cStick: A Calm Stick for Fall Prediction, Detection and Control in the IoMT Framework

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Abstract. Falls are constant threats to older adults and can minimize their ability to live independently. To help mitigate the occurrences and effects of such unfortunate accidents, it is imperative to find an accurate, reliable, robust and convenient solution to make life easier for elder adults who may have visual or hearing impairments. In order to reduce such occurrences, a calm stick, cStick is proposed. cStick is an IoT (Internet of Things) enabled system which has a capability to predict falls before their occurrence, to warn the user that there may be an incident of fall, to detect falls and also provide control remedies to reduce their impact. cStick monitors the location of the user, the physiological changes that occur when a person is about to fall and also monitors the surroundings the user is in when having an incident of fall. Based on the changes in the monitored parameters, the decision of fall i.e., a prediction, warning or detection of fall is made with an accuracy of approximately 95%. Control mechanisms to reduce the impact of the fall along with connection capabilities to the help unit are provided with the cStick system.

Keywords: Smart Healthcare · Healthcare Cyber-Physical System (H-CPS) · Internet of Medical Things (IoMT) · Fall Detection · Fall Prediction · Elderly Falls · Visually Impaired · Hearing Impairment · IoT-Edge Computing

1 Introduction

Falls are accidents that come with age. Every year, 37.3 million falls are recorded from the elderly, 65 years and above. As a matter of fact, one among four older people falls each year but less than half tell their doctor [4, 31]. The probability of having multiple falls increases after having the first fall [21]. Every 11 seconds, there is an older person being treated for an incident of fall [1]. Statistics indicate that fall incidence rates have increased by 31% from 2007 to 2016 and the rate is expected to grow in the future [3].

The occurrences and causes of falls are many. 67% of falls do not happen from a height but happen when a person trips or slips. Ill-fitting clothes and shoes can also be a reason for the older person to fall [8]. Hearing impairments in older adults cause three times the risk of an accidental fall than other older adults [18]. Medical conditions, sedatives and antidepressants such as Parkinson's disease, insomnia, sedation, and obesity also contribute to the increased risk of falling in older adults [7, 17]. Isolation and physical inactivity due to the pandemic also has an effect on the increased risk of falling in older adults [23, 24].

The impact of falls on the elderly human body is very high. Falls can cause broken bones, wrists, arms, ankles and hips. In 2014, 29 million older adults received injuries from falls. 95% of the cases involving falls lead to hip fractures [1]. In 2013, 50% of the cases involving falls resulted in traumatic brain injuries in older adults [32]. In 2016 alone, there were 29,668 deaths in older adults caused due to falls [13].

In order to reduce such accidents, cStick, a calm stick to monitor falls in older adults is proposed. cStick has been designed in such a way that it can assist both visually and hearing impaired older adults. cStick has an ability to not only detect falls but to also predict the incident of fall so as to reduce their occurrences. cStick can monitor the surroundings, warn the user if there was a previous fall detected at a certain location, and update the location and its surroundings to the user. The device prototype of the proposed cStick is represented in Figure 1.

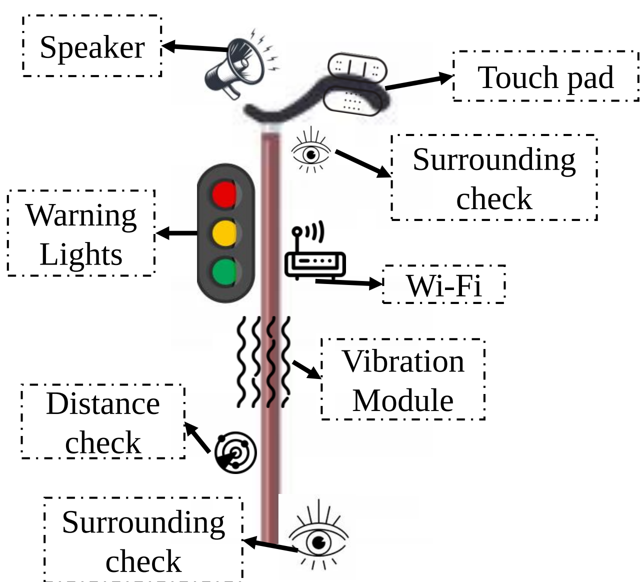

Fig. 1. Proposed Device Prototype of cStick.

cStick ia a state-of-the-art device in the IoMT framework. IoMT stands for Internet of Medical Things and it is a subset of Internet of Things (IoT). IoT is defined as the network of devices which are connected and are capable to transfer information as they have a unique IP addresses [19]. When the fundamentals, tools, techniques and concepts of such applications and devices with Internet capabilities are related to healthcare domains, the IoT is known as the IoMT [27]. There are many applications ranging from Smart Healthcare, Smart Transportation, Smart Supply Chain, Posture Recognition, Smart cities, etc., that involve the IoT and the IoMT [20].

cStick is an IoMT-enabled edge computing device as it has the capabilities to process and analyze the information at the user end and store the information at the cloud end. Applications or devices proposed in this framework require little to no human intervention [19]. The IoMT framework has many components as represented in Figure 2 [28].

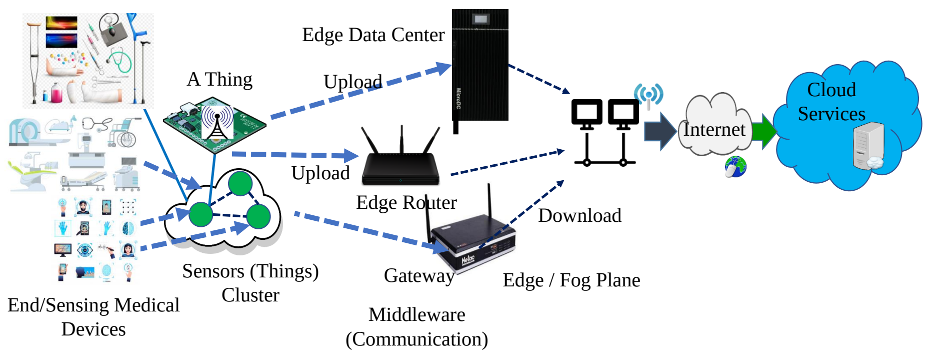

Fig. 2. IoMT Framework used in cStick.

Edge computing is defined as a distributed computing paradigm that allows data processing and analysis done at, or near the source of the data, i.e, closer to the user. With edge computing, the dependency on the cloud to process and analyze the data can be reduced. Major advantages of edge computing include reduction in latency or delay which means data can be real-time; reduction in the bandwidth utilization, therefore less network traffic; reduction in total costs, increase in application efficiency, and increase in the security and privacy aspects of the devices [11]. The edge computing paradigm is represented through Figure 3.

The main motivation for cStick is to provide real-time data analysis on the status of older adults in terms of falls, to constantly protect them, to reduce the incidents of fall, to provide instant support and help in the event of a fall and to propose a system that works for all elders, even with visual and hearing impairments.

The organization of the paper is as follows: Section 2 provides the state-of-the-art literature and marketable products for elderly healthcare followed by issues in these. Section 3 provides the novel contributions that are proposed through cStick and how it provides an excellent solution to all the missing aspects. Section 4 provides a detailed understanding of the physiological parameters considered in cStick. Section 5 provides a representation of the architectural flow used for fall prediction and detection in cStick. Section 6 describes the design process involved in cStick for fall prediction, detection and control. Section 7 is comprised of the implementation and validation of the IoMT-

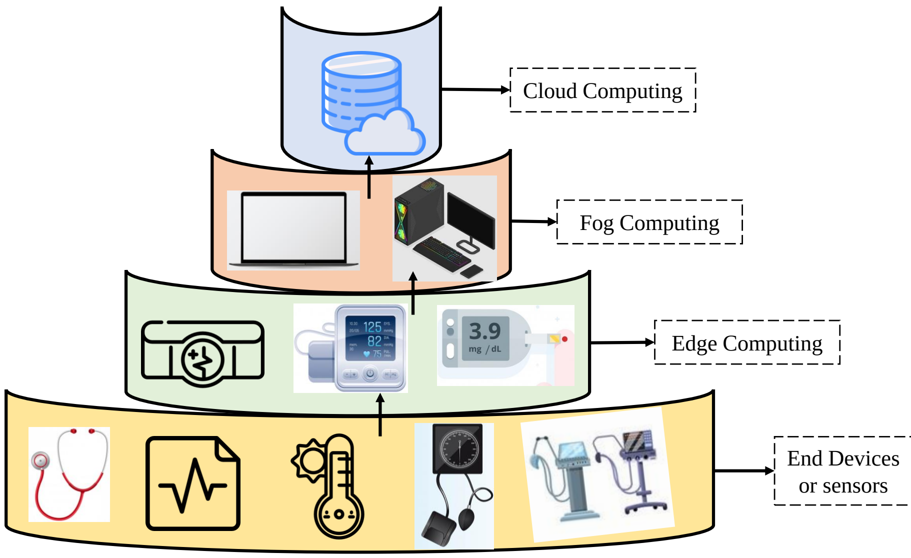

Fig. 3. IoMT-Edge Computing Paradigm used in cStick.

Edge computing proposed in cStick followed by conclusions and future directions of this research in Section 8.

2 Related Prior Research

Though there is a good number of wearables in the market that provide care for older adults, most of them only focus on fall detection and not prediction. Some wearables proposed are able to detect trips and slips but not specifically fall. Also most of them use only accelerometers as the physiological feature and need the user to request help after a fall. A detailed presentation of these works is provided in Table 1. Some of the major disadvantages of these wearables are the generation of false positives and false negatives which can cause unnecessary alerts, monthly maintenance charges and privacy concerns.

Some works which detect falls in elderly are provided in Table 2. These articles only detect falls with no fall prediction. Also, most of them only consider a single physiological signal for monitoring falls which lacks in efficiency of the system proposed.

2.1 Major Issues with the Existing Solutions

Some of the major issues with the existing solutions are:

- There is no unified detection as there are not many physiological signal data that are being considered to make the decision of fall.
- There are no fall prediction mechanisms or strategies included.

Table 1. Wearable Products for Elderly Healthcare.

Wearable	Activity	Physiological Data	Prediction	Detection	Drawback
Owlytics [22]	Walk, trip and slip	Accelerometer	Partially Yes	Yes	Users need to manually request for help. It only uses one physiological signal to detect falls.
Smart Watch [2]	Physical Activity	Accelerometer	No	Yes	It uses only accelerometers, does not work on low thresholds like double carpet, bathroom, hardwood floors. The user must manually select the option SOS and as a result it fails if the person is unconscious. Users may remain on the floor with no help for long hours.
Vayyar Home [15]	Bathroom activity monitoring	Radars	No	Yes	Location constraint as its mounted on a wall inside bathroom. User needs to manually request help by talking to the device. Connectivity issues may arise.
Hip Hope [16]	Physical Activity	Accelerometer	No	Yes	The location of the wearable placement can be an inconvenience. Malfunction of the device will have additional injuries for hips as its located around hips.

- Most of them are location constrained and can only be used at a specific location.
- Users need to manually or verbally request help upon falls and this can be an issue if the user is unconscious.
- Wearables or the device prototypes proposed may be inconvenient for the users to wear.
- Generation of false positives and negatives can be higher due to which unnecessary alerts can be generated.
- Cost for the installation and maintenance can be higher as most need monthly subscriptions.

3 Novel Contributions

cStick is designed to provide constant care for older adults by continuously monitoring the physiological parameters while a person is walking. It has IoT capabilities and it can be a part of any network or device [26]. The novel contributions that are proposed through cStick are:

- Accounting for multiple physiological signal data to analyze the decision of falls.
- Continuous data monitoring to predict the occurrences of falls in order to reduce the number of accidents.

Table 2. Research Contributions for Elderly Healthcare

Name	Prototype	Activities	Sensors	Prediction	Detection	Accuracy
Han, et al. [12]	No	Walk, sit, fall, lean	Accelerometer, gyroscope	Partially yes	Yes	No.
Pongthanisorn, et al. [25]	No	Sleeping Positions	Piezoelectric and weight	No	Yes	No.
Engel, et al. [9]	No	Walk, trip, stumble, fall	Accelerometer	No	Yes	94.
Razmara, et al. [29]	No	Questionnaire	None	No	Yes	90

- Continuous surrounding monitoring to allow the users to understand the environment in order to reduce tripping and injuries.
- Continuous monitoring of general health signals so as to have to a detailed understanding on the causes of the fall.
- Location tracking of the user to not only provide immediate support but also to notify the user with a warning.
- Ability to have two-way communication with the device, when needed.
- Assisting visually impaired and hearing impaired elders by incorporating audio and touch response systems, respectively.
- Having a capability to connect to any wearable or health monitoring device to provide more adaptable elder fall monitoring systems.

4 Physiological Parameters Considered in cStick

There are many physiological changes that occur inside a human body throughout the course of the day. Not all signals have a defined relationship with falls. For example, though body temperature and sweat change according to the actions done by the human being, these changes are discarded as there are may be external reasons such as weather, environment etc., which can cause fluctuations in them [26]. So here are the physiological parameters considered to analyze falls in cStick. Upon careful consideration, cStick is designed in a way that it can monitor:

4.1 Grasping Pressure

When a person is about to fall or losing strength, the tendency to hold surroundings - be people or objects, increases. Based on this, cStick monitors the grasping pressure that is applied on the cane. The individual baselines for each individual can be different, so cStick monitors sudden changes in the squeezing force.

4.2 Dietary Habits

cStick monitors the blood sugar levels of the older adults. The total occurrences of falls can be linked with low sugar levels (hypoglycemia). When the sugar levels are below 70mg/dL the chances of having falls increases as the older adults may feel weak, tired, anxious, shaky, or suffer strokes and unconsciousness [10].

4.3 Posture

The posture of the human body tells a lot about its orientation. If there is a leaning in any direction, the chances of losing the balance are high. Such scenarios can lead to side and back falls causing injuries to hips or the head.

4.4 Blood Oxygen Levels

Older adults have lower saturation levels than younger adults. Oxygen saturation levels about 95% are considered normal for older adults. Lower levels may cause shortness of breathe, asthma, excess sweating, low heart rate and sometimes leads to unconsciousness in older adults [14].

4.5 Irregular Heart beats per minute

Cardiac output decreases linearly at a rate of about 1 percent per year in normal subjects past the third decade [5]. The resting supine diastolic blood pressure for younger men was 66$\pm$6 and 62$\pm$8 for older men and higher heart rates can result in shortness of breathe, fatigue, stroke and unconsciousness [6].

4.6 Surroundings of the User

Surroundings have a larger impact on the human body when a fall occurs. Monitoring the surroundings helps to reduce the impact of falls. cStick is designed in such a way that it can detect the reason behind the accident of fall. Surrounding objects, human beings or any other moving or non-moving things are continuously monitored to eliminate the accidents of falls.

4.7 Location of the User

The location of the user plays a very important role as it allows notification of the user to stay alert. Warning the user about a previously occurred fall will make him aware of the surroundings. Also, location tracking helps to provide required help without the user asking for it.

A schematic representation of cStick is represented in Figure 4. Here, the Edge-data analyzed and the decision of fall are sent to the doctor and/or caregivers using the IoMT.

5 Architectural Flow for Fall Prediction and Detection in cStick

The architectural flow of the proposed system begins with the data collection from the wearable sensors. The data from the stick is compared and analyzed to make the decision of fall or a prediction of a fall. This decision is provided to the user using fall response mechanisms which are both compatible for visually or hearing impairment elders and are described in the next sections. The architectural flow is represented in Figure 5.

Fig. 4. Schematic Representation of cStick.

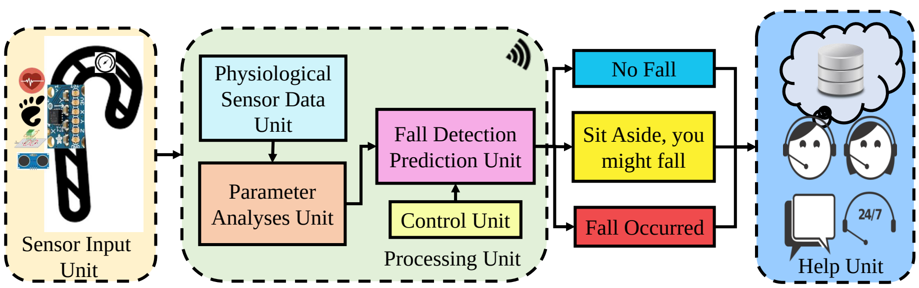

Fig. 5. Architectural View of cStick.

5.1 Physiological Sensor Data Unit

The physiological parameters that are considered in designing the cStick are explained in Section 4. In this section the detailed presentation of the sensors which are used to analyze the falls and predict the possible falls is discussed.

Accelerometer The accelerometer sensor parameter in cStick is used to measure the non-gravitational or linear acceleration. The accelerometer is located inside the stick and is designed to respond to the vibrations associated with any movement. The microscopic crystals that undergo stress when in vibration help in providing a voltage which is generated as a reading on any acceleration. When there is a movement in human body, the axes of accelerometer x,y and z are continuously changing. When a 3-g spike in the y axis is noticed, it means that the person is sitting down. If the g-force of the y axis exceeds ± 3 g's, the accelerometer would pass the threshold to detect a fall.

Gyroscope In cStick a gyroscope sensor parameter is used to detect the changes in the orientation of the human body. The gyroscope is used to measure the rate of rotation around a particular axis with which the direction of the fall can be determined. For example, if the person is about to or has fallen in front, towards the back or side.

Heart Rate Variability In cStick the heart rate variability is considered to measure sudden changes in the breaths per minute as a sudden change in the heart rate is abnormal [30]. According to [6], the maximum heart rate in older adults is lower (at around 162±9 beats/min) than the maximum heart rate in younger men (191±11 beats/min).

Blood Sugar Levels Blood sugar levels are very important in older adults and can have significant role in detecting falls, as discussed in Section 4. Hypoglycemia and hyperglycemia have significant effects on the strength, cognitive ability and heart rates in older adults and so their continuous monitoring is provided in cStick.

Blood Oxygen Saturation ($\boldsymbol{SpO_2}$) Levels Continuous monitoring of $Sp\emptyset_2$ levels is provided in cStick as hypoxemia or low blood oxygen levels creates shortness of breath, excessive sweating, low heart rate and even unconsciousness in older adults [14].

5.2 Parameter Analysis Unit

The relationship between the sensor parameters to the falls in older adults is discussed here. As explained in Sections 4 and 5.1, the distance of the user to the nearest object, the ± 3-g for the y axis from the accelerometer which is the threshold, the gyroscope reading to indicate the direction of fall, the sugar levels of the user, sudden spike in heart rate, the duration of pressure or squeeze applied on the stick and the blood oxygen levels are considered to make the decision of the falls. The parameter ranges for the decisions of prediction and detection are represented in Table 3.

Table 3. Parameter Range Descriptions for Fall Prediction and Detection in cStick.

Distance	Pressure	HRV	Sugar Levels	SpO_2 Levels	Accelerometer	Decisions
$>$ 50cm	Small	60-90bpm	70-80 mg/dL	$>$ 90	$<$ Threshold	No fall. Happy walking!
$<$ 30cm	Medium	90-105bpm	30-70 mg/dL	80-90	$>$ Threshold	Take a break, you tripped!
$<$ 10cm	Large	$>$105 bpm	$<$ 30 mg/dL or $>$ 160 mg/dL	$<$ 80	$>$ Threshold	Definite fall. Help is on the way!

5.3 Fall Prediction and Detection Unit

The decision of falls is made from the analysis represented in Table 3. Prediction of the fall is defined as a mechanism to let the user know that the user might have an accident and taking a break might be good for him/her. Detection is stating that there has been a definite accident of fall and the user needs assistance.

5.4 Control Unit

As there is continuous monitoring of the vital signal data in cStick, any other additional cause an older person may fall is also taken care of. This includes monitoring the heart rate, sugar levels and blood oxygen levels. If there is anyone of these that are causing the user to loose cognitive ability, strength or even consciousness, cStick will be able to help the user by warning the user to take a break, in other words by predicting the user that there may be an accident.

In addition, as the location of the user along with the surroundings are also monitored, the chances of having falls or any other accidents can also be reduced.

6 Design Flow for Fall Prediction and Detection in cStick

The design flow of the working principle involved in cStick is represented with the Algorithm 1.

The buzzer, vibrator and microphone attached are activated depending not only on the decision of the fall but also when there is an abnormal reading in the vital signals. The location of the user will be updated throughout the time period the user is using the stick. The design flow of cStick is also represented in Figure 6.

7 Implementation & Validation for Fall Prediction and Detection in cStick

7.1 Physiological Data Acquisition

For the implementation and validation in cStick, a dataset of 9670 samples based on Table 3 was used. For the baseline and as a validation the data from [33] has been taken. Here the decision of the fall was done based on the 14 volunteers who participated in the study.

7.2 Machine Learning Model for Edge Computing used in cStick

The well shuffled dataset with 6 features and 3 classes in the label was trained in TensorFlow. The 6 features here are: Heart rate variability, accelerometer, blood oxygen levels, sugar levels, pressure applied on the stick and distance from the nearest object. The classes for the label i.e., for the decision are no fall detected, a fall is predicted i.e., the user has tripped or slipped and a fall has detected i.e, a definite fall. The scatter plot of two of the features considered in cStick is represented in Figure 7.

Algorithm 1 Working Principle for Fall Prediction and Detection in cStick.

1: Declare and initialize the input variables d for distance, h for HRV, sl for sugar levels, s for SpO_2 to zero.
2: Declare and initialize the output variables b for buzzer, v for vibrator and l for location to zero.
3: Declare string variables decision of the fall d, p for pressure, m for microphone or speaker and a for accelerometer to zero.
4: **while** $p \neq 0$ **do**
5: Start monitoring and gathering physiological signal data which are a, h, sl, s and l.
6: **if** $d >$ 50cm && p == 'small' && 60>h<90 && 70>sl<80 && $s >$ 90 && $a <$ 'Threshold' **then**
7: d = 'No fall. Happy walking!'.
8: l = 1.
9: **else if** $d <$ 30cm && p == 'medium' && 90>h<105 && 30>sl<70 && 80>s<90 && $a >$ 'Threshold' **then**
10: d = 'Take a break, you tripped!'.
11: m = 'Take a break, you tripped!'.
12: b = 1 && v =1 && l =1.
13: **else if** $d <$ 10cm && p == 'Large' && $h >$ 105 && $sl <$ 30 && $sl >$ 160 && $s <$ 80 && $a >$ 'Threshold' **then**
14: d = 'Definite fall. Help is on the way!'.
15: m = 'Fall detected, help is on the way!'.
16: b = 2 && v =2 && l =1.
17: **end if**
18: **if** p == 0 **then**
19: Stop monitoring and gathering physiological signal data.
20: **else**
21: Repeat steps from 5 through 12.
22: **end if**
23: **end while**
24: Repeat the steps from 4 through 18 whenever a user is using cStick.

The model that is used in cStick to define the relationship between the features and the label is a fully connected neural network or dense model. Here, a linear stack of layers with 6 nodes in the input layer, two dense layers with 20 neurons each and three nodes in the output layer are considered. The rectified linear function is used as an activation function for the hidden layers and the sigmoid function is used for the output layer. 200 epochs are provided with batch size of 32 and 0.01 learning rate for the model.

The predictions of the model without training and predictions of the model after the training are represented through Figure 8.

With loss and accuracy as the metrics and a stochastic gradient descent algorithm as the optimizer, 7736 samples for training and 1934 samples for testing, the model has produced 96.67% accuracy, as shown in Figure 9. The software verified implementation is implemented on IoMT-Edge computing platform in the following sections.

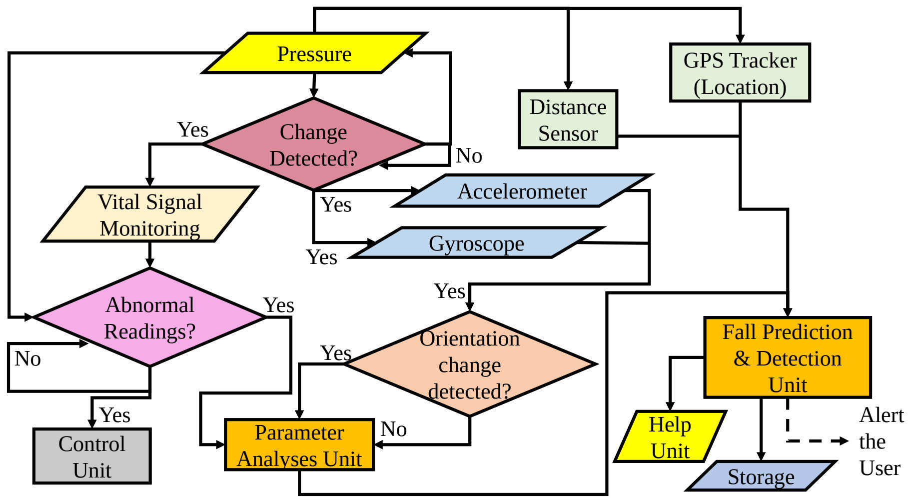

Fig. 6. Design Flow of cStick.

7.3 Real-Time IoMT-Edge Computing Validation in cStick

For the IoMT-Edge computing, a controller has been chosen with real time sensor data from various sensors which monitor the required parameters considered in cStick, as discussed in Section 4. The Edge Computing setup is represented in Figure 10.

The location of the user is also validated in cStick along with the conceptual validation as shown in Figure 12.

The serial monitor display of the sensors along with the dataset data is represented in Figure 11. Here, the squeeze or the pressure applied by the user on the stick, distance from the nearest object or person, heart rate variability, location of the user, sugar levels, blood oxygen levels are continuously monitored and the buzzer with various voltage levels and a speaker are provided as output sources.

A brief comparison with existing research is presented in Table 4.

8 Conclusions and Future Research

8.1 Conclusions

Elderly care requires utmost attention with the technological developments happening day by day. Keeping that in mind, a cStick, also known as calm stick, is proposed with which the users are not only provided with a fall detection monitoring device but also a fall prediction device with an accuracy of approximately 96.67%. cStick also monitors the vital signals of the older adults and this allows in the early detection of accidents including falls. It has a capability of connecting to any smart or IoMT device to enhance its performance. cStick can also be used by visually or hearing impaired older adults as it has autonomous control mechanisms.

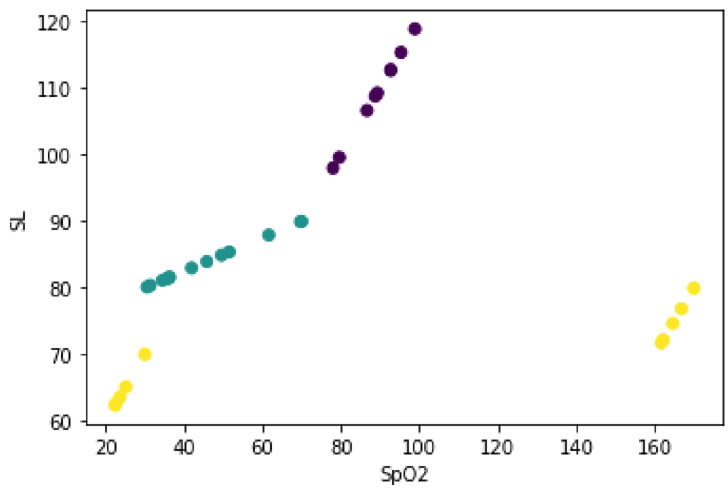

Fig. 7. Scatter plot of Features in cStick.

Prediction: [2 2 2 2 2 2 0 2 0 2 2 2 0 0 0 2 2 2 2 2 0 2 2 0 2 2 2 2 2 2 2 2]
Labels: [1 2 1 1 2 0 0 1 0 2 1 1 0 0 0 2 2 0 0 1 0 2 1 0 1 0 1 1 2 1 1 0]

[[1, 1], [2, 2], [0, 0], [1, 1], [1, 1],[1, 1], [0, 0], [2, 2],[1, 1], [2, 2],[2, 2], [0, 0], [2, 2], [1, 1], [1, 1], [0, 0], [1, 1], [0, 0], [0, 0], [2, 2], [0, 0], [1, 1], [2, 2], [1, 2], [1, 1], [1, 1], [0, 0], [1, 1], [2, 2], [1, 1]]

Fig. 8. Predictions Before and After Training in cStick.

8.2 Future Research

As cStick strives to be an improvement in the existing technology and research for elderly healthcare, in future work more focus will be placed on considering many other vital signals and physiological and psychological parameters.

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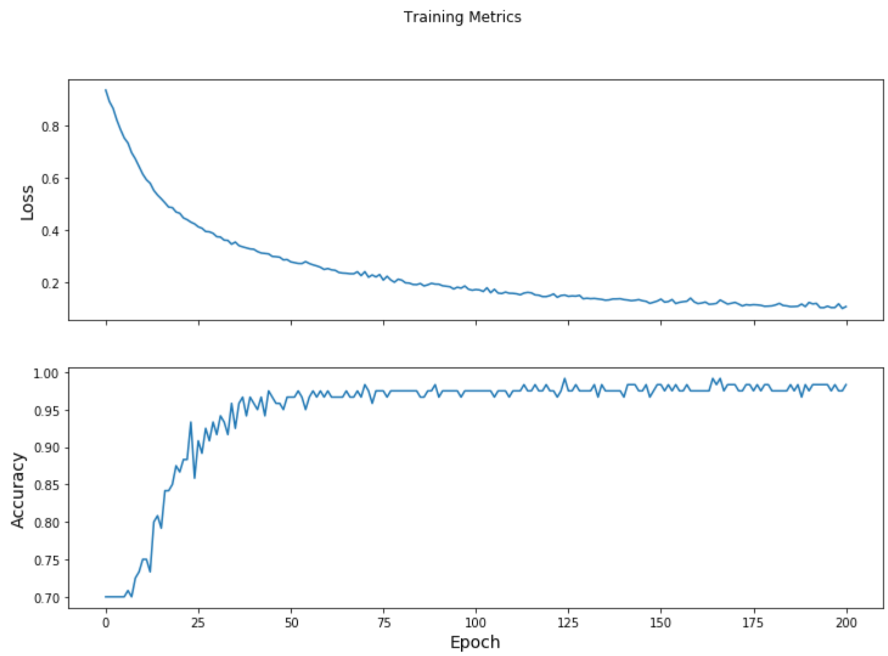

Fig. 9. Loss and Accuracy Obtained in cStick.

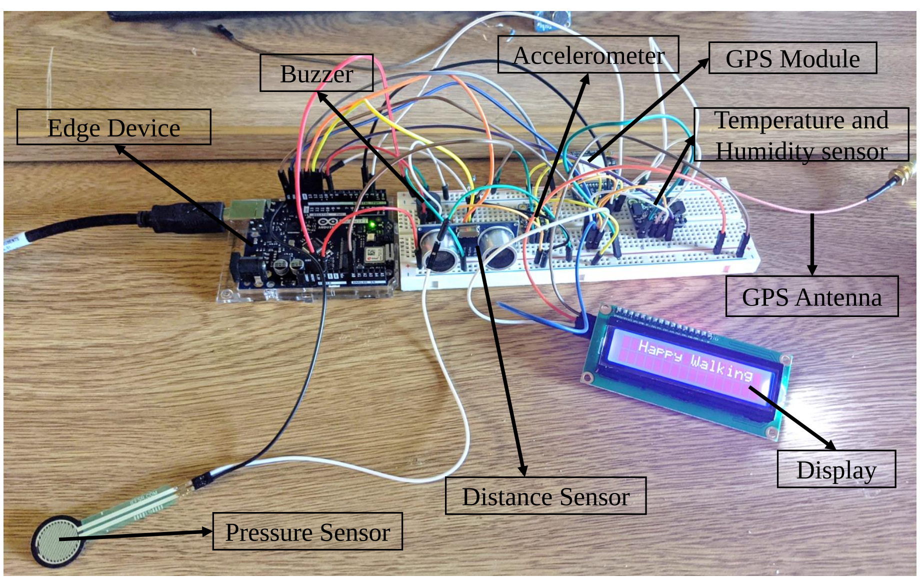

Fig. 10. Real-Time IoMT-Edge Implementation in cStick.

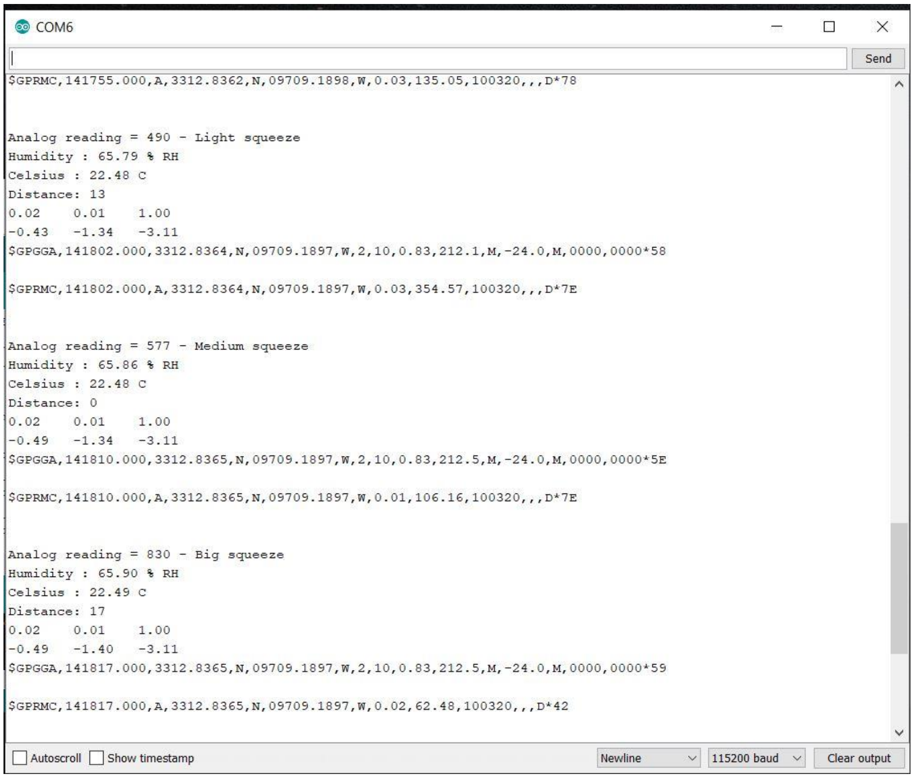

Fig. 11. Serial Monitor Display in cStick.

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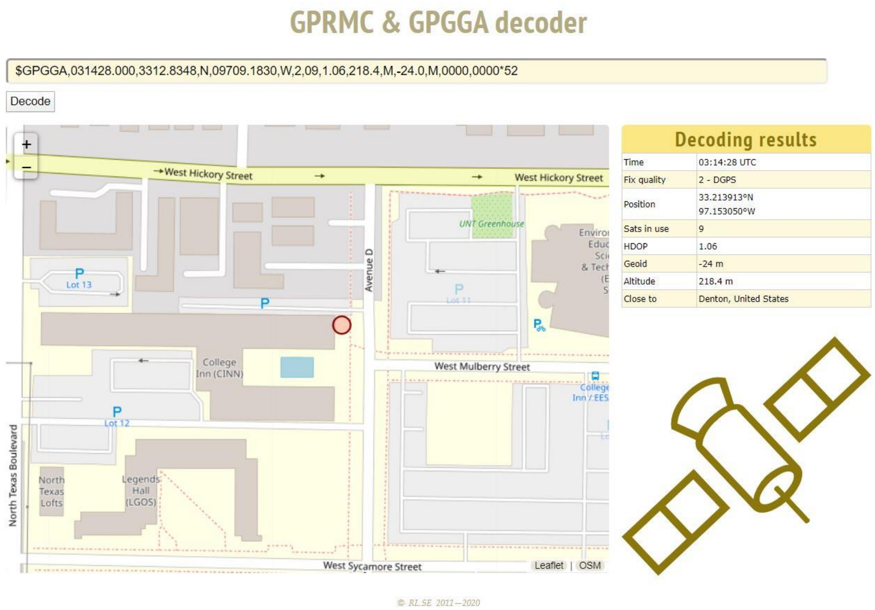

Fig. 12. User Location Validation in cStick.

Table 4. Comparison with the State-of-the-Art Research.

Name	Prototype	Activities	Sensors	Prediction	Detection	Accuracy
Han, et al. [12]	No	Walk, sit, fall, lean	Accelerometer, gyroscope	Partially yes	Yes	No.
Pongthanisorn, et al. [25]	No	Sleeping Positions	Piezoelectric and weight	No	Yes	No.
Engel, et al. [9]	No	Walk, trip, stumble, fall	Accelerometer	No	Yes	94%.
Razmara, et al. [29]	No	Questionnaire	None	No	Yes	90%.
cStick (current paper)	Yes, a calm stick	Walking - Vital signal monitoring	Accelerometer, HRV, Pressure, Sugar levels, SpO2, Gyroscope	Yes	Yes	96.67%.

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