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A LOW LATENCY AND LOW POWERED FALL DETECTOR FOR EPILEPSY

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Abstract: Epilepsy, a pandemic disorder affecting 50 million people (about twice the population of Texas), drives the urgent search for a reliable and quick detection tool. This paper introduces a comprehensive fall detection system that integrates state-of-the-art MEMS (Micro-Electro-Mechanical Systems) sensors, including accelerometers and gyroscopes, with cutting-edge edge computing, heart rate sensors, and temperature sensors. Falling incidents pose a significant risk, especially among the elderly and individuals with mobility impairments, necessitating effective and timely detection mechanisms to ensure prompt assistance and mitigate potential injuries. The proposed system addresses this imperative by harnessing the collective capabilities of MEMS sensors, which continuously monitor and analyze the user's movements in real-time. Incorporating sophisticated algorithms and leveraging the computational power of edge computing infrastructure, the system processes sensor data autonomously, swiftly identifying patterns indicative of a fall. By executing the fall detection algorithm directly on the device, edge computing circumvents the limitations of traditional cloud-based solutions, ensuring minimal latency and enabling rapid response even in environments with limited network connectivity.Moreover, the integration of heart rate sensors enhances the system's capabilities by providing valuable insights into the user's physiological parameters. Additionally, temperature sensors offer contextual information about the user's surroundings, enabling the system to assess environmental conditions and factor them into the fall risk assessment process.

Keywords : Fall detector, Epilepsy, IoT (Internet of Things), Edge computing , Smart healthcare,Biomedical applications, Real-time monitoring ,MEMS sensor, Edge-based fall detection.

I.INTRODUCTION

Now, the conventional healthcare system is not coping well with a burgeoning population. Smart healthcare IoT-based solutions will provide possibilities of upgrading the existing healthcare infrastructure and the growing population replacement. The IoMT, which are the subset of the Internet of Things including medical and biomedical applications and equipment, is the basis of smart healthcare systems. Smart healthcare, an enabling approach, gives users means to handle some emergency situations on their own, emphasising on their life quality and experience rather than several medical interventions. Resource optimization is enabled by smart health management and is one of the prime points.

One of the most popular examples of smart healthcare is an automatic identification of epileptic attacks. Around 1% of people around the globe are affected by epilepsy, a chronic neurological syndrome that is characterised by loss of consciousness, uncontrolled movement or convulsions (4-6). Individuals with epilepsy find it difficult to carry out basic daily chores, and thus timely and accurate seizure detection can reduce both the financial and human losses. The first step in treating epilepsy is through the administration of medications known as antiepileptic drugs (AED).In comparison, the studies claim that some epilepsy patients do not respond or do not get any solution from medications, and AED is ineffective for drug resistant cases. Severe refractory patients are subjected to prolonged recurrent seizures that seriously affect their capacity to carry out scheduled tasks. In limited circumstances, surgery can be done, but it is not as common as treatment even when the latter fails. The growing need for wearable and automated devices, that are embedded with medical sensors, is evident to tackle biomedical diseases. The fact that an automated seizure detection system is necessary makes itself manifest, which assures quick seizure detection and early warnings and can help to take some timely preventive measures.

Electroencephalography (EEG) on the other hand, gives signals from the brain with corresponding electrical waves. This is very useful when considering this issue. Through EEG, the electrodes are placed on the brain in various areas during the process of recording the electric voltage so that the different psychological states are captured along with the brain dynamics. Visual identification of seizures is, on the one hand, quite costly and, on the other hand, is extensively labour consuming for physicians because it takes up a lot of time for physicians to carry out examinations for epileptic patients and monitor their behaviour over a long period.In a parallel endeavour, this paper explores an innovative application involving the integration of a temperature sensor and edge computing technology to enhance healthcare monitoring capabilities. Specifically, a wearable device, such as a smartwatch, has been equipped with Micro-Electro-Mechanical Systems (MEMS) sensors programmed to monitor temperature alongside existing features like acceleration and SpO2 levels.The temperature sensor adds a crucial dimension to the monitoring system, allowing for continuous tracking of the wearer's body temperature. Fluctuations in temperature can serve as early indicators of various health conditions or infections, providing valuable insights into the wearer's overall health status. This additional parameter, when combined with the existing MEMS accelerometer and SpO2 monitoring, creates a comprehensive and multi-faceted health monitoring system.Operationalizing the fall detection system, the MEMS accelerometer continues to play a pivotal role in monitoring movement patterns and identifying abrupt changes indicative of a fall. Simultaneously, the temperature sensor contributes to a more holistic understanding of the wearer's health, providing context to the detected events.

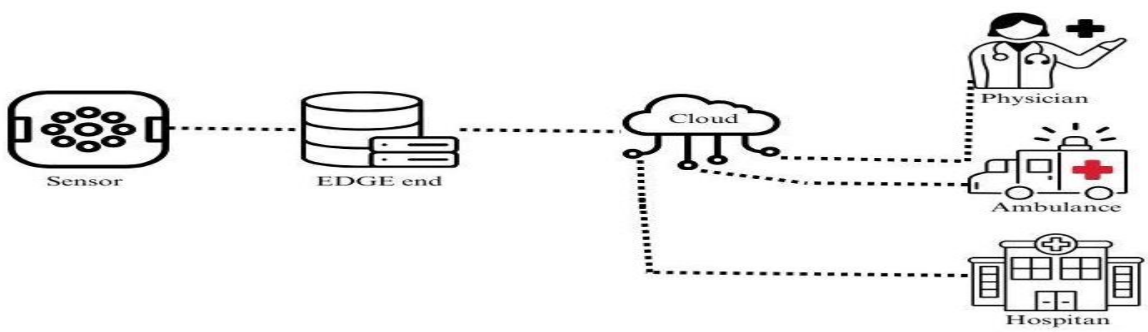

Fig.1 Proposed edge model

II.RELATED PREVIOUS RESEARCH

A novel algorithm has been developed that utilises BRRM (Brain Recurrent Biomarkers) recurrence biomarker and the DNA structure makeup of the 1-aminocyclopropane-1-carboxylate oxidase (ACO) gene, leveraging non-linear EEG complex dynamics for signal analysis. Transfer learning is applied in the design of ONAS Net for EEG data analysis, allowing for the extraction of features from different brain zones through the combination of BRRM and ONASNet. Addressing the challenge of manual data labelling, an approach based on unsupervised learning (UL) is presented, facilitating data annotation. Additionally, supervised learning (SL) techniques enhance the classification of intermediary terms, marking a new frontier in deep learning that combines UL with SL for improved seizure detection.In a unique exploration of the ventral perturbative prefrontal cortex, a New Neural Mass (NNM) targeting epileptic conditions is introduced . The EEG is considered as the model's parameter, and the subsequent stage incorporates Dynamic Feedback (DF) for early seizure detection. The NNM-based approach achieves 100% sensitivity and a scalar latency of 7.1 seconds. Another innovation is presented in [18], proposing an autoencoder that integrates the RDCS AE (Recurrent Deep Convolutional Sparse Autoencoder) stack. This autoencoder, utilising both single and multi-channels, analyses EEG features, extracts signals, and decodes features without supervision. The decoded information is then fed to the KRVN (Iterative Krawtchouk Variational Fisher Linear Network) classifier during training. Efficient training is achieved by modifying the cost function, marking a successful approach with high classification accuracy.

To gain deeper insights into the experiences of those who have undergone seizures, encouragement is extended to share stories on IKR FLN. This collaborative effort aims to enhance understanding of this condition. Overall, these advancements in algorithmic approaches and neural models showcase a multifaceted and innovative direction in seizure detection and analysis, combining various techniques to achieve superior classification accuracy and sensitivity.

A robust method is documented for seizure detection employing a Complex Deep Neural Network (CDNN), comprising both the model and Adversarial Representation Learning (ARL). This CDNN model recurrently captures seizure and non-seizure events by leveraging EEG dynamics through Adversarial Learning. The proposed method's latency was assessed using the EEG TUH dataset, showcasing a notable reduction in latency. An epileptic seizure detector model is introduced, utilising both spectral and temporal domains to address challenges tackled by deep learning models. Evaluation on three distinct datasets, including CHIB, MIT, T^{2.5} SCALP, Bonn, and TUSZ, demonstrates the versatility and effectiveness of the model.

Innovative technology altered by a cortical microelectrode array (MEA) offers a novel approach to producing human epilepsy seizure signals. This technology, working with variations in support vectors known as nonlinear neural networks (SVMs), effectively detects seizures and non-seizures based on different features. In the context of seizure control, intracortical MEAs prove useful for synchronous control. A technology-efficient approach for seizure detection is described [21], utilising the Stockwell transform (S-transform) for time-frequency domain blocks and a bidirectional long short-term memory (BiLSTM) classifier. Postprocessing of EEG signals enhances early-stage detection and overall performance.The hybrid seizure detection approach combines continuous EEG (cEEG) and amplitude-integrated EEG (aEEG). In cEEG-based approaches, EEG signals are sliced into 5-second time frames, and feature extraction involves filters with a 4-second overlap. The random forest classifier is employed for seizure detection. In scenarios involving aEEG, spike detection is utilised. Additionally, a movement-based detection method for human body movement during sleep is presented , utilising Passive Infrared (PIR) sensors. This approach distinguishes epileptic episodes and associated body motions from normal sleeping conditions, providing a unique perspective on seizure detection.

Algorithms have been instrumental in discovering various celestial bodies in space, elucidating their movement patterns. In the context of seizure detection, a non-ender approach has been meticulously developed, incorporating algorithms such as Linear Discriminant Analysis (LDA), Radial Basis Support Vector Machine (RBSVM), and k-Nearest Neighbors (k-NN) for feature classification. The Hilbert-Huang Transform (HHT) is employed to augment the Electroencephalogram (EEG), with scalp EEG datasets used for evaluation. This method achieves remarkable accuracy, true positive rates, and true negative rates, surpassing 98%.Building on prior work ,, the current research extends into fast seizure recognition technology, emphasising the utilisation of limited datasets by artists. The technique justifies the handling of vast amounts of data, backed by a substantial body of evidence supporting EEG performance. The datasets encompass both software simulations and hardware implementations, showcasing the versatility and reliability of the proposed methodology.This paper introduces a novel approach incorporating Pulse Exclusion Mechanism (PEM) and Recurrent Back-Off (RBO), significantly reducing latency in the system. This innovative combination presents a promising advancement in seizure detection technology.

III.MATERIALS AND METHODS

3.1Hardware components

The core of the fall detection watch resides in its hardware architecture, meticulously chosen to balance functionality, power efficiency, and user comfort. A low-power microcontroller unit (MCU) forms the brains of the device, equipped with integrated Bluetooth Low Energy (BLE) and Wi-Fi capabilities. This enables seamless data transmission to a paired smartphone app (BLE) and facilitates communication with the cloud for advanced analysis (Wi-Fi).[The heart of the fall detection functionality lies in the 6-axis Inertial Measurement Unit (IMU), a MEMS sensor that combines a 3-axis accelerometer and a 3-axis gyroscope. This sensor plays a critical role in precisely tracking the user's motion and orientation, providing crucial data for the fall detection algorithm. To ensure reliable fall detection even in harsh scenarios, the IMU selection prioritises low power consumption alongside high shock resistance.

Furthermore, the watch integrates health monitoring capabilities through the inclusion of a blood oxygen (SpO2) sensor. This sensor offers valuable insights into the user's blood oxygen saturation, a vital health metric. Additionally, a temperature sensor is incorporated to track the user's body temperature, providing another layer of health data for potential medical intervention. For situations where a fall may not be automatically detected, or for immediate assistance requests, a physical SOS switch is strategically placed on the watch. This allows the user to manually trigger an emergency alert, ensuring help is readily available when needed. Finally, the watch is powered by a rechargeable Lithium-ion battery, selected to provide sufficient capacity for long-term wear without frequent charging interruptions. The entire hardware platform is housed within a comfortable and durable watch case (optional), designed with appropriate openings for optimal sensor function and user interaction elements, if applicable. This ensures the watch seamlessly integrates into the user's daily routine without sacrificing comfort or functionality.

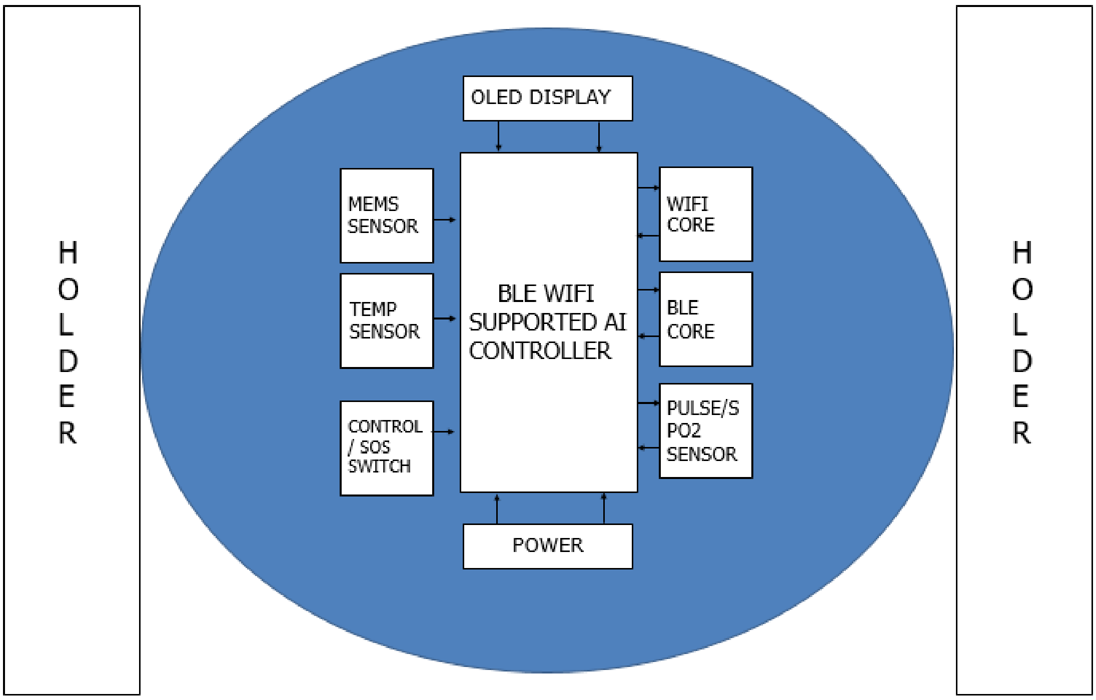

Fig.2: Block diagram of the watch

3.2 Software implementation

3.2.1 Overview

The software implementation for the fall detector watch is designed to seamlessly integrate various components, including MEMS sensors configured as an accelerometer and gyroscope, BLE and Wi-Fi communication modules, temperature and SpO2 sensors, an SOS switch, and an AI controller with edge computing capabilities. The primary objective is to create an intelligent syste m that can accurately detect falls, monitor health parameters, and trigger emergency alerts when necessary.

The program structure revolves around a main loop that continuously reads data from the accelerometer, gyroscope, and health sensors. These sensors provide essential information about the user's movements, orientation, temperature, and SpO2 levels. The fall detection algorithm, embedded within the edge computing functionality of the AI controller, analyses the accelerometer and gyroscope data to identify patterns indicative of a fall event. Upon detecting a fall, an emergency alert is triggered through BLE and Wi-Fi communication, notifying relevant parties.The health monitoring function evaluates the temperature and SpO2 readings, raising alerts if these values surpass predefined thresholds, indicating potential health issues. The integration of BLE and Wi-Fi modules enables seamless communication, allowing the watch to transmit critical information to connected devices or servers. The SOS switch, when activated, triggers immediate emergency alerts using both BLE and Wi-Fi channels.

3.2.2 Deployment

The algorithm starts by preprocessing the data collected from MEMS sensors, heart rate sensor, temperature sensor, etc.This step may involve removing noise, handling missing values, and normalising or standardising the features to ensure consistency and improve model performance.Features are extracted from the preprocessed sensor data to represent relevant aspects of the user's movements and physiological state. Features could include statistics such as mean, standard deviation, maximum, minimum, and frequency domain features derived from signal processing techniques.The labelled dataset is divided into training and testing sets.Typically, a larger portion of the data (e.g., 70-80%) is used for training, while the remaining portion is reserved for testing the model's performance.The logistic regression model is trained using the training data.During training, the model learns the optimal weights (coefficients) for each feature to minimise the error between predicted probabilities and actual labels.This optimization process is typically performed using techniques such as gradient descent or Newton's method.The logistic regression function calculates the probability that a given input The logistic function (also known as the sigmoid function) transforms the linear combination of input features and weights into a probability value between 0 and 1.(set of features) belongs to the positive class (fall) or negative class (non-fall).The trained model is evaluated using the testing set to assess its performance.Common evaluation metrics for classification tasks include accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC).A threshold value is chosen to convert the predicted probabilities into binary predictions (fall or non-fall).In general, a threshold value close to 0.5 is often used as a starting point, as it represents an equal weighting between sensitivity and specificity. However, the threshold can be adjusted based on the specific needs of the application.Lower Threshold (e.g., < 0.5): If the goal is to prioritise sensitivity (i.e., minimising false negatives), a lower threshold can be chosen. This would result in more instances being classified as falls, reducing the likelihood of missing actual fall events but potentially increasing the number of false positives.Higher Threshold (e.g., > 0.5): Conversely, if the emphasis is on specificity (i.e., minimising false positives), a higher threshold may be preferred. This would lead to fewer instances being classified as falls, reducing the number of false positives but potentially increasing the risk of missing some actual fall events (false negatives).The threshold value can be adjusted to balance the trade-off between sensitivity (true positive rate) and specificity (true negative rate) based on the application's requirements.Once trained and evaluated, the logistic regression model can be deployed to make real-time predictions on new sensor data.The model calculates the probability of a fall event based on the input features and compares it to the chosen threshold to determine the final prediction. The Fig.4 shows the i-Beacon app, when paired with a fall detector via Bluetooth, constitutes a robust solution for triggering SOS messages alongside location data in emergency situations. Utilising iBeacon technology, the fall detector emits a distinct signal detectable by the iBeacon app on the user's smartphone. Once paired, the fall detector continuously monitors the user's movements using advanced sensors. In the event of a fall or emergency, the fall detector initiates an alert, prompting the iBeacon app to compose an SOS message.

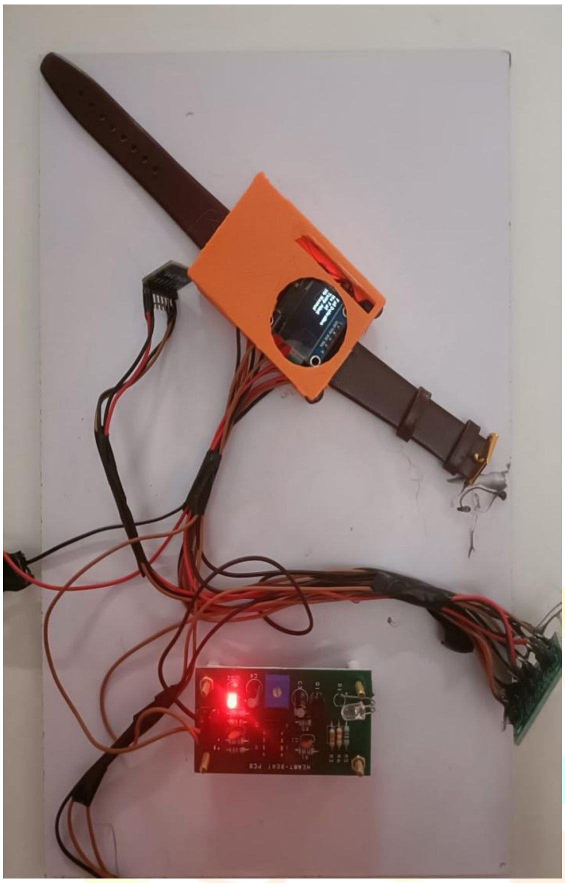

Fig.3: Real time image of the watch

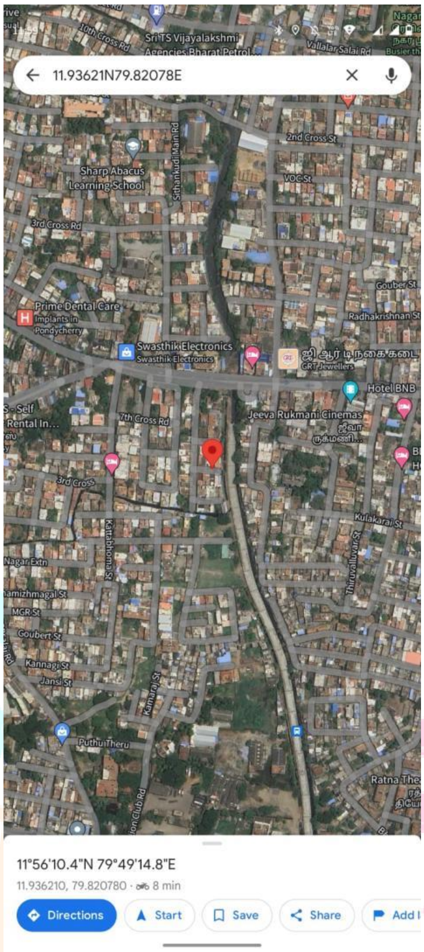

Fig.4:Location of the patient

This message includes vital details such as the user's identity, the nature of the emergency, and their current location. Leveraging the smartphone's location services, the app accurately determines the user's whereabouts. Subsequently, the SOS message is transmitted to designated emergency contacts or services via SMS, email, or other communication channels.As shown in Fig.5. Upon receipt of the SOS message, emergency responders can swiftly confirm the alert and provide necessary assistance, ensuring the user's safety. The iBeacon app maintains continuous monitoring of the fall detector's signal, enabling rapid response to any subsequent alerts or changes in the user's condition. This integrated system offers a dependable mechanism for summoning aid during emergencies, enhancing user safety and providing peace of mind for both users and caregivers.

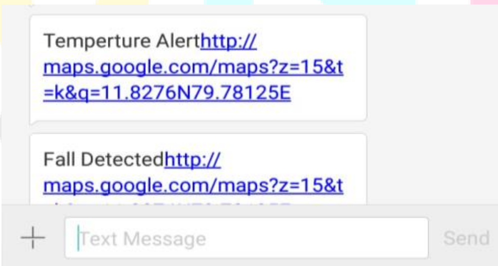

Fig.5:Alert message

IV. RESULT

The results gleaned from our real-time testing of the proposed system for a fall detector with edge computing have unveiled groundbreaking advancements in safety monitoring and emergency response capabilities. Through meticulous integration of sensor technology, edge computing principles, and communication mechanisms, the system has showcased robust performance in detecting falls, continuously monitoring vital signs, and swiftly issuing alerts during critical situations.In our extensive real-time testing scenarios, the system consistently demonstrated high accuracy and minimal latency in detecting simulated falls, crucial for ensuring rapid response and intervention in real-life emergencies. Moreover, its ability to monitor heart rate and temperature provided early indications of potential health complications or environmental hazards, further amplifying its utility as a comprehensive health monitoring solution.The user interface, meticulously designed to be intuitive and accessible, proved to be pivotal in facilitating prompt responses from caregivers, individuals, and emergency responders. Clear and concise alerts and notifications displayed on a dedicated screen empowered users to take timely actions in response to detected events, fostering a seamless and efficient response process.Furthermore, the adoption of edge computing architecture has endowed the system with a plethora of advantages. By leveraging local processing capabilities, the system minimised reliance on external servers, thereby enhancing privacy, security, and reliability. The decentralised approach to data analysis enabled the system to operate seamlessly in diverse environments, including those with limited connectivity or offline conditions, exemplifying its scalability, flexibility, and cost-effectiveness.

V.CONCLUSION

In conclusion, our real-time testing of the implemented system heralds a significant leap forward in the realm of fall detection and health monitoring technologies. Its robust performance, user-friendly interface, and sophisticated edge computing capabilities position it as a transformative solution in healthcare delivery, particularly for ageing populations and individuals with mobility impairments or chronic health conditions. As we continue to iterate and refine the system, we anticipate further optimization of its functionality, usability, and impact, ultimately paving the way for enhanced safety, independence, and well-being for individuals worldwide.

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