Healthcare Cyber-Physical System (H-CPS) - Demystified

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Outline

- Healthcare → Smart Healthcare
- Smart Healthcare - Characteristics
- Smart Healthcare - Components
- Smart Healthcare - Examples
- Smart Healthcare - Challenges
- Conclusions and Future Directions
Healthcare to Smart Healthcare
Human Body and Health

Human Body

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

Health

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

- Physical presence needed
- Deals with many stakeholders
- Stakeholders may not interact
- May not be personalized
- Not much active feedback
- No follow-up from physicians
Telemedicine is the use of telecommunication and information technology to provide clinical health care from a distance.
Electronic Health (eHealth)

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

Connected Health (cHealth)

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

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

Quality and sustainable healthcare with limited resources.

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

Smart Healthcare - Characteristics
What is Smart Healthcare?

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

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

Healthcare Cyber-Physical Systems (H-CPS)

Smart Healthcare - 4-Layer Architecture

IoMT based H-CPS

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

Patient

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

Improved inter-device connection and synchronization

Data driven health **prediction**

Real-time tracking and intervention

Healthcare **Cyber-Physical Systems (H-CPS)**

Wearable Medical Devices (WMDs)

- Fitness Trackers
- Headband with Embedded Neurosensors
- Insulin Pump
- Embedded Skin Patches

Source: https://www.empatica.com/embrace2/
Medical grade smart watch to detect seizure

Source: https://www.webmd.com
Implantable Medical Devices (IMDs)
Smart Healthcare – 7Ps

Participatory

Persuasive

Predictive

Personalized

Preventative

Programmable

Perpetual

Smart Healthcare - Tasks

Daily Healthcare

(ii) Daily Diagnosis
- Wearable Medical Sensor (WMS)-based diagnosis

(i) Daily Prevention
- Fitness checkup
- Activity tracking
- Emotion analysis
- Disease risk prediction

(v) Daily Treatment
- Out-patient therapy
- Ambient healthcare
- Disease status monitoring
- Precision medicine

Clinical Boundary

(iii) Clinical Diagnosis
- Physician variance reduction
- Personalized diagnosis

(iv) Clinical Treatment
- Treatment plan selection
- Treatment method evaluation
- In-patient monitoring
- Precision medicine

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

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

Source: http://internetofthingsagenda.techtarget.com/definition/IoMT-Internet-of-Medical-Things
Smart Healthcare Sensors

Types of Sensors

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

Electroencephalogram (EEG)
Electrocardiogram (ECG)
Oximeter
Electrodermograph
Electromyograph
Photoplethysmography (PPG)
Glucose monitoring
Thermal sensor
Pulse sensor
Accelerometer
Gyroscope
Magnetometer
Altimeter

Smart Pill
# Smart Healthcare Communication

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

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.
Smart Healthcare - Framework

**Smart Healthcare - System and Data Analytics : To Perform Tasks**

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

**Machine Learning Engine**

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

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

**Machine Learning Engine**

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

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

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.

BCI - Applications

BCI Allows paralysis patients to Type

BCI Allows paralysis patients to move a wheelchair

BCI Types

Based on Location

Non-invasive
Semi-invasive
Invasive

Based on Signal

EEG
MEG
fNIR
fMRI

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


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Virtual Reality in Healthcare

In Surgery

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

For Therapy

Source: http://medicalfuturist.com/5-ways-medical-vr-is-changing-healthcare/
Crowdsourcing for Smart Cities

- Smart Healthcare Data Gathering (Diet Dataset, Healthcare Dataset)
- Urban Data Gathering (Bike Data, Energy Usage Data)
- City Service Monitoring (Park Maintenance, Waste Disposal)
- Last-Mile Logistics (Package Pickup Delivery)
Smart Healthcare – Specific Examples
Stress is a Global Issue

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

Source: http://www.gostress.com/stress-facts/
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.
**Smart Healthcare - Stress Monitoring & Control**

Advising Examples: Specific Music, Shower, Physical Exercise, Breathing Exercise, Meditation, Yoga, …

### Sensors

<table>
<thead>
<tr>
<th>Sensor</th>
<th>Low Stress</th>
<th>Normal Stress</th>
<th>High Stress</th>
</tr>
</thead>
<tbody>
<tr>
<td>Accelerometer (steps/min)</td>
<td>0-75</td>
<td>75-100</td>
<td>101-200</td>
</tr>
<tr>
<td>Humidity (RH%)</td>
<td>27-65</td>
<td>66-91</td>
<td>91-120</td>
</tr>
<tr>
<td>Temperature °F</td>
<td>98-100</td>
<td>90-97</td>
<td>80-90</td>
</tr>
</tbody>
</table>


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## Consumer Electronics Devices – Can Provide Data for Stress Detection

<table>
<thead>
<tr>
<th>Brand</th>
<th>Device</th>
<th>Signals</th>
<th>RTI</th>
<th>Ambulant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Empatica</td>
<td>E4 wristband</td>
<td>PPG, GSR, HR, ACC, ST</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Garmin</td>
<td>Vivosmart</td>
<td>HR, HRV, ACC</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Zephyr</td>
<td>BioHarness 3.0</td>
<td>HR, HRV, GSR, ACC, ST</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>iMotions</td>
<td>Shimmer 3+ GSR</td>
<td>GSR, PPG</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>BIOPAC</td>
<td>Mobita Wearable</td>
<td>ECG, EEG, EGG, EMG, and EOG</td>
<td>Yes</td>
<td>No</td>
</tr>
</tbody>
</table>

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

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)?

Stress-Lysis: From Physiological Signals

Stress-Lysis: Experiments

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)?

## Consumer Electronics Sleep Trackers

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

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

Heart Rate
Snoring
Respiration Rate

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

Person On Pillow:
Physiological Sensor Data Monitoring Starts

Person Off Pillow:
Physiological Sensor Data Monitoring Ends

Period 1. Lying on bed but not Sleeping

Period 2: Trying to Sleep

Period 3: Drift from Wakefulness to Sleep

Period 4: Deep Sleep

Period 5: Awake Person

Data Processing

Secure Data Transfer

Secure Data Storage

Secure Data Access

User Applications

## Parameter Ranges

<table>
<thead>
<tr>
<th>Snoring Range (dB)</th>
<th>Respiration Rate (bpm)</th>
<th>Heart Rate (bpm)</th>
<th>Stress State</th>
</tr>
</thead>
<tbody>
<tr>
<td>50-60</td>
<td>17-19</td>
<td>54-57</td>
<td>LSS</td>
</tr>
<tr>
<td>60-70</td>
<td>19-21</td>
<td>57-60</td>
<td>MLSS</td>
</tr>
<tr>
<td>70-80</td>
<td>21-22</td>
<td>60-64</td>
<td>MSS</td>
</tr>
<tr>
<td>80-89</td>
<td>23-25</td>
<td>65-70</td>
<td>MHSS</td>
</tr>
<tr>
<td>90+</td>
<td>25+</td>
<td>70+</td>
<td>HSS</td>
</tr>
</tbody>
</table>

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

SaYoPillow – Uses deep learning for 96% accuracy with blockchain based security features
iFeliz: Research Question

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

iFeliz: Proposed System

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


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iFeliz: Stress Control Approaches

iFeliz: Prototyping

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>
<thead>
<tr>
<th>App Name</th>
<th>Downloads</th>
<th>Reviews</th>
<th>Rating</th>
<th>Image</th>
<th>Food-Label in Image</th>
<th>Manual Scan</th>
<th>Speech Recognition</th>
<th>Database Search</th>
<th>Calories</th>
<th>Nutrition</th>
</tr>
</thead>
<tbody>
<tr>
<td>MyFitnessPal</td>
<td>50 M</td>
<td>2 M</td>
<td>4.6</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>FatSecret</td>
<td>10 M</td>
<td>268 k</td>
<td>4.5</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>My Diet Coach</td>
<td>10 M</td>
<td>144 k</td>
<td>4.4</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Lose It</td>
<td>10 M</td>
<td>77 k</td>
<td>4.4</td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>MyPlate</td>
<td>1 M</td>
<td>31 k</td>
<td>4.6</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>mynetdiary</td>
<td>1 M</td>
<td>31 k</td>
<td>4.5</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
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<td>X</td>
<td>X</td>
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<tr>
<td>Macros</td>
<td>500 k</td>
<td>3 k</td>
<td>4.5</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Cron-o-meter</td>
<td>100 k</td>
<td>1 k</td>
<td>4.2</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Eating Habit</td>
<td>100 k</td>
<td>549</td>
<td>4</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>21 day Fix</td>
<td>100 k</td>
<td>470</td>
<td>3.7</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
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<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Bite Snap</td>
<td>50 k</td>
<td>2k</td>
<td>4.7</td>
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<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
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<tr>
<td>MealLogger</td>
<td>50 k</td>
<td>225</td>
<td>3.5</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
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<tr>
<td>EatRight</td>
<td>10 k</td>
<td>220</td>
<td>4.5</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Keto Meal Plan</td>
<td>10 k</td>
<td>19</td>
<td>2.6</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>YouAte</td>
<td>10 k</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>KudoLife</td>
<td>1 k</td>
<td>11</td>
<td>3.4</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Calorific Ate</td>
<td>19</td>
<td></td>
<td>3.2</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
<td></td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Foodlog</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
</tbody>
</table>

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

- **Diet Tracking**
  - **Manual**
    - Hand and Mouth Movement
  - **Automatic**
    - Food Weight Sensing
    - Food Image Processing
Captures Food Images → Automatic Food Image Analysis → IoT Cloud

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

Accuracy of detecting food - 97%

Smart Healthcare – iLog

Reference Image

Edge Platform
- Classification
- Feature Extraction
- Object Detection
- Nutrition Dataset
- Database

Cloud Platform
- Mobile Application Interface
- Stress-Eating Analysis

iLog- Fully Automated Detection System with 98% accuracy.


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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.

Smart Healthcare – Diet Prediction

Computer Vision Methods using Machine Learning Models

OCR

Nutrition Facts of the Food item

Start

Automatic food quantity estimation

Food Item ID

Obtain Nutrition information for each food item

Nutrient Value of the food item

Timestamp when weight of the food item is altered

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

Classify the food items using a machine learning model

For Future Meal Predictions

Meal ID

Nutrient Value of the meal

Food item quantity

Timestamp to compute meal type


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Smart Healthcare – Diet Prediction

Layer 1
Input Layer
Type of Meal

Layer 2
Hidden Layer 1
Weight of the meal

Layer 3
Hidden Layer 2
Time consumed

Layer 4
Hidden Layer 3
Intended Nutritional goal

Layer 5
Output Layer
Nutritional balance of the meal

Balanced Meal

Bayesian Network for classifying food items

Neural Network for computing Nutritional balance

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

Epileptic Seizure

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

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

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

Seizure Detection

Electroencephalogram (EEG)

Time Domain

Frequency Domain

Wavelet Domain

Non-EEG
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

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

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

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

  Source: https://www.empatica.com/embrace2/
Drawbacks of Existing Works?

- High seizure detection latency.
- Not suitable for real time IoMT deployment.
- Intervention mechanism after detection is lacking.
Smart Healthcare - Seizure Detection & Control

Seizure Detection Approaches

Cloud Vs Edge Computing

<table>
<thead>
<tr>
<th></th>
<th>Latency</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cloud-IoT based Detection</td>
<td>2.5 sec</td>
<td>98.65%</td>
</tr>
<tr>
<td>Edge-IoT based Detection</td>
<td>1.4 sec</td>
<td>98.65%</td>
</tr>
</tbody>
</table>


Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
Our Neuro-Detect: A ML Based Seizure Detection System

Spatial modeling or Variography - Correlation Function is "Variogram"

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

Kriging based Seizure Detection

Signal Denoising
Wavelet Transformations

Feature Extraction
Fractal Dimension

Seizure State Classification
Kriging Classifier

Seizure Status

<table>
<thead>
<tr>
<th>Works</th>
<th>Extracted Features</th>
<th>Classification Algorithm</th>
<th>Sensitivity</th>
<th>Latency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our Proposed</td>
<td>Petrosian fractal dimension</td>
<td>Kriging Classifier</td>
<td>100.0%</td>
<td>0.85 s</td>
</tr>
</tbody>
</table>

Seizure Control Methods

- Epileptic Seizure Control
  - Common Epilepsy Treatment
    - Antiepileptic Drug
    - Surgery
  - Drug Resistant Epilepsy Treatment
    - Therapies
      - Deep Brain Stimulation
      - Responsive Neurostimulation
      - Vagus Nerve Stimulation
      - Stereotactic Laser Ablation
      - External Nerve Stimulation
    - Direct Drug Injection
      - Focal Drug Delivery

Implantable for Seizure Detection and Control

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

**Piezoelectric:**
- Latency: 1.8 sec
- Power: 29 mW
- Flow Rate: 3 mL/min

**Electromagnetic:**
- Latency: 1.8 sec
- Power: 12.81 mW
- Flow Rate: 0.34 mL/min


Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
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.

## Consumer Electronics for Fall Detection

<table>
<thead>
<tr>
<th>Wearables</th>
<th>Drawbacks</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Apple watch</strong></td>
<td>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.</td>
</tr>
<tr>
<td><strong>Philips Lifeline</strong></td>
<td>Uses only accelerometers and barometric sensors for pressure changes. After the fall, the system waits for 30 sec and directly connects to help.</td>
</tr>
<tr>
<td><strong>Lively Mobile by greatcall and Sense4Care Angel4</strong></td>
<td>Monitors fluctuations using only accelerometers.</td>
</tr>
<tr>
<td><strong>Bay Alarm Medical and Medical Guardian</strong></td>
<td>Use only accelerometers. Have huge base stations limiting the usage and location access.</td>
</tr>
</tbody>
</table>
Issues of Existing Research

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

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

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

Good-Eye: Elderly Fall Detection

Obtaining r,g,b values

\[
\begin{align*}
\text{func}_r(x,y) &= \{ \text{return } \frac{x+y}{100} \times 256; \} \\
\text{func}_g(x,y) &= \{ \text{return } (1 - \frac{x+y}{100}) \times 256; \} \\
\text{func}_b(x,y) &= \{ \text{return } (1 - (0.5 - \frac{x+y}{100})^2) \times 20; \}
\end{align*}
\]

Distance Formula for r,g,b

Check if the d is above the threshold

Decision of fall

Good-Eye: Prototyping

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

Diabetes is a Global Crisis

Estimated Number of Adults with Diabetes (in Millions)

Blood Glucose Monitoring – Invasive Vs Noninvasive

Invasive Approach (Capillary Glucose Measurement)

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

Invasive Approach (Serum Glucose Measurement)

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

Non Invasive Approach

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

Traditional – Finger Pricking

Invasive Approach – Processing Blood/Serum

Noninvasive – Wearable

Noninvasive Approach – Processing Light
Noninvasive Glucose-Level Monitoring

Photoplethysmogram (PPG)

Near Infrared (NIR)

PPG Signal Analysis

- LED
- Detector
- Specific Wavelengths are not required
- Logged signal for pulse analysis and features extraction

NIR Spectroscopy

- LED
- Detector
- Specific Wavelengths needed for glucose molecule detection
- Logged voltage values after absorption and reflectance of light from glucose molecule
Our Vision – iGLU (Intelligent Noninvasive Monitoring and Control)

Continuous Glucose Monitoring

Display of Parameters

Insulin Secretion

Artificial Pancreases System (APS)

Privacy-Assured Health Data Storage

Security-Assured System

Cloud Storage

Hospital

Doctor

Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
**iGLU 1.0: Capillary Glucose**

**Near Infrared (NIR) Emitters**
- Transmitted Wave
- Vibrations (Stretching, Wagging, Bending)
- Infrared Detector

**Attenuated Wave**
- Infrared Detector
- Analog-to-Digital Converter (ADS1115)

**Cost** - US$ 20
**Accuracy** - 100%

Clinically tested in an hospital.

iGLU 2.0: Serum Glucose

Technology for Visually Impaired

Detection Part
(Localizes the marker from the other objects)

Visual Marker

Recognition Part (QR code)

Smart Healthcare – Some Challenges
Smart Healthcare Architecture – Requirements

- Low power
- Higher efficiency
- Small form factor
- Inter operability
- Continuous connectivity
- High speed
- Security
- Privacy
Users are Integral Part: For Them and By Them

Connecting people to the Internet for more valuable communications

**Implantable Medical Device (IMD)**

**Wearable Medical Device (WMD)**

**People**

Collecting data and leverage it for decision making

**Data**

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

**Process**

Perform decision making whenever necessary

**Things**

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

**Internet of Everything (IoE)**

Crowdsourcing

Smart Healthcare – Data Quality

Validity

Integrity

Reliability

Relevance

Objectivity

Completeness

Generalizability

Utility

Machine Learning Challenges

- 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.

**PREDICT:** Integrate trained models into applications.

**Needs Significant:**
- Resource
- Energy

---


Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
DNN Training - Energy Issue

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

Source: Mohanty iSES 2018 Keynote
Smart Healthcare - Security Challenges

Selected Smart Healthcare Security/Privacy Challenges

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

Information Privacy

One privacy misstep can land healthcare organizations in hot water.

By Leslie Feldman


Health Insurance Portability and Accountability Act (HIPPA)

HIPPA Privacy Violation by Types

- Data Physically Stolen: 55%
- Data Compromised by Hackers: 6%
- Improper Disposal Of Data: 5%
- Data Lost and Not Accounted For: 12%
- Data Disclosed Without Authorization from Patient: 20%
- Other: 2%
IoMT Device Security Issue is Scary

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

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

- FDA Issues Recall For Medtronic mHealth Devices Over Hacking Concerns:
  
IoMT Security – Selected Attacks

Impersonation Attacks

Eavesdropping Attacks

Smart Healthcare

Reverse Engineering Attacks

Radio Attacks

Physical Attack

Network Attack

Software Attack

Encryption Attack

Security Threats for IoMT

IoMT Security Measures is Hard

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

- Radio Attacks
- Reverse Engineering Attacks
- Eavesdropping Attacks
- Impersonation Attacks

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

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

Ethical Issues Include:

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


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

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

- 62 Automated external defibrillators
- 59 Pacemakers (pulse generator)
- 46 Other infusion pumps
- 103 Insulin infusion pumps
- 31 Mechanical heart pumps (VAD)
- 93 Implantable cardioverter defibrillators (ICD)
- 82 Tissue heart valves
- 51 Pacemakers (leads)
- 42 Endovascular stent grafts
- 29 Aortic stent grafts

Central Illustration: Cardiac-Implantable Electronic Devices: Technical and Safety Considerations

Factors Influencing Safety

- MR magnet:
  - Magnet strength
  - Radiofrequency power
  - Magnet position

- Cardiac implantable device:
  - Ferromagnetic material
  - Presence of reed switch
  - Device programming

- Leads:
  - Ferromagnetic material
  - Lead stability

- Patient:
  - Patient position
  - Patient size

Small Potential Risks

- Heating effects:
  - Tissue injury (Mainly theoretical)
  - Strategy to minimize risk: Lead designed to limit current induction

- Mechanical effects:
  - Device movement (Mainly theoretical)
  - Strategy to minimize risk: Limitation of ferromagnetic materials

- Electromagnetic effects:
  - Altered sensing/capture
  - Inhibited therapies
  - Inappropriate therapies
  - (No significant adverse patient outcomes)
  - Strategy to minimize risk: Lead designed to limit current induction, replacement of reed switch with Hall sensor, temporary device reprogramming

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


CBC NEWS
Source: Health Canada & ICIJ
Smart Healthcare – Some Solutions
H-CPS - Multi-Objective Tradeoffs

Non-recurring Design Cost

Recurring Operational Cost

Energy Consumption, Battery Life

Security, Privacy, IP Rights

Performance, Latency

Intelligence

Safety

Source: Mohanty ICCE 2019 Keynote
Smart Healthcare – Edge Vs Cloud

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

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

End Security/Intelligence

Edge Security/Intelligence

Cloud Security/Intelligence

- Big Data
- Lots of Computational Resource
- Accurate Data Analytics
- Latency in Network
- Energy overhead in Communications
Hierarchical ML to Reduce Training Time - Bootstrapping

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

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

Proposed Kriging-Bootstrapped DNN Model

Seizure Signal

Kriging Model

HJC – Hjorth Complexity
ENT – Signal Entropy
PFD – Petrosian Fractal Dimension

Extracted Features

4-Layer Deep Neural Network (DNN) Model

Layer 1
Hidden Layer 1

Layer 2
Hidden Layer 2

Layer 3
Hidden Layer 3

Layer 4
Output Layer

Seizure State

Layer 0
Input Layer
Extracted EEG Features

Experimental Results

Distributed Machine Learning to Reduce Training Time

General Machine Learning
Data needs to be uploaded to the server affecting privacy and data integrity

Federated Learning
No data is uploaded to server


Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
**Model Training or Learning Process**

Our Distributed Kriging-Bootstrapped DNN Model

Experimental Results: Dataset A

<table>
<thead>
<tr>
<th>Models</th>
<th>DNN</th>
<th>Ordinary Kriging</th>
<th>Kriging DNN</th>
<th>Distributed Kriging DNN</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tr. Data Size</td>
<td>10000</td>
<td>2000</td>
<td>10000</td>
<td>10000</td>
</tr>
<tr>
<td>Tr. Epochs</td>
<td>45000</td>
<td>NA</td>
<td>1500</td>
<td>1500</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>0.00001</td>
<td>NA</td>
<td>0.001</td>
<td>0.001</td>
</tr>
<tr>
<td>Training Acc.</td>
<td>99.99%</td>
<td>100.00%</td>
<td>99.92%</td>
<td>99.92%</td>
</tr>
<tr>
<td>Testing Acc.</td>
<td>97.50%</td>
<td>99.78%</td>
<td>100.00%</td>
<td>100.00%</td>
</tr>
<tr>
<td>Training Time</td>
<td>173.57s</td>
<td>72.24s</td>
<td>43.83s</td>
<td>15.56s</td>
</tr>
</tbody>
</table>

Experimental Results: Dataset A

<table>
<thead>
<tr>
<th>Models</th>
<th>Detection Latency</th>
</tr>
</thead>
<tbody>
<tr>
<td>DNN</td>
<td>0.80s</td>
</tr>
<tr>
<td>Ordinary Kriging</td>
<td>0.86s</td>
</tr>
<tr>
<td>Krig-DNN</td>
<td>0.80s</td>
</tr>
<tr>
<td>Dist-Krig-DNN</td>
<td>0.80s</td>
</tr>
</tbody>
</table>

Our Secure by Design Approach for Robust Security in Healthcare CPS

Threat Model

Our Secure by Design Approach for Robust Security in Healthcare CPS

## Proposed Approach Characteristics

<table>
<thead>
<tr>
<th></th>
<th>Value (in a FPGA / Raspberry Pi Platform)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time to Generate the Key at Server</td>
<td>800 ms</td>
</tr>
<tr>
<td>Time to Generate the Key at IoMT Device</td>
<td>800 ms</td>
</tr>
<tr>
<td>Time to Authenticate the Device</td>
<td>1.2 sec - 1.5 sec</td>
</tr>
</tbody>
</table>

Blockchain in Smart Healthcare

Can it preserve privacy?

## Traditional Versus Blockchain EHR

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

Smart-Yoga Pillow (SaYoPillow) - Idea

SaYoPillow: Blockchain Details


Healthcare CPS -- Prof./Dr. Saraju P. Mohanty
SaYoPillow: Prototyping

Smart Healthcare – COVID-19 Perspectives
Comorbidities with Pre-existing medical conditions for COVID-19

- Diabetes (9.2%)
- Chronic Respiratory Disease (8.0%)
- SARS-CoV-2 (COVID-19)
- Cardiovascular Disease (13.2%)
- Hypertension (8.4%)

Impact of COVID-19 on Diabetes Patients

Unbalance Glucose Insulin

Increase the level of Diabetic Ketoacidosis (DKA)

SARS-CoV-2 Connect with Angiotensin-Converting Enzyme 2 (ACE2)

High Blood Sugar

Body is not generating enough insulin to burn excess amount of generated ketones

Cellular receptor (ACE2) binds easily with the virus SARS-CoV-2

ACE2 → damage of pancreas islets → insufficient insulin secretion

Our Intelligent Non-Invasive Glucose Monitoring with Insulin Control Device (iGLU)

Noninvasive Glucometer (iGLU)

Hospital

IoMT-Cloud

Healthcare Provider

Insulin Secretion through Pump

Insulin Pump

Diet Automatic Monitoring and Control for Blood Glucose Level

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 in 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.
- IoE will need robust data, device, and H-CPS security need more research.
- Security of IWMDs needs to have extremely minimal energy overhead to be useful and hence needs research.
- Integration of blockchain for smart healthcare need research due to energy and computational overheads associated with it.
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