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Advancements in Wearable Health Monitoring - Analyzing the Developments of Wearable Sensors and Machine Learning for Epileptic Seizure Detection to improve Athletic Performance

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Abstract:- Wearable technology (WT) is a revolution in real-time data analytics and sports performance tracking. Both new and professional athletes depend on wearable technology to improve their competitive outcomes and training efficiency. However, further studies are needed to gain complete understanding to optimize their full potential in sports. A warning before the onset of seizure is important to improve quality of life (QoL) of athletes who have epilepsy. There is a need to evaluate the feasibility of wearable sensors to predict seizures with machine learning (ML).

Epilepsy poses different challenges to manage and monitor because of unpredictable seizures. Wearable devices provide real-time data collection and constant monitoring to provide insights to trends and patterns related to seizure. Wearable technology is helpful to manage seizure as it allows early prediction, detection, and personalized intervention to empower healthcare providers and patients. This study explores latest advancements in wearable sensors designed for managing epilepsy. The findings of this study has highlighted the importance of wearable devices to improve accuracy in seizure detection, improve patient health with real-time monitoring, and promote data-based decision-making. However, this study recommends further research to validate reliability and accuracy of those devices in different clinical settings and populations. Combined efforts are needed among clinicians, researchers, patients, and technology developers to drive advancements and innovation in wearable technology for managing epilepsy, ultimately improving quality of life and outcomes for people with this neurological disorder.

Keywords:- *Wearable Technology, Machine Learning, Epilepsy, Seizures, Wearable Sensors.*

I. INTRODUCTION

Epilepsy is a prevalent cause of mortality and morbidity, especially among youth, irrespective of technological advances (Beghi, 2020). Accurate tracking and monitoring of seizures are needed to determine the burden of disease, risk of recurrence, and treatment response. Out of hospital, seizure tracking depends upon self-reporting by families and patients, which is usually not reliable because of underreporting, difficulties of patients to recall seizures, and caregivers missing seizures (Elger et al., 2018; Blachut et al., 2017). Even though "electroencephalography (EEG)" is the gold standard for "epilepsy monitoring unit (EMU)" for evaluating epilepsy and diagnosing the same, it is also costly and time-consuming and it can be considered as stigmatizing, and puts a lot of burden on caregivers and patients than using wearable devices and seizure monitoring (Shih et al., 2018). As per previous studies, there is an urgent medical attention and clinical gap to detect a lot of seizures, along with "generalized tonic-clonic seizures (GTCSs)" and "focal to bilateral tonic-clonic seizures (FBTCSs)" with wearable devices (Elger & Hoppe, 2018; Verdhu & Van Paesschen, 2020; Leijten et al., 2018).

Recent advances in developing and using seizure detection devices which are not based on EEG using different modalities and sensors have provided a lot of opportunities to monitor patients in outpatient setting. Some of the great examples are arm-worn and wrist-worn devices, devices on mattresses and chest, which are not much stigmatized and tolerated by patients in long-term use (Beniczky et al., 2018; Bruno et al., 2018; Simblett et al., 2020; Beniczky et al., 2021). In addition, analyzing recording of signals with AI models have improved performance of seizure detection. ML models are trained to detect patterns of signals of seizures automatically.

Early studies have shown the feasibility of using machine learning and, especially deep learning models, to classify and detect seizures as per EEG data (Saab et al., 2020; Asif et al., 2020). Even though similar models are used to monitor data from mobile devices to detect tonic-clonic and tonic seizures (Onorati et al, 2017), detecting other types of seizures with data is limited from wearable devices. It is critically important to ensure non-intrusive, automatic, and reliable approaches to detect additional types of clinical seizure. As per the recent studies published related to health monitoring and wearables, this study analyzes different types of sensors and technologies.

II. LITERATURE REVIEW

Yang et al. (2024) provided an insight to different smart wearables as well as their applications in sports and health, introduced "wireless body area sensor network (WBASN)",

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and categorized machine learning models for connectivity in wearables. In addition, they discussed directions for development and potential challenges which could redefine the future of smart wearables and proposed the right solutions for constant improvement. They provided important insight to great potential of smart wearables to transform sports and healthcare.

Wearable technologies have added fastest growing tools in personal gadgets. Apart from being equipped with modern hardware technologies and fashionable like "communication modules and networking", wearable devices can fuel AI approaches with different valuable data. Several AI techniques like "semi-supervised, supervised, unsupervised, and reinforcement learning" have been widely used for various tasks. Nahavandi et al. (2022) conducted a review of recent wearable applications which have used AI to fulfill those goals. in design and development, the most significant challenge is presented with computation burden of adopting AI models. Finally, they presented future opportunities and challenges for wearable devices.

Healthcare sector is going through a transformative stage from the revolution of "Internet of Things (IoT)", defined by improved financial efficiency, technological advancements, as well as positive social implications. With smooth connection of medical devices, patients, and healthcare providers, healthcare services are provided with improved accuracy and effectiveness. This transformation encourages people to engage in their healthcare management actively and can revolutionize preventive care and medical treatments to improve overall wellbeing globally. Nissar et al. (2024) conducted a review on IoT-based technologies for healthcare. They evaluated current research in a chronological order, focusing on the trends and advancements in this field. They explored the IoT healthcare evolution over time and determined healthcare applications, services, and industry trends related to IoT-based solutions. In addition, they completely analyzed specific "privacy and security" features of IoT needed for smart healthcare, such as, privacy and security, security needs, threat models, and attack taxonomies from the perspective of healthcare. In addition, this study has explored how innovative approaches like Blockchain, cloud, big data, RFID, and ambient intelligence can be used in smart healthcare. Finally, they discussed open issues and challenges related to IoT-based healthcare and provided avenues for future studies as per gaps identified.

Chowdhury (2024) explored the connection of top-performing sports landscape of technologies to improve mental wellbeing in context of changing paradigms in the realm of sporting. The researcher had conducted primary research with digital interviews to know attitudes and perceptions related to mental wellbeing in sports and how adoption and emergence of technologies are playing a vital role in this discourse. From both primary and secondary sources, the acquired insights were organized and synthesized. They explored existing state of technological integration and mental wellbeing in top-performing sports. This study focused on technologies having two vital domains, i.e., developing mental skills and mental health in elite sports.

Epilepsy is a neurological disorder with different origins. An imbalance between inhibition and excitation and hyperexcitability causes seizures. Hence, Habtamu et al. (2023) designed and developed economical, efficient, and automatic device to detect epileptic seizure in real-time. They built the prototype and subjected to various iterations and tests. They tested the proposed device for cost-effectiveness, accuracy, and ease of use. They achieved the acceptable range of accuracy for pulsoxymeter, accelerometer, and vibration sensor readings, as well as prototype which was developed only with component cost of below US$40, barring manufacturing, design, and other expenses. They tested the design to find out if it fits the design requirement and findings of the tests revealed that a lot of scientific processes used are effective to detect seizures. This study is targeted objectively to come up with a medical device with multimodal programs to detect seizures accurately by detecting common symptoms with episode of seizure and informing a healthcare provider for quick support.

➤ *Research Gap*

There is a huge research gap in leveraging wearable sensors and technologies for epileptic care and seizure detection to improve athletic performance.

➤ *Research Objectives*

- To discuss the key hardware and software Wearable Technologies to improve Athletic Performance
- To discuss key functionalities, types, and advancements in Wearable Digital Health Technologies used in Epilepsy Management and Seizure Detection
- To propose Machine Learning-based "Epileptic Seizure Prediction System"

III. METHODOLOGY

To fulfil the above objectives, this bibliographic study is based on secondary data collected through various studies published in databases like Web of Science (WoS), IEEE, Wiley, MDPI, etc. using keywords like "wearable technology", "WT", "sports", "seizure", "epilepsy", "wearable sensors", "machine learning", and others. We refined the search query to cover articles published from 2015 to 2024, written in English language, and related to wearable technology and sports.

IV. DATA ANALYSIS

A. Key Wearable Technologies to Improve Athletic Performance

At its core, wearable technologies (WT) are "Internet of Things (IoT)" devices and have three layers (Figure 1) – network, processing, and sensor. Processor and sensor consist of all operations which are performed only on electronic hardware. In addition, several external devices, communication protocols, and computing approaches are combined into network layer as part of wearable technology.

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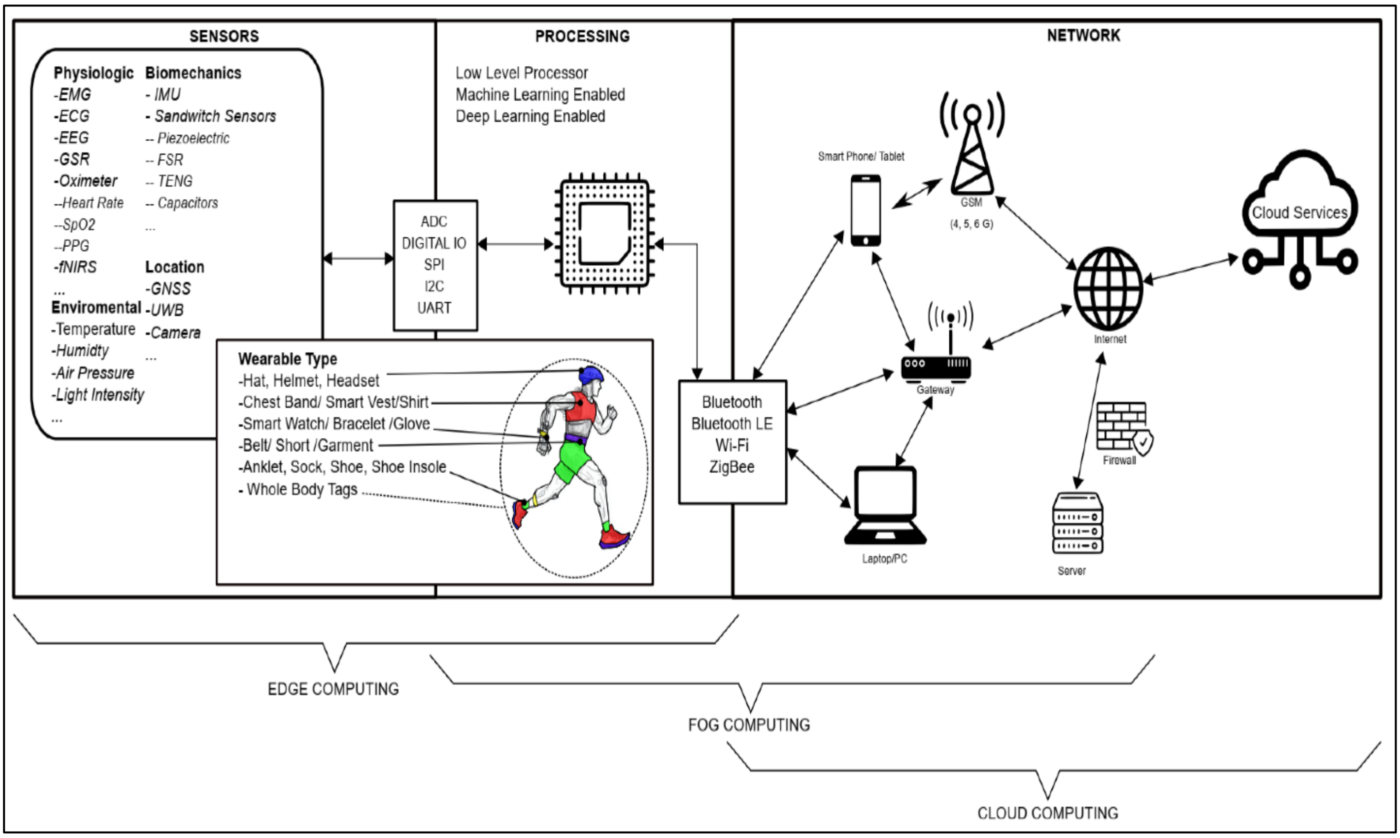

Fig 1 An illustration of WT Layered Structure
Source – Seçkin et al (2023)

➢ *Sensor Layer*

It is the first layer where data collected from the body through different ways is transferred to the processor as signals with "analog-to-digital converters (ADC)", "Inter-Integrated Circuit (I2C)", digital inputs, "Serial Peripheral Interface (SPI)", "Universal Asynchronous Receiver/Transmitter (UART)", and other approaches. In modern sports domain, wearable technologies with sensor systems or sensors provide important data by tracking motion, physiological, position, and environment.

- *Physiological Sensors –*

Physiological data consists of data from biological processes taking place in the human body, working as an important source of data into individual's performance, health, or overall condition. Some of the well-known devices are prominent to capture physiological data among the sensors like "Electrocardiography (ECG), Electromyography (EMG), and Electroencephalography (EEG)." In addition, acquiring physiological data goes way beyond to cover a lot of sensors like "Oximeter, functional Near-Infrared Spectroscopy (fNIRS), Blood Pressure Sensors (BPS), respiratory monitoring sensors, and Galvanic Skin Response (GSR)."

In terms of sports and other fields, "biometric data" is the term is sometimes used to define physiological data collected from athletes (Nithya & Nallavan, 2021; Casher, 2019; Garlewicz, 2020). However, it is vital to differentiate this use from the field of engineering, where "biometric data" consists of data used for identifying people by analyzing their biological events and characteristics (Seçkin et al., 2023). Biometric verification depends on immutable behavioral or physical attributes which are different for each person and it is known to be unalterable. Security systems and governments use biometrics as a strong approach of personal data (Shavers & Bair, 2016). It is worth knowing that data collected from sensors measuring physiological responses of an athlete don't have the same individual characteristic. On the other hand, it is recommended to exercise caution when it comes to apply "biometric data" in athletic research as this misalignment in terminology which can cause ethical or legal consequences and it can also lead to confusion in scientific community.

EMG measures electrical muscle activity. By providing data like muscle strength and contractions, they can provide data on muscle performance and activity (Taborri et al., 2020). Those electrodes are placed to detect electrical signals that come from the muscles. At the time of muscle relaxation and contraction, neurons produce electrical signals in the muscle fibers. It is related to the changes or movements of muscles. EMG electrodes record and identify the electrical muscle activity by recording the same. The EMG signals are obtained and recorded with data recorders and amplifiers. EMG signals show the duration, magnitude, coordination, and timing of contractions of muscles.

The technique of ECG provides data and records cardiac activity on cardiovascular health, cardiac arrhythmias, and "heart rate variability (HRV)" (Leite et al., 2016; Sarubbi et al, 2023). ECG is an important tool to evaluate performance

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and health of athletes as "metabolic demand", "autonomic nervous system control", and cardiac adaptation can be reflected to exercise. ECG is a vital tool to monitor performance and health of athletes, assess heart health, and optimize exercise programs (Löllgen & Leyk, 2018). ECG electrodes are positioned on certain locations of limbs and torso to gather signals created by repolarization and heart depolarization. Some of the commercially available wearable technologies like wristbands and smartwatches claim to detect ECG, but they determine "single-lead ECG" which is ideal to detect cardiac disorders or training load than offering modern ECG analysis (Isakadze, N., & Martin, 2020; Sarhaddi et al., 2022). The traditional ECG acquisition is usually intrusive and inconvenient as it needs various wires and electrodes which may interfere with natural athlete movement.

EEG sensors monitor electrical brain waves and provide brain activity data (Thompson et al, 2008; Perrey & Besson, 2018). Such data can offer data on brain activity, concentration, and sleep quality of an athlete. EEG places metal plates known as sensors or electrodes on the scalp. They can detect electrical activity. Usually, the electrodes are placed at certain points on the scalp for capturing electrical signs from various brain areas. Neurons or brain cells generate and transmit signals. It is because of possible differences generated as neurons to communicate with one another. EEG electrodes record and detect such activities to obtain patterns in brain wave. EEG signals include various components like "high-frequency and low frequency brain waves." They can reflect various brain activities like wakefulness, sleep, focus, or various mental conditions (Casson, 2019).

- *Biomechanics Sensors –*

It refers to application of principles of mechanical engineering to living organisms and it includes studying at joint levels and tissue levels (Koff, 2015). It forces biological systems and includes impact of forces on the human body (Howell, 2019). In this scope, motion data includes sensors to monitor muscle activities and skeletal movements of athletes. For motion sensing, primary sensor used in sports is the IMU and other sensors like EMG sensors and force sensors. IMU is a kind of "microelectromechanical system (MEMS)" sensor which includes various sensors. An IMU consists of gyroscope, accelerometer, and magnetometer sensors. The accelerometer can track changes in acceleration due to forces applied. Compass measures the position of the sensor as per the magnetic field of Earth. The gyroscope evaluates the volume of angular rotation. The compass supports sensor for fusion with gyroscope and accelerometer to evaluate the magnitude and direction of motion (Fonseca et al, 2019; Wilk et al., 2020; Waqar et al., 2021). IMU sensors serve different purposes like posture analysis, swimming, and tracking workout (Kos & Umek, 2018; Benson et al., 2018; Ahamed et al., 2018). Different sensors can be used for motion and force detection in sports. Some of these are sandwich ones like resistor, piezoelectric, magnetic elements, and capacitor (Kos & Kramberger, 2017; Liu et al.,2019; 2022; Gao et al., 2022; Kreil et al., 2008).

- *Location Sensors –*

They can track changes in position and movements of athletes. Some of the most important wearable positioning systems are "Ultra-wideband (UWB) positioning" systems, "Global Navigation Satellite System (GNSS)", Bluetooth, Wi-Fi, wearable marker positioning, and RFID systems (Rico-González et al., 2020; Waqar et al., 2021; Liu et al., 2023). Some of the most widely used approaches are UWB, GNSS, and camera-based systems for marker positioning.

- *Environmental Sensors –*

These sensors track environmental conditions like humidity, air quality, air pressure, temperature and level of UV light (Li et al, 2016; Kamišalić et al., 2018). They can track environmental conditions where athletes are there. Air quality sensors track the impact of factors like allergens and air pollution by tracking respiratory conditions of athletes at the time of exercise. Humidity sensors monitor humidity levels in the environment, while sensors track changes in temperature. Air pressure sensors monitor changes in atmospheric pressure and can calculate altitude. UV sensors track exposure to sunlight for athletes.

- *Processing Layer*

It is the second layer which is either single-board processor or microcontroller which can be integrated in physical boundaries of wearable technology. The processors and microcontrollers have low-level potential in terms of processing power, memory, and operational time. Edge computing can be performed only with hardware to another layer, enabling creation of feedback with methods like feature engineering, signal processing, machine learning, or data compression. Actuators like LEDs, screens, speakers and vibration motors on wearable technologies help in interaction between humans and computers by producing alerts or responses. Tasks in wearable technology like SpO2 measurement, heart rate monitoring, and step counting. They don't cover wireless communication and at the level of edge computing. To manage more complicated tasks, wireless communication helps in achieving access to third and fourth layers and it needs higher processing potential.

Existing wearable units can be categorized into three levels as per their power consumption, processing capabilities, features and size – ML-enabled microcontrollers, low-level microcontrollers, and single-board computers. The parameter of memory capacity and processing capacity measures computation of memory and processing unit. Processing power evaluates the complexity and types of tasks which can be done by processing unit like signal processing, data acquisition, and machine learning. Memory affects the pace of data access, storage capacity, and power consumption. Power consumption evaluates heard dissipation, battery life, and processing unit size.

- *Network Layer*

Wearable technologies have size and power limitations, limited processing capacity, and require data in the process with wireless communications like Wi-Fi, Zigbee, and Bluetooth if they need more complex outputs. Wireless technologies communicate wirelessly in the third layer to

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transmit data with higher processing potential like smartphones, computers, gateways, and other devices to produce smarter output. At this level, the computational operations are known as fog computing. Cloud computing can be used if these devices hardly perform the operations needed or when more modern services are required. Fog computing consists of processing of data at closest gateways or cloud solutions with higher processing. At this level, data is transmitted to cloud services for data mining, deeper analysis, and various complicated operations. For cloud computing, wearables communicate with servers directly with high processing potential, either through computer, smartphone, or gateway device or stand-alone.

B. Functionalities, Types, and Advancements in Wearable Digital Health Technologies

Wearables are electronic devices used for tracking fitness, health and other data (Hayes, 2022). These devices include smart glasses, smartwatches, implants, and fitness trackers that are powered by sensors to analyze, detect, and transfer data like ambient information, vitals, and biofeedback (Hayes, 2022). They are used for different purposes, like entertainment and communication to fitness and health improvement (Hayes, 2022). There are different applications of wearable technology in different fields like medicine, health, aging, fitness, education, disability, enterprise, transportation, gaming, finance, and music (Happiest Minds, 2022). Wearable devices are mainly used to integrate into daily lives of people and improve efficiency in different sectors.

Challenges like addressing concerns related to data security and ensuring customer engagement are important for a large-scale adoption of wearables (Happiest Minds, 2022). Wearables have been an important aspect of daily life, offering real-time potential for tracking data resulting in physical performance improvement and health monitoring in sports sector (Builtin, n.d.). Additionally, they provide immersive gaming with devices like haptic feedback and VR headsets (Builtin, n.d.). The fashion sector has embraced wearables with innovations like smart rings used for tracking sleep patterns or steps and smart jackets having sensors to regulate body temperature (Builtin, n.d.). Figure 2 illustrates the types of wearables.

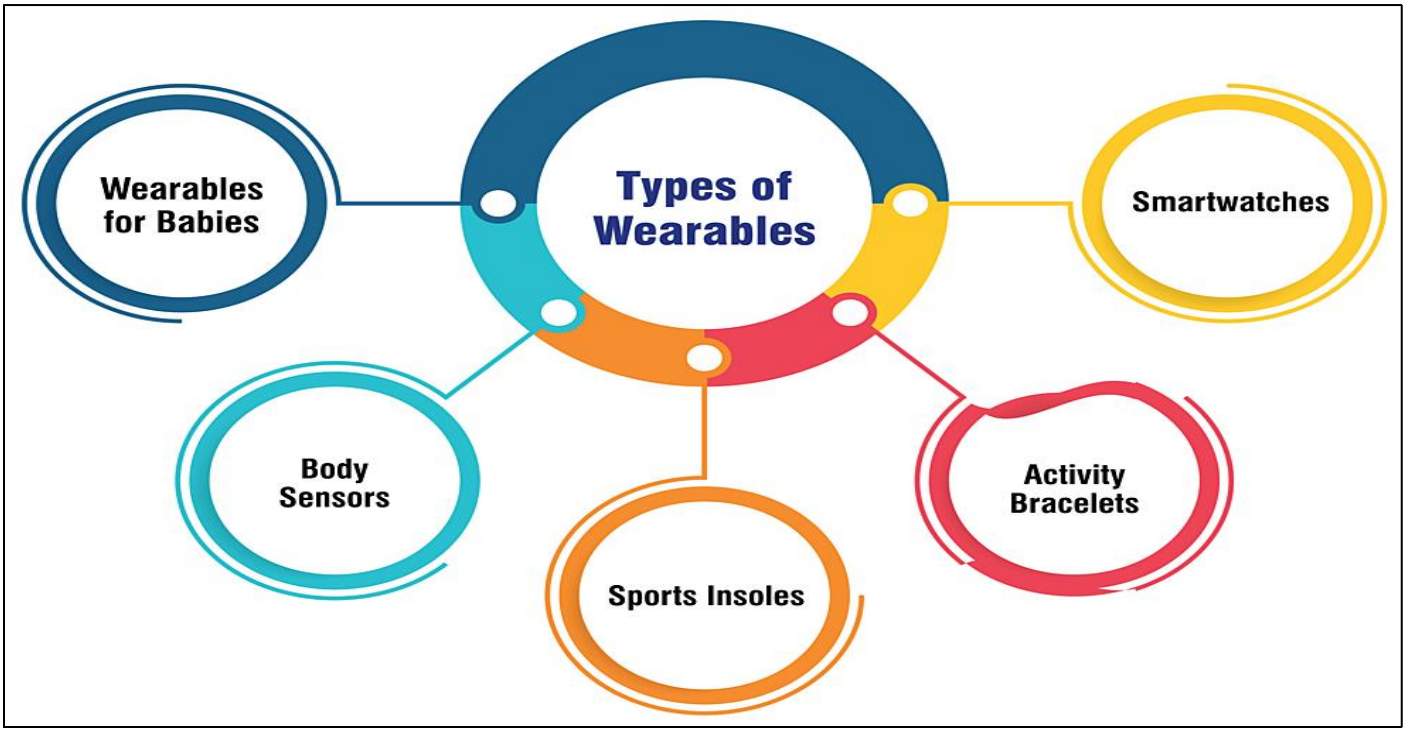

Fig 2 Types of Wearables
Source – Ahuja et al. (2024)

➤ *Key Functionalities and Features for Epilepsy Wearables*

Wearables serve different functions like managing and tracking epilepsy, using different physiological signals for proper intervention and assessment. These devices use sensors to gather physiological signals like electrodermal activity, accelerometry, EEG, photoplethysmography, and electrodermal activity, resulting in quality data that is used for routine tracking (Ong et al, 2022). Innovations in wearables range in extracerebral monitoring of signals, exemplified by devices like ambulatory EEG systems and in-ear EEG devices, offering non-invasive monitoring (Johansson et al, 2018). Those advancements extend the scope of monitoring to improve comfort and accessibility for patients going through epilepsy management. One important aspect of wearables in managing epilepsy is differentiation and seizure detection, especially in hospitals.

Wearable devices are vital to differentiate and detect seizures, help in tailored management and timely intervention (Ong et al, 2022; Johansson et al, 2018). In addition, wearables integrate prediction solutions as per heart signals, using machine learning models to achieve specificity and sensitivity levels (Ong et al, 2022). These prediction solutions improve proactive epilepsy management by identifying potential episodes early on. Complementing alarm and prediction systems embedded in wearables result in improved monitoring. For example, ethernet motion sensors are designed to detect motion irregularities in epileptic patients, resulting in added layer of alerting functionalities and added layer of monitoring (Ong et al, 2022).

Wearable devices have resulted in drastic shift in epilepsy management, advancing well-being and patient safety with predictive capabilities, real-time monitoring, and improved alarm mechanisms (Ong et al, 2022). These technological advancements underline transformative improvement in epilepsy care with wearable technology. Figure 3 illustrates some of the key functionalities and features of wearables for epilepsy management.

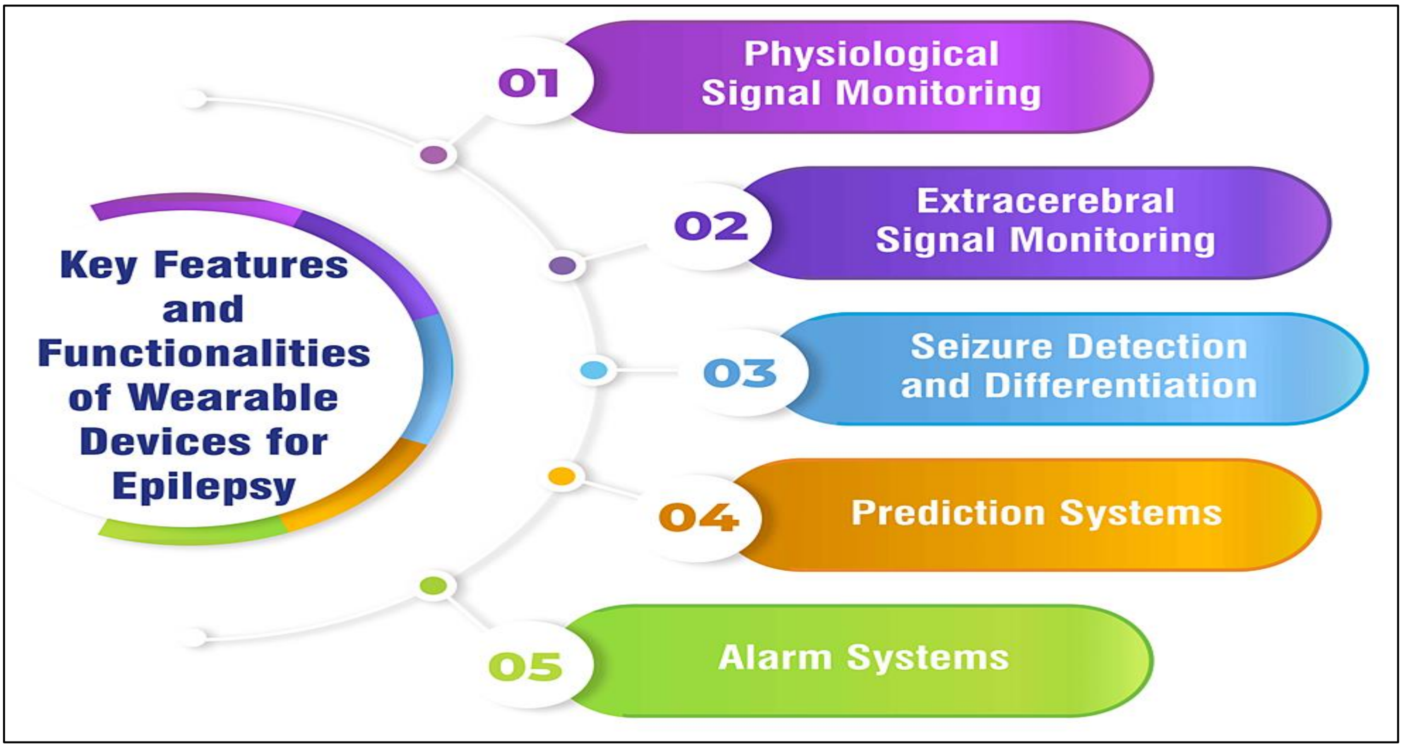

Fig 3 Key Functions and features of Wearables
Source – Ahuja et al (2024)

- *Advancements in Wearables for Epilepsy Management*

- *Seizure Detection*

✓ *Sensors and Algorithms –*

Wearables made for seizure detection have literally advanced epilepsy management. A recent study has determined the efficiency of ML models in combination with wearables like electrodermal activity, body temperature, photoplethysmography, and accelerometry when it comes to detect seizures. It is observed that these models can detect different types of seizures more accurately. It provides non-stigmatizing tool to improve overall health outcomes and lifestyle quality of patients (Tang et al, 2021). These digital and wearable health technologies constantly track and monitor seizure, providing valuable data for proper epilepsy management. They use different technologies like motion sensors, EEG data, and heart rate monitors for seizure detection and predict the odds of future episodes for personalized treatment and early intervention plans (Ahuja et al, 2024). Though these devices provide real-time alerts to caregivers and patients and reduce the risk of premature death, they have certain issues. For example, they may not be able to detect all kinds of seizures or everyone cannot afford. It is important to work with healthcare providers to choose the best device as per factors like accuracy in detecting type of seizure, false alarm, comfort, and budgets (DerSarkissian, 2023).

✓ *Real-Time alert and Monitoring –*

A sturdy wearable device has been designed for automated epileptic seizure detection using sensors like pulse oximeters, accelerometers, and vibration sensors to track heart rate change, body movement, jerky movements, and oxygen saturation (Habtamu et al, 2023). This device aims to detect epileptic seizures economically and efficiently in real-time, offering a promising solution for improved patient care. Wearable technology helps in seizure monitoring and detection. Smartwatches are the devices used to respond to constant shaking resulting in seizure by alerting loved ones or caregivers for quick support (Epilepsy Foundation, n.d.).

Though there are different benefits of wearable devices like detecting seizure defined by movements, they may not detect all types of seizures and can be expensive for some people. It is observed that using wearable sensors and machine learning models can help in detecting different seizures automatically with utmost accuracy (Tang et al, 2021). These advancements in wearable technology not just

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improve lifestyle for people with epilepsy, but also reduce mortality related to seizures, especially in environments with lack of resource where there is a limited access to treatment and expertise (Rukasha et al, 2020).

➢ *Seizure Prediction*

- *AI and Machine Learning for Predictive Analytics –*

Advancement in wearables for epilepsy tracking and management have come a long way. Researchers are using wearable devices and ML models for predicting seizures to improve patient's quality of life and safety (Tang et al, 2021; Sylver, 2022; Yamakawa et al., 2020). These innovations result in development of wearable devices and algorithms which analyze the brain wave of patients in real-time for predicting seizures, empowering people with epilepsy to take proactive steps like administering medication or looking for safe environment to anticipate imminent seizure (Sylver, 2022). ML models are widely used to reduce false alarms and improve precision in prediction, which is very important for drug-resistant epilepsy (Tang et al, 2021).

In addition, wearable devices are designed for predicting seizures with anomaly detection in changes in heart rate, showing the potential for predictive and non-invasive methods which can be integrated well in smartphones and smart devices (Yamakawa et al., 2020). It is observed that feasibility in using deep learning algorithms can detect seizures automatically and classify the types of seizures as per EEG data, which lays the foundation for more tailored and accurate seizure management (Tang et al, 2021). To summarize, these advancements highlight the synergy between machine learning models and wearable technology to promote early detection, personalized care, and intervention for people with epilepsy, and to transform epilepsy management.

- *Feedback Systems –*

Wearables for seizure prediction has resulted in a lot of strides over the years, especially in ML-based anomaly detection of "heart rate variability (HRV)". Yamakawa et al. (2020) have devised wearable "epileptic seizure prediction system" and used ML models to compute T2, scrutinize HRV indices, and Q values to detect anomalies. This system has provided promising results to predict seizures as per HRV information. In another approach, wearable technology is used to predict the odds of seizures by analyzing biomarkers of epileptic cycles and seizure. For example, temperature and heart rate are the biomarkers (Stirling et al, 2021). Seizures have been known to sync with underlying multi-day and circadian cycles in heart rate, showing the tendency for seizures to take place at specific levels of heart rate cycles (Stirling et al, 2021). Along with HRV analysis, wearable sensors and ML models are used for seizure detection (Tang et al, 2021). These devices can detect physiological signals and anomalies like skin conductance, changes in heart rate, onset of seizure, and acceleration (Li et al, 2022). All in all, wearable devices are promising in personalized prediction for seizure forecasting and detection, improving the quality of life for epileptic people with early intervention and detection and personalized strategies (Stirling et al, 2021).

➢ *Seizure Management and Tracking*

- *Data Analysis and Visualization Tools –*

Healthcare outcomes can be improved by developing data analysis and visualization tools designed for wearable technology. A data analytics dashboard, CarePortal, was developed to interpret and visualize wearable data (Sadhu et al, 2023). Researchers have used a participatory design with doctors with innovative web application to manufacture symptomatic data garnered from smartwatches (Sadhu et al, 2023). Wearables are used to improve lifestyle by mining physiological data. Designing algorithms is important to interpret raw data from wearable devices. It can promote precise diagnosis and personalized care in peer group (Angelides et al, 2018).

Attractive visualizations are important to reveal relevant patterns in health from wearable devices to capture vital data in different sensors. It is an iterative process which helps decipher health patterns and make informed decisions as per amassed data (Suter et al, 2022). Researchers have used observational data from wearables and consumer apps to scrutinize health, delineating best practices to track large-scale data gathered with regular use of smartphone apps and commercial wearables. These analyses are based on weight, physical activity, sleep, diet, heart rate monitoring, and blood pressure (Hicks et al, 2019). The combination of data science, AI, and wearables resulted in transformative stage in automative tasks, healthcare, providing personalized plans, dividing vast datasets for instant diagnosis, tracking chronic illnesses, and bolstering efficiency and accessibility in healthcare (Bajwa et al, 2021).

- *"Electronic Health Records (EHRs)" and Wearables -*

Integrating EHR with wearable devices shows a lot of strides in healthcare technology. With real-time synchronization among wearables and EHR, healthcare providers can track patient health signs and improve treatment outcomes (Prajapati, 2022; Syscreations, 2023). It promotes smooth transfer of vitals data to EHR from wearable devices, removing manual intervention and ensuring timely and accurate access to health data of patients (Prajapati, 2022). Integrating wearables with EHR and augmenting remote capabilities for patient monitoring helps healthcare experts to constantly track health outcomes of patients and increase care (PrognoCIS, 2024).

In addition, this integration makes telemedicine practices easier, helping care providers with complete vista of healthcare data of patients while proving improved coordination (PrognoCIS, 2024). Wearables like smartwatches, fitness bands, and sensors can smoothly transmit data like activity levels, heart rate, sleep patterns, etc. to improve the quality and quantity of data to caregivers (PrognoCIS, 2024). In essence, interoperability is promoted by the fusion of EHR systems and wearable technology. It makes the process of data collection easier and augments patient care with telemedicine and monitoring initiatives (Prajapati, 2022; Syscreations, 2023; PrognoCIS, 2024). Integrating with EHR programs improves quality care and

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patient outcomes (Prajapati, 2022; Syscreations, 2023; PrognoCIS, 2024).

C. Machine Learning-based "Epileptic Seizure Prediction System"

The wearable system mainly includes the time between two R-waves of QRS ECG signals, i.e., R-R interval (RRI) along with a smartphone. A lot of wearable monitors for tracking heart rate are available commercially. They have limited functions. The proposed system needs over 500 Hz of sampling rate for HRV data analysis, automated control, and device-based RRI calculation in real-time to reduce smartphone's calculation load. Hence, Yamakawa et al. (2020) developed a telemeter to realize functions in a lightweight and small design in the upper part of Figure 4.

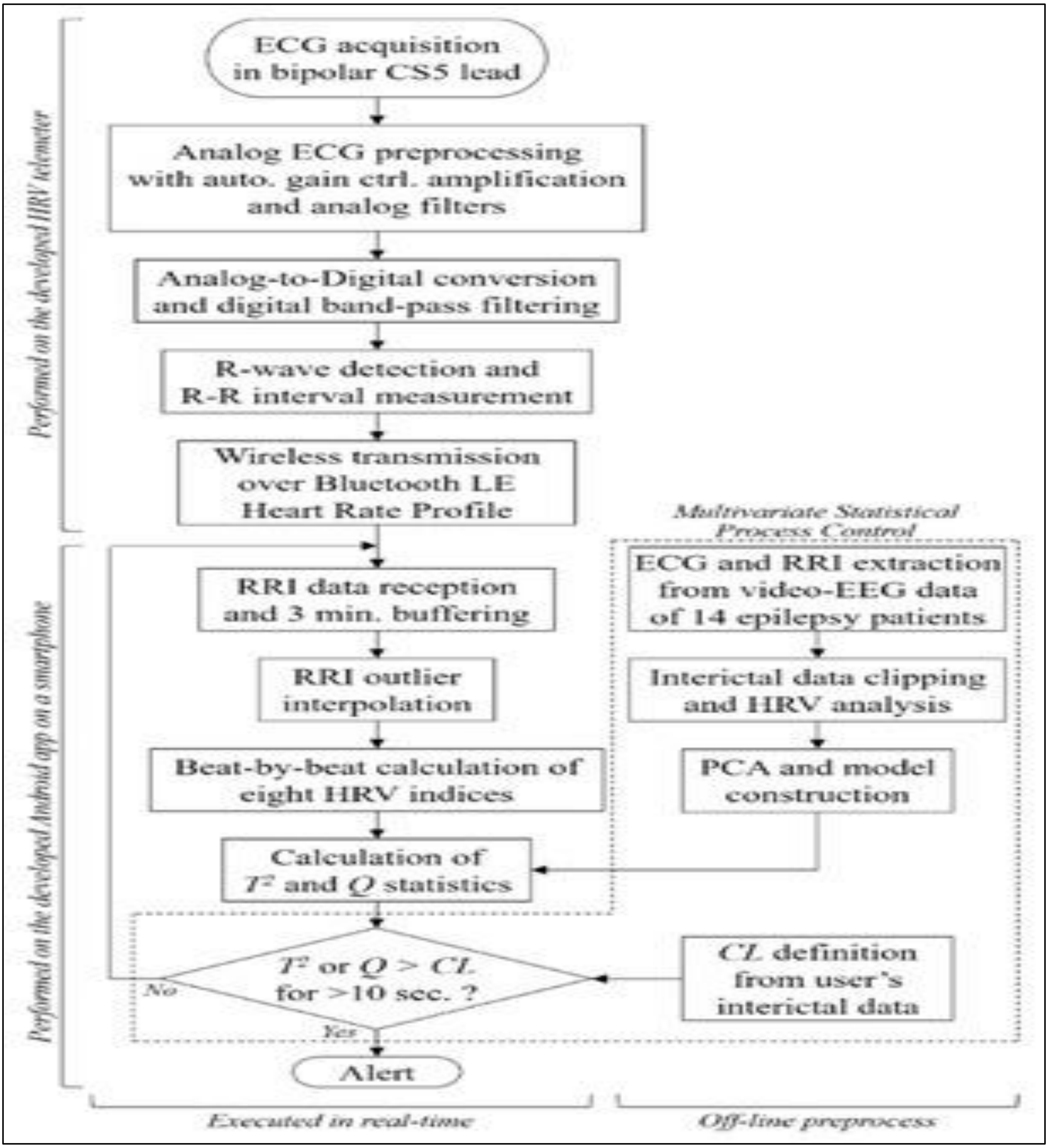

Fig 4 A Flowchart and Overview of Seizure Prediction System
Source - Yamakawa et al. (2020)

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Figure 5a illustrates a telemeter for measuring EEG's RRIs in a block diagram. The device has 12mm thickness and 74x34 mm dimensions, exclusive of three 1m wires of ECG lead (Figure 5b), along with a long battery life for wearable applications. The telemeter consists of front-end analog circuitry which amplifies the ECG signal coupled by AC from 3 disposable electrodes with arrangement amplifier and cuts noise with a "variable gain low-pass filter" and 50/60 Hz notch filter. Preprocessed in analog front-end, ECG signals are tested by "1 kHz 10-bit analog-to-digital converter" and analyzed with R-wave threshold-based detection" (Yamakawa et al, 2007) in a "cortex-M0 microcontroller". The sampling frequency could support EEG video data sampled with 1 kHz used for validation of phase 1 (Fujiwara et al, 2015).

In a simple discrimination of threshold, the "P- and T-waves (with same polarity as R-waves in Standard Lead II configuration)" and low-frequency drift of baseline of ECG signals may result in "R-wave" false positives. Accordingly, a "quasi-band-pass" filtering" evaluates the width of the pulse in digitized electrocardiogram and sends the same to a comparative with 3-50 ms of pulse width. The RRIs are transmitted and counted by a timer to a smartphone through a wireless "Bluetooth 4.0" connection, which operates under the heart rate profile of a smartphone. For 60 beats, the RRIs are stored in the memory of the telemeter to avoid the loss of data because of transmission errors (Yamakawa, 2012; Yamakawa et al, 2013).

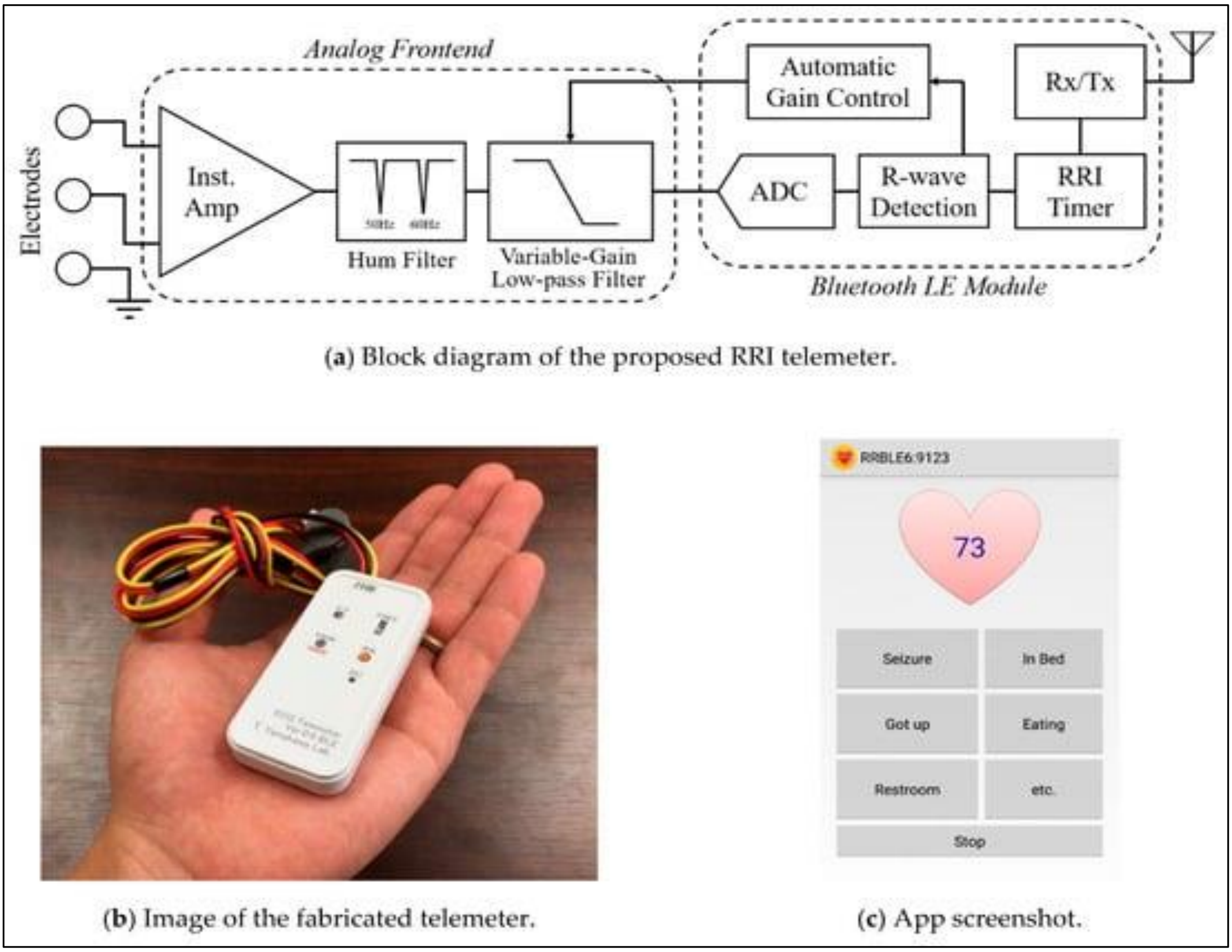

Fig 5 (a) A block diagram of for measuring RRIs; (b) RRI telemeter; (c) memo buttons in an Android app (heart rate is shown on the heart while tracking)
Source – Yamakawa et al. (2020)

In Figure 5(c), the proposed Android application analyzes and receives RRI data to originate HRV indices of autonomous nervous activities in real-time. For epileptic seizure prediction, the HRV indices includes 4 "time-domain indices, standard deviation of RRI (SDNN), mean of RRI (meanNN), root mean square of the differences of adjacent RRIs (RMSSD), and the number of pairs of adjacent RRIs" with difference above 50ms in the given "length of measurement time (NN50)" (Malik et al, 1996). HRV indices are based on frequency/statistical analysis of 3-minute window.

V. RESULTS

Wearable devices act as a promising solution to track different health metrics. However, their reliability and accuracy are subject to variations in several parameters. These devices have been very accurate in lab settings when it comes to measure heart rate (Fuller et al, 2020). Some brands like Fitbit, Garmin, and Apple Watch are likely to perform better in heart rate monitoring, even though there are differences in accuracy among device brands (Fuller et al, 2020; Shei et al, 2022). Wearable devices are accurate in measuring step count in controlled settings. There are still variations in device type and brand. Brands like Samsung and Apple Watch are less studied but they have consistent measurements of step count in tight ranges (Fuller et al, 2020). Wearable devices should be more accurate to estimate energy usage.

Fitbit devices are more likely to measure energy use in acceptable range. There is a lot of variability in estimates and accuracy may vary as per specific model (Fuller et al, 2020). More accuracy may be needed in wrist-based activity trackers when it comes to estimate oxygen saturation for healthcare applications and sports. Even though devices like Garmin and Apple Watches are more accurate than other brands, they still need to undergo proper validation (Shei et al, 2022). There is limited research on reliability and accuracy of wearable devices for epilepsy monitoring. It is vital to consider overall reliability and accuracy of those devices when it comes to evaluate their potential to manage and monitor epileptic seizures (Brinkmann, 2021). Wearable devices are highly promising in different health metrics. It is important to consider their reliability and accuracy for proper use in healthcare.

There are several challenges wearable technology is facing related to data security, user acceptance, and ethical concerns, requiring proper implementation (Challener, 2020). It is observed that people using smartwatches for reminders related to medication timings have shown improvements when adhering to treatment plans (Challener, 2020). Chronic illnesses drastically affect the apprehensions and acceptance of innovative sensors for health monitoring (Materia & Smyth, 2024). Hence, it is vital to understand those parameters in future studies to devise effective interventions to meet unique needs.

Closed-loop systems can be developed for personalized intervention as they are promising to improve treatment efficiency and health outcomes. These systems use real-time tracking and wearable technologies to provide personalized and integrated solutions to patients to improve their health (Johnson et al, 2021). Healthcare providers can manage interventions designed to meet unique needs for more targeted and effective care (Yang et al, 2019). In this domain, research endeavors are focused on designed closed-loop, personalized controllers for different applications like handling medical comas in ICUs (Yang et al, 2019). These systems track intra-and inter-subject varieties in response of the brain to treatments like anesthetic infusion, boosting therapy deliveries, and promoting accurate control (Yang et al, 2019).

By integrating real-time tracking, closed-loop solutions can improve clinical feasibility, control accuracy, and reduce interruptions (Yang et al, 2019). These systems surpass traditional interventions to cover stimulation of brain for bioenergy treatments and mental disorders for integrated care (Zhang et al, 2023). New avenues have been opened by these innovative approaches for effective and personalized interventions, laying the foundation for integrated and smart medical systems designed to meet unique patient needs (Zhang et al, 2023). All in all, the closed-loop advancements proclaim vast stride in healthcare by providing personalized care to improve treatment outcomes and patient care.

It is important to address disparities when it comes to access wearables to ensure ideal health outcomes. Studies have focused on a lot of inequalities in using wearable devices with factors like education, income, and age on the impact of adoption among people with risk of heart disease or with cardiovascular disease (American Heart Association, 2022). Focused efforts are needed to position wearables and improve access to various health tools to mitigate disparities and improve healthcare outcomes. Education and cost are known to play a vital role in access to wearables, focusing on the affordability and awareness of those devices in marginalized communities (Raza et al, 2023).

VI. CONCLUSION

To conclude, this study has discussed the vital role that wearable technology plays in epilepsy management, addressing the challenges in previous approaches will exploring new avenues of personalized care. With real-time data collection and constant monitoring, these devices provide important insights to trends and patterns in seizure, enabling healthcare providers and patients to make informed decisions while taking proactive measures. Implications are significant for clinical practice as wearables enable more timely and comprehensive interventions, potentially improving quality of life and health outcomes for people with epilepsy.

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