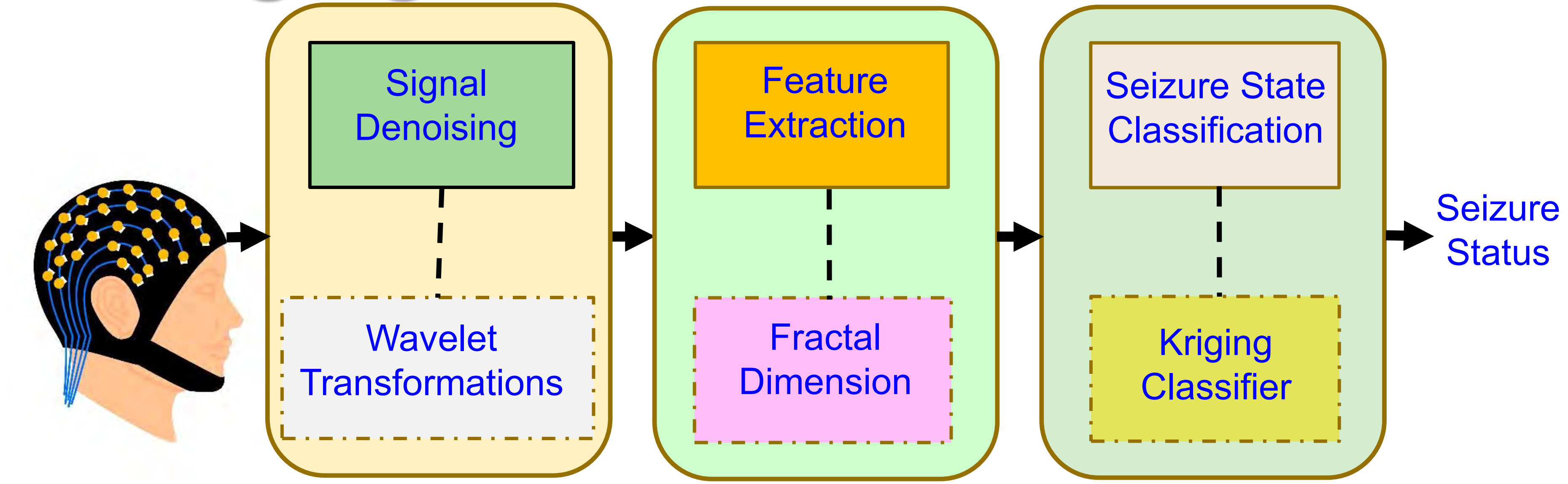
Spatial modeling or Variography
- Correlation Function is "Variogram"

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

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

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

Kriging based Seizure Detection

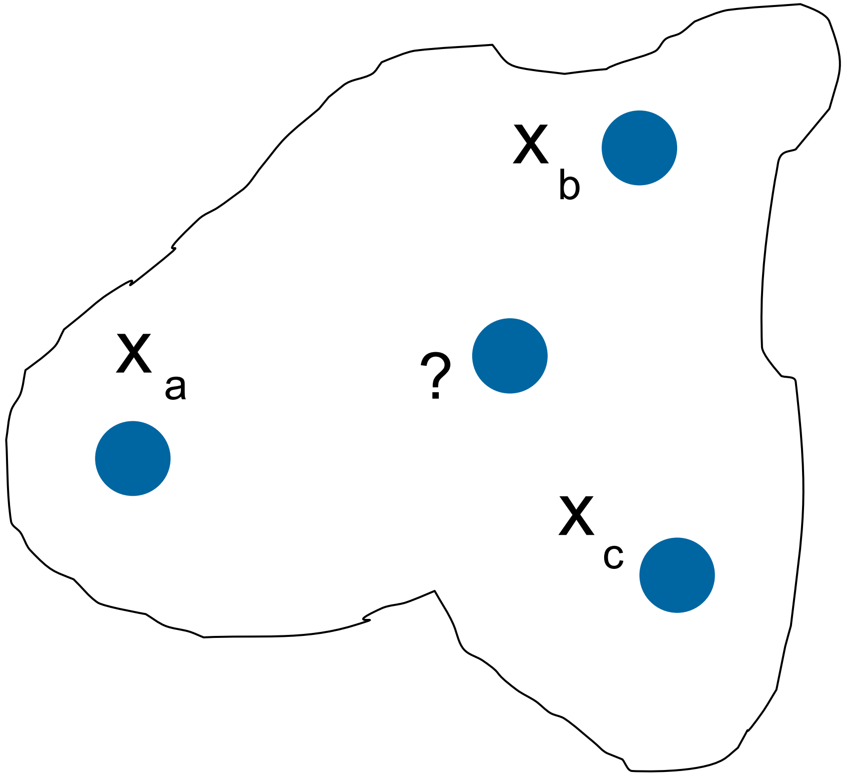


Works	Extracted Features	Classification Algorithm	Sensitivity	Latency
Zandi, et al. 2012 [23]	Regularity, energy & combined seizure indices	Cumulative Sum thresholding	91.00%	9 sec.
Altaf,etal. 2015 [24]	Digital hysteresis	Support Vector Machine	95.70%	1 sec
Vidyaratne, et al. 2017 [25]	Fractal dimension,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

Kriging Method – Basic Idea

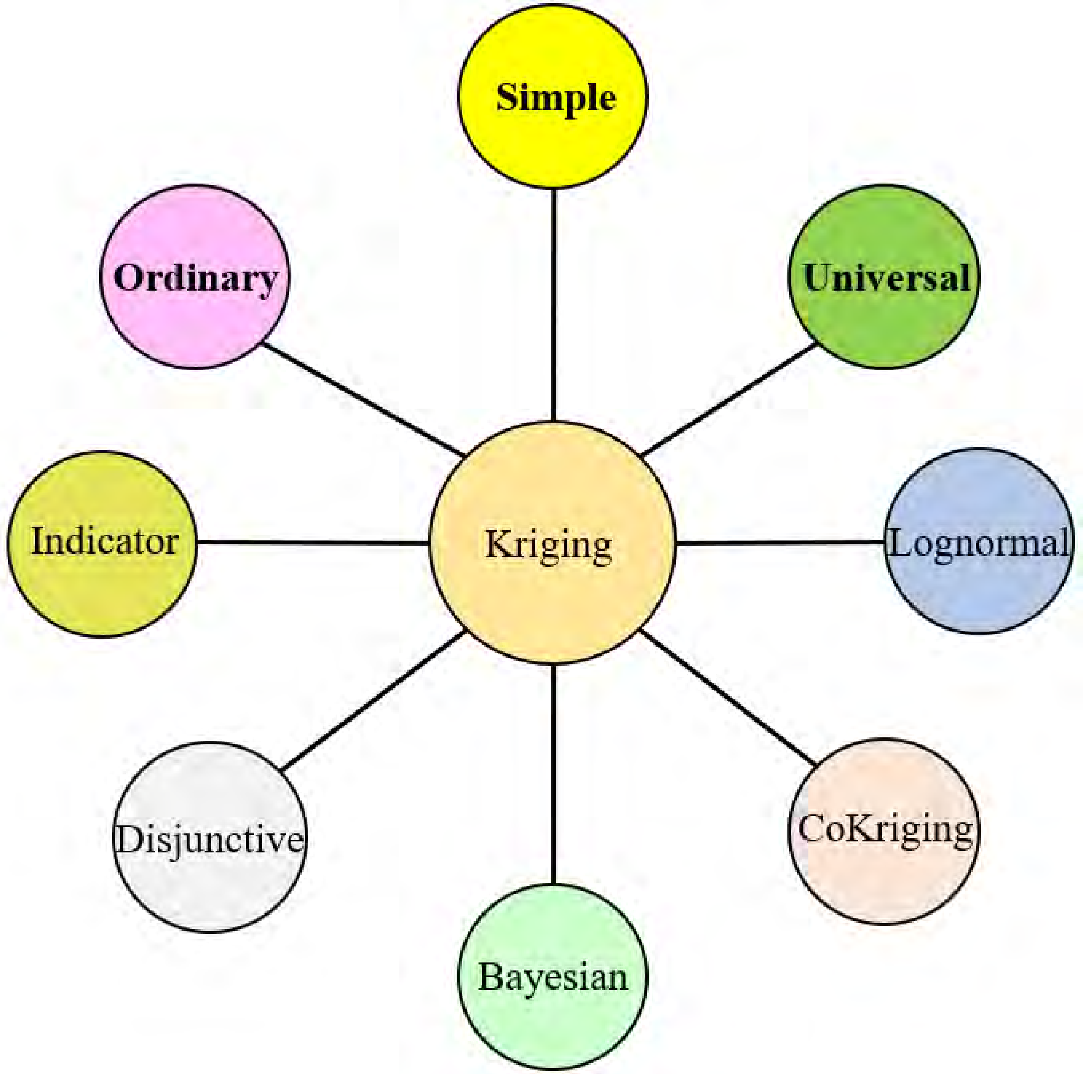
- Kriging was originally developed as a geo-statistical model for spatial prediction.
- It is a stochastic process that is governed by a mean value and the relative co-variances of known data points with respect to an unknown.



Why Kriging?

- The brain can be modeled as a spatial map on which spatial data processing methods can be applied.
- Kriging method performs very well even on a relatively small dataset unlike machine learning algorithms. This is very important because of the difficulty in obtaining biomedical datasets.
- Kriging model comes with a variance estimate which gives the level of confidence of the model in a given prediction.
- Kriging model is very reliable without requiring the use of many hyperparameters.

Kriging Method - Types



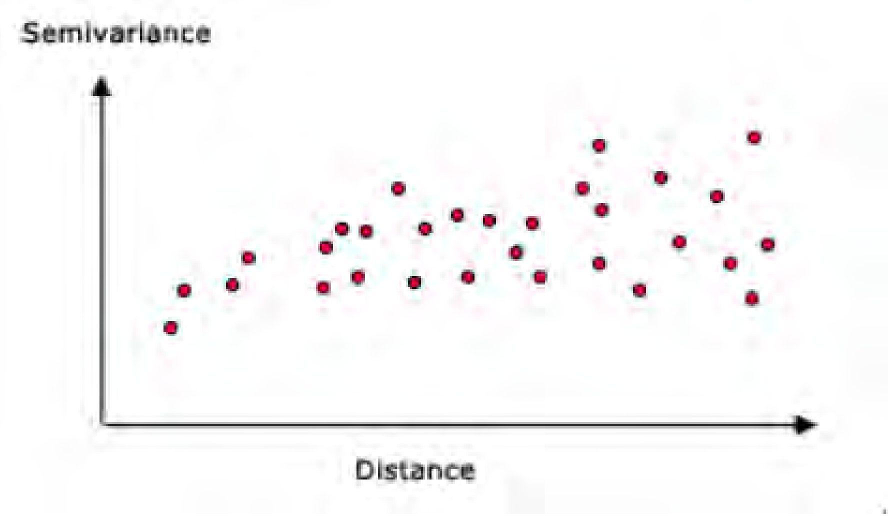
The Kriging Process

- There are three important steps in the application of Kriging methods.
- First is the establishment of spatial continuity through the semi-variogram which is a function of the variations in values over distance.
- Second is fitting a model to the generated semi-variogram.
- The final step is the actual estimation through the fitted model.

The Semi-Variogram

- The semi-variogram is merely a scatter plot with each point representing the average variation among a group of location pairs with common distance known as the lag vector h.
- where Ɣ(h) represents the semi-variogram at the lag vector h between two points, N(h) is the number of lag vectors h considered for a single point on the semi-variogram plot.

$$\gamma(\mathrm{h}) = \frac{1}{2\mathrm{N}(\mathrm{h})} \sum_{i=1}^{\mathrm{N}(\mathrm{h})} (\mathrm{Z}(\mathrm{x}_i) - \mathrm{Z}(\mathrm{x}_i + \mathrm{h}))^2,$$



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

Semi-Variogram Model

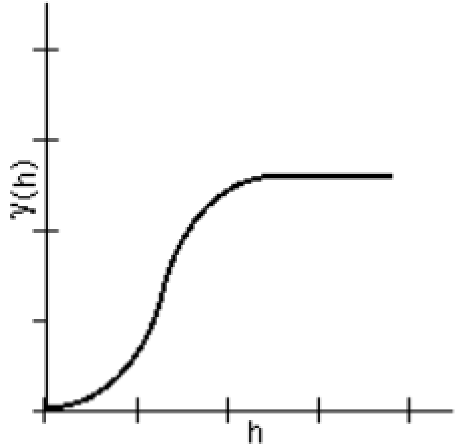
- The semi-variogram model simply fits a line or curve on the scatter plot represented by the semi-variogram.
- There are different types of Semi-Variogram Models as shown below:

- Semi Variogram Model
  - Linear
  - Nugget Effect
  - Spherical
  - Exponential
  - Gaussian

Gaussian Semi-Variogram Model

- EEG time-series recorded from normal and epileptic patients were congruent with Gaussian stochastic process. Hence the choice of Gaussian Semi-Variogram Models.

$$\gamma(\mathrm{h}) = \begin{cases} C\left[1 - \exp\left(-\frac{\mathrm{h}^2}{a^2}\right)\right] & \mathrm{h} > 0 \\ 0 & \mathrm{h} = 0 \end{cases}$$



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

- C is the sill (total variance contribution) and a is the range (distance on the horizontal axis corresponding to the sill).

Kriging Estimates

- Given the following set of observations $\mathbf{x}_1$, $\mathbf{x}_2$, ..., $\mathbf{x}_n$ as inputs, and $y(\mathbf{x}_1)$, $y(\mathbf{x}_2)$, ..., $y(\mathbf{x}_n)$ as outputs, the input-output relationship based on Kriging is given by:

$$y(\mathrm{x}_i) = \mu + Z(\mathrm{x}_i),$$

- *Where* i is the data point index, μ is a mean constant and $Z(\mathbf{x}_i)$ is a Gaussian process.
- The weights between the unknown and each of the known can be obtained by solving the following equation, where C(.) is covariance between two points:

$$\sum_{j=1}^{n} \lambda_j \mathrm{C}(\mathrm{x}_i, \mathrm{x}_i) = 2\mathrm{C}(\mathrm{x}_o, \mathrm{x}_i).$$

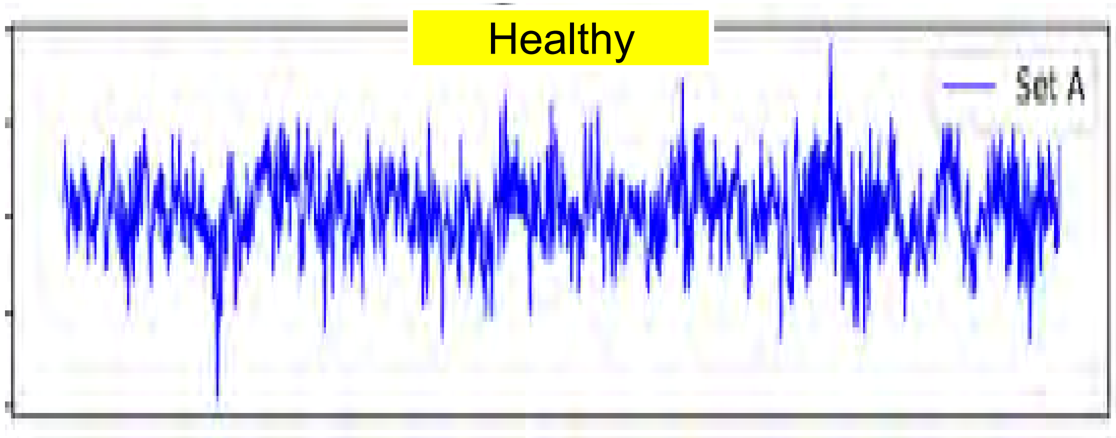
- Hence, the final estimate can be obtained as:

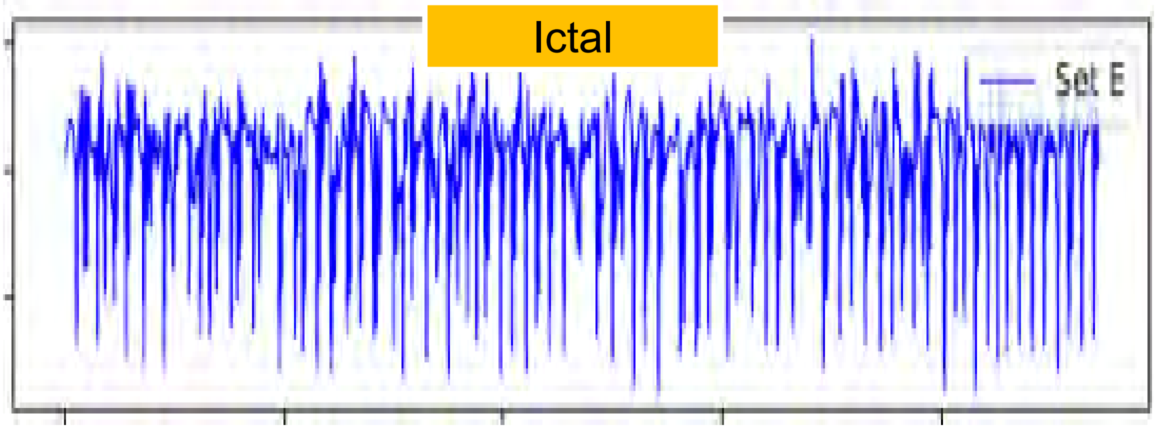
$$y(\mathrm{x}_o) = \sum_{i=1}^{n} \lambda_i Z(\mathrm{x}_i) + (1 - \sum_{i=1}^{n} \lambda_i)\mu_z,$$

Experimental Results - EEG Dataset

BONN DATASET

- The datasets were originally collected from 5 healthy volunteers & five epilepsy patients by the University of Bonn. 5 different sets of data were collected as sets A, B, C,D&E.
- Sets A&B are healthy signals, C&D are inter-ictal signals while E is the only set with ictal signals. Each of the sets comprises 100 EEG segments which were collected with a 128-channel EEG system sampled at 173.61 Hz.

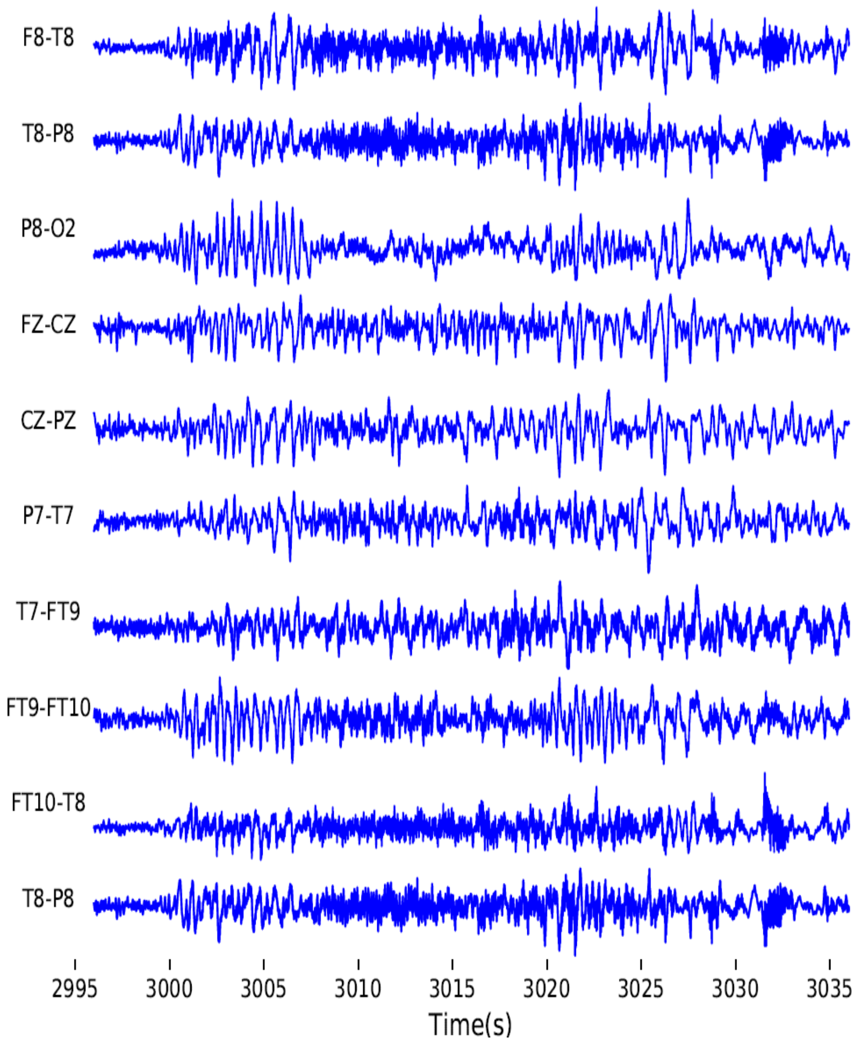




Experimental Results - EEG Dataset

CHB-MIT SCALP EEG DATASET

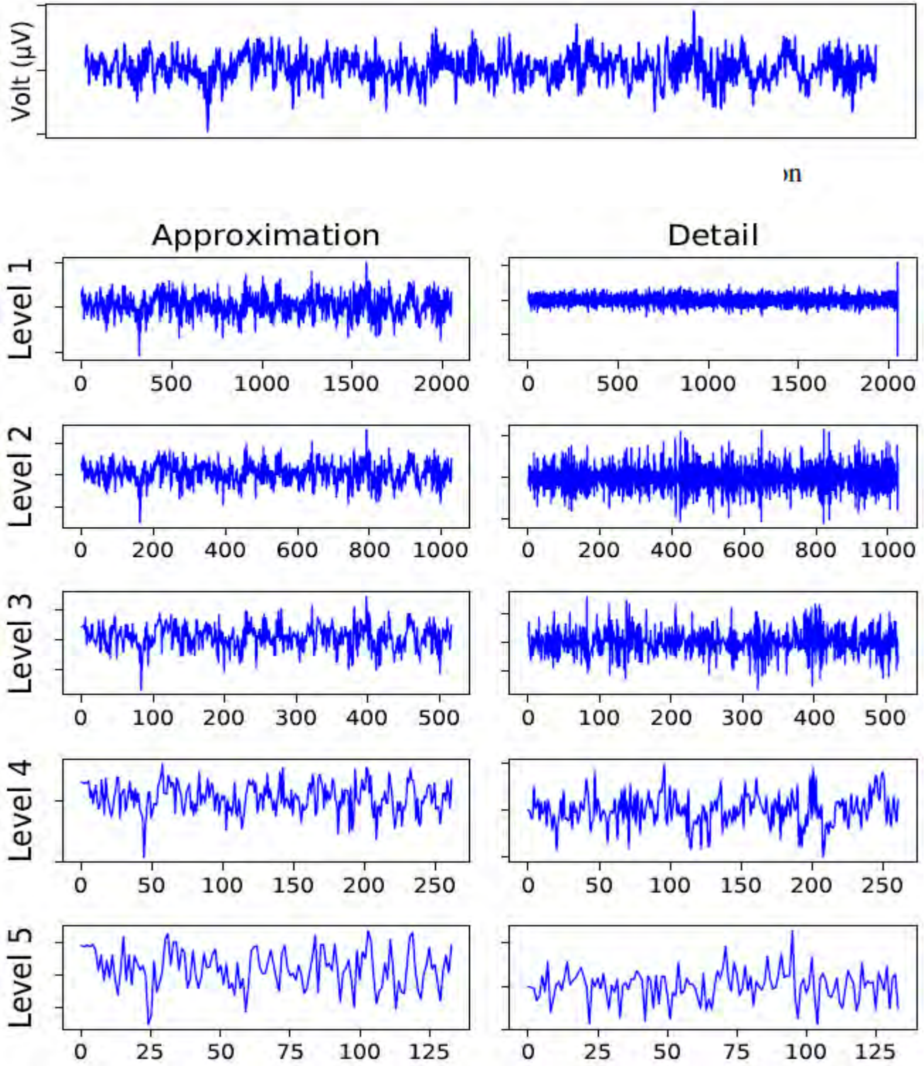
- This dataset was collected at the Children Hospital Boston (CHB) in conjunction with the Massachusetts Institute Of Technology (MIT). It is therefore referred to as the CHB-MIT Scalp EEG Database.
- The EEG signals were collected from 22 epileptic patients of CHB using a 23-channel EEG, sampled at 256Hz and labeled according to the subjects as chb01 to chb23.
- The dataset consists of a total of 916 hours of continuous EEG recordings across all 22 subjects.



EEG Signal Processing

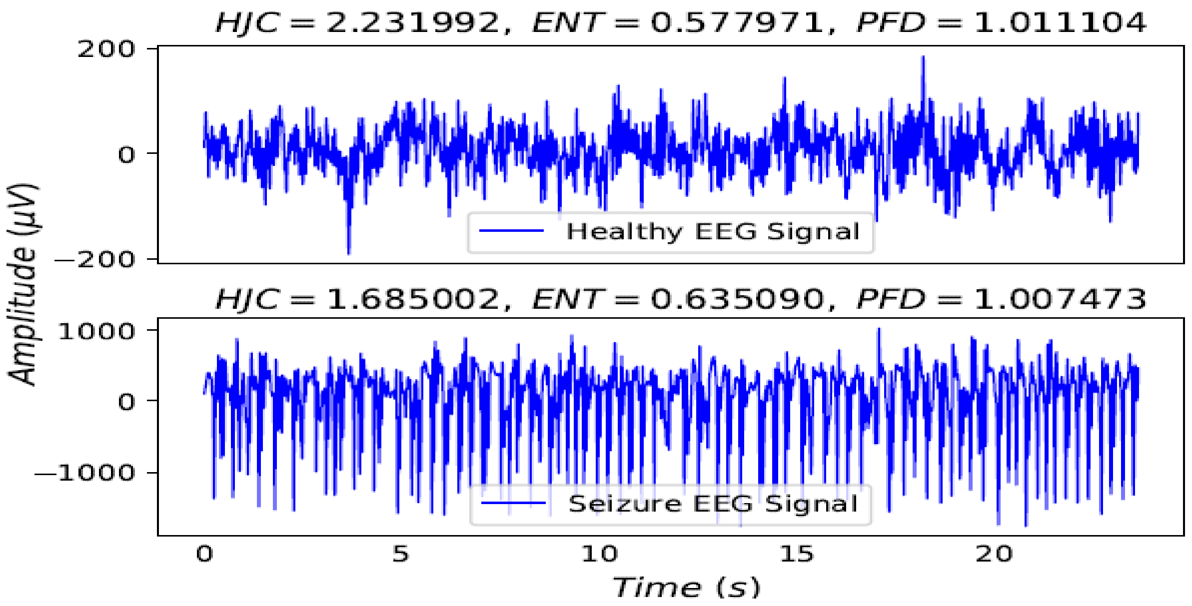
- Figure shows the plot of the Discrete Wavelet Transformation (DWT) coefficients after decomposition using Daubechies Wavelet of order four (db4).
- The final output of the decomposition is shown in the table below:

Coefficients	Frequency (Hz)
D1	43.4 - 86.8
D2	21.7 - 43.4
D3	10.9 - 21.7
D4	5.4 - 10.9
D5	2.7 - 5.4
A5	0 - 2.7

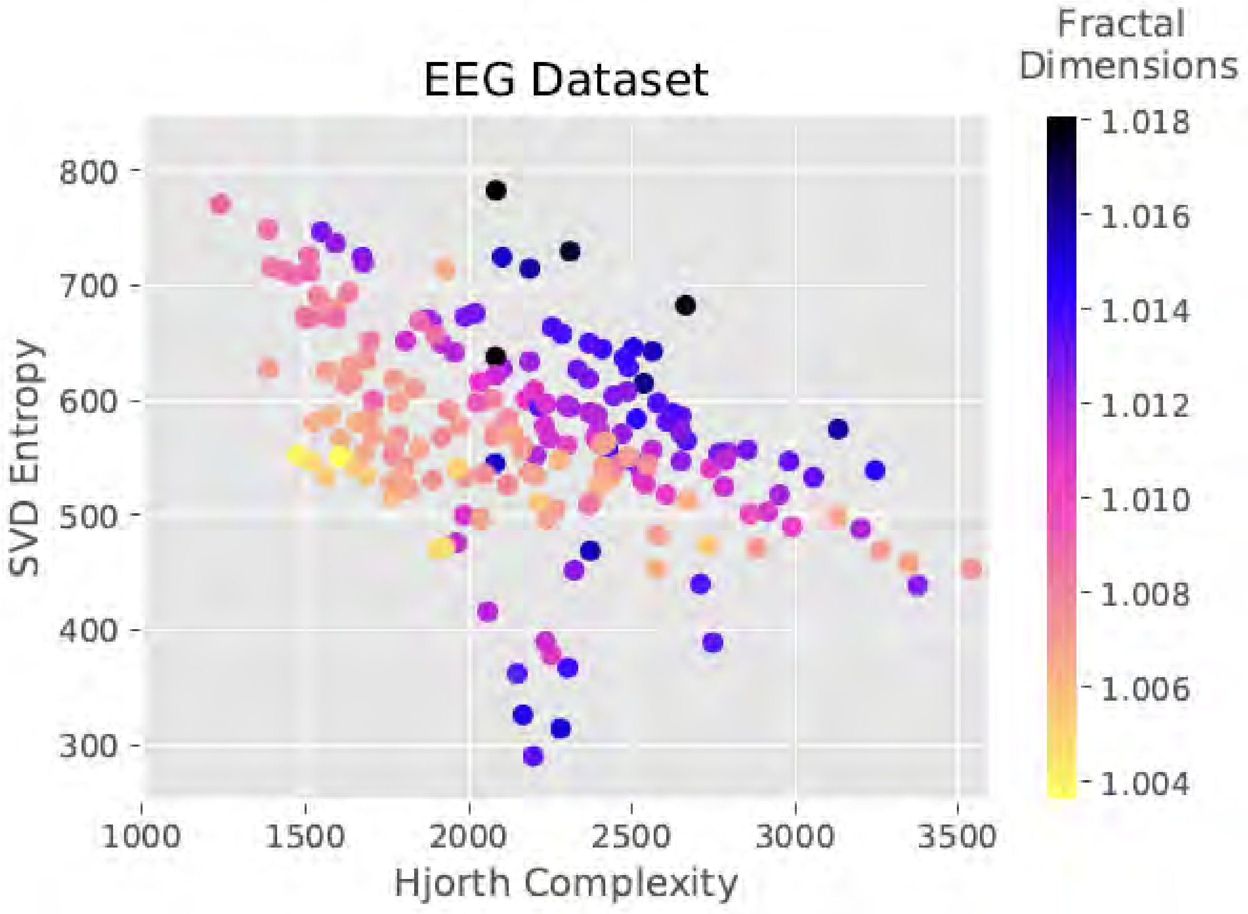


Features of EEG Signal

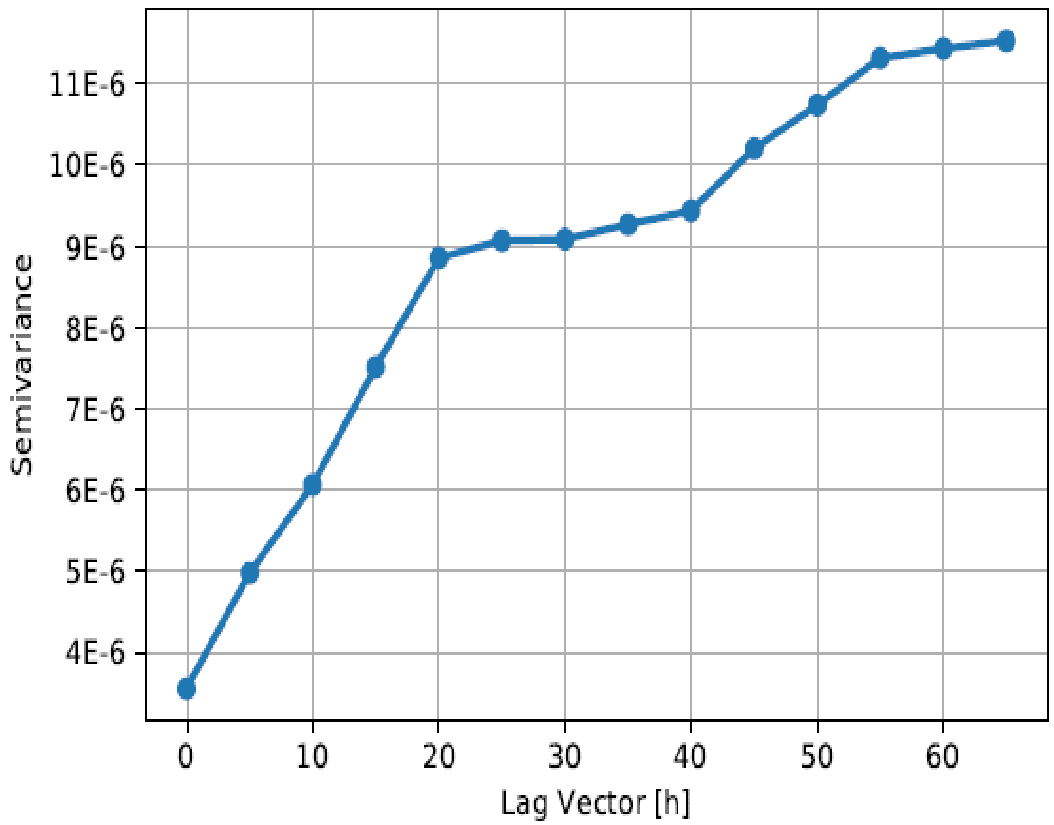
- Signal Entropy
- Fractal Dimension
- Signal Power
- Standard Deviation
- Singular Value Decomposition Entropy
- Maximum Fractal Length
- Hjorth Parameters
- Hurst Exponent
- Lyapunov Exponent etc.

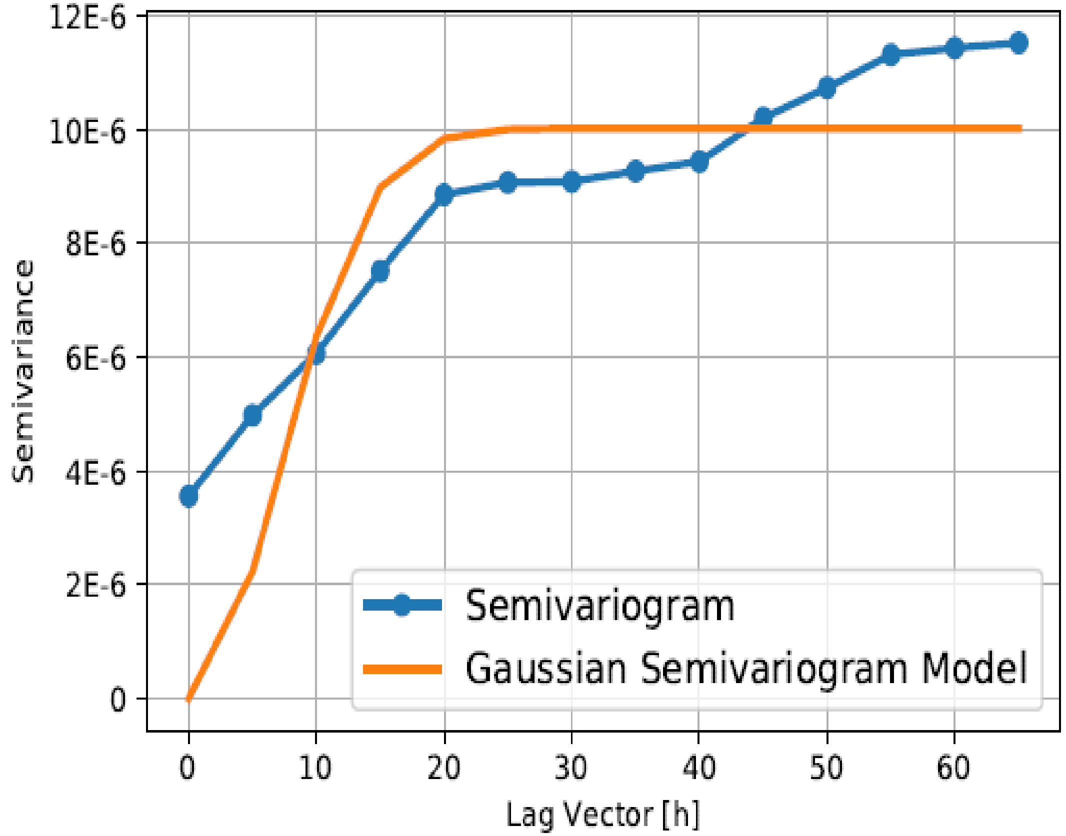


Feature Representation of Dataset

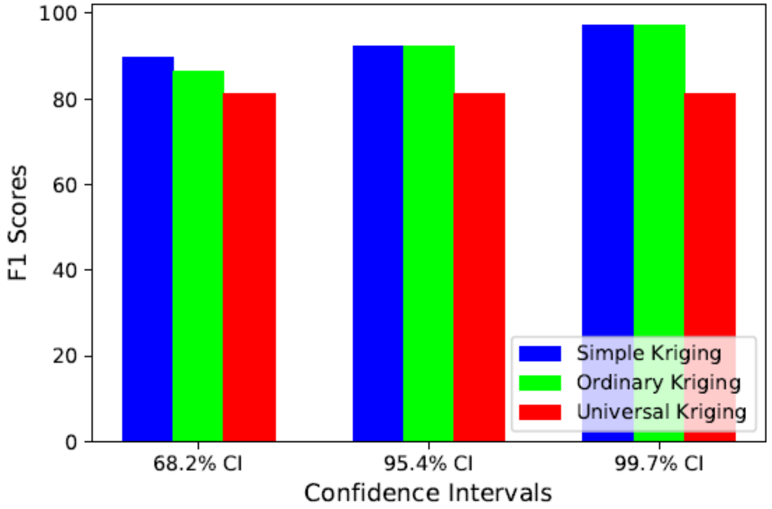


Experimental Results





Experimental Results



C. Int. (CI)	Kriging Models	Accuracy	Sensitivity	Specificity
99.7% CI	Simple Kriging	97.50%	94.74%	100.00%
	Ordinary Kriging	97.50%	94.74%	100.00%
	Universal Kriging	80.00%	89.47%	71.43%
95.4% CI	Simple Kriging	92.50%	94.74%	90.48%
	Ordinary Kriging	92.50%	94.74%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%
68.2% CI	Simple Kriging	90.00%	89.47%	90.48%
	Ordinary Kriging	87.50%	84.21%	90.48%
	Universal Kriging	80.00%	89.47%	71.43%

Kriging Models	Detection Latency
Simple Kriging	**0.81s**
Ordinary Kriging	0.86s
Universal Kriging	16.25s

Comparison with Related Works

Published Works	Extracted Features	Classification Algorithm	Accuracy	Sensitivity	Detection Latency
Shoeb, et al. 2010	Spectral, temporal and spatial features.	Support Vector Machine (SVM)	NA	96.00%	4.2 sec.
Zandi, et al. 2012	Regularity, energy & combined seizure indices	Cumulative Sum (CUSUM) thresholding	NA	91.00%	9 sec.
Altaf, et al. 2015	Digital hysteresis	Linear Support Vector Machine (LSVM)	NA	95.70%	1 sec.
Vidyaratne, et al. 2017	Fractal dimension, spatial/temporal features	Relevance Vector Machine (RVM)	99.80%	96.00%	1.89 sec.
Sayeed, et al. 2019	Hyper-synchronous pulses	Signal Rejection Algorithm (SRA)	NA	96.90%	3.6 sec.
Our ICCE 2020 Paper	Petrosian fractal dimension	Kriging Classifier	100.00%	100.00%	0.85 sec.
Curr. Paper	Fract dim., Hjorth comp.& Entropy	Kriging Classifier	97.50%	94.74%	**0.81 sec.**

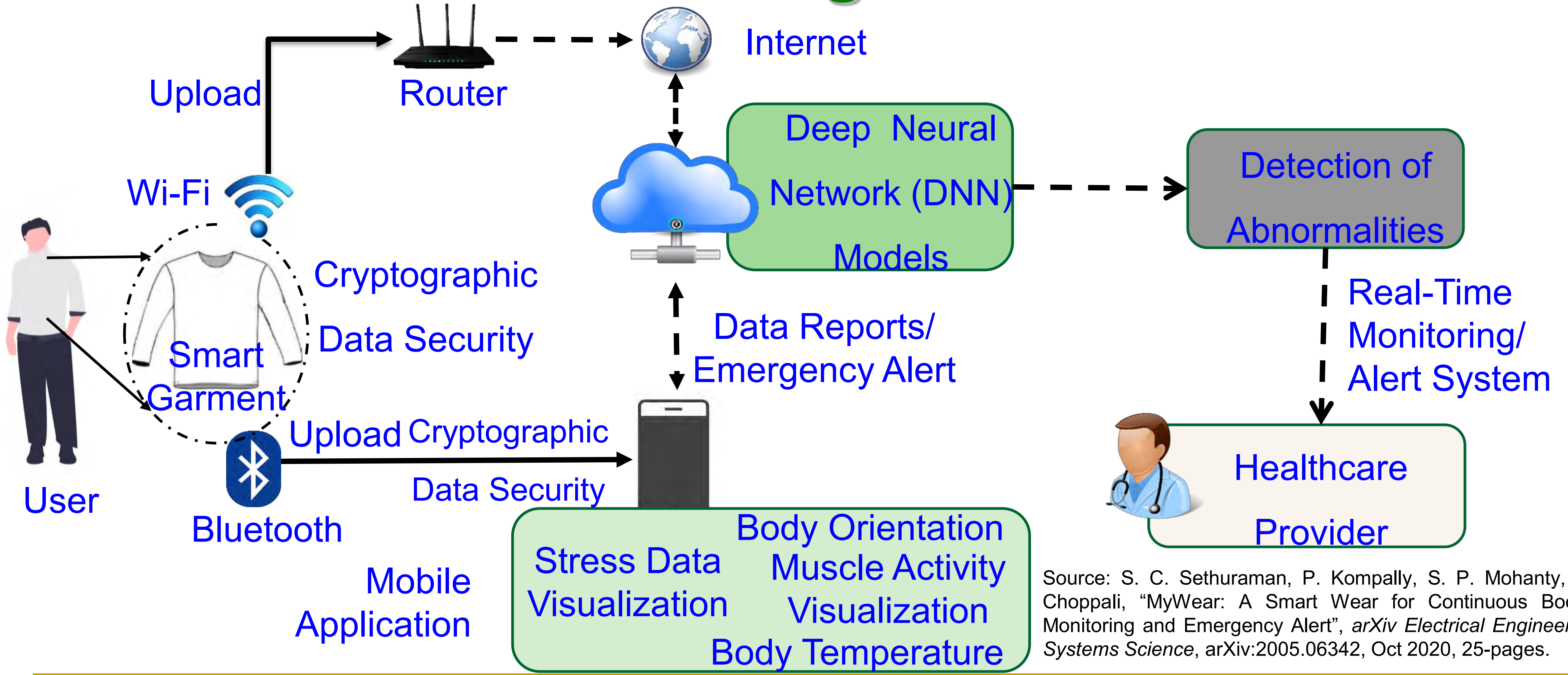
Conclusions

- This results in this presentation demonstrate the effectiveness of Kriging method for accurate and early seizure detection.
- The detection of seizure onset takes place in near real time with an average detection latency of 0.81 second which is better than previous models in the literature.
- Three different Kriging methods were compared for Seizure Detection and results show that Simple Kriging is a slight favorite over Ordinary Kriging while Universal Kriging is far behind them.

Future Research

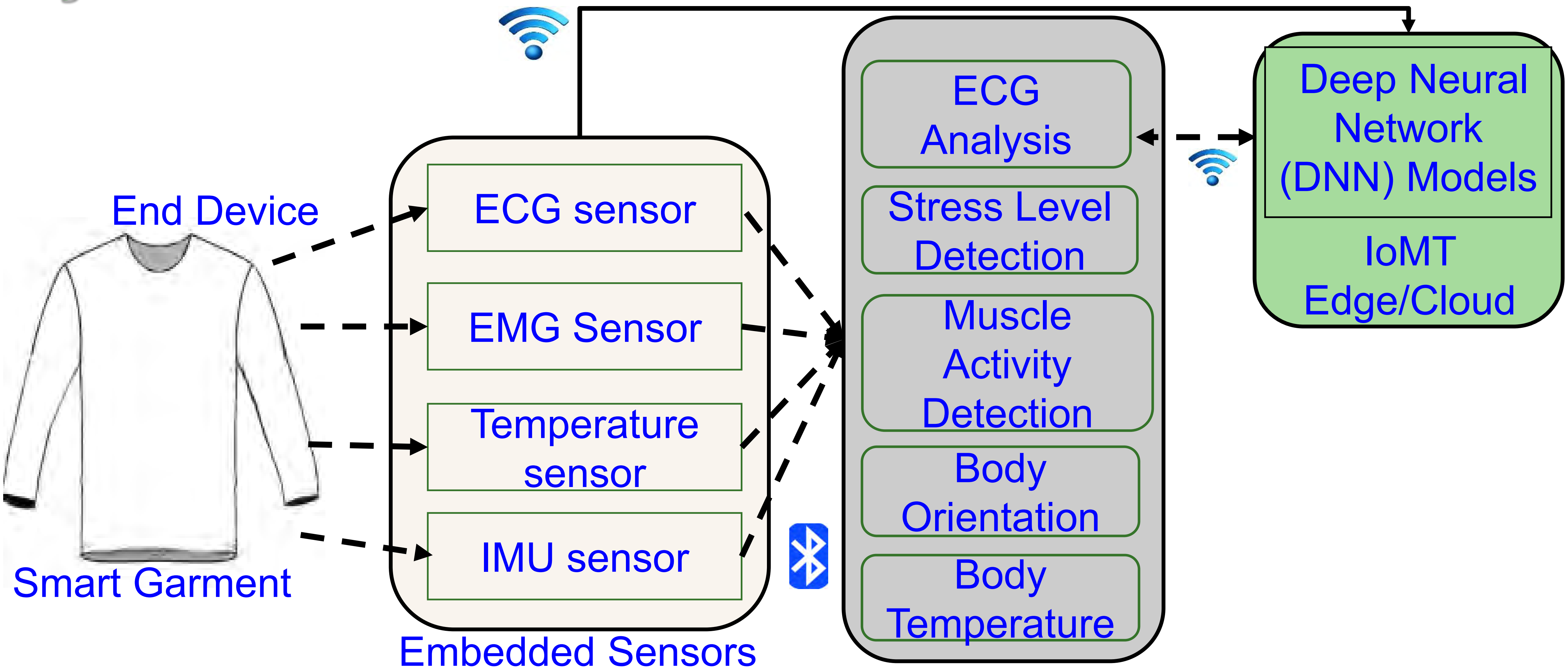
- In future, we will investigate seizure prediction, which means having prior knowledge that a seizure will occur before it actually does.
- Another future research is to have unified systems that detects seizure before it happens, and then injects drug or performs other control measures right after that.
- We also intend to add security and privacy features to the overall system as it is IoMT-enabled and always connected to Internet.
- We will also use more sophisticated and power-efficient edge devices such as IBM's neurosynaptic hardware in validating our models.

MyWear – A Smart Wear for Continuous Body Vital Monitoring - ECG based



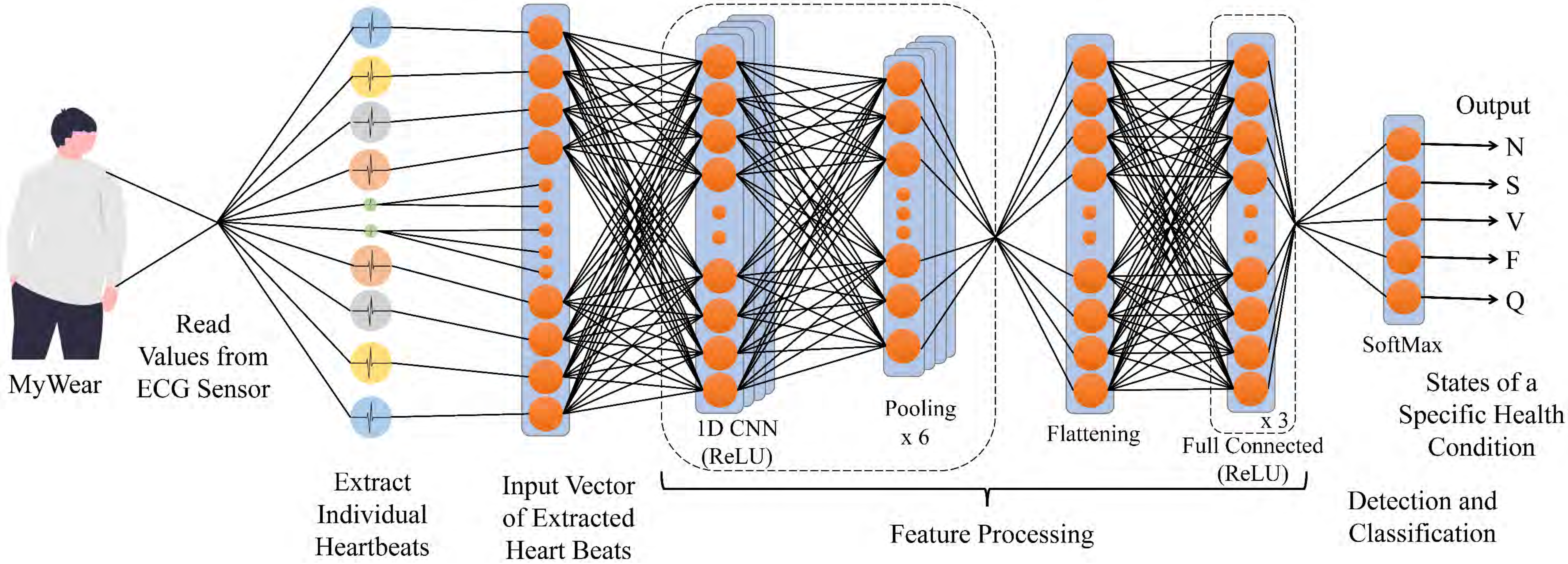
Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, "MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert", *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

MyWear – 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

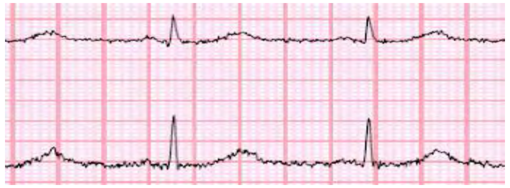


Source: S. C. Sethuraman, P. Kompally, S. P. Mohanty, and U. Choppali, “MyWear: A Smart Wear for Continuous Body Vital Monitoring and Emergency Alert”, *arXiv Electrical Engineering and Systems Science*, arXiv:2005.06342, Oct 2020, 25-pages.

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

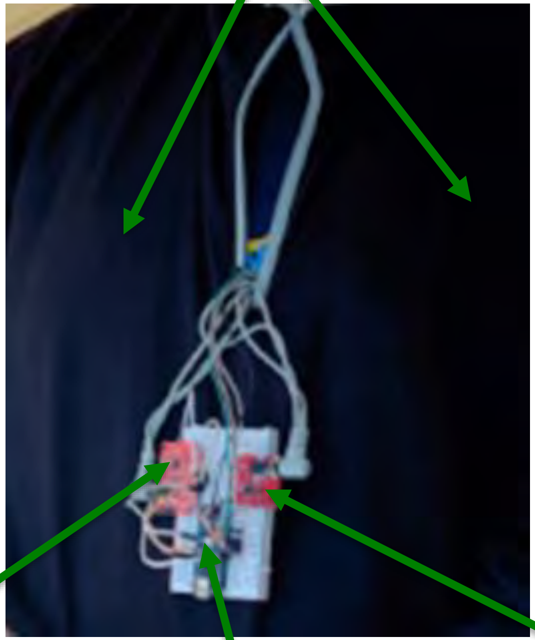
Obtain the Stress Level of the User

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 – Prototyping

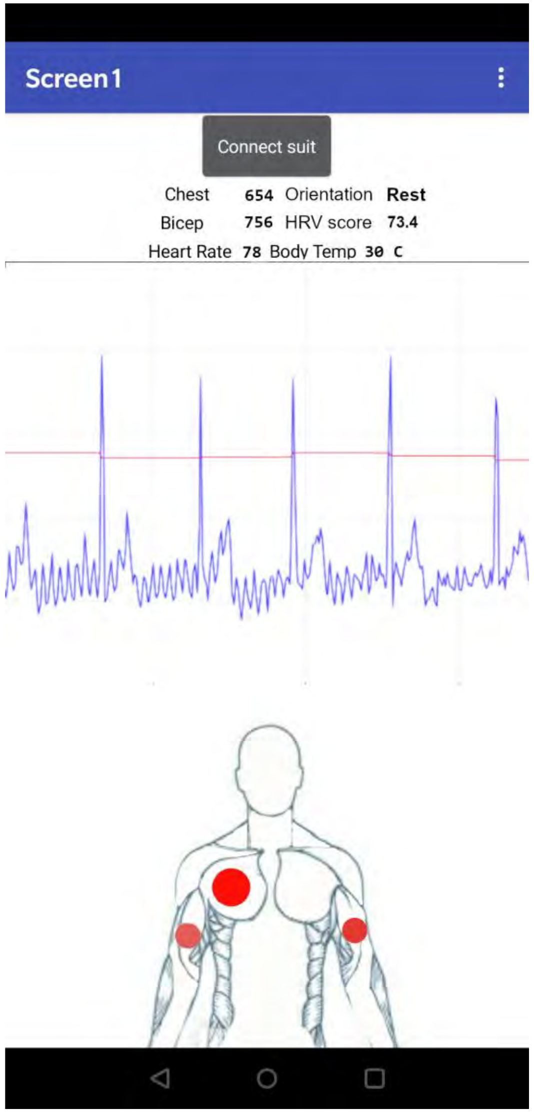
Embedded Electrodes inside MyWear



ECG Sensor

Microcontoller

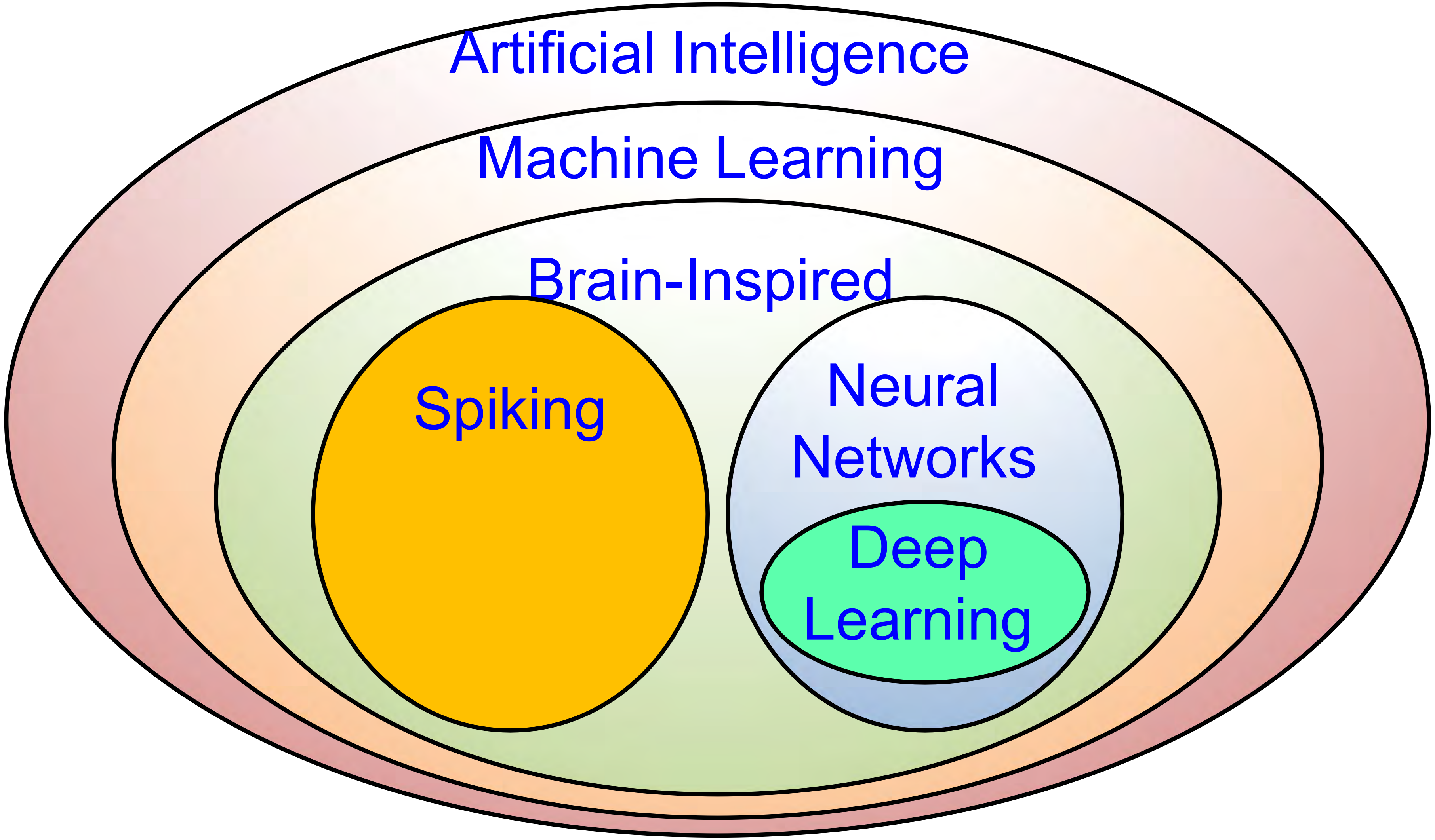
EMG Sensor



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.

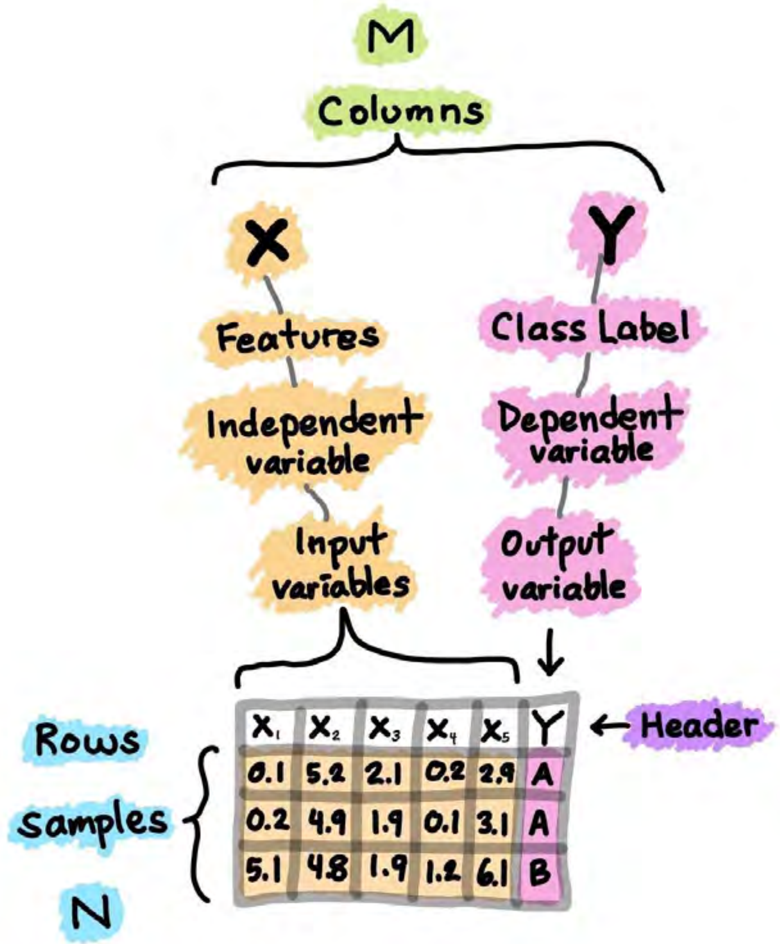
AI/ML Fundamentals

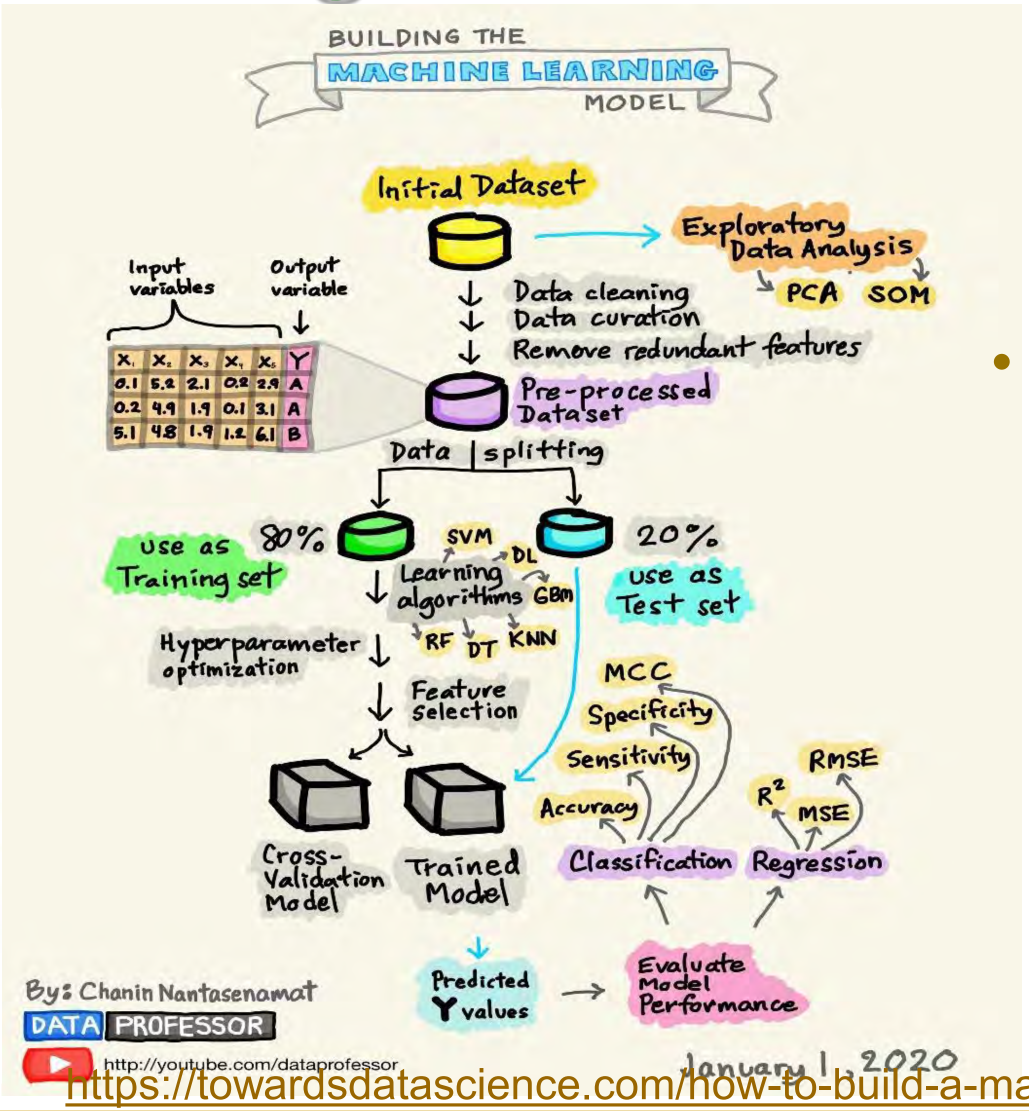
Artificial Intelligence – Big Picture



Source: https://www.rle.mit.edu/eems/wp-content/uploads/2019/06/Tutorial-on-DNN-01-Overview.pdf

Building a ML Model

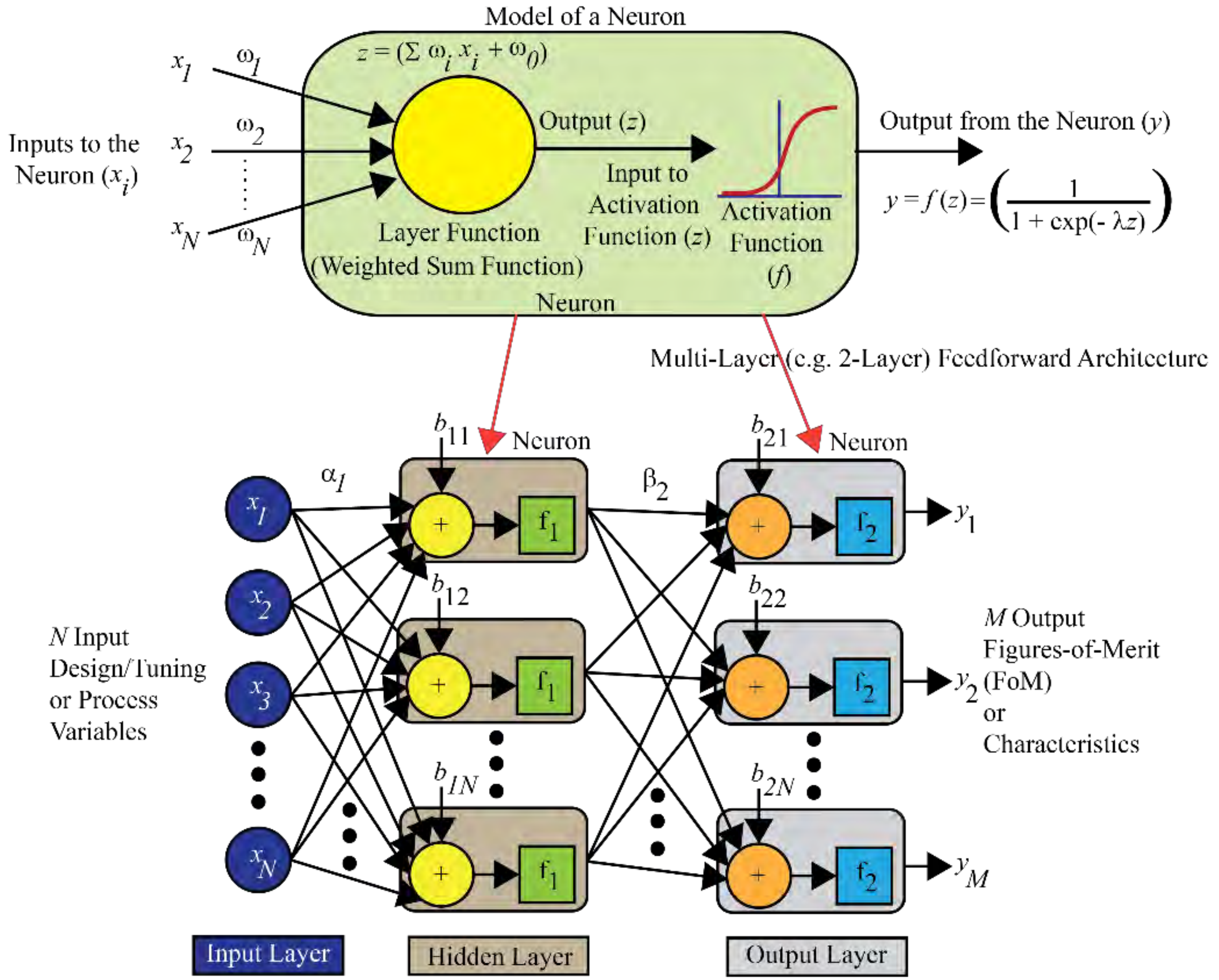




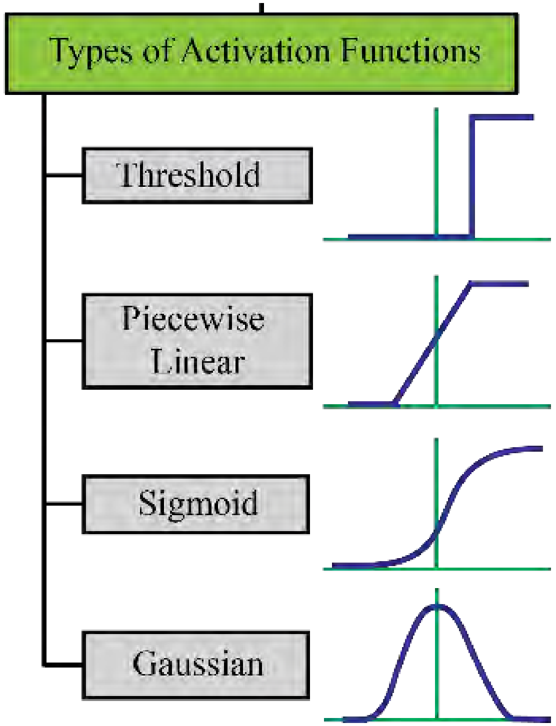
https://towardsdatascience.com/how-to-build-a-machine-learning-model-439ab8fb3fb1

- **Examples of Learning Algorithms:**
  - Linear Regression
  - Logistic Regression
  - kNN
  - SVM
  - etc.

Artificial Neural Networks

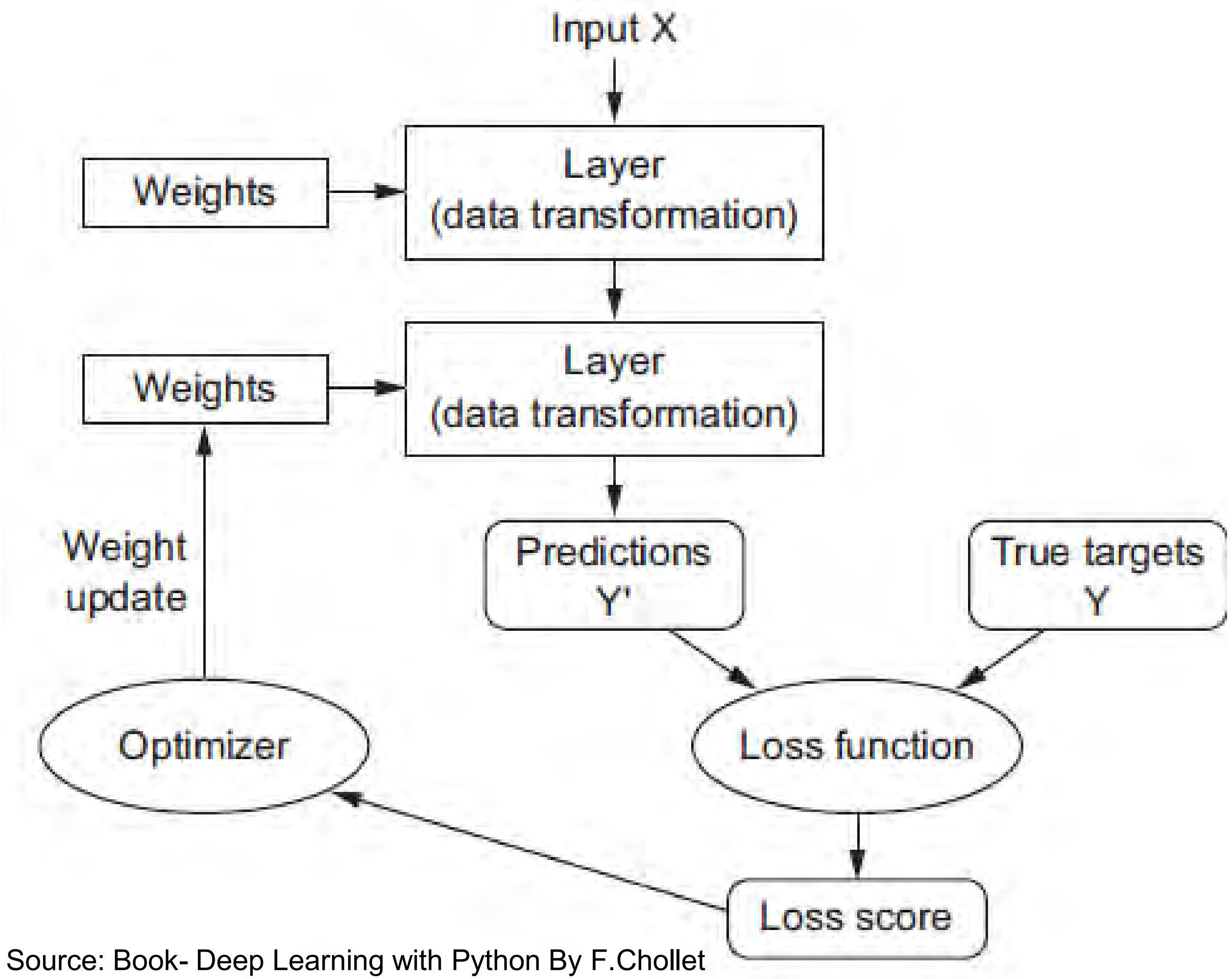


(a) Architecture of Neural Network (NN) Source: Mohanty McGraw-Hill 2015



- Type of architecture?
- Number of layers?
- Type of activation function?
- Datasets: training and verification?
- Training algorithm?
- Accuracy metric?

Building a DNN Model



Source: Book- Deep Learning with Python By F.Chollet

- Layers: Building Blocks of Deep Learning
- Models: Networks of Layers
- Loss function: Gets minimized during training.
- Optimizer: Says how the network gets updated. (Algorithm Part)

Types of DNN Networks

- Multilayer Perceptron (MLP)
- Convolutional Neural Networks (CNNs)
- Long Short Term Memory Networks (LSTMs)
- Recurrent Neural Networks (RNNs)
- Autoencoders
- Generative Adversarial Networks (GANs)
- Radial Basis Function Networks (RBFNs)
- Self Organizing Maps (SOMs)
- Deep Belief Networks (DBNs)
- Restricted Boltzmann Machines(RBMs)

Which Model to Choose?

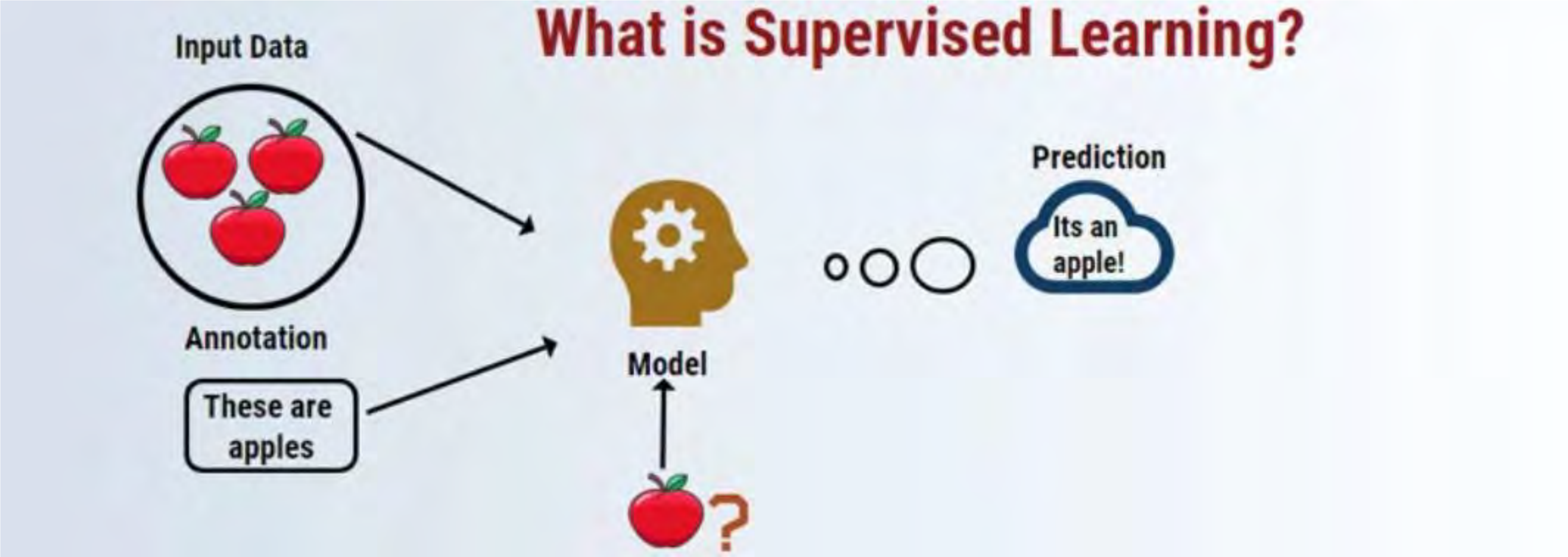
Data Sector	Use Case	Input	Transform	Neural Net
Text	Sentiment analysis	Word vector	Gaussian Rectified	RNTN or DBN (with moving window)
	Named-entity recognition	Word vector	Gaussian Rectified	RNTN or DBN (with moving window)
	Part-of-speech tagging	Word vector	Gaussian Rectified	RNTN or DBN (with moving window)
	Semantic-role labeling	Word vector	Gaussian Rectified	RNTN or DBN (with moving window)
Document	Topic modeling/ semantic hashing (unsupervised)	Word count probability	Can be Binary	Deep Autoencoder (wrapping a DBN or SDA)
	Document classification (supervised)	TF-IDF (or word count prob.)	Binary	Deep-belief network, Stacked Denoising Autoencoder
Image	Image recognition	Binary	Binary (visible and hidden)	Deep-belief network
		Continuous	Gaussian Rectified	Deep-belief network
	Multi-object recognition			Convolutional Net, RNTN (image vectorization forthcoming)
	Image search/ semantic hashing		Gaussian Rectified	Deep Autoencoder (wrapping a DBN)
Sound	Voice recognition		Gaussian Rectified	Recurrent Net
				Moving window for DBN or ConvNet
Time Series	Predictive analytics		Gaussian Rectified	Recurrent Net
				Moving window for DBN or ConvNet

Source: https://www.quora.com/How-does-one-choose-between-various-Deep-Learning-Methods-in-particular-when-to-use-Deep-Belief-Networks-over-Recurrent-Neural-Network#!n=12

ML Algorithms – By Learning

- Supervised: Logistic Regression & Back Propagation Neural Network
- Unsupervised: Apriori & K-means
- Semi-Supervised: Extension of Other Algorithms
- Reinforcement: Monte Carlo, Q-Learning

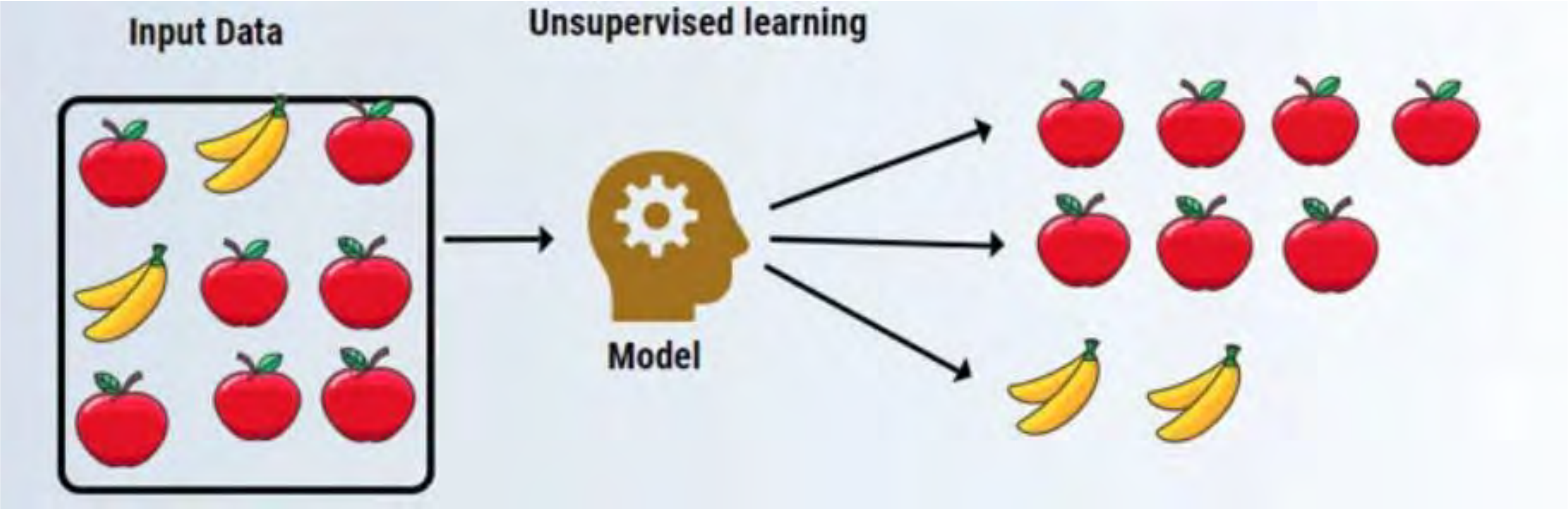
Supervised Learning



https://www.educba.com/what-is-supervised-learning/

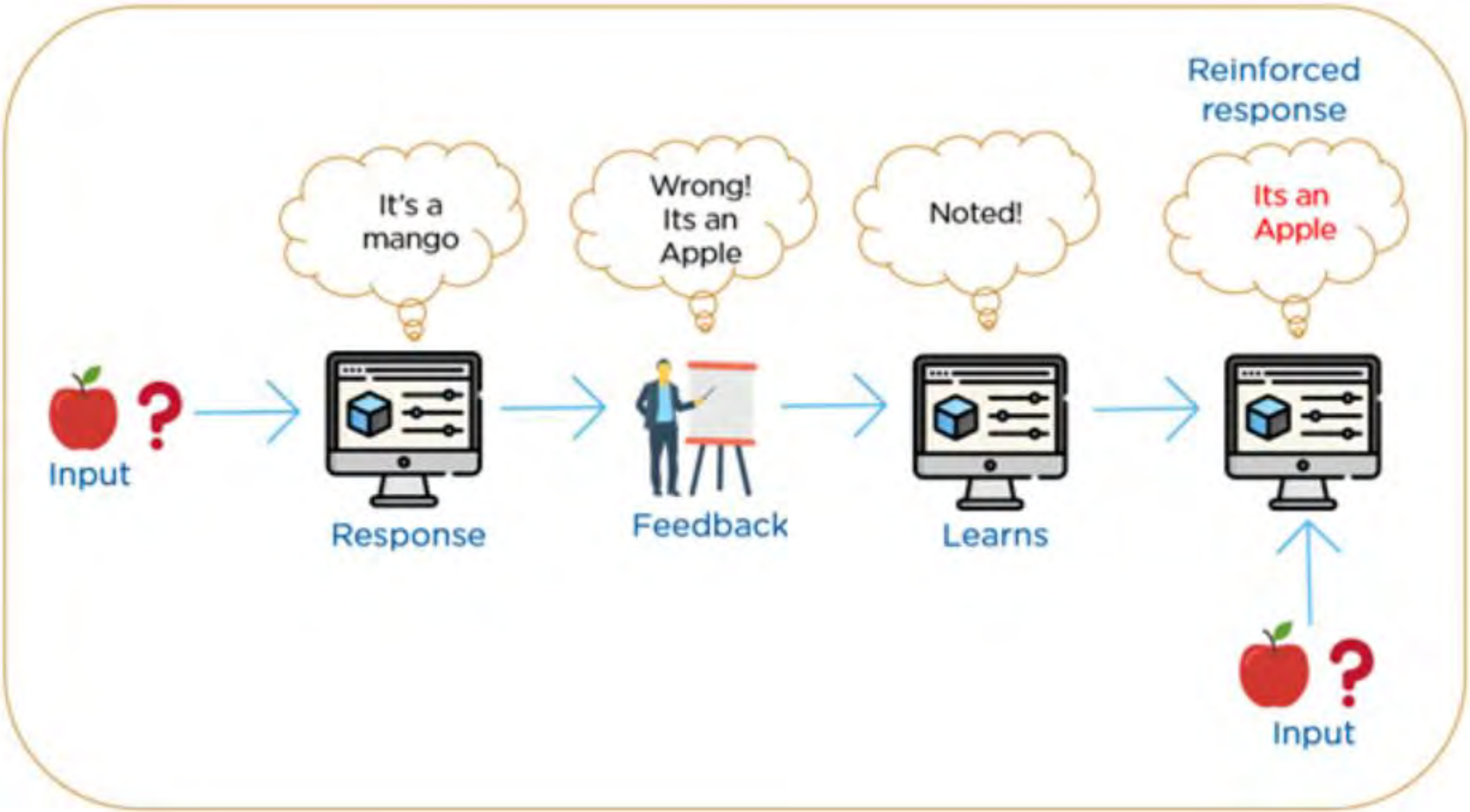
LABELED DATA

Unsupervised Learning



https://www.educba.com/what-is-supervised-learning/

Reinforcement Learning



https://towardsdatascience.com/an-introduction-to-reinforcement-learning-1e7825c60bbe

ML Algorithms – By Similarity

Regression
•Ordinary Least Squares Regression (OLSR)
•Linear Regression
•Logistic Regression
•Stepwise Regression
•Multivariate Adaptive Regression Splines (MARS)
•Locally Estimated Scatterplot Smoothing (LOESS)

Instance Based
•k-Nearest Neighbor (kNN)
•Learning Vector Quantization (LVQ)
•Self-Organizing Map (SOM)
•Locally Weighted Learning (LWL)
•Support Vector Machines (SVM)

Regularization Based
•Ridge Regression
•Least Absolute Shrinkage and Selection Operator (LASSO)
•Elastic Net
•Least-Angle Regression (LARS)

Decision Tree Based
•Classification and Regression Tree (CART)
•C4.5 and C5.0 (different versions of a powerful approach)
•Chi-squared Automatic Interaction Detection (CHAID)
•Decision Stump
•M5
•Conditional Decision Trees

Bayesian Based
•Naive Bayes
•Gaussian Naive Bayes
•Multinomial Naive Bayes
•Averaged One-Dependence Estimators (AODE)
•Bayesian Belief Network (BBN)
•Bayesian Network (BN)

Clustering Based
•k-Means
•k-Medians
•Expectation Maximization (EM)
•Hierarchical Clustering

ML Algorithms - By Similarity

Association Rule learning Based
- Apriori algorithm
- Eclat algorithm

Artificial Neural Network Based
- Perceptron
- Multilayer Perceptron (MLP)
- Back-Propagation
- Stochastic Gradient Descent
- Hopfield Network
- Radial Basis Function Network (RBFN)

Ensemble Algorithm
- Boosting
- Bootstrapped Aggregation (Bagging)
- AdaBoost
- Weighted Average (Blending)
- Stacked Generalization (Stacking)
- Gradient Boosting Machines (GBM)
- Gradient Boosted Regression Trees (GBRT)
- Random Forest

Deep Learning Based
- Convolutional Neural Network (CNN)
- Recurrent Neural Networks (RNNs)
- Long Short-Term Memory Networks (LSTMs)
- Stacked Auto-Encoders
- Deep Boltzmann Machine (DBM)
- Deep Belief Networks (DBN)

Dimensionality Reduction
- Principal Component Analysis (PCA)
- Principal Component Regression (PCR)
- Partial Least Squares Regression (PLSR)
- Sammon Mapping
- Multidimensional Scaling (MDS)
- Projection Pursuit
- Linear Discriminant Analysis (LDA)
- Mixture Discriminant Analysis (MDA)
- Quadratic Discriminant Analysis (QDA)
- Flexible Discriminant Analysis (FDA)

https://machinelearningmastery.com/a-tour-of-machine-learning-algorithms/

ML Languages

- Python: a popular language with high-quality machine learning and data analysis libraries
- C++: a middle-level language used for parallel computing on CUDA
- R: a language for statistical computing and graphics

Source: https://www.altexsoft.com/blog/datascience/the-best-machine-learning-tools-experts-top-picks/

ML Tools / Frameworks

- TensorFlow
- PyTorch
- Keras
- Chainer
- ONNX
- MATLAB

Evaluation Metrics

- Evaluation Metrics explain the performance of a model.
- Building machine learning models works on a constructive feedback principle.
  - Build a model.
  - Get feedback from metrics.
  - Make improvements and continue until you achieve a desirable accuracy.
- Building a predictive model is not the motive.
- Creating and selecting a model with high accuracy on out of sample data.
- It is crucial to check the accuracy of your model prior to computing predicted values.
- Selection of metric depends on type of model and implementation plan.

Source: https://www.analyticsvidhya.com/blog/2019/08/11-important-model-evaluation-error-metrics/

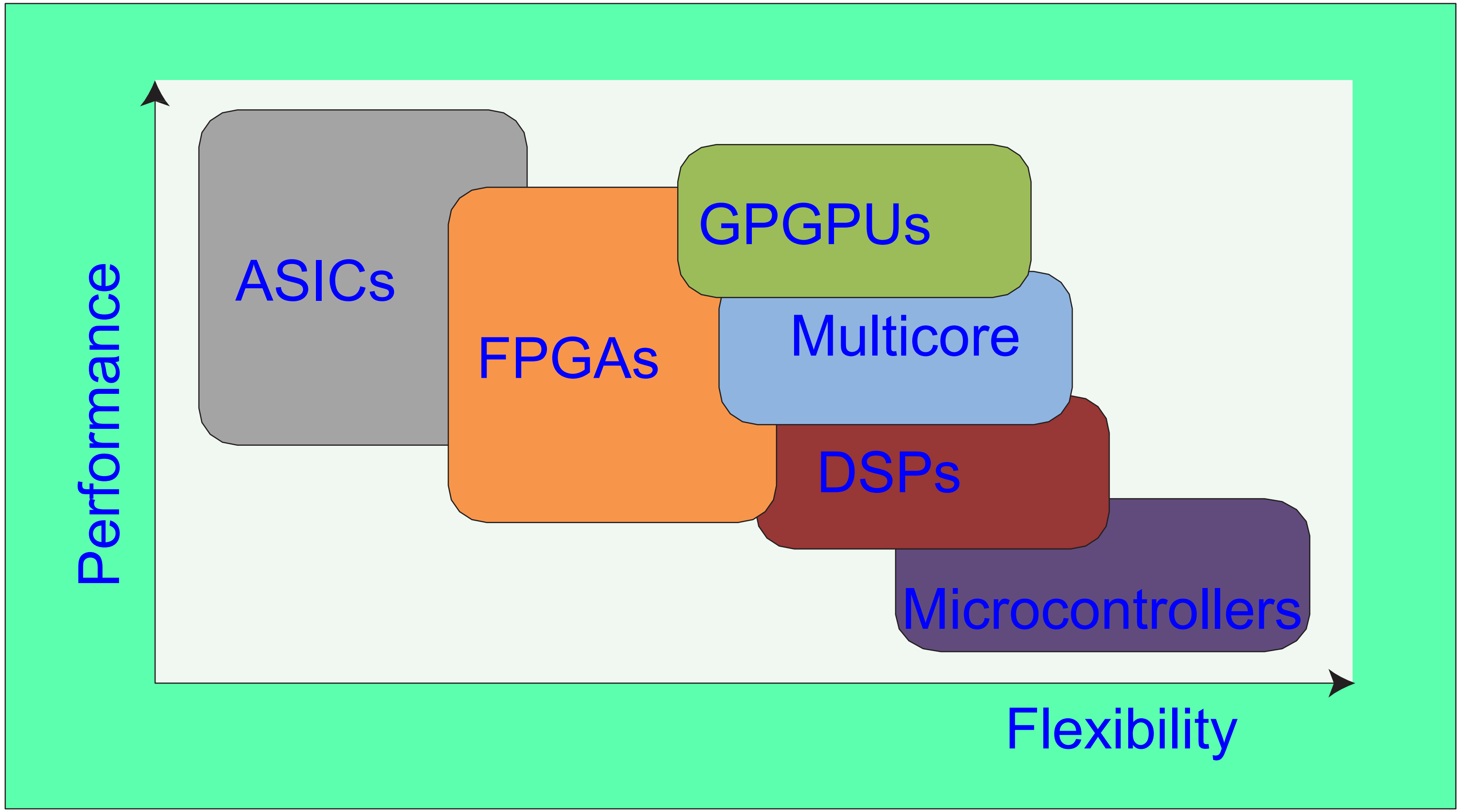
Confusion Matrix Formation

	Prediction	
Truth	TP (a)	FN (b)
	FP (c)	TN (d)

- Positive Predictive Value or Precision =a/(a+c)
- Negative Predictive Value =d/(b+d)
- True Positive Rate or Sensitivity or Recall = a/(a+b)
- False Positive Rate = c/(c+d)
- True negative Rate or Specificity = d/(c+d)
- Accuracy = (a+d)/(a+b+c+d)

Source: https://www.analyticsvidhya.com/blog/2019/08/11-important-model-evaluation-error-metrics/

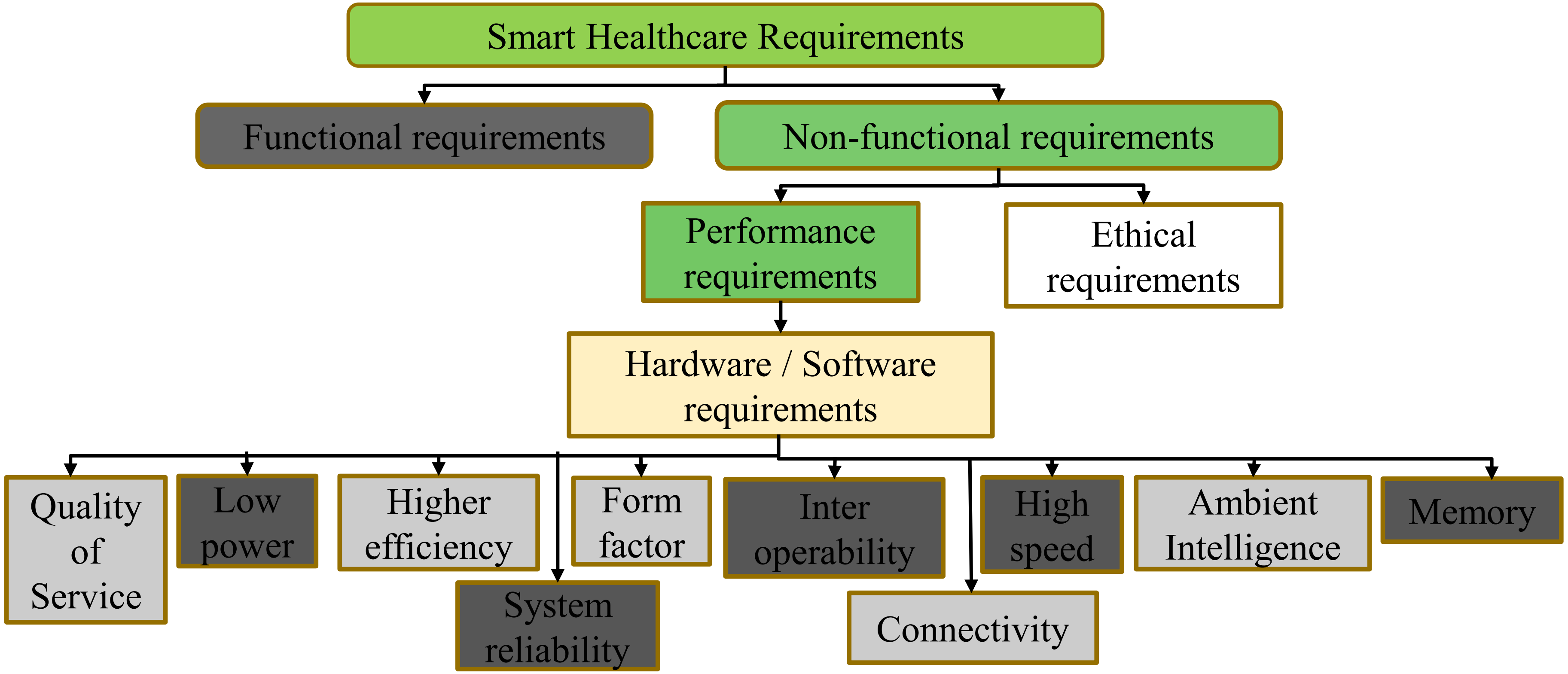
Some Hardware for Deep Learning



Source: R. Fernandez Molanes, K. Amarasinghe, J. Rodriguez-Andina and M. Manic, "Deep Learning and Reconfigurable Platforms in the Internet of Things: Challenges and Opportunities in Algorithms and Hardware," *IEEE Industrial Electronics Magazine*, vol. 12, no. 2, pp. 36-49, June 2018.

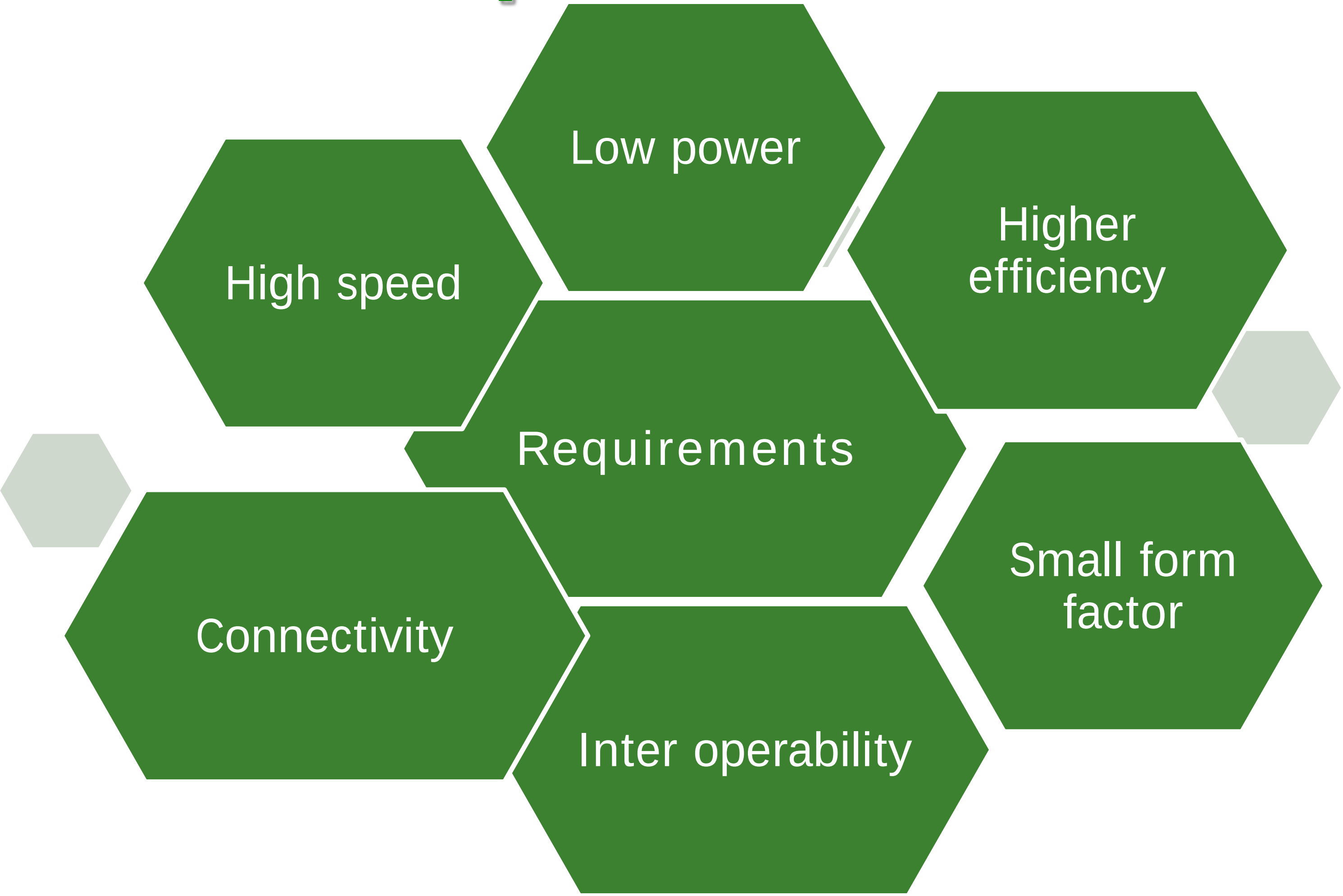
Smart Healthcare – Some Challenges

Smart Healthcare – Requirements

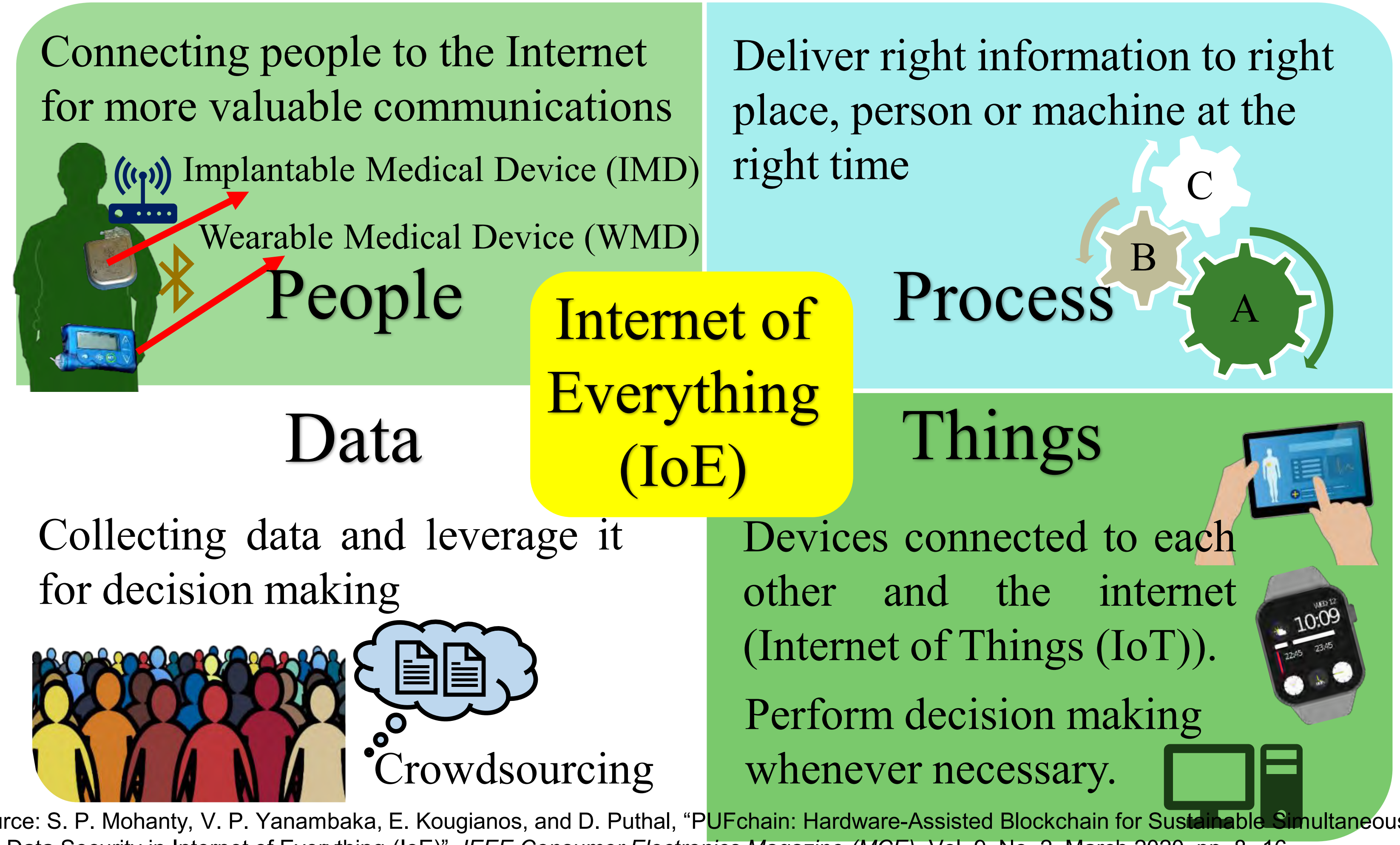


Source: P. Sundaravadivel, E. Kougianos, S. P. Mohanty, and M. Ganapathiraju, "Everything You Wanted to Know about Smart Health Care", IEEE Consumer Electronics Magazine (CEM), Volume 7, Issue 1, January 2018, pp. 18-28.

Smart Healthcare Architecture – Requirements



Users are Integral Part: For Them and By Them



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

Smart Healthcare – Personalization and Autonomy

Personalization

Autonomy

	Provides input	Receive outputs
Set goals/ standard	User/Patient Healthcare provider Vendor	User/Patient
Collect & store data	Sensor User/Patient	User/Patient Healthcare provider Vendor
Report results	Stored data Goal/ target/ norm Data from comparison group	User/Patient Healthcare provider Specified others
Provide feedbacks	Results User/ Patient preferences User/ Patient characteristics User History	User/ Patient

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, 2019, Accepted.

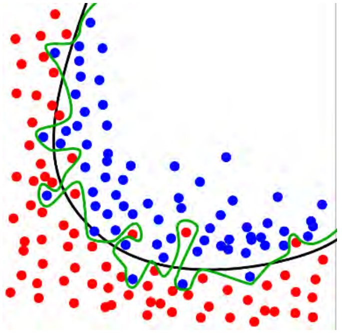
Smart Healthcare – Data Quality

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

Machine Learning Challenges

Machine Learning Issues

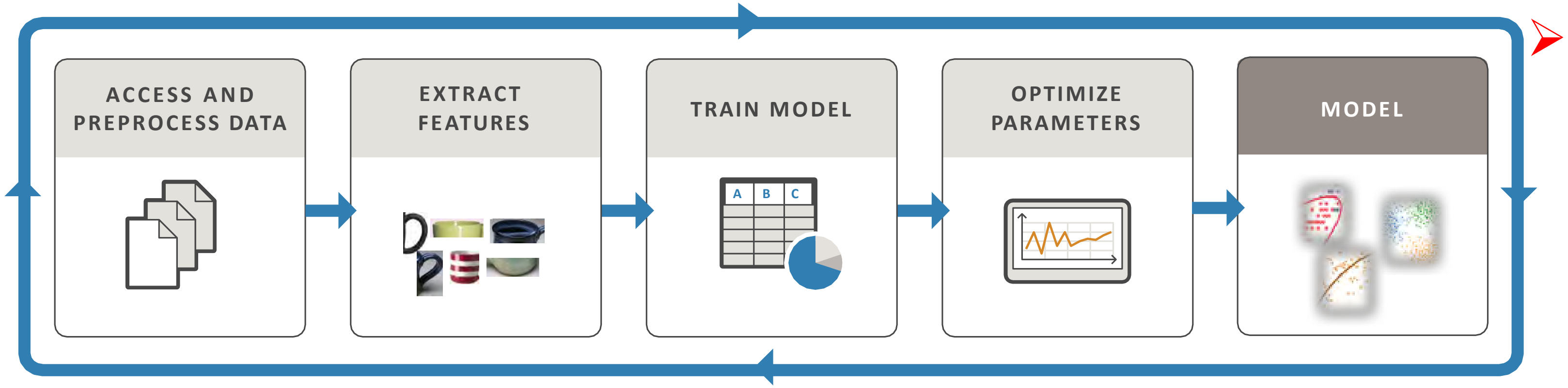
- High Energy Requirements
- High Computational Resource Requirements
- Large Amount of Data Requirements
- Underfitting/Overfitting Issue
- Class Imbalance Issue
- Fake Data Issue



Source: Mohanty ISCT Keynote 2019

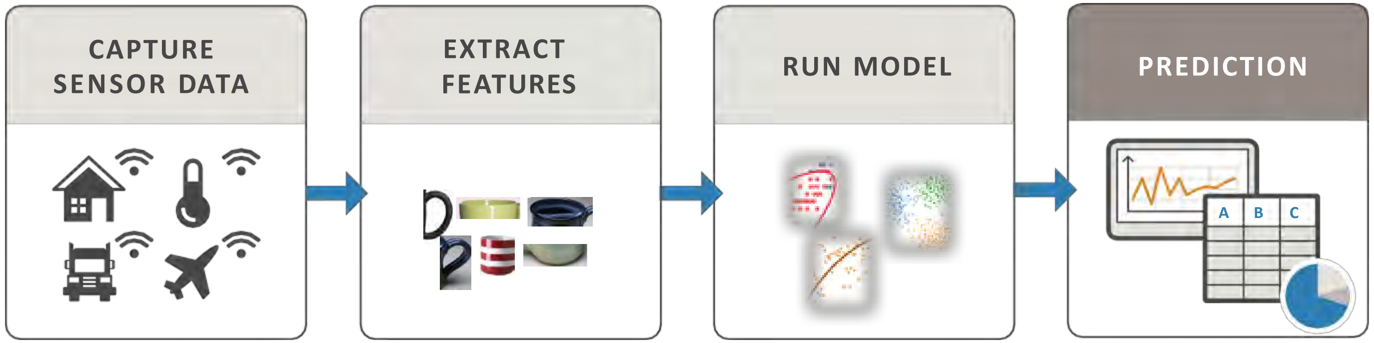
Deep Neural Network (DNN) - Resource and Energy Costs

TRAIN: Iterate until you achieve satisfactory performance.



Needs Significant:
- Resource
- Energy

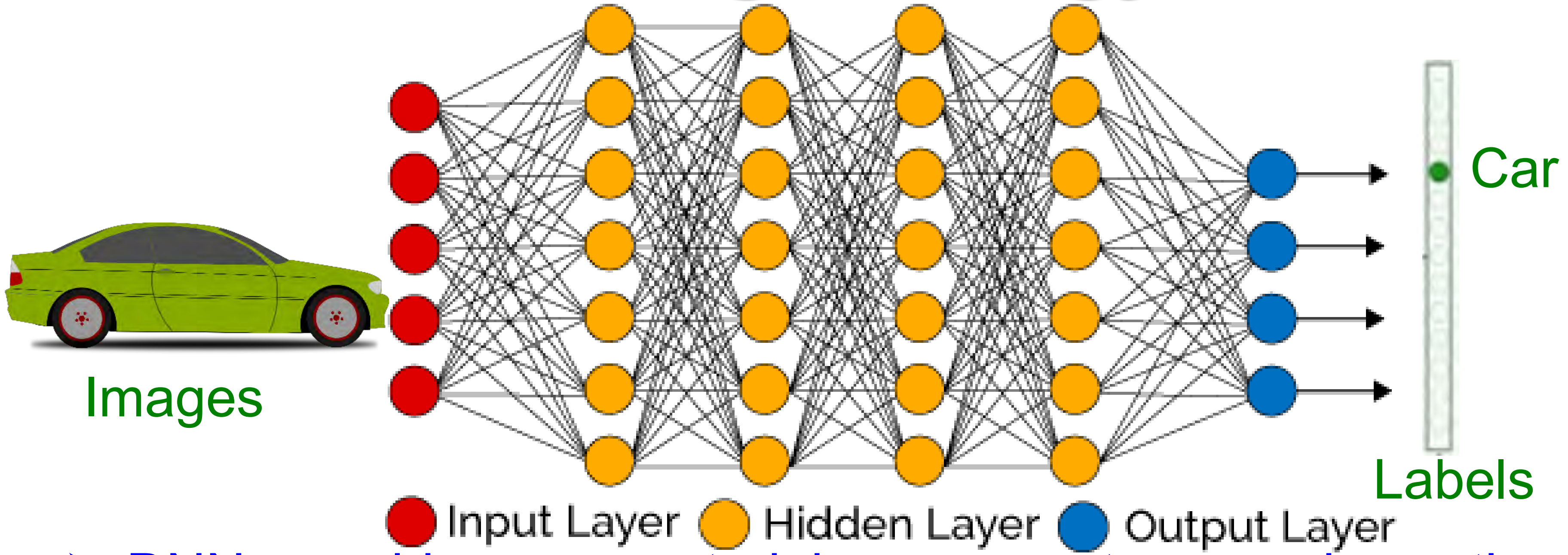
PREDICT: Integrate trained models into applications.



Needs:
- Resource
- Energy

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

DNN Training - Energy Issue

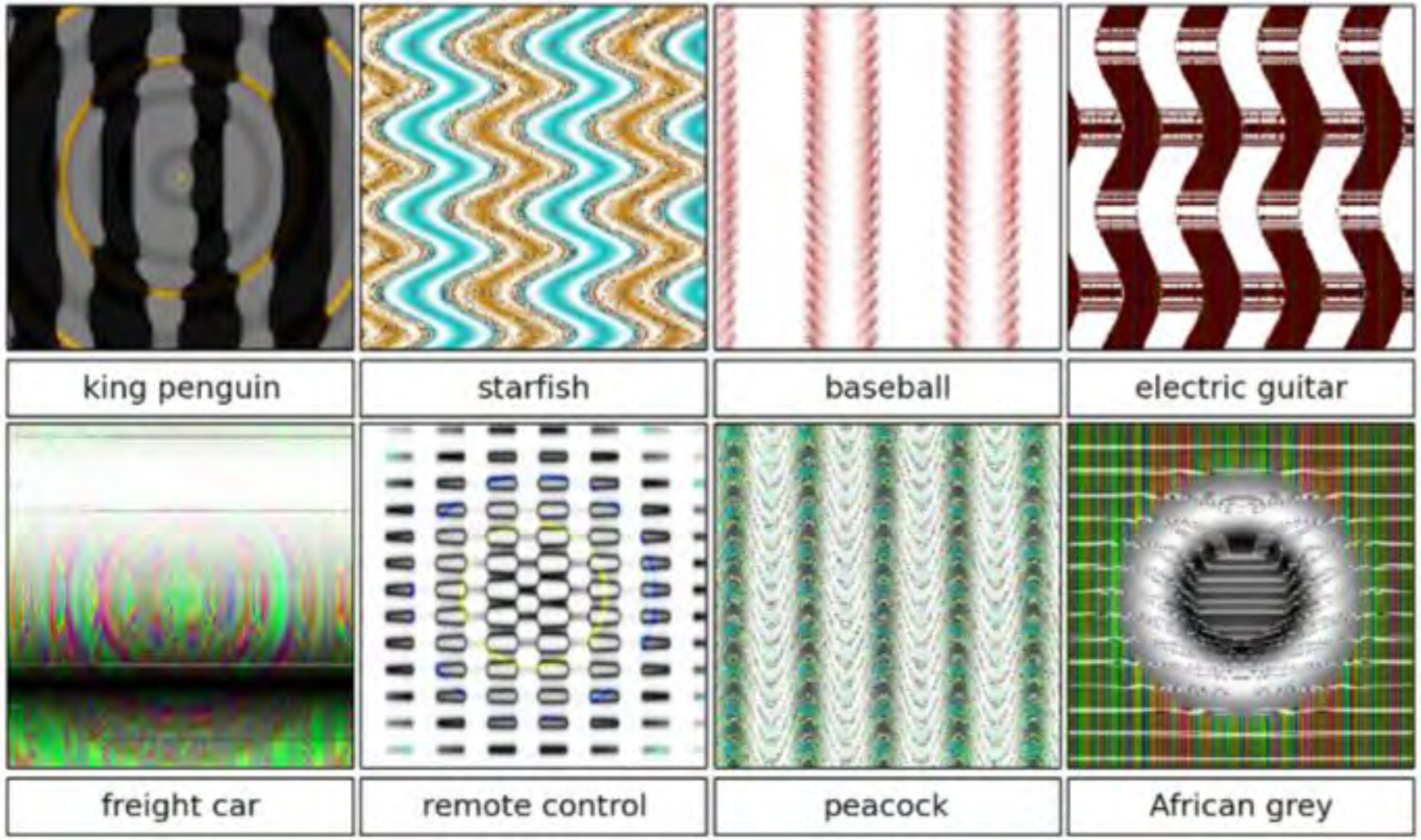


- DNN considers many training parameters, such as the size, the learning rate, and initial weights.
- High computational resource and time: For sweeping through the parameter space for optimal parameters.
- DNN needs: Multicore processors and batch processing.
- DNN training happens mostly in cloud not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

Source: Mohanty iSES 2018 Keynote

DNNs are not Always Smart

DNNs are not Always Smart

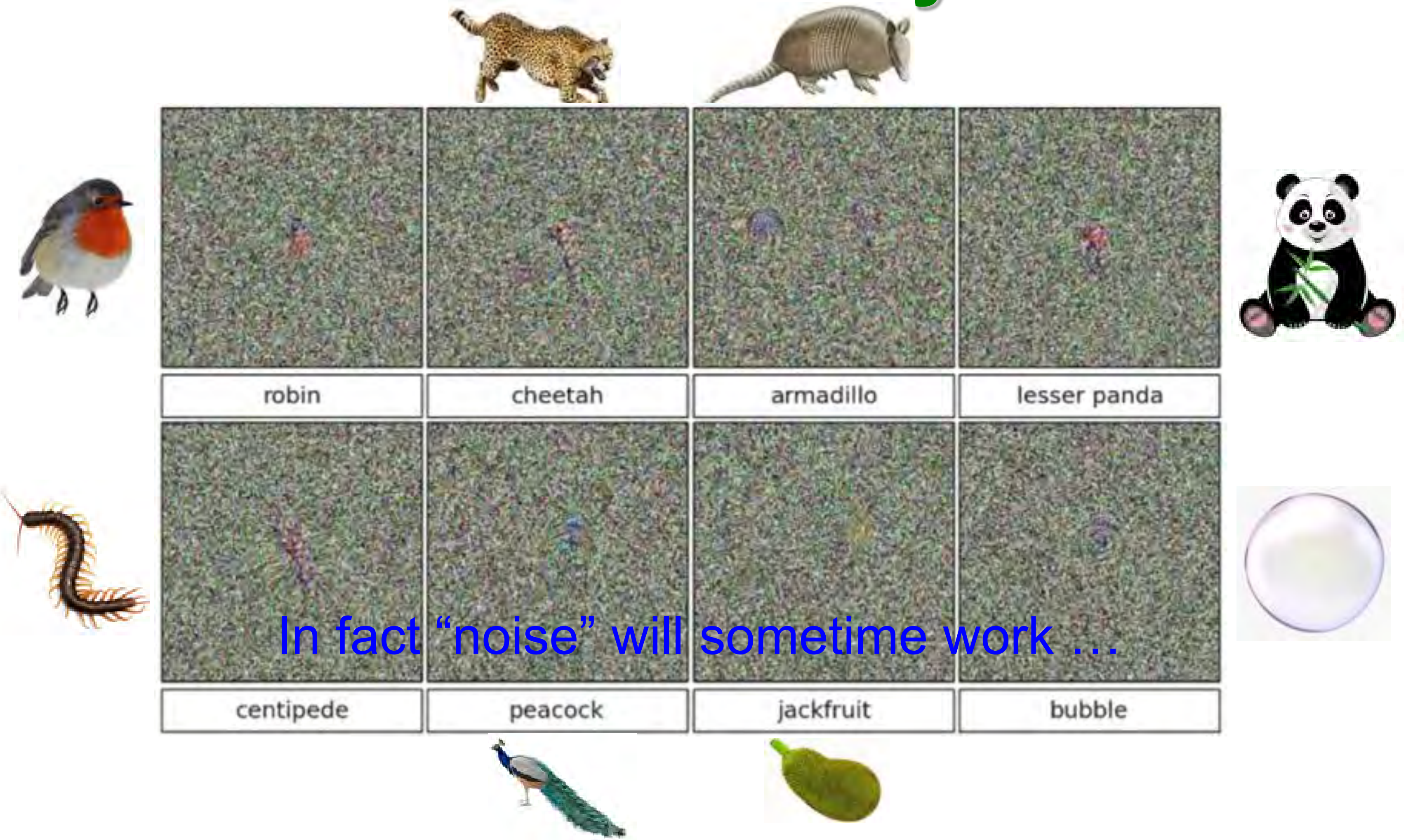


DNNs can be fooled by certain “learned” (Adversarial) patterns …

Source: Nguyen, et al. 2014 - Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images

Source: Corcoran Keynote 2018

DNNs are not Always Smart



Source: Nguyen, et al. 2014 - Deep Neural Networks are Easily Fooled: High Confidence Predictions for Unrecognizable Images

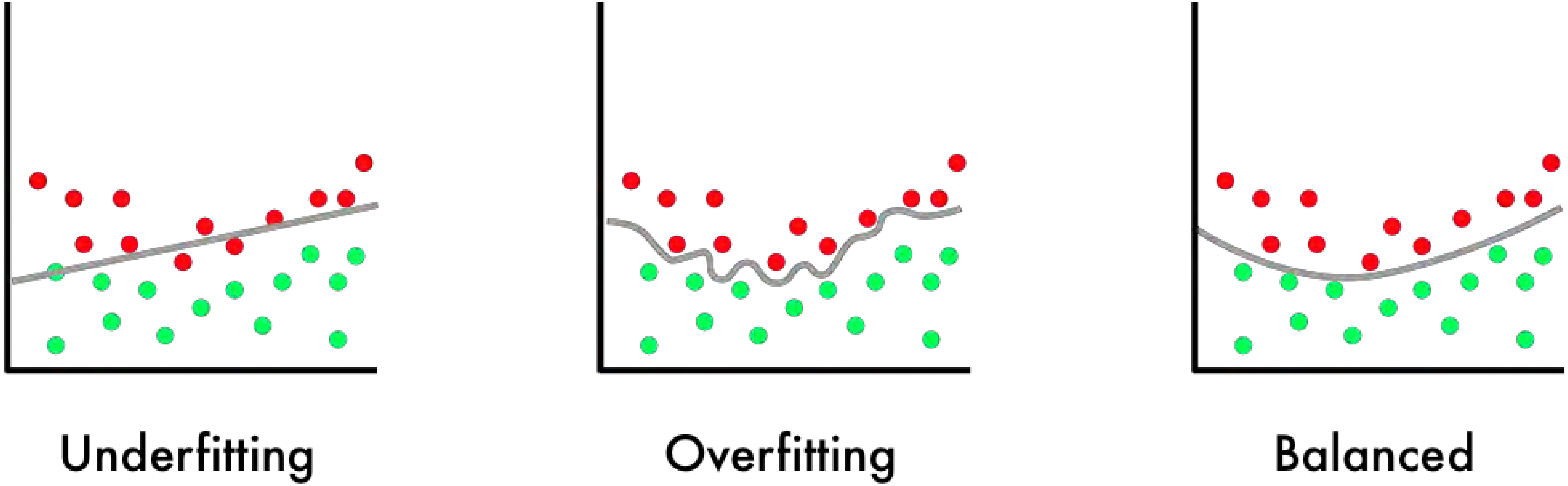
Source: Corcoran Keynote 2018

DNNs are not Always Smart

- Why not use Fake Data?
- "Fake Data" has some interesting advantages:
  - Avoids *privacy issues* and side-steps *new regulations* (e.g. General Data Protection Regulation or GDPR)
  - Significant cost reductions in data acquisition and annotation for big datasets

Source: Corcoran Keynote 2018

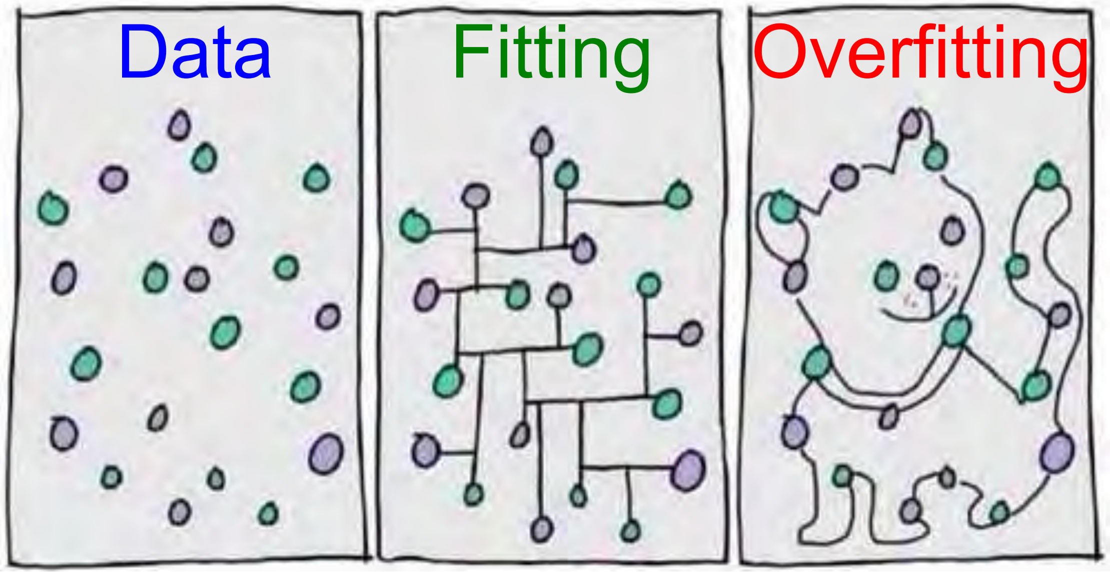
DNN: Underfitting and Overfitting Issues



Source: https://medium.freecodecamp.org/deep-learning-for-developers-tools-you-can-use-to-code-neural-networks-on-day-1-34c4435ae6b

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

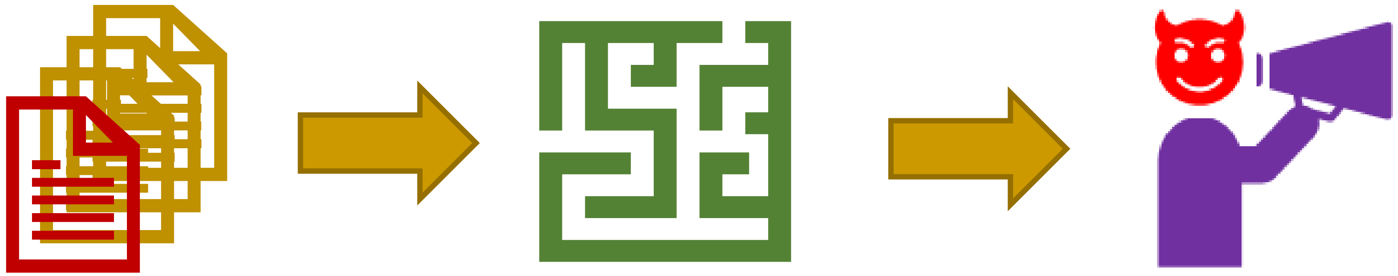
- Class imbalance is a classification problems where the classes are not represented equally.
- Solutions: Use Precision, Recall, F-measure metrics
  Not only RMSE like accuracy metrics

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

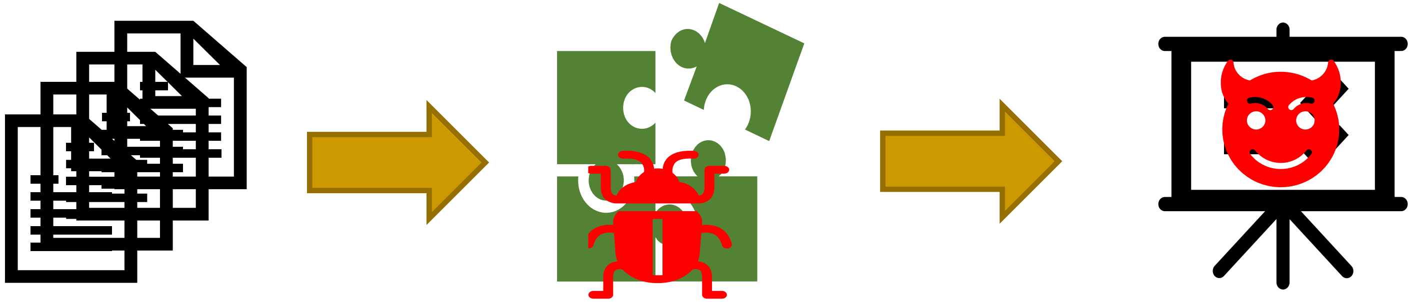
Source: Sandip Kundu ISVLSI 2019 Keynote.

AI/ML – Cybersecurity Issue



Corrupted Input Dataset | Predictive modelling | Corrupted Decision/ Prediction

Input attack in machine learning

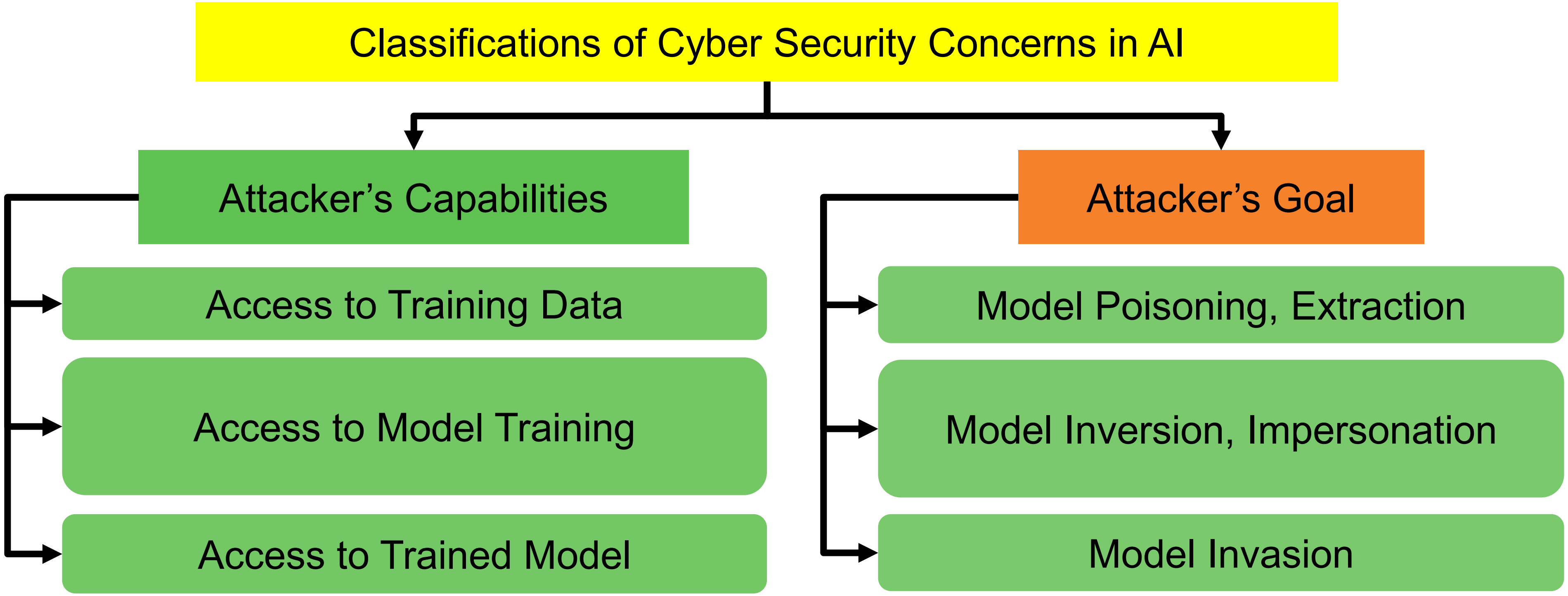


Input Dataset | Attacked training Process | Corrupt Classifications

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.

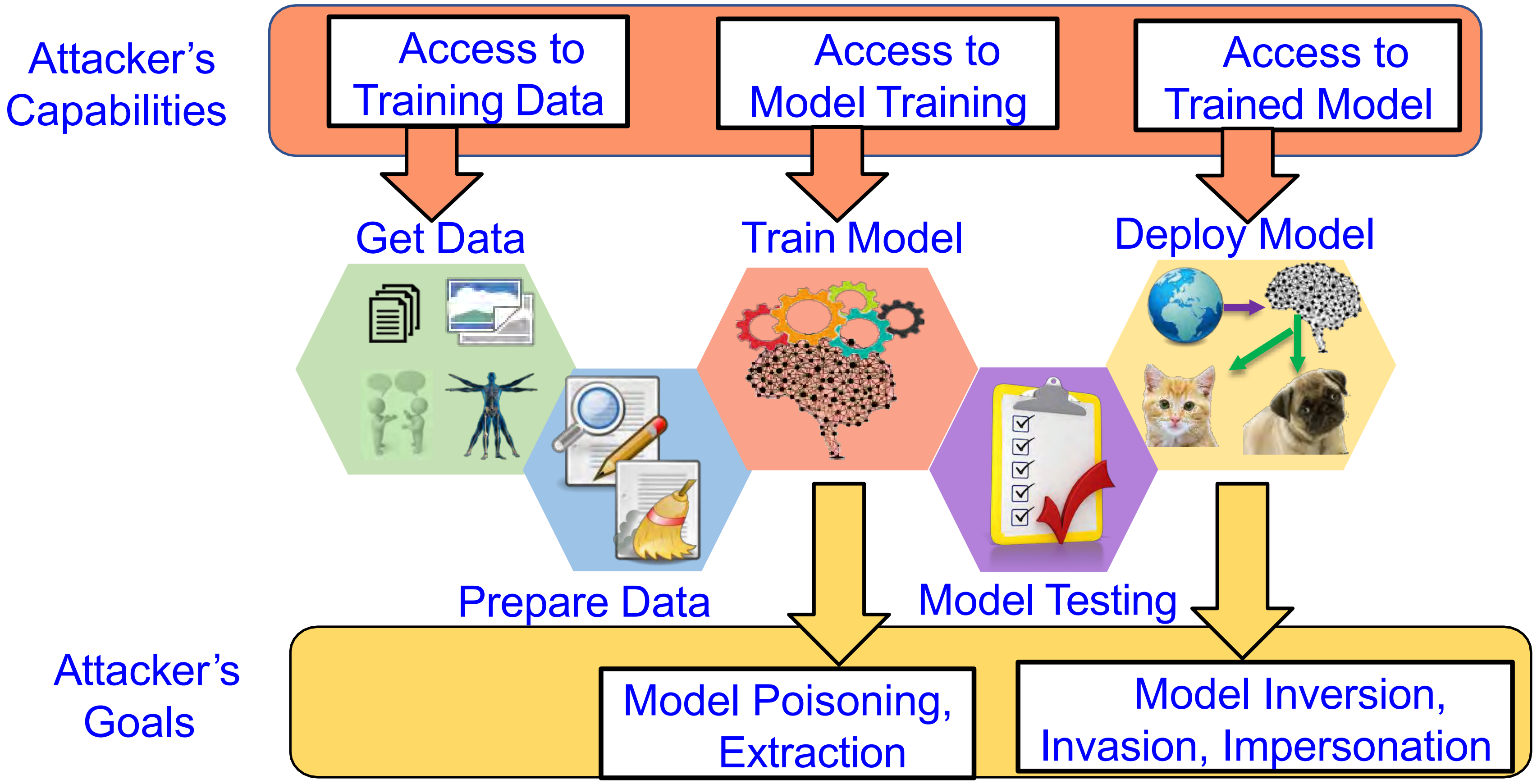
AI/ML Models - Classification of Security and Privacy Concerns

- Attacker's Goals
  - extract model parameters (model extraction)
  - extract private data (model inversion)
  - compromise model to produce false positives/negatives
- (model poisoning)
  - produce adversary selected outputs
- (model evasion)
  - render model unusable

- Attacker's Capabilities
  - access to Black-box ML model
  - access to White-box ML model
  - manipulate training data to
- introduce vulnerability
  - access to query to ML model
  - access to query to ML model with confidence values
  - access to training for building model
  - find and exploit vulnerability during
- classification

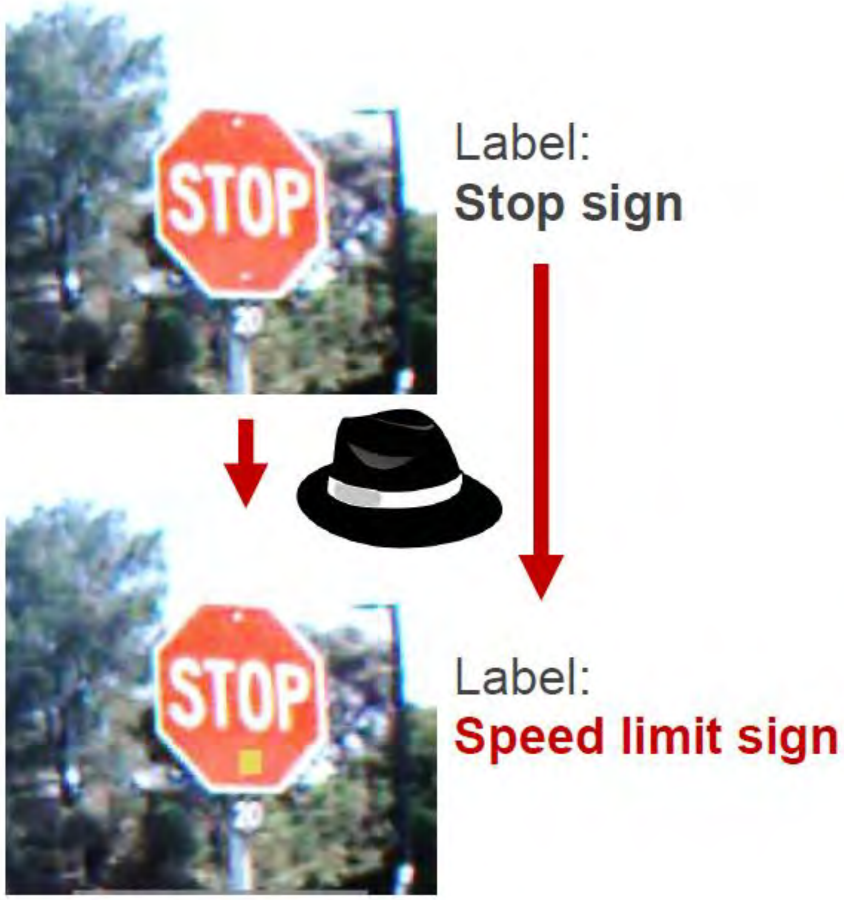
Source: Sandip Kundu ISVLSI 2019 Keynote.

AI Security - Attacks



Source: Sandip Kundu ISVLSI 2019 Keynote.

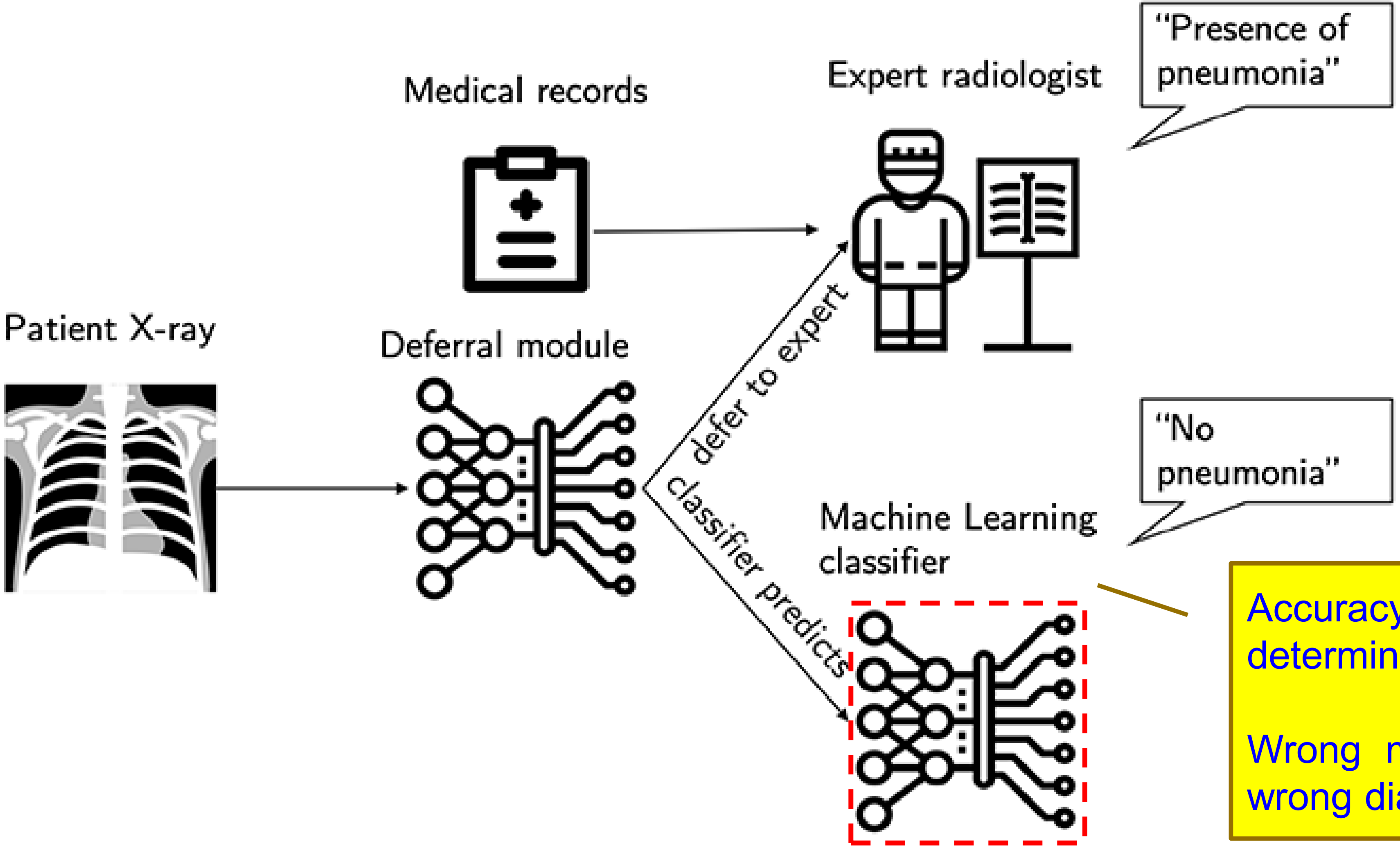
AI Security - Trojans in Artificial Intelligence (TrojAI)



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



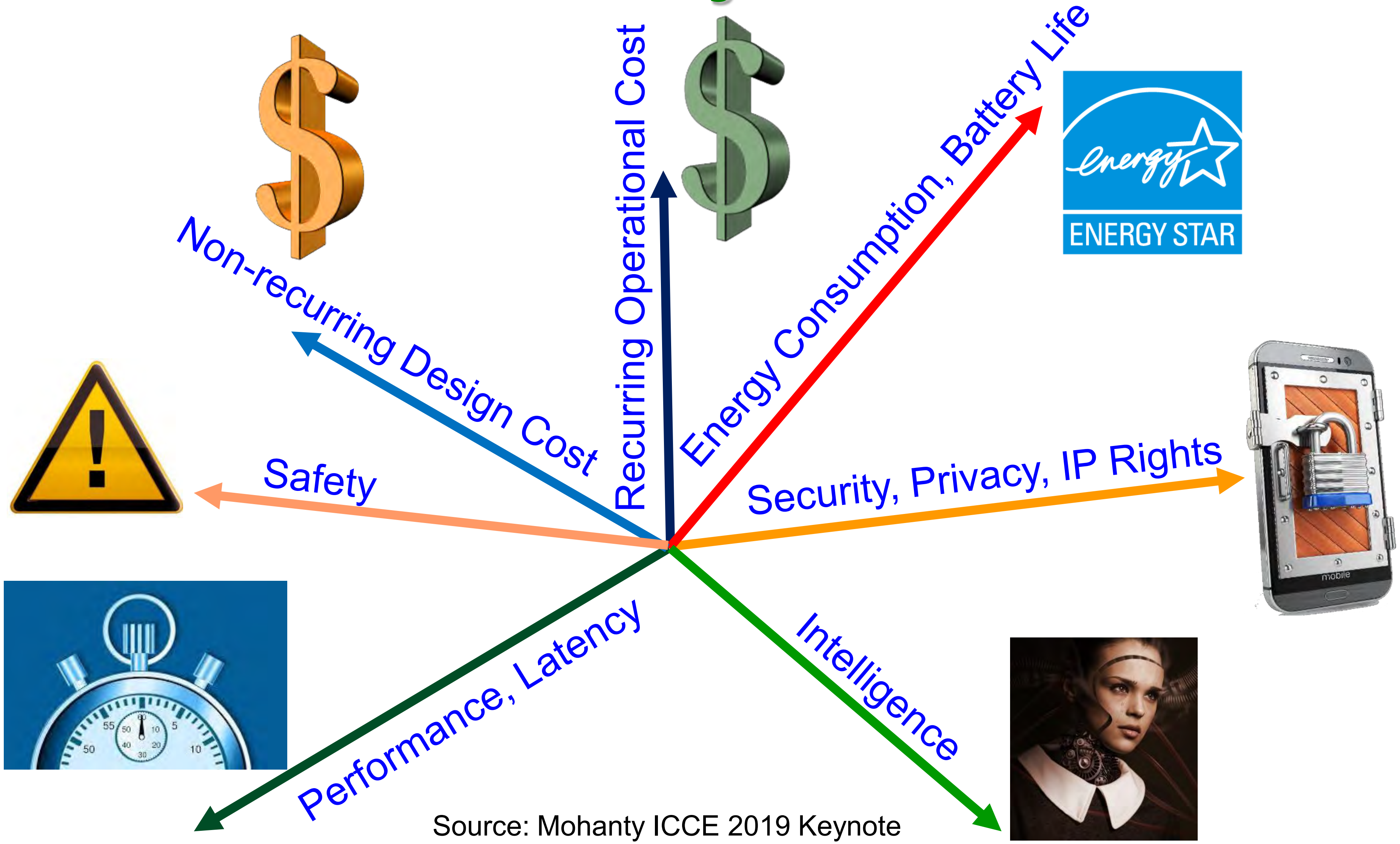
Accuracy is important determine pneumonia

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

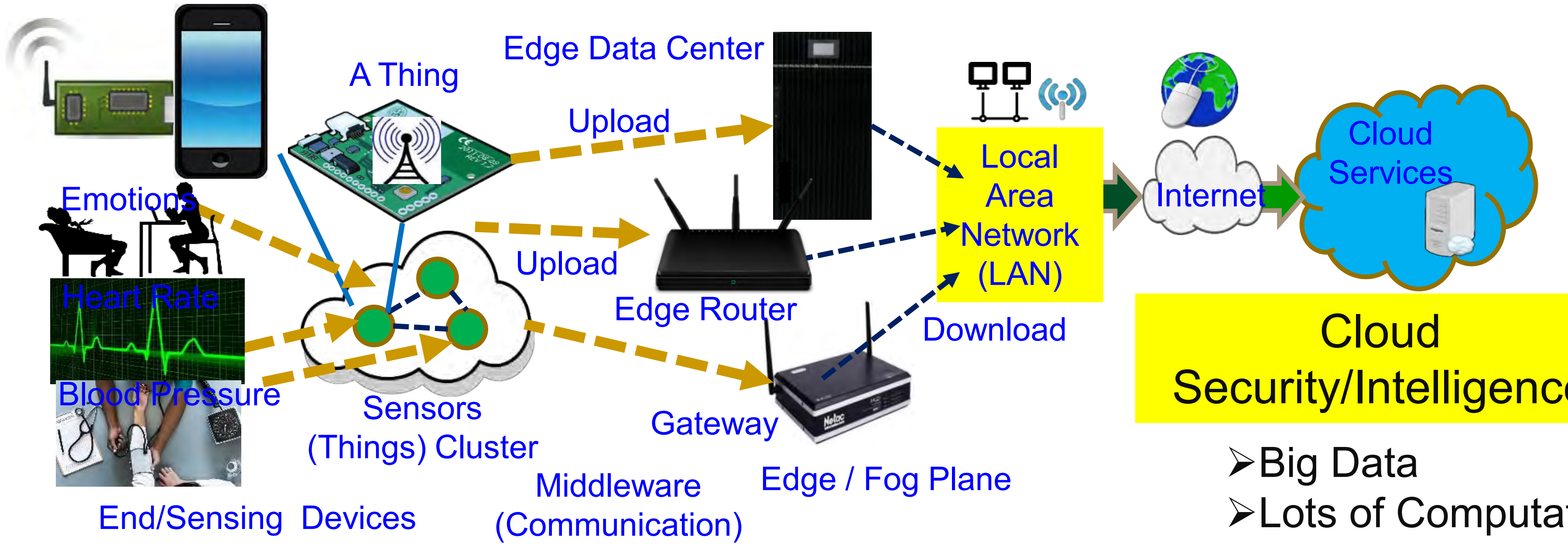
Smart Healthcare – Some Solutions

H-CPS - Multi-Objective Tradeoffs



Source: Mohanty ICCE 2019 Keynote

Smart Healthcare – Edge Vs Cloud



Cloud Security/Intelligence

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

End Security/Intelligence

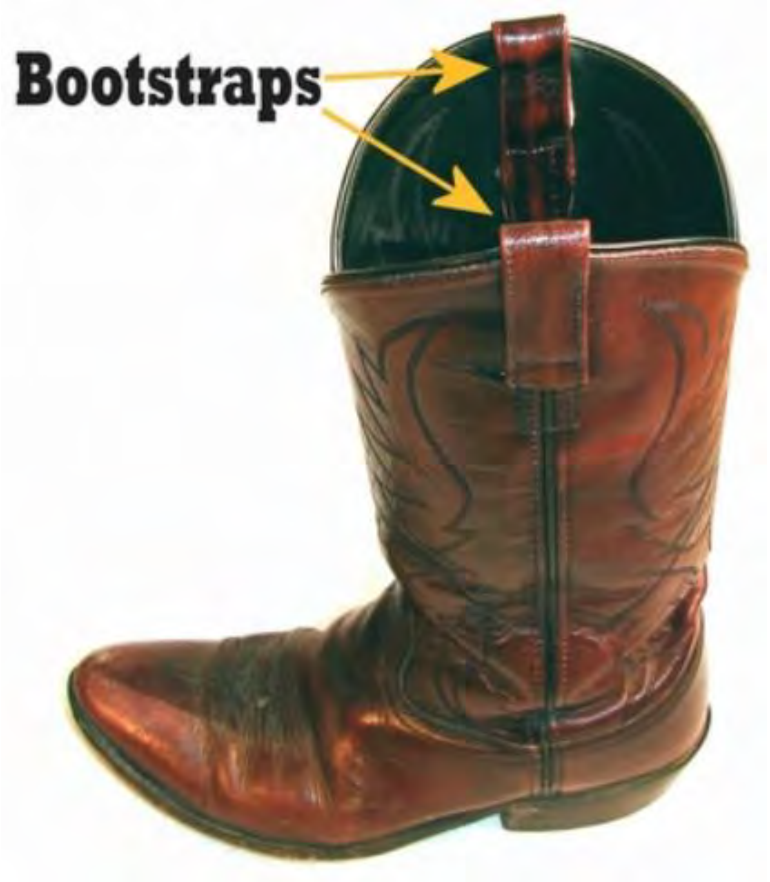
- Minimal Data
- Minimal Computational Resource
- Least Accurate Data Analytics
- Very Rapid Response

Edge Security/Intelligence

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

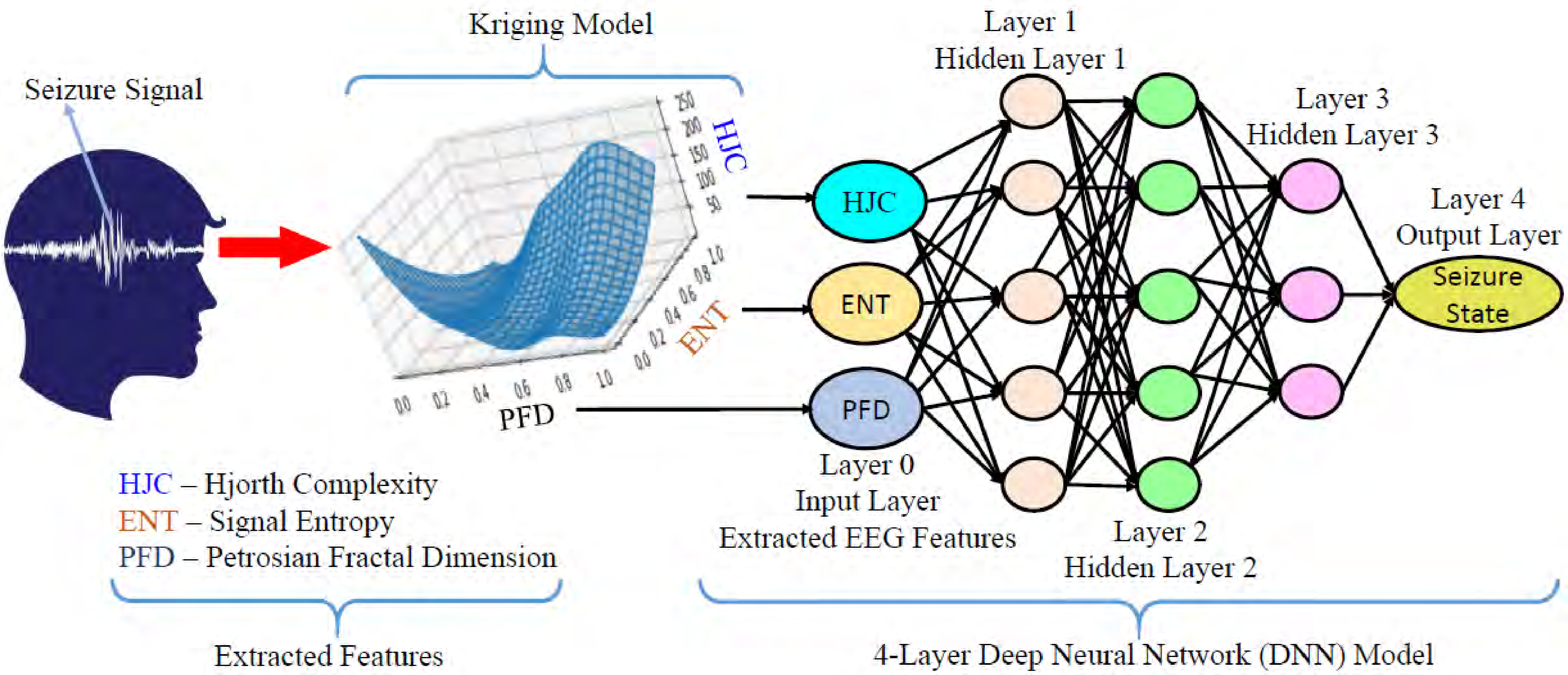
Hierarchical ML to Reduce Training Time - Bootstrapping

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



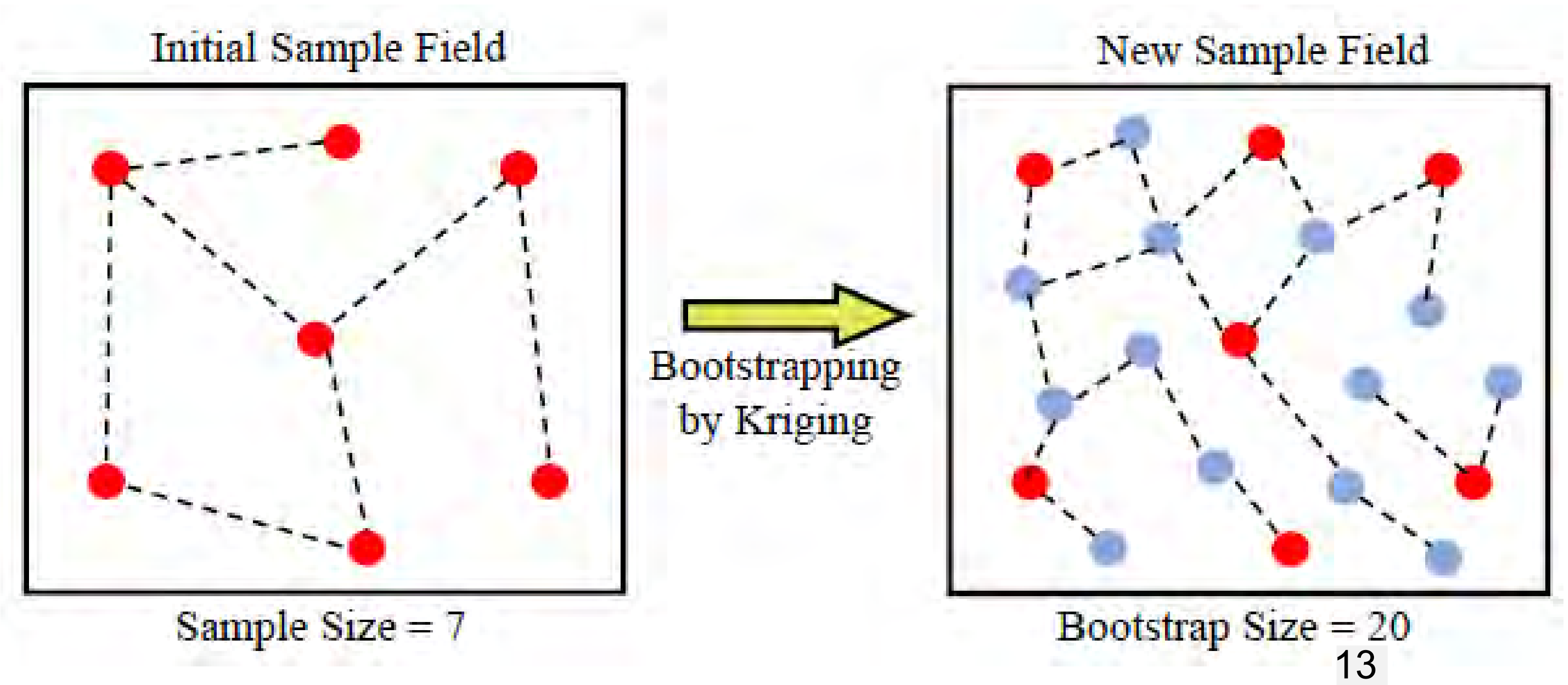
Source: http://www.lemen.com/dictionary-b.html#bootstrap

Our Kriging-Bootstrapped DNN Model



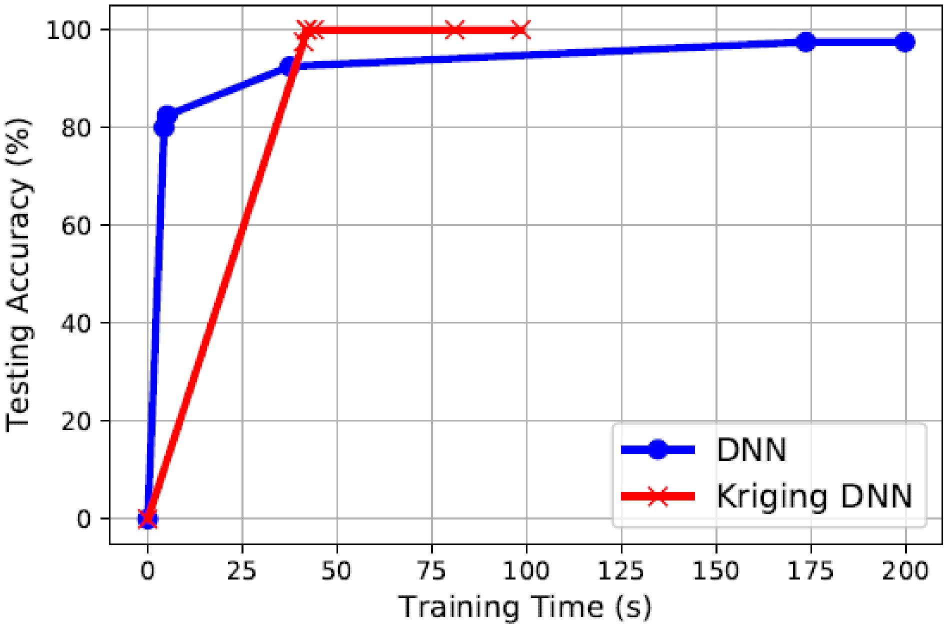
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

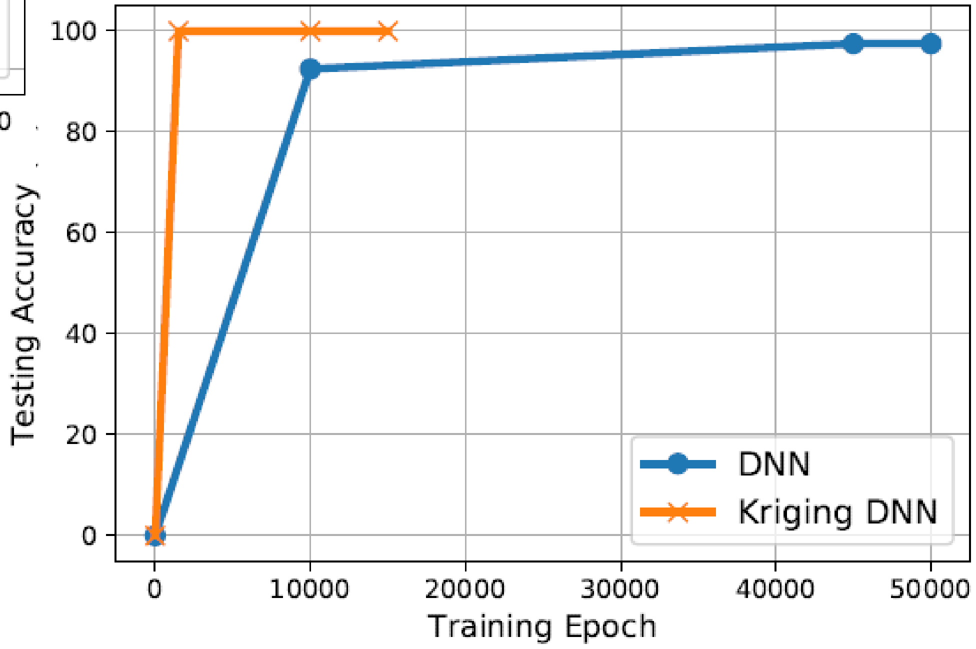
Bootstrapped Kriging



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

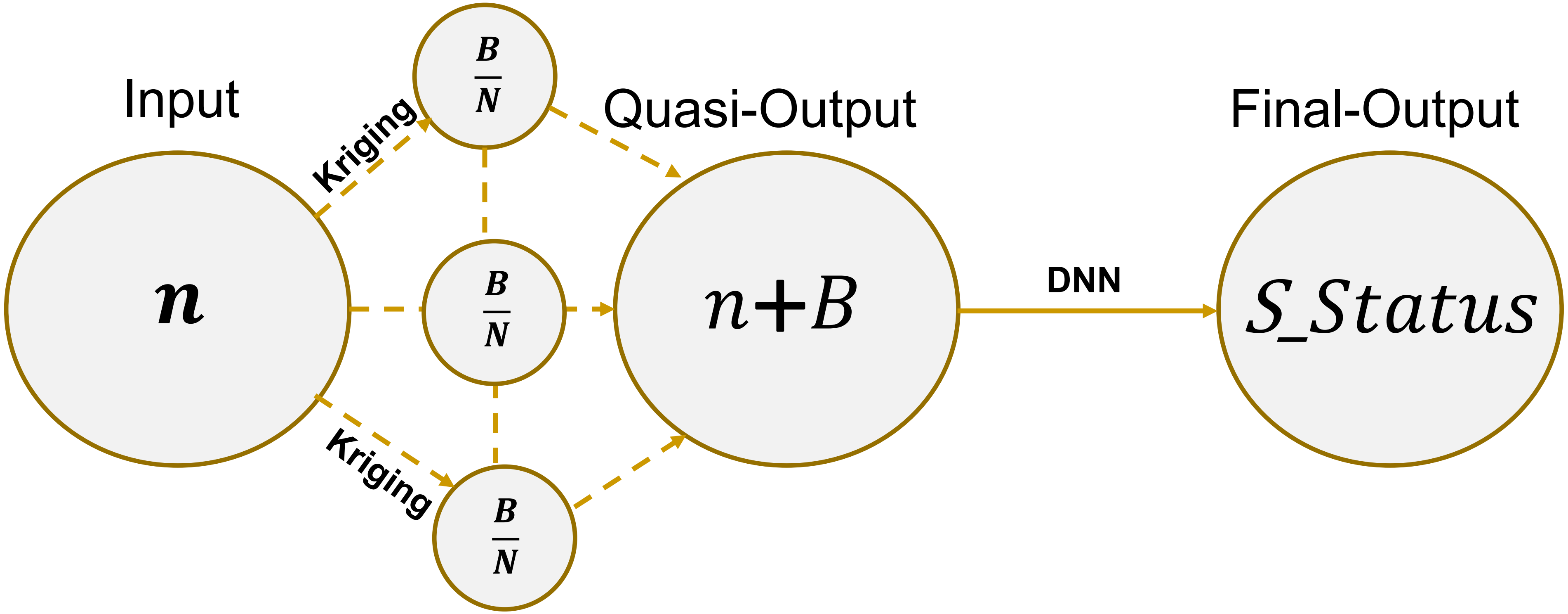
Experimental Results





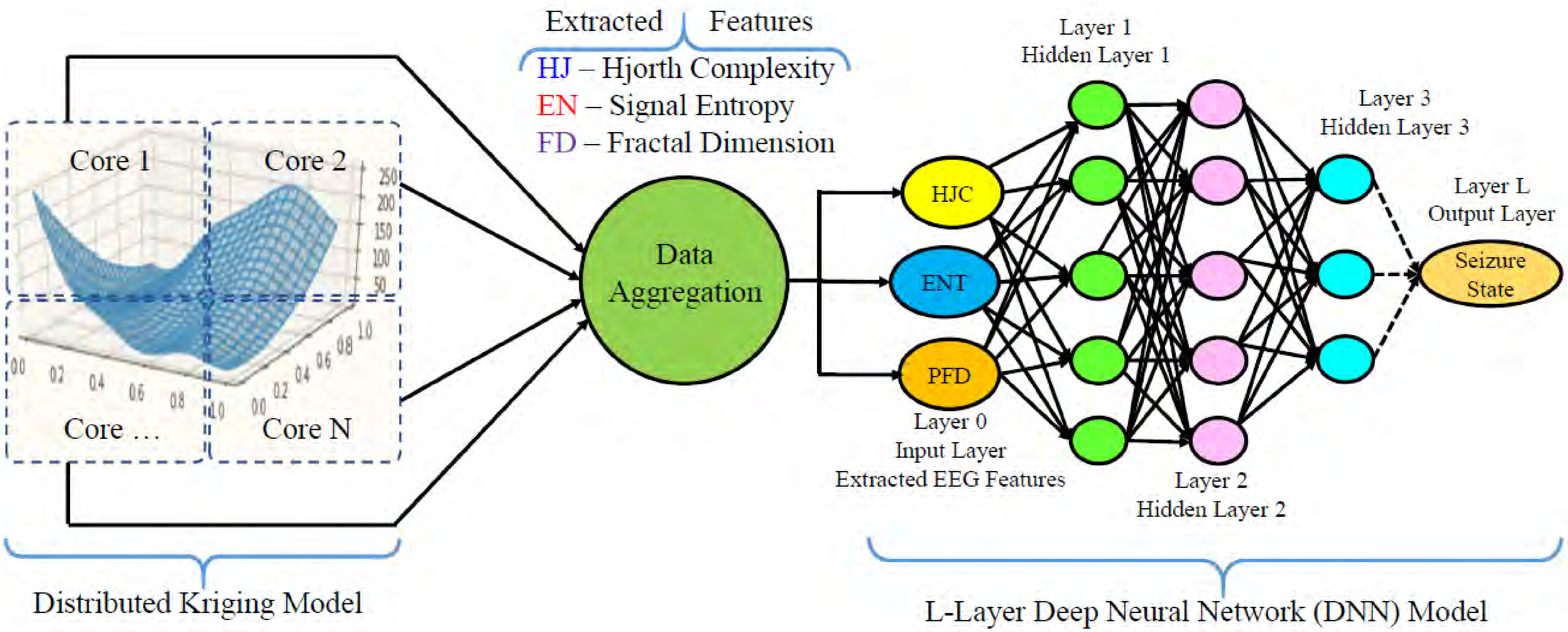
Source: I. L. Olokodana, S. P. Mohanty, and E. Kougianos, "Kriging-Bootstrapped DNN Hierarchical Model for Real-Time Seizure Detection from EEG Signals", in *Proceedings of the 6th IEEE World Forum on Internet of Things (WF-IoT)*, 2020

Distributed Learning Process



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

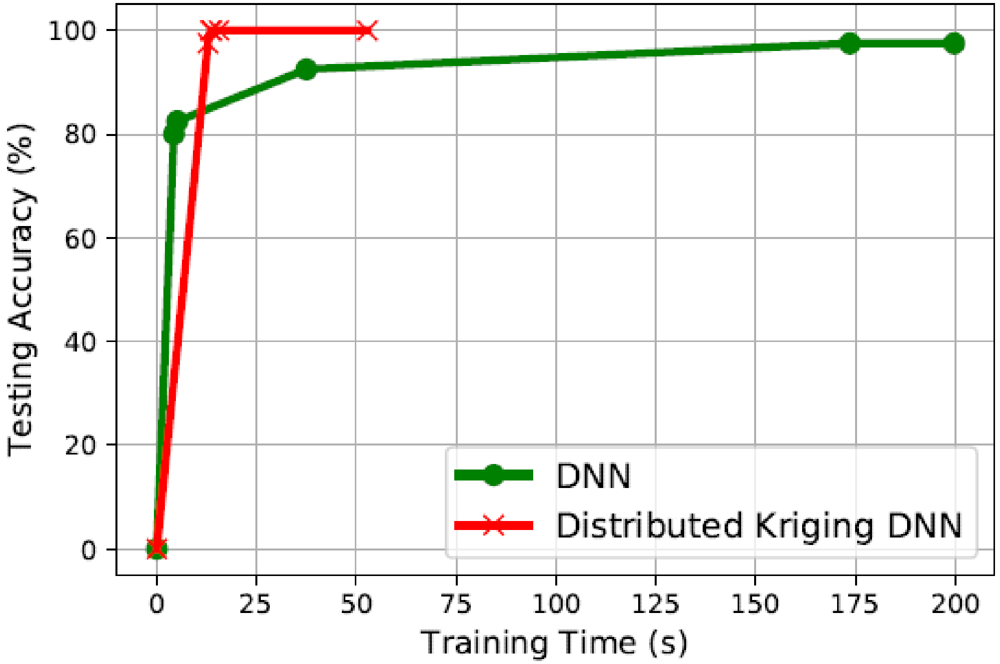
Our Distributed Kriging-Bootstrapped DNN Model



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

Experimental Results: Dataset A

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

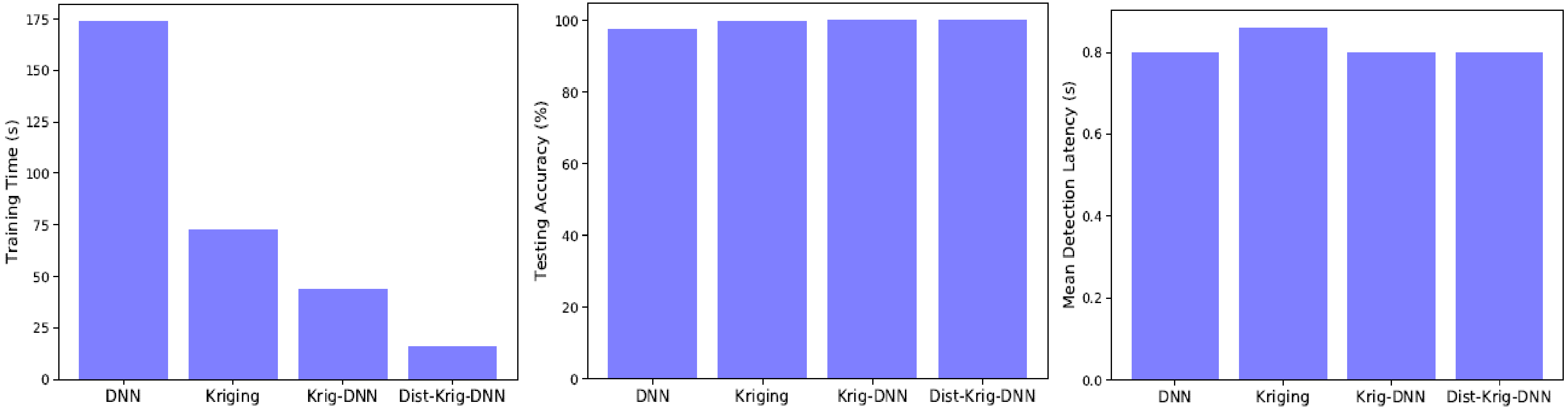


- Training Time reduced by 91%

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

Experimental Results: Dataset A

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



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

What is Federated Learning (FL) ?

- Federated Learning is way of model training in ML for heterogeneous and distributed data.

- It preserves the Privacy of data.

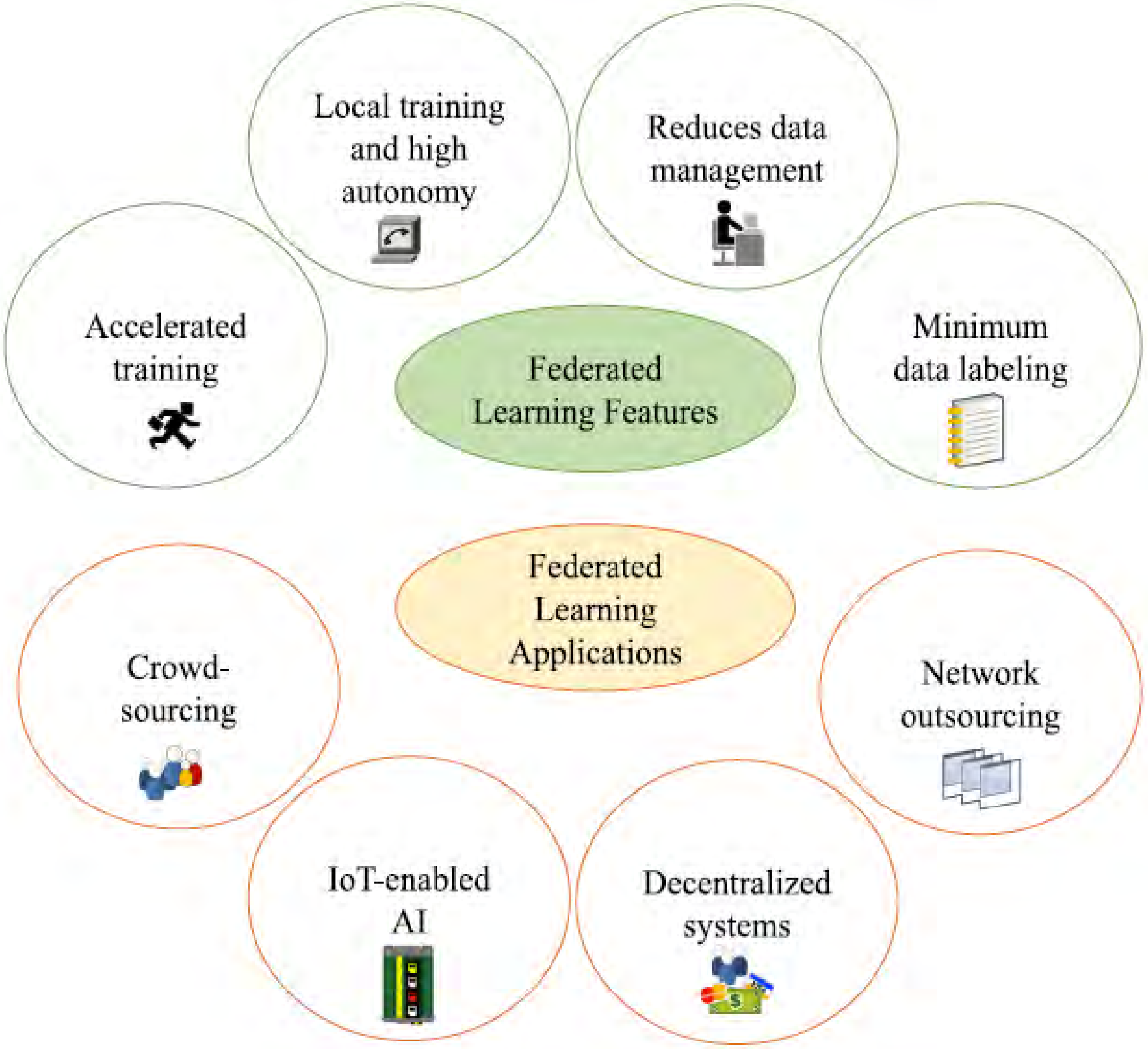
- Data does not come to the Model. Here Model is taken to the data.

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.

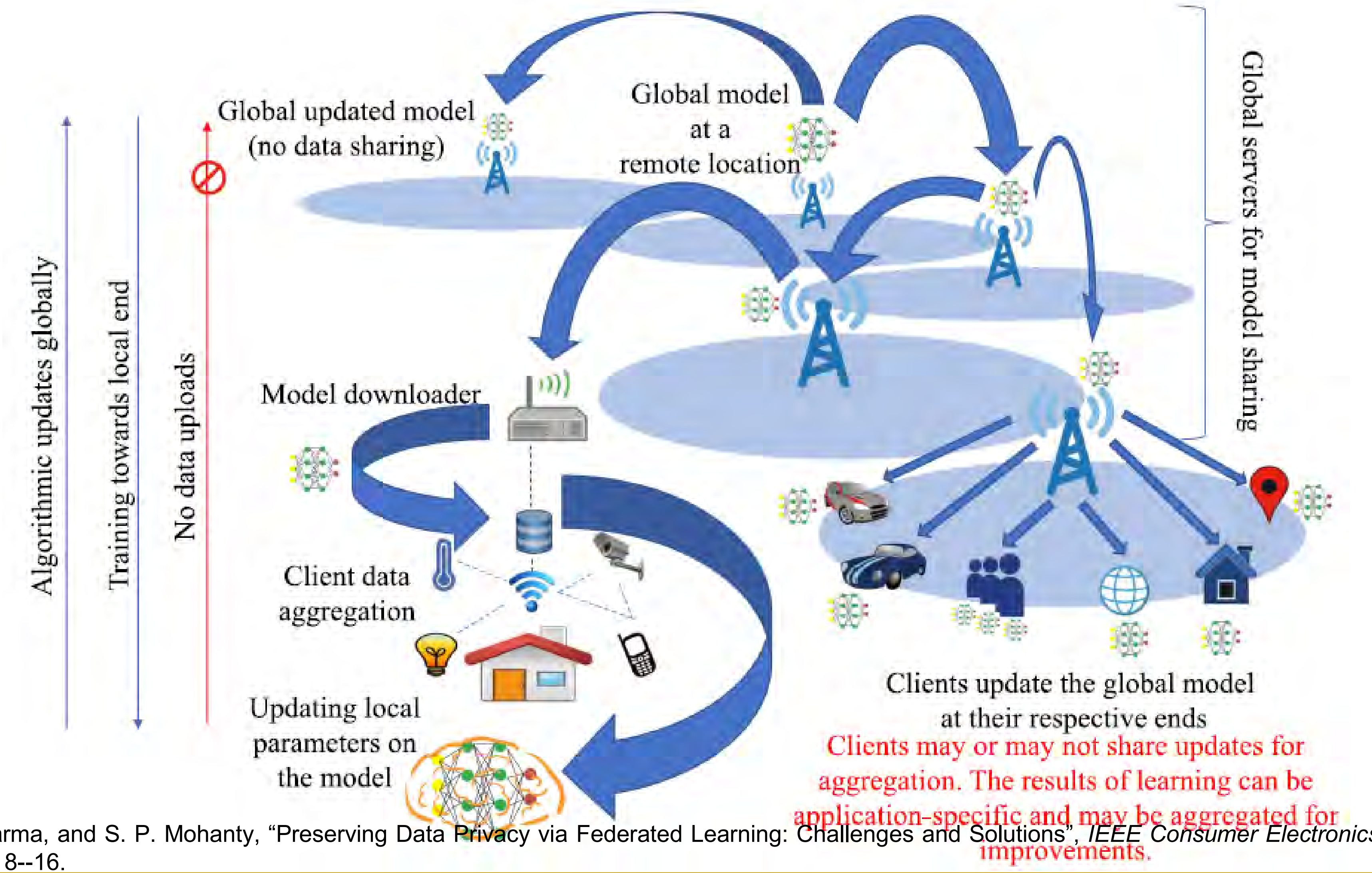
Motivation of Federated Learning (FL)

- 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.

Features and Application of FL

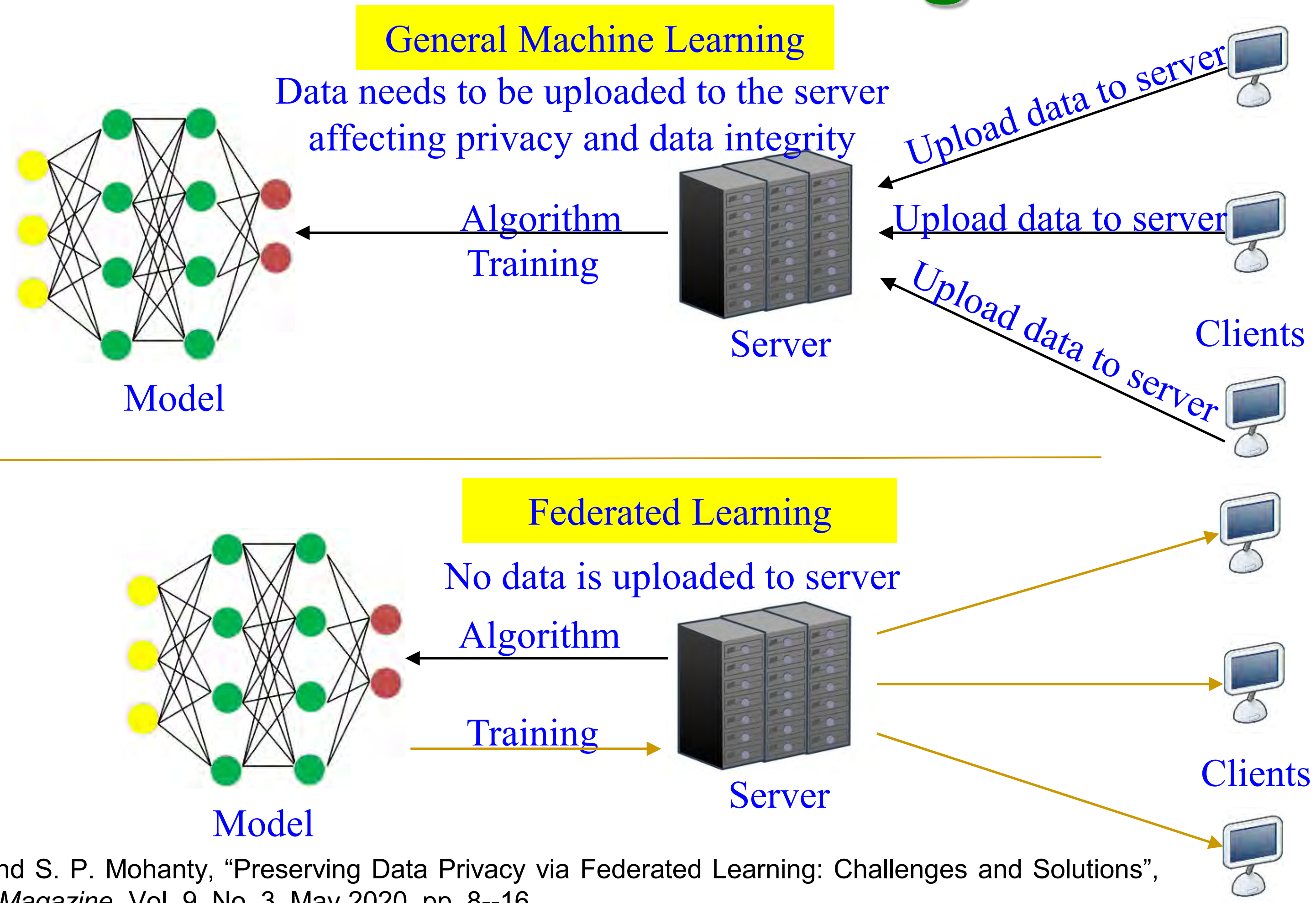


FL In Modern Network



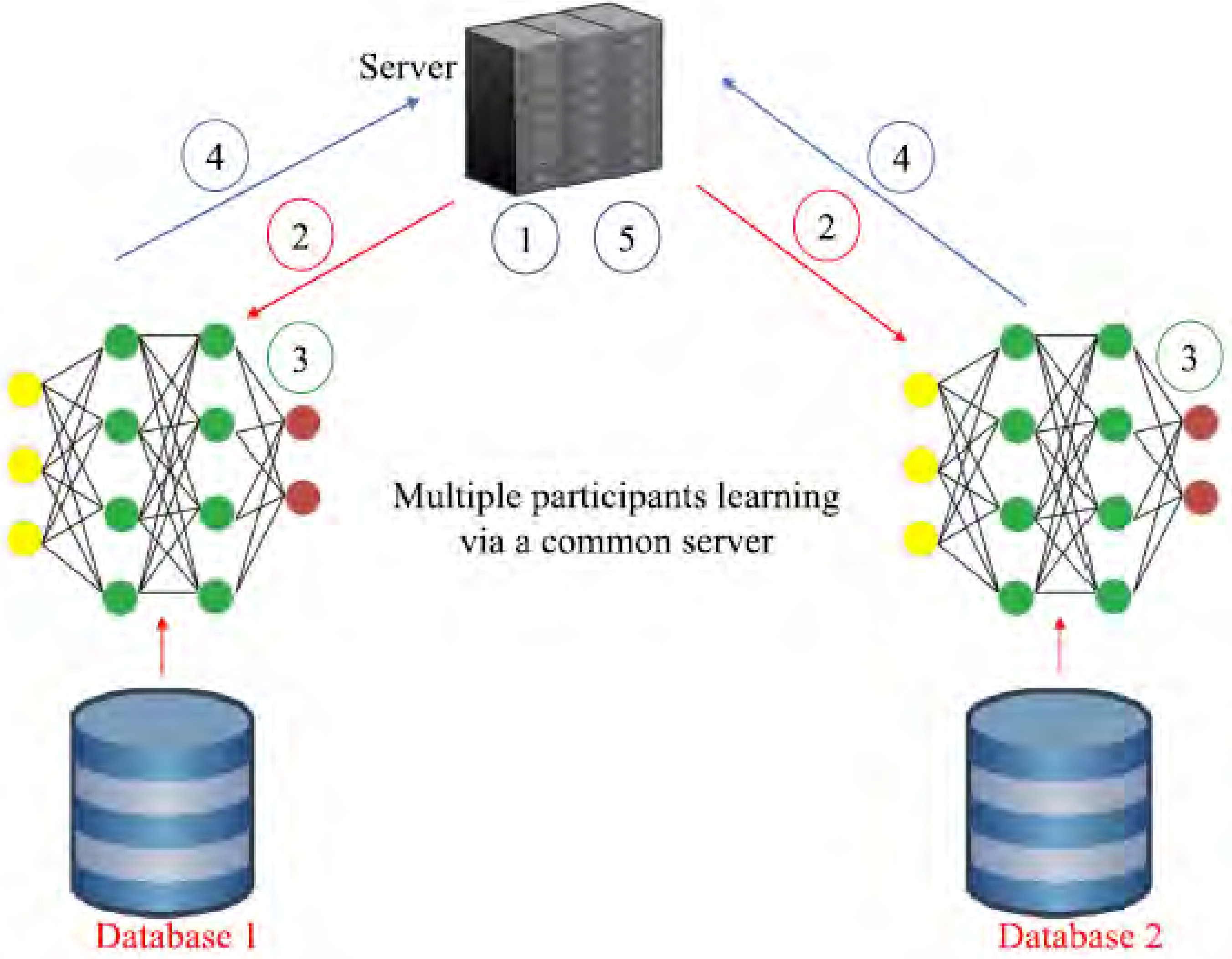
Source: Z. Li, V. Sharma, and S. P. Mohanty, "Preserving Data Privacy via Federated Learning: Challenges and Solutions", *IEEE Consumer Electronics Magazine*, Vol. 9, No. 3, May 2020, pp. 8--16.

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.

Approaches of Sending Updates

- Federated Stochastic Gradient Descent (FedSGD)

  - FedSGD is an extended SGD that assumes there are k participants Pj (j ∈ [1, k]) of the training data, and n elements in the input data while forming the global objective function.

- Federated Averaging (FedAvg)

  - In FedSGD, each client performs gradient descent on the deployed model by using the local data, then the server calculates the average of the resulting models. The FedAvg is designed by adding more computation to each client. Specifically, FedAvg iterates the local update multiple times before the averaging step.

FedSGD & FedAvg

- Federated Stochastic Gradient Descent (FedSGD)

  - Each edge device needs to send gradients or parameters to the server, which averages gradient or parameters and applies to new parameters. It is naive than FedAvg but needs frequent communication between devices and servers.

- Federated Averaging (FedAvg)

  - FedAvg enables each edge device to train and update parameters by using gradient descent iteratively. Therefore, even though FedAvg has a higher requirement for the edge devices, it results in better performance than FedSGD.

How Does FL Solve the Challenges of AI?

- Challenge: How to Hide Updates?

- Solution: Fully homomorphic encryption (FHE)

All operations in a NN except for activation functions are sum and product operations which can be encoded using FHE. Activation functions are approximated with different higher degree polynomials and then implemented as part of homomorphic encryption schemes.

How Does FL Solve the Challenges of AI?

- Challenge: How to Optimize Communication and Computation Complexity?

- Solution: Secure Aggregation Protocol

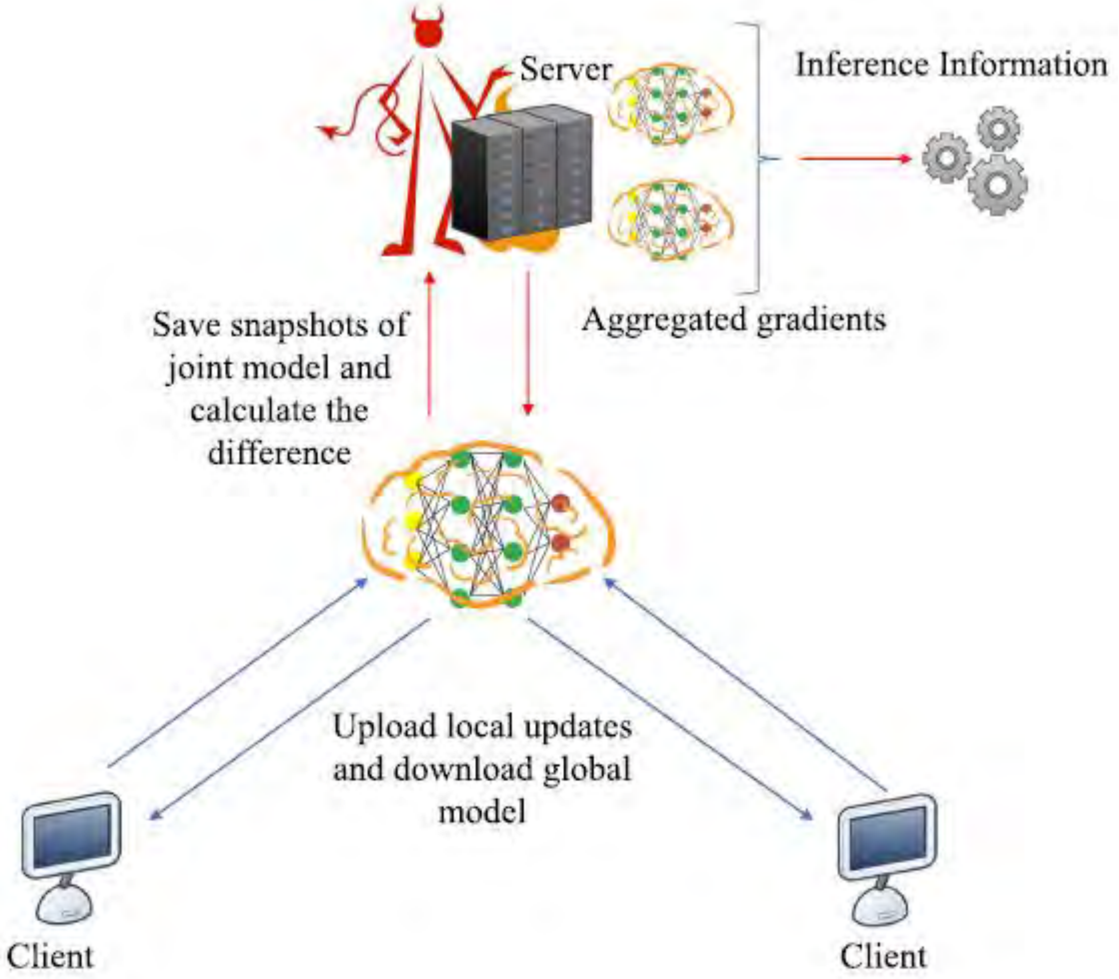
Multiparty computing (MPC) and FHE can solve the problem. FHE-based MPC can be executed in limited rounds. Therefore, to reduce the communication and computation overhead, a constant (at most 3) rounds threshold FHE based MPC protocol can be designed under the common reference string model.

How Does FL Solve the Challenges of AI?

- Challenge: How to Defend Inference Attacks?

- Solution: Differential Privacy

It provides efficient and statistical guarantees against learning for an adversary. It can be done by adding noise to the data to obscure sensitive items such that the other party cannot distinguish the individual's information.

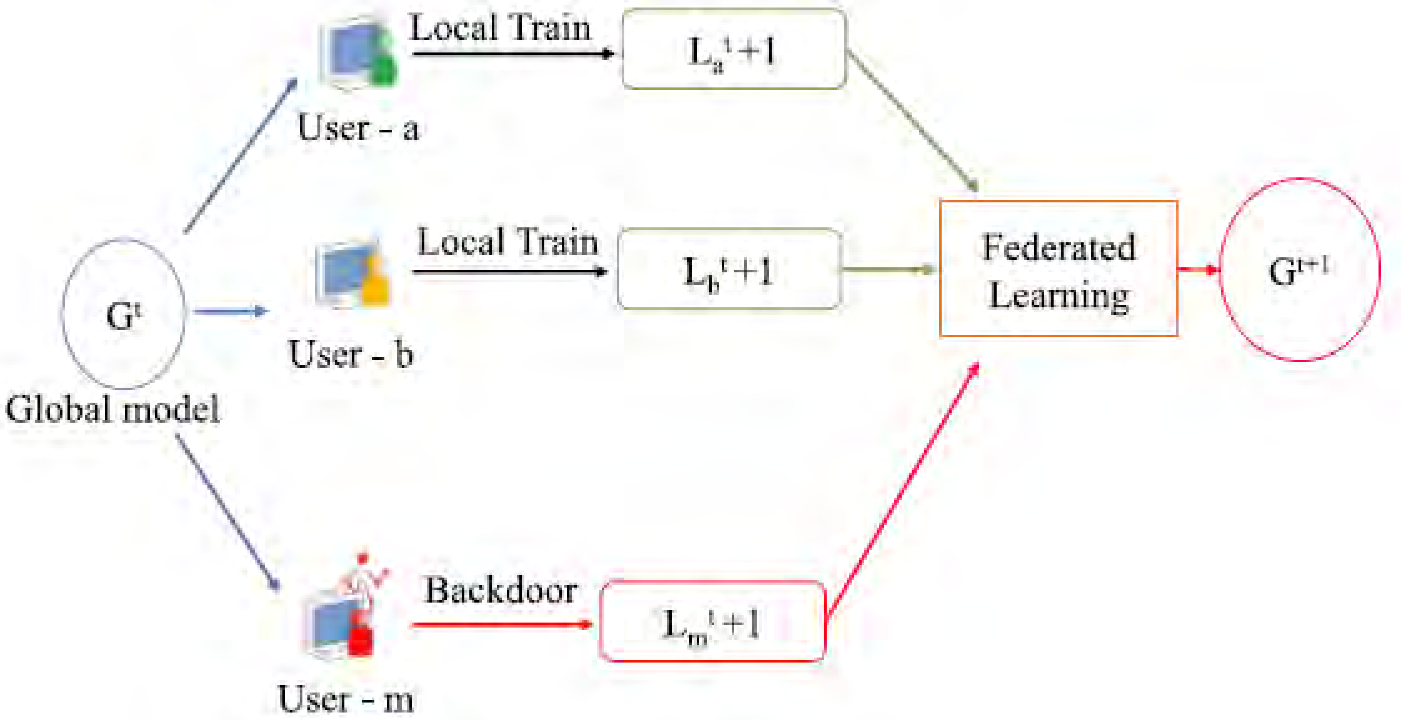


Source: Z. Li, V. Sharma, and S. P. Mohanty, "Preserving Data Privacy via Federated Learning: Challenges and Solutions", *IEEE Consumer Electronics Magazine*, Vol. 9, No. 3, May 2020, pp. 8--16.

How Does FL Solve the Challenges of AI?

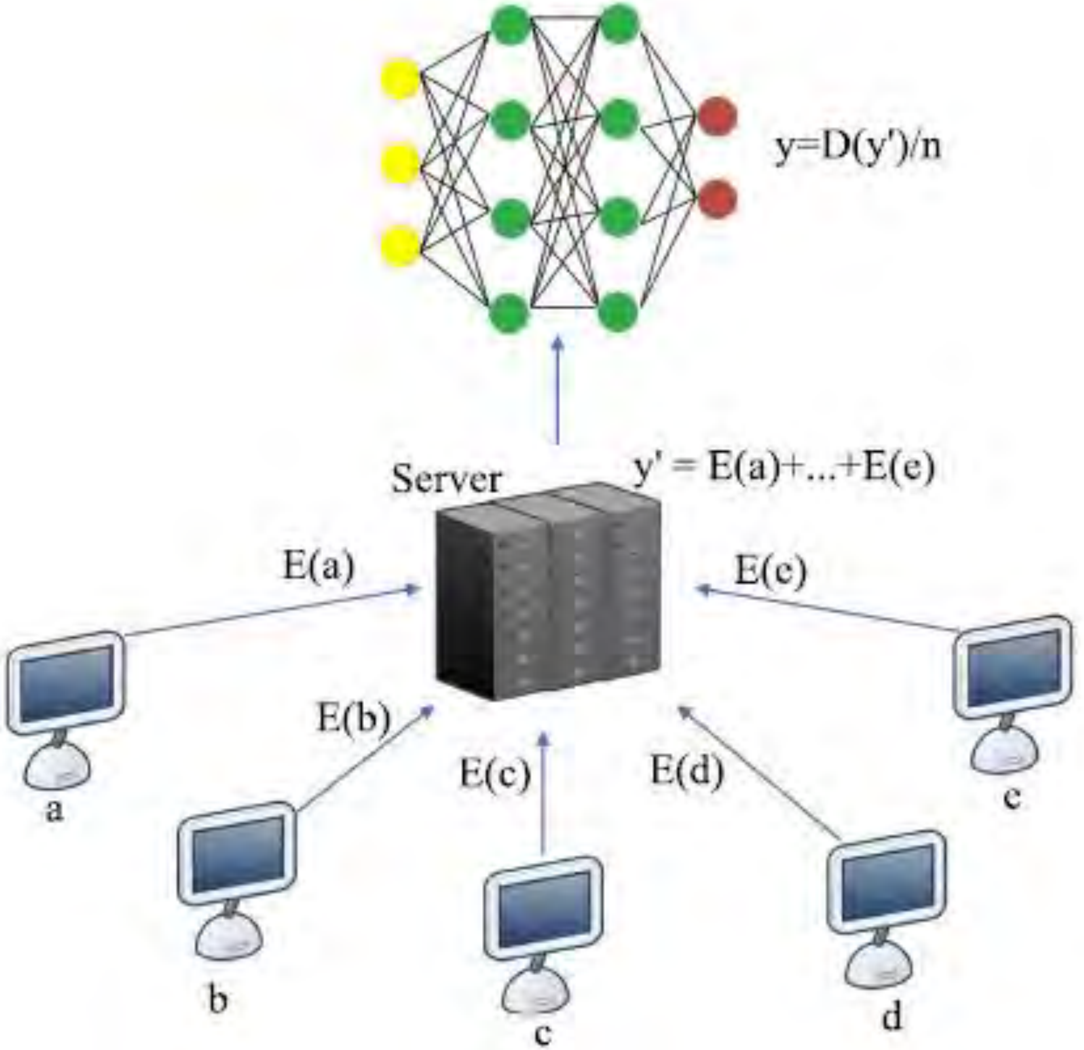
- Challenge: How to Prevent Model Poisoning Attacks?
- Solution: Different Solutions are being proposed.

Controlling the participating edge node is a difficult problem.



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.

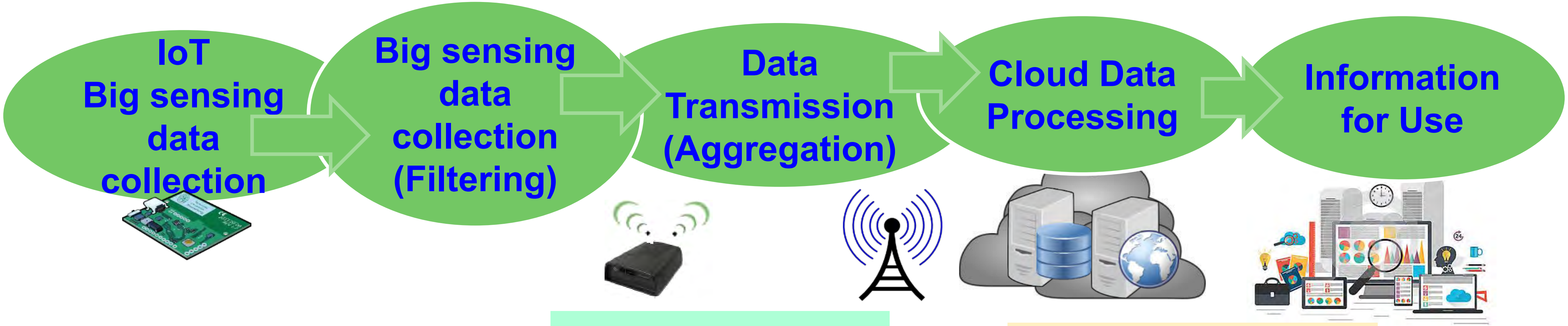
Aggregation of Vertical FL



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?



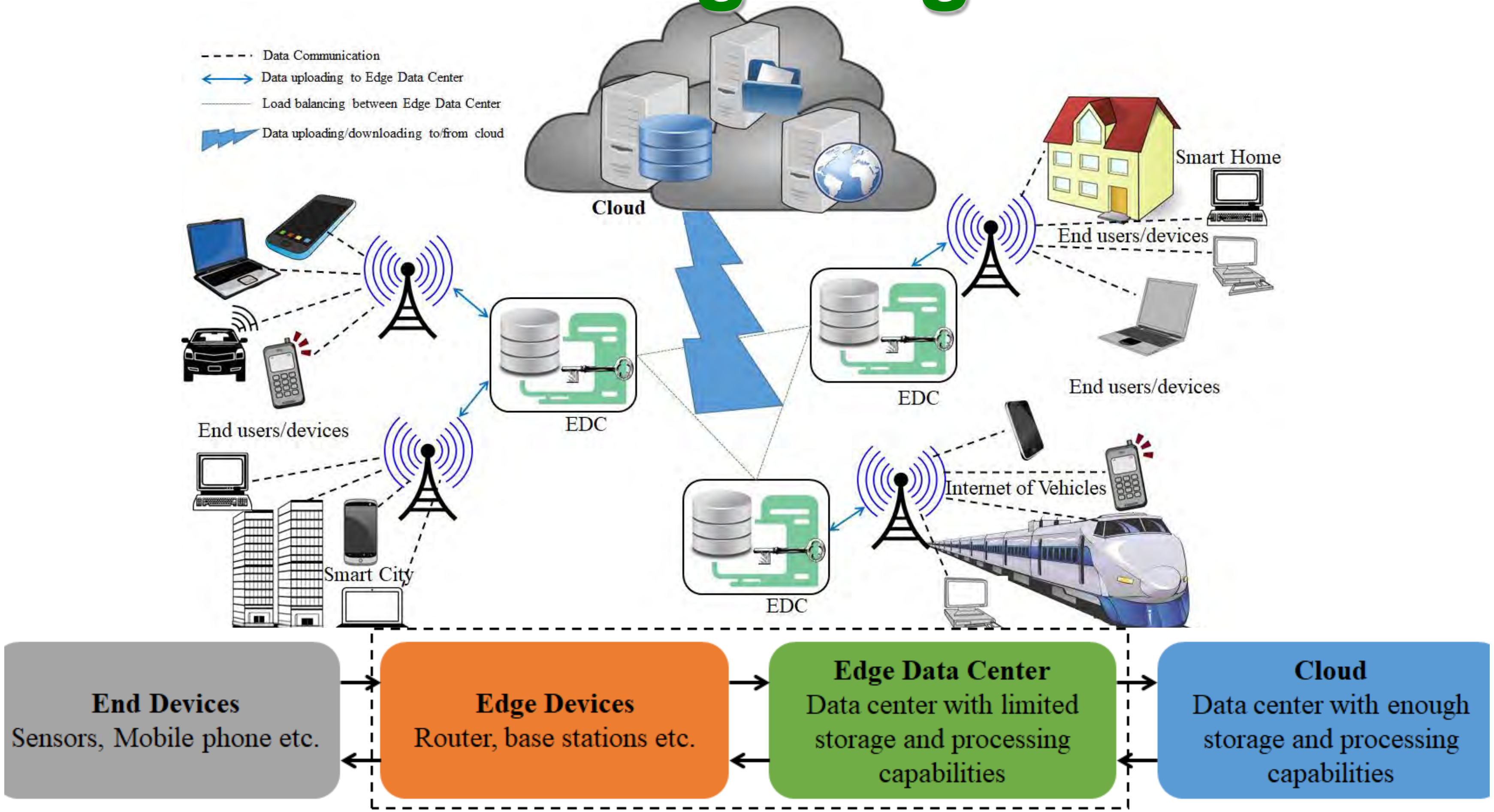
Edge Training:
- ➢ Data Signature
- ➢ Model Signature

Fake Data Defense:
- Stop (Shield)
- Detect

Cloud Training:
- ❖ Data Signature
- ❖ Model Signature

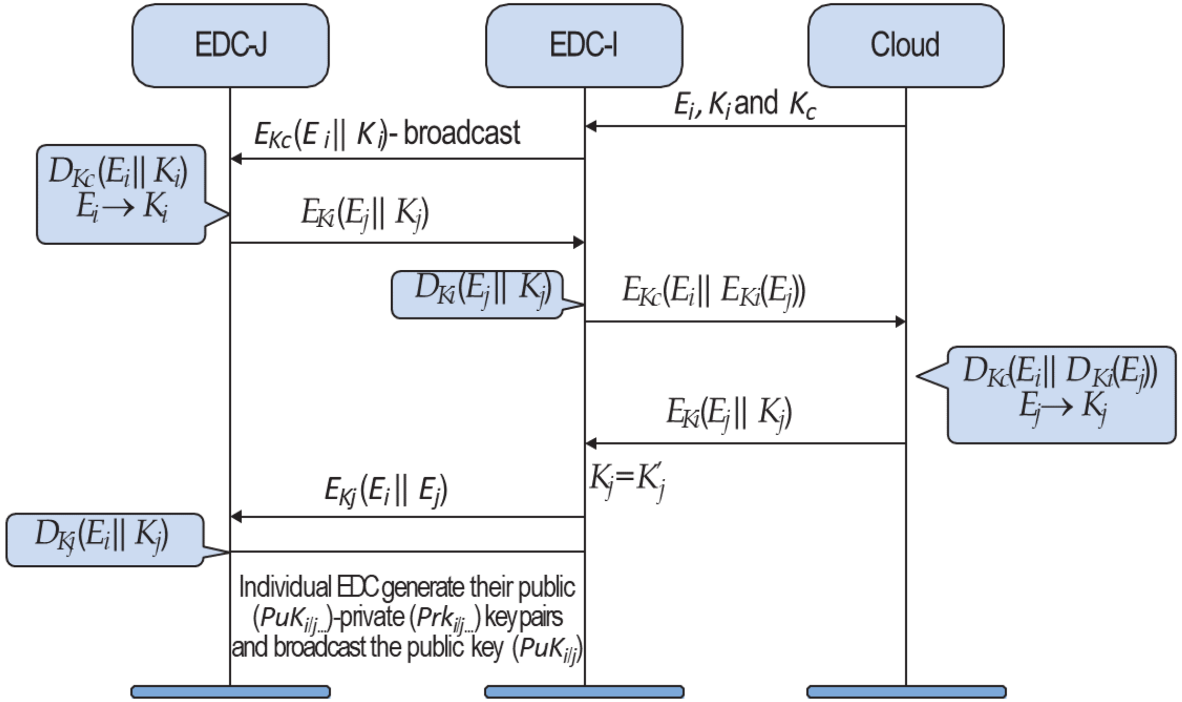
Source: C. Yang, D. Puthal, S. P. Mohanty, and E. Kougianos, “Big-Sensing-Data Curation for the Cloud is Coming”, *IEEE Consumer Electronics Magazine (CEM)*, Volume 6, Issue 4, October 2017, pp. 48--56.

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

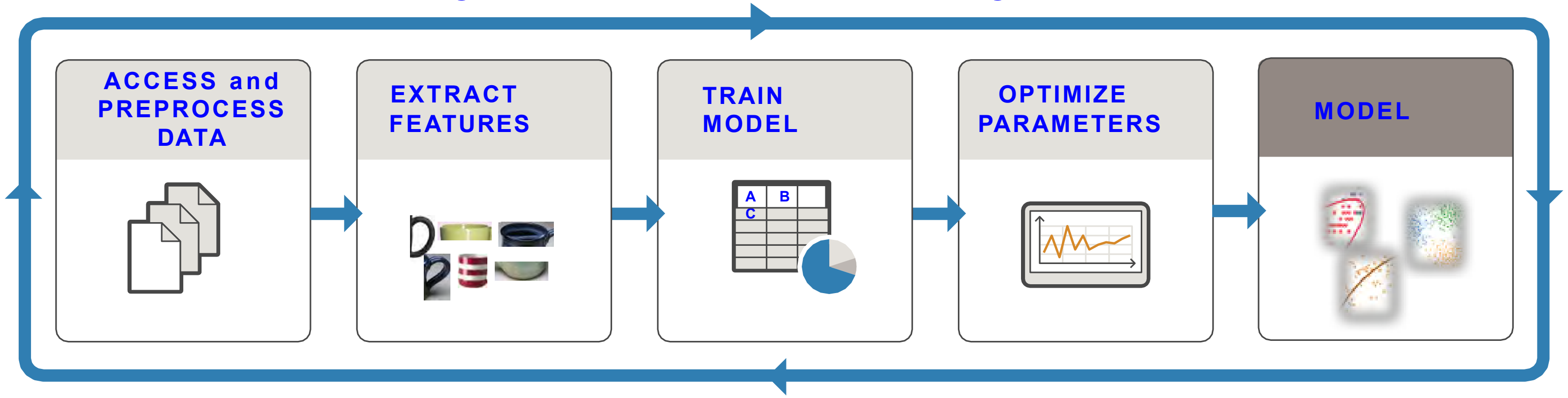
1. If (EDC-I is overloaded)
2. EDC-I broadcast (E_i, L_i)
3. EDC-J (neighbor EDC) verifies:
4. If (E_i is in database) & ($p \leq 0.6$&L_i<<(n-m))
5. Response $E_{Kpu_i}(E_j||K_j||p)$
6. EDC-I perform $D_{Kpr_i}(E_j||K_j||p)$
7. $k'_j \leftarrow E_j$
8. If $(k'_j = k_j)$
9. EDC-I select EDC-J for load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

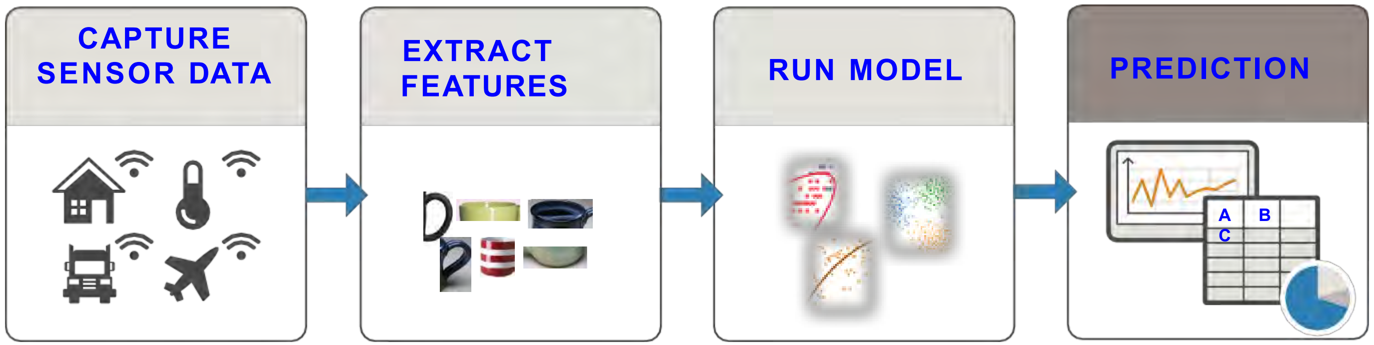
TRAIN: Iterate until you achieve satisfactory performance.



Needs Significant:
- ➢ Computational Resource
- ➢ Computation Energy

Solution: Reduce Training Time and/or Computational Resource

PREDICT: Integrate trained models into applications.

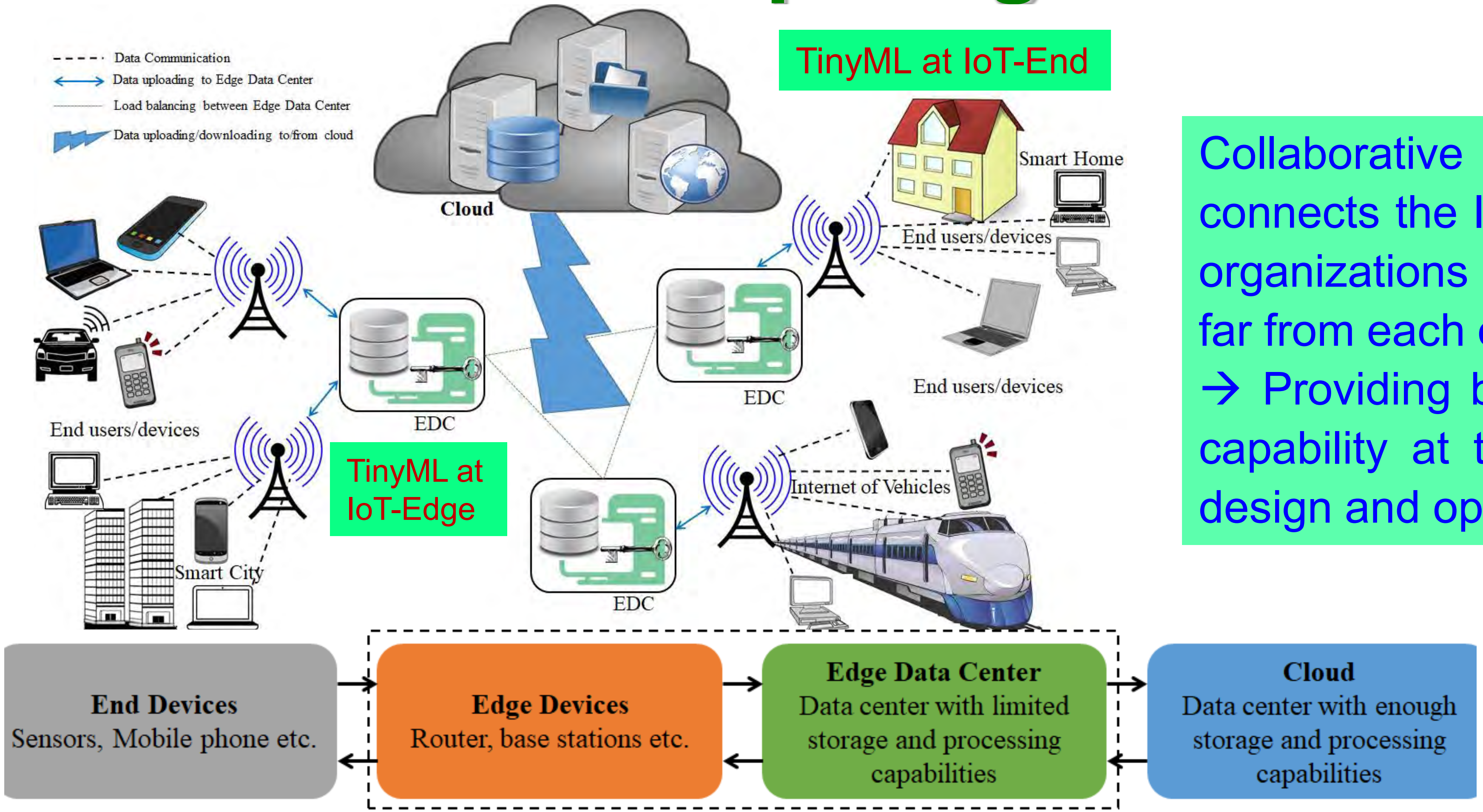


Source: https://www.mathworks.com/campaigns/offers/mastering-machine-learning-with-matlab.html

Needs:
- ➢ Computational Resource
- ➢ Computation Energy

Solution: TinyML

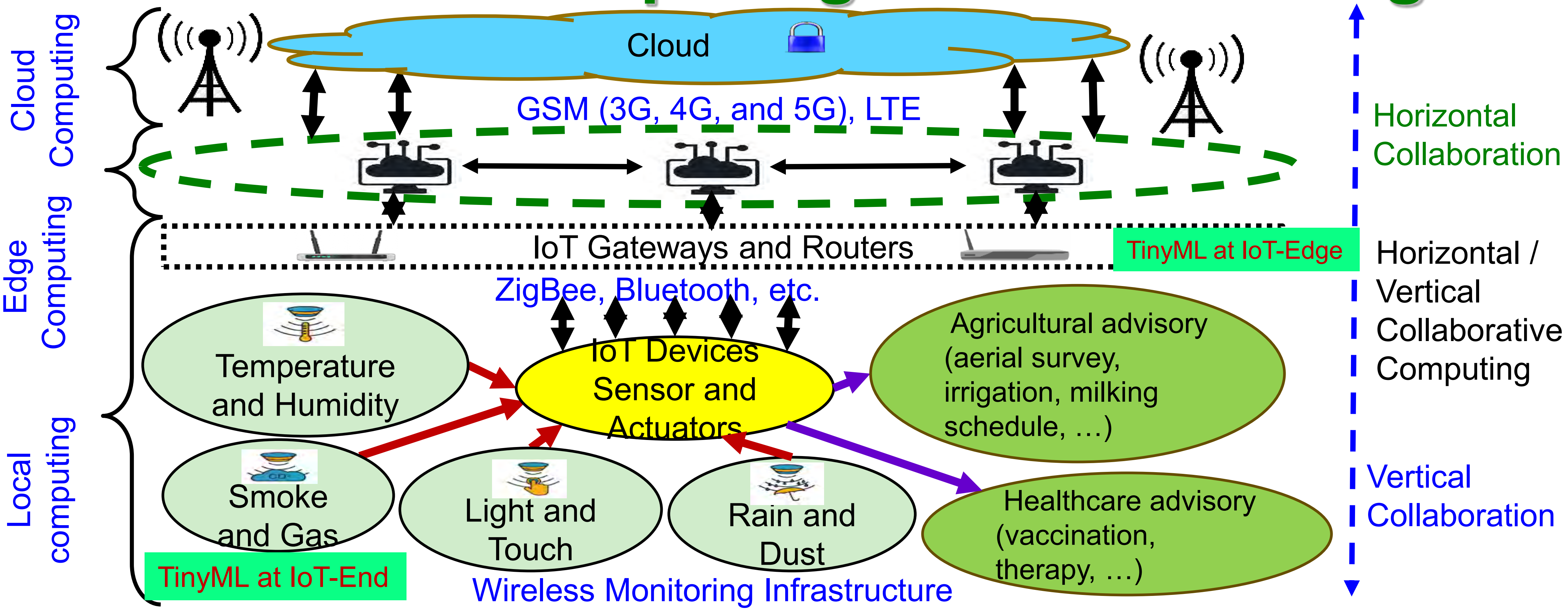
Collaborative Edge Computing is Cost Effective Sustainable Computing for Smart Villages



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.
- Smart Healthcare can be effective during stay-at-home scenario during pandemic.

Future Research

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