Jamil, D., Bajwa, M. T. T., Khalil, T., Farooq, H. O., Naeem, I., and Shahzad, K. (2023). Smart Life: A Lifesaving Wearable System for Senior Citizen. *Bulletin of Business and Economics*,12(2), 260-268. https://doi.org/10.5281/zenodo.8375298

Bulletin of Business and Economics
ISSN - 2409 - 9368

SMART LIFE: A LIFESAVING WEARABLE SYSTEM FOR SENIOR CITIZEN

DANIAL JAMIL[1], MUHAMMAD TALHA TAHIR BAJWA[2], TAHIR KHALIL[3], HUMERA OMER FAROOQ[4], IRAM NAEEM[5], KHADIJA SHAHZAD[6]

ABSTRACT

Deterioration in an aged person's mobility, self-determination, and quality of lifestyle. This paper proposes a special Internet of Things-based system for recognizing indoor falls among the elderly by combining lightweight devices mobile sensing connections, big data, cloud computing, and smart appliances. For this, we use a wrist-worn sixLowPAN device equipped with an accelerometer with three axes to monitor the exact location and motion of senior citizens in real-time. A powerful IoT network analyzes the sensor signals is applying machine learning algorithms, which helps resulting in resulting in improved recognition of falls outcomes. For systems, we employ an incremental model with a long-memory framework. for the classification of falls, and economical Portable detecting gadget from Apache Flink and MbientLab, with a free software encoder. Using the initial data set, that is freely accessible "MobiAct," we evaluate the most effective Nyquist rate, sensor location, and multi-transmitting data modification. Our system for edge computing uses analytics on information streams in real-time to identify falls with a 95.87% efficiency ratio.

KEYWORDS: IOT, Sensor Networks, LSTM, Apache, Fall Detection, MobiAct

1. INTRODUCTION

Trauma and serious injuries (such as broken bones or traumatic brain injury) are common results of falls [1,2]. Elderly persons have a higher incidence of falling, The effects of such falls tend to be more dangerous. Data shows that 30% of people over 65 and 50% of people over 81 fall each year, which can have serious consequences. High morbidity from falls (falls result in major traumas are near about 20) [3] (see Figs. 10 and 11) accounts for nearly 45% are admitted in nursing homes. A patient's self-esteem and mobility may suffer as a result of their fear of falling [4]. As a result, the patient's ability to engage in social activities is diminished, and the patient's overall activity level drops, leading to depression [5,6]. People's desire to adopt fall sensors devices. The chance of serious problems following an accident may be reduced with early medical intervention. In this way, it helps reduce treatment costs while also increasing the likelihood of a successful outcome. Writers in Ref. [7] wearable technology, ambient sensors, and cameras were used to create a trifold classification of fall detection systems. Since gadget-driven solutions tend to be more effective at recognizing slip accidents even though the patient's place of residence and have no impact with the patient's own or their everyday tasks, they are the best option for fall detection. they are becoming increasingly widespread

Wearable equipment often records information on movement like motion track, and rushing [8]. Wearable sensor nodes have a challenge in differentiating between fall occurrences and regular daily activities or immediately alerting doctors. Because mobile nodes have limited computing power, a more efficient method is needed to help decrease the number of computationally intensive packs they must process.

Maintaining performance, for instance, storage space and power interruptions while processing less computationally intensive sensor packs is essential. IOT is a best option for such kind of structures because it uses the latest innovations like smart sensors, centralized computing, and detection to connect computer-generated models of things with the world around them. Wearable tech could benefit from IoT-based solutions that is dependent on computation tasks from implants to Smart Web-based interfaces. For instance, sophisticated fall detection algorithms can be executed by the gateways. Modern interfaces have advanced skills like click alarms for errors that happen in simultaneous moment or local drive for keeping data brief. These features help improve the standard of service even more.

Users of electronic gadgets will be able to considerably decrease their power usage because of IoT's capabilities to facilitate task sharing. However, the Internet of Things isn't a guarantee that wearable tech will run efficiently all the time Wearable sensor nodes use a lot of power for things such as receiving and sending data. If a portable sensor node fails to utilize energy well, it could be inefficient and give poor performance.

[1] Computer Sciencce & IT. Ghazi University, Dera Ghazi Khan, Pakistan, Danialjamil05@gmail.com
[2] Department of Computer Science, University of Agriculture Faisalabad, Pakistan, talhabajwa6p@gmail.com
[3] Department of Computer Science, University of Agriculture Faisalabad, Pakistan, toortahir427@gmail.com
[4] College of Art & Design, University of the Punjab, Lahore, Pakistan, humera.cad@pu.edu.pk
[5] MPhil(ELM) ,Punjab School Education Department Lahore, Pakistan, Irumnaeem44@gmai.com
[6] MS Leadership & Management, Islamia University Bahawalpur, Pakistan, Khadija.shahzad890@gmail.com

The system consists of intelligent sensor nodes, a server infrastructure, and an intelligent gateway [9]. The gateways outfitted with fog layers [10,11] assist sensor nodes conserve energy. In that study, a 3D detector is placed on the upper body and sends information to a smart hub via Bluetooth Low Energy. In this way the Smart ports need a lot of equipment and power from an electrical source. the bulk of the calculation (an accidental monitor algorithm) is performed near gateway

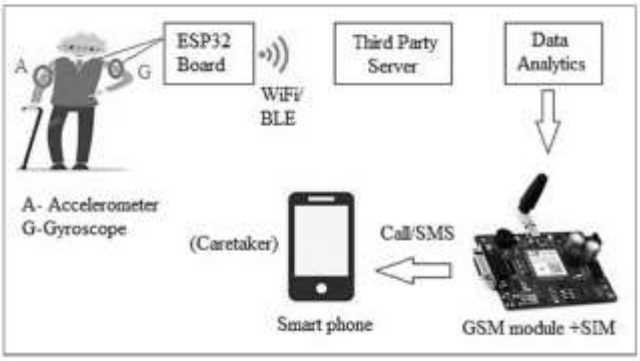


Figure 1: Survey View

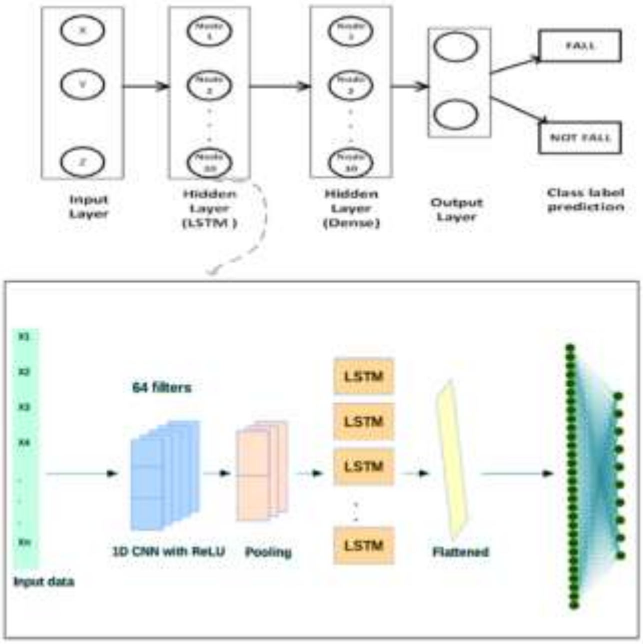


Figure 2: Long Short-Term Memory Development

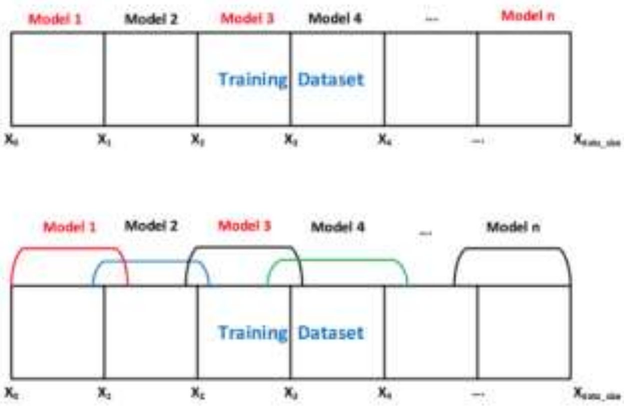


Figure 3: Entries in the training dataset were duplicated

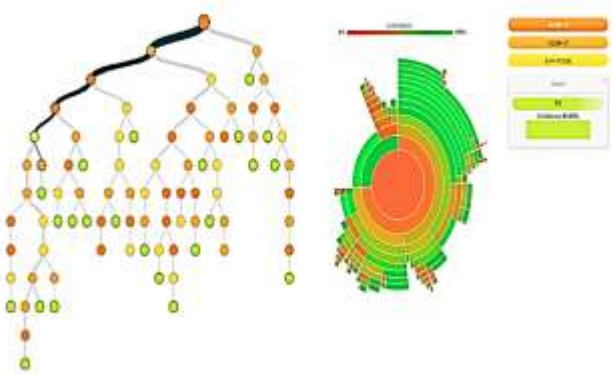


Figure 4: Fall competence model and illustration

detection algorithm) is performed in the gateway. The study presents a plethora of analyses of the energy consumption of significant communication interface buses. Serial Peripheral Interface (SPI) was found to use less power than both I2C and UART, but being capable of higher data transfer rates.

The work reported here is a substantial extension of what we just reported. An accident-tracking gadget is used as a component of the Internet of Things (IoT). we wanted to investigate and find ways to lessen the energy requirements of the wearable sensor node. We also look into issues that were missed in earlier work but are now revealed. There is an overview of the advantages and disadvantages of software-based SPI provide as is data on how it affects the consumption of power of a sensor node. We also look at the amount of power the node hosting the sensor needs under various scenarios for communication at various distances. We further look at how different gadgets, like a motion detector, gaussmeter, and accelerometer, affect the sensing points total consumption of energy and how well it recognizes falling objects. We examine the accurateness of the slip accident recognition program in uncommon conditions, like when handlers assume non-standard stances. Furthermore, other problems that have plagued similar efforts in the past (such P2P communication) and provide comprehensive answers to them. Important contributions made by the suggested model are to develop and put into operation a portable smart devices sensor node that utilizes a enhanced nRF chip to conserve energy and suggest multiple communication channels between sensor networks.
To make and use an operational sensing device that uses an altered nRF circuit to save energy and gives numerous possibilities for sensor nodes and connections to communicate to each other and exchange data.

- To a certain level, this assists in fixing the issues that have plagued P2P networks up until now. The nRF element, which was previously connected to the Arduino via UART, is now employing SPI as the transmission connection, rather than Bluetooth Low Energy. Because of this, there is now a problem with using several SPI ports on an individual chip. The the amount of complexity, possibility, and sustainability of potential solutions to these issues will be assessed. The suggested mobile node for detection is cheap, portable, small, flexible, and uses minimal energy.
- It can be used with a variety of algorithms that detect falling based on mobility. The node that senses things may provide a convenient, lightweight device for daily use. In addition, We change the way we found falls accident in our earlier study so that it can be used with the sensor that was suggested node. This improves performance.

Here are the other portions of my paper:
The works cited can be found in Section 2 of this study. In Section 3, we'll go over the components and technologies that make up our Smart devices or IOT based fall accident recognition infrastructure. Section 4 details the methods used and the outcomes of the experiments. Section 5 contains the analysis and summary.

2. RELATED WORK AND RESEARCH GAP

A few various concepts have been put forward for how to use portable nodes of sensor technology to detect falls. Casilari et al. use the speed gauge in a smartwatch to find falls is the example .

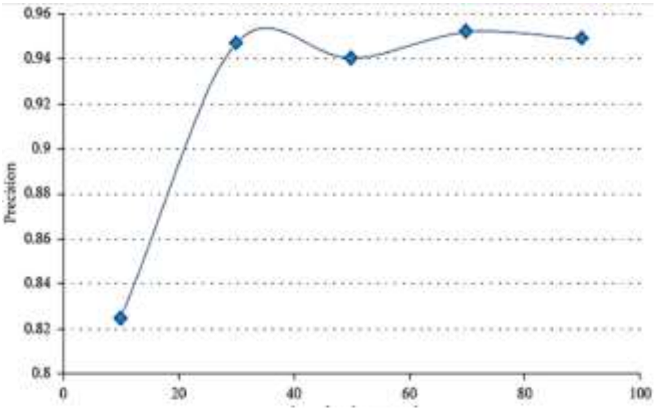
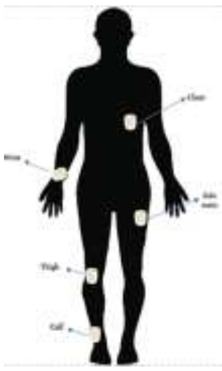


Figure 5: Performance (accuracy) of the model compared

Smartwatches transmit acceleration data to a smartphone through Bluetooth Low Energy, which is then analyzed to detect falls. The smartphone is acting as way to sending a notice to the online network like cloud through 4G or 3G [12]. In a different study, a motion sensor and a the Kinect sensor (depth camera) were used. [13] To improve the way fall recognition works. Panda Board examines at the information in real-time to find falls.

Fundamental Technology



In [14], it explains how to use a portable mobile sensor point to track injuries. The mobility component, which is about a third the dimensions of a two euro token, functions at minimal average power cycles of 50% as well as 100%, or fifteen mA and twenty-five mA, each. Each point has a Wi-Fi chip (CC2420) for communicating data through wireless and an immersive tracker (ADXL345) to calculate motion and sending it to a portal. Sensors that can be are suggested in [15] as an efficient means to find people who have fell. The low-power, low-cost MEMS sensors send data to the instruments using radio frequency (RF). Installing monitors at home can help figure out where the person who fell.

[16] Encourages the use of a MOBILE sensor in a smart home. The smart gadgets use a motion sensor and a gyroscope as tools to gauge speeds and angles in three different dimensions. This device transmits the data through ZigBee to a board running Arduino Uno that is connected to a Cpu so that the data can be interpreted and a fall can be detected. Use k-nearest neighbors to express a method used in data mining for a technique for predicting a fall [17]. The structure of smartwatch is assembled on a component that can be used for multiple purposes and has motion detection. In another study [18], the authors suggest a way to identify falls using a node of sensors with a multidimensional accelerometer and a global positioning system (GPS) link. With this technology, a fallen structure can be found without delay.

In other studies, The Arduino Fio and Arduino Uno are functioning universal devices that are used as the basis for fall-detecting node sensor systems. [19,20]. Despite being affordable and providing certain key functions, this sensor system have significant drawbacks, including using a lot of power as well as having a big dimension It is well-known that generic circuit boards include redundant parts like power regulators and FTDI USB to UART chips that is the waste of power

Many studies have demonstrated that many types of sensing devices such as magnetic sensors, accelerometers, or gyroscopes, are used to recognize node locations based on statistics about how they move. Most of the time, a sensor structure or a group of sensors in a certain device points are selected based on its capabilities and features. Yet, the power use of the sensors is not appropriately taken into version. In example, applications frequently utilize motion sensors and sensors to improve their capacity of fall identification. This article offers a more comprehensive explanation of how DLT can assist with specific IoT needs than previous research publications.

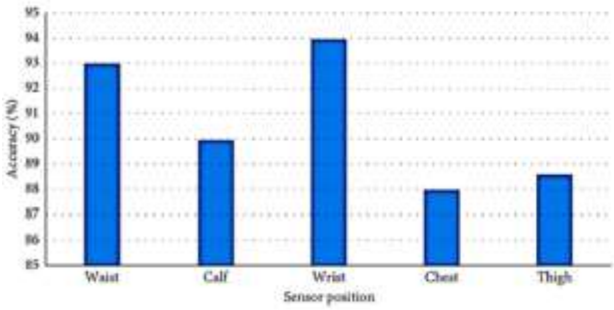


Figure 6: Sensor location accuracy

It has several limitations, Such things as connections from P2P and a complex structure with various side view could make the cost of services go up and maintain the use of energy from being as good as it could be. As a result, in order to overcome BLE's limits while maintaining good service quality, We're looking into other lightweight wireless interaction techniques..

In this study, we look at the variables that affect how much energy a smart device uses. These components comprise a microprocessor, wireless transmission data rate, rate sampling, wave sensors (accelerometer, gaussmeter speedometer, and spinner), software, and distance transmission. A novel lightweight portable device network with such low efficiency that a large amount of energy may be given is possible by fusing the greatest hardware strategy and software approaches.

3. PREFERRED METHODOLOGY'S

The smart device, the Smart IoT gateway, the wireless connection network, and "The Cloud"-Based Technology are the four key components of the Fall Detection system depicted in Fig. 1. To determine the location of a fall, each component is crucial.

3.1. TECHNOLOGY THAT YOU WEAR

The NUCLEO-L152RE, ST Microelectronics' sensor expansion boards, and extension boards with sub-2GHz RF connections that operate at processing speed 868 or 916 MHz were used to construct a prototype of the clothing sensors. The NUCLEO-L152RE contains an ARM 32-bit Cortex-M4 CPU that can analyze digital data quickly, efficiently, and with little power consumption. There are several tiny, low-power components on the sensor chip. But when an adult is falling or doing ADLs, only the MEMS chip module (LSM6DS0) is employed to assemble data on affecting items. The full-scale speed range of the LSM6DS0 (3D-axis accelerometer) is 2/6/8 g. The foundation for smart software is "Contiki," an open source OS for confined networks. Over 6LowPAN, Contiki OS is interoperable with the complete IoT stack. This contains CoAP (through Erbium), RPL, and 6lowPAN. Erbium is a lightweight REST processor developed in C that enables RESTful access to the functionalities of a linked component. CoAP's REST component has also utilized. It uses Uniform Resource Identifiers (URIs), resource abstraction, RESTful interactions (acquire, POST, PUT, and DELETE to acquire various services), and customizable header configurations. CoAP is a straightforward IoT paradigm [23]. However, for machines and networks with constrained resources, CoAP utilizes fewer resources compared to HTTP. This makes it suitable for a few IoT scenarios. The fitness trackers have a CoAP Server built in so you can read the accelerometer's data. By supplying the Internet Protocol Version 6 address of the CoAP Server as well as its connection port information, the CoAP GET technique is often used to obtain information about the path of the intimate link.

3.2. NETWORK FOR COMMUNICATION OVER WIRELESS NETWORKS

Data transmission and reception between a computer and Sensible IoT devices are made possible by the IEEE 802.15.4 protocols, which enable IPv6 (6LowPAN) display technologies. Compared to Wi-Fi and Bluetooth, 6LoWPAN enables the interoperability and connection of a wide range of wireless smart networks at a cheaper cost and with fewer limitations. This technology works well for IoT-enabled devices, particularly those with little resources because of benefits .A larger address space, better accessibility, and an easier establishing and maintaining process are just some of the positives. The mobile device and the border network are the two elements that make up the idea we layout for a 6LoWPAN system. Within our 6LowPAN the internet, 6LoBR plays an essential part in both as well as external connections. The part of the 6LoBR include (i) relaying data between wearables and the cloud devices, (ii) forwarding data, and (iii) traffic routing inside the 6LoWPAN network. The 6LoBR acts as the Smart IoT gateway in this configuration.

3.3. GATEWAY FOR THE IOT

Four components make up the Smart Internet of Things Platform.:

- INTEROPERABILITY
- DATA CONVERSION,
- BIG DATA INVESTIGATION
- EMERGENCY WARNINGS ADMINISTRATION.

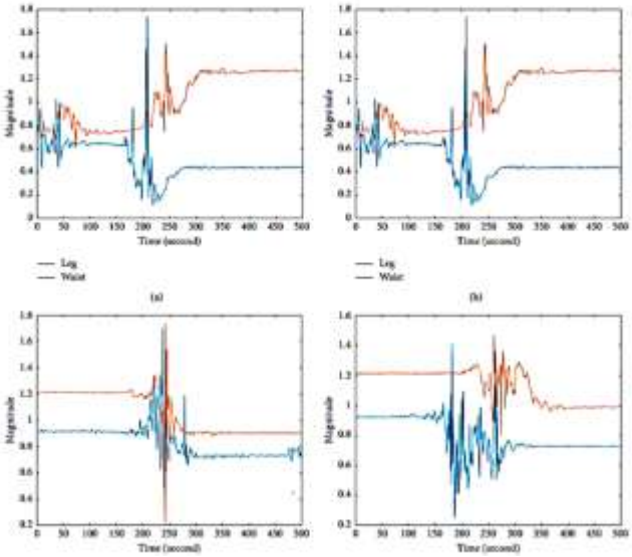


Figure 7: The leg (calf) sensors that reported the greatest amplitude were: a) FOK, b) FOL, and c) BSC. d) SDL.

3.4. INTEROPERABILITY

In order to link and facilitate smooth communication between system components, the Smart IOT Entrance creates a bridge between 6LowPAN and cloud services. IPv6/IPv4 and CoAP/MQTT communication conversions are included in the 6LowPAN transmission mechanisms.

3.5. DATA PROCESSING THAT GIVES TWO TASKS

It obtains movement information (velocity values for x, y, and z) and applies a first-order IIR low-pass filter to data. Additionally, it maps and analyzes the data in a CSV file. A sorted velocity value is kept in each local storage location for use as an input by the big data analysis component.

3.6. MACHINE LEARNING MODEL

There aren't many configurable hyperparameters in conventional ML. A prior extraction of feature information is necessary for conventional machine learning. Before supplying the data for the real-world training, feature selection and extraction must occur. Experts in the field must explicitly state the features to be collected. Therefore, the level of expertise and experience of the researchers has a significant impact on how helpful the structures are [24]. Each source in a time sequence has different spectral and temporal investigation characteristics. However, there are several ways to adjust the hyper-parameters using deep learning algorithms. Thus, the shortcomings of conventional machine learning approaches can be solved by deep learning techniques [25].

RNN is a deep learning technique method for processing language, document analysis, and time series data [26]. Recursive neural networks known as LSTMs are ideally suited for handling temporal information since they have peers for input, output, and overlook [27]. We've displayed the fundamental structure model in Fig. 2. There are three layers of an LSTM that are input, hidden (LSTM), and dense Layer outcome. Our input image's x, y, and z vectors represent for three neurons' worth of raw data. The first LSTM layer has 30 neurons and the xt, ht□ 1, ct□ 1 stands for the the matrices and the vectors, and Wq, Uq represent the input values and recurring linkages, respectively. Q is the input/output (I/O) gate, memory (C/F) cell, or forget (F) gate.

$$f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \quad (1)$$

$$i_t = \sigma_g(W_f x_t + U_i h_{t-1} + b_i) \quad (2)$$

$$o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \quad (3)$$

$$c_t = f_t \circ c_{t-1} + i_t \circ \sigma_c(W_c x_t + U_c h_{t-1} + b_c) \quad (4)$$

$$h_t = o_t \circ \sigma_h(c_t) \quad (5)$$

c0 = 0 and h0 = 0. Hadamard goods are represented by o and the time-to-step index, t. The g, c, and h values also correspond to the sigmoid, hyperbolic tangent, and nonlinear activation functions. To stack, ensemble DL is used in this study. In comparison to a single LSTM model, assembly improves recall and lowers false positives. The new LSTM model assemblage may outperform the single model, according to this study's hypothesis. The heap method develops several LSTM models for testing. The whole training set or a part of it were utilized for instruction LSTMs. Through overlap, each of the models can have data chunks of the same size.

The primary processes for data allocation for each model are revealed in Algorithm 1. The dataset distribution for each model is shown in Fig. 3. 10 networks with a 15% overlap in size, 10,000 data sets, and 1110 observations per LSTM model. Weights are randomly allotted to each recreation by a meta-algorithm. The weight value reveals the significance of each model's prognosis. The weight list is modified and final values are assessed by the meta-primary classifier.

Algorithm 1. Data assignment for layers of high density and 30 neurons.

The output of the last layer, which includes two nodes, creates a probability classifier using the SoftMax function. Since backpropagation is used to train LSTM models, the n-step training process has an impact on the model's performance. The model won't recognize every move if it is just trained with a few steps. If the model is trained across numerous time steps, it will take into account irrelevant data. Each LSTM cell's operations are specified by eqs. (2)– (5)(6). Specifically, input values decide.

Caregivers get fall warnings and the GPS location of the old person's home through a MQTT broker. Figure 4 shows an example of an alert. These details are received using cloud computing. MQTT was chosen due to its security and portability. End-to-end security and SSL-based dependability are offered via MQTT. To assure communication delivery, it has many QoS levels, ranging from QoS0 to QoS2. For our elderly services healthcare system, QoS 2 was created.

Input : no-model , m-overlap, list-models, start, end, data-size. Output: Indices of training data to be assigned for each model.
1. Rows Per Model=Round (Data-Size/((M Overlap-1)*(No-Models-1)+1)). 2. Total 1=Data Size / No – Models. 3. Total = Math. Floor (Total 1) 4. List – Models [Start][0]=0 5. List- Models [End] [0] = Total + M- Overlap 6. For I In Range (1, No- Models) Do 7. List –Models[Start] [I] = Total *I- (M-Overlap) 8. List – Models [End] [I]= List – Models[Starts][I] + Total+2* M- Overlap 9. List-Models [Start][No-Models-1]=Total * (N0-Models-1)-M-Overlap 10. List-Models [End][No-Models-1]=Data-Size

The Raspberry Pi 3 is the heart of the Smart Internet of Things Interface. It has a 1.3 GHz quad-core ARM Cortex CPU, 1 GB of RAM with expandable storage, 4 USB ports, 1 HDMI port, 1 RJ-45 port, and uses 700 mA (3.5 W) of power. Every part of the Smart IoT Platform is run by a Raspberry Pi 3 and a 32 GB class 10 SD card. The Ublox NEO-6M GPS module is attached to the Raspberry Pi board. This makes it possible to track the houses of older people. The 6LoBR node's STM32 Nucleo board (NUCLEO-L152RE) gets data from devices and sends it to the tiny computer via a USB serial link (X-NUCLEO-IDS01A5). Both the 6LoBR node and the wearable device use the 'Contiki' running system. By setting up RPL, you can connect your 6LoWPAN networks to your Smart IoT Gateway. Using tunslip6, which runs on Contiki OS, a tunneling-virtual network adapter is set up on the Raspberry Pi to change data from 6LoWPAN nodes to IPv6/IPV4 and back again. To get acceleration data from the smart device, the coap package, which is based on Python 3 sequential I/O, is used to set up a CoAP server on a Raspberry Pi.

3.7. Services hosted in the cloud

After being received by Cloud Services from those nodes, MongoDB stores the incoming data from Smart the Gateway Server.. The model will be created and learned online using BigML's REST API after a fall has taken place before being locally instantiated in the gateway. After every fall, this procedure is repeated.

Table 1
[illegible]

[illegible]	Explanation
[illegible]	[illegible]
[illegible]	[illegible]
[illegible]	[illegible]

Table 2
Details of experiments.

[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	Falls
1	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
2	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
3	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Table 3
The effectiveness of LSTM Model.

Experiment	Precision	Recall	Overall accuracy (%)
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]
[illegible]	[illegible]	[illegible]	[illegible]

Table 4
[illegible]

Ref.No.	Methods	Accuracy (%)
[illegible]	Threshold	[illegible]
[illegible]	[illegible]	[illegible]
[illegible]	LSTM	[illegible]

4. RESULTS

The efficiency and functionality of our edge computing platform are displayed in this section. Real-time activity and fall data were gathered from human participants, which we analyzed using our algorithm to determine if anybody fell. Data was gathered with the Meta-Motion R accelerometer from MbientLab. Four distinct accidents are trained to students. Yoga mats that prevent injuries were available. Test subjects are listed in Table 3. Using accelerometer magnitude data, a final dataset of 64 slip accidents was labeled. Activities in fall and those not in autumn were webcast separately. These research evaluated the information flow and established the proper single and multi-sensory investigation parameters, including the timing and location of data collection. (Table 4).

Stage 1: Fall statistics were collected at 12.5 Hz, 25 Hz, 50 Hz, 100 Hz, and 200 Hz. In all of the studies, examines were set up on the waist.

Stage 2: Sensor location is flexible, but sample frequency is fixed. The device was located at a number of physiological locations, including the center of the right thigh, the left side of the chest, four types of fall data may be recorded by placing the sensor on the right wrist, the side waist, or the center of the thigh at the ideal frequency identified in stage 1. In Fig. 6, we see the body's many sensors.

Phase 3: The optimal sensor locations and frequencies were selected using the two smart devices with a static specimen rate and chip position based on phases 1 and 2. There were four autumn datasets gathered. Fig. 7 displays the presentation of the LSTM model at various sampling speeds. It was preferable to sample at 50 Hz. In contrast, frequencies below 50 Hz failed to detect any declines, according to our research. Daily statistics storage was dropped from 2.3 GB to 0.33 GB by switching to 50 Hz from 200 Hz. Data reduction results in information loss, hence [28]'s mixed approach is preferable. Data from 50 Hz was moved to 200 Hz when a fall was suspected. This is achieved via their energy-efficient technique. When the sensor is placed at various body places, model performance is depicted in Figure 6 (check Table 1). The graph determines that the hand, waist, and calf are the sensor locations with the greatest accuracy. The waist, which was steadiest and quietest, was quieter than the thigh. For the most accurate outcomes, we place smart devices in the waist, the wrist, and the knee. Three people were wearing the first set of sensors, and three people wore the second set. Figure 7 and Figure 8 show the sizes of the waist + leg (calf) and waist + wrist falls. Typically, legs collapse before waists. These facts might be used to develop fall prevention strategies. Falls might be distinguished from other occurrences and detected simultaneously using the wrist and waist combined. Effectiveness of sensor combinations is shown in Table 2 (Fig. 9).
Assessment based on MobiAct. The model recognized a fall in real time with 0.85 accuracy, 0.66 memory, and 86.2% accurateness using a waist-mounted 50 Hz sensing chip. Both waist + leg and waist + wrist could identify a fall in multistream data with equal accuracy and memory, neglecting the 1s latency described in Section 4. The waist-wrist combination obtained the highest performance, with 0.96 precision, 0.97 recall, and 97.8% accuracy. Falls appear to be reliably identified using data from multiple streams. Table 3 compares significant research results.
Table 3 shows that the threshold-based fall detection technique from Ref. [30] achieved worse than the two others. Additionally, they revealed slip accidents related actions based on the location of the user's smart cell phone, such as in a shirt pocket, pants pocket, or when messaging.
The k-NN classifier in Ref. [28] LSTM model performs best in recognition and following. Our investigation revealed the perfect sensing chips setup and data collecting cycle for tracking and recognition. The model recorded false information when the sensor and edge controllers lost contact. Before deploying the system on a large scale, it should be verified with another network interface to ensure that the second unit will deliver reliable service in situations in which the first station drops connectivity.

5. CONCLUSION

Fall detection technology makes it possible to provide better care to the senior citizens, who are more likely to slips accidents. We develop a system for edge automated service that can recognize individual falls through real-time monitoring using reasonably priced wearable sensors. According to the outcomes of our experiment, our LSTM model has a 99% success rate in correctly identifying falls. In this study, we used a computational framework and our LSTM fall classification algorithm to track patients' activities in real-time and spot any falls that were happened. We used wireless sensors made by MbientLab and called MetaMotionR on people to track their movements. These sensors provided an edge device with real-time data transmission. We built up an automated study of the pipeline on a laptop, utilizing several APIs from MbientLab, Apache Flink, and TensorFlow to handle the stream sensor data. We were able to build up an automated examination of the process thanks to the APIs. The research showed that when trying to identify falls using real sensor data, our technique was 95.9% accurate. We concluded that the waist and 50 Hz were the most suitable places for the detectors based on our empirical investigation. We showed that performance can be increased by increasing the number of sensors and data streams. The models have been proven to be efficient, making them appropriate for use in the field.

REFERENCES

[1] D.A. Sterling, J.A. O'Connor, J. Bonadies, (2001). Geriatric falls: injury severity is high and disproportionate to mechanism, *J. Trauma Acute Care Surg.* 50 (1),116–119.
[2] J.A. Stevens, (2006). The costs of fatal and non-fatal falls among older adults, *Inj. Prev.* 12 (5), 290–295.
[3] M.E. Tinetti, M. Speechley, S.F. Ginter, (1988). Risk factors for falls among elderly persons living in the community, N. Engl. *J. Med.* 319 (26), 1701–1707.
[4] S.M. Friedman, (2002). Falls and fear of falling: which comes first? A longitudinal prediction model suggests strategies for primary and secondary prevention, J. Am. Geriatr. Soc. 50 (8), 1329–1335.
[5] A.C. Scheffer, (2008). Fear of falling: measurement strategy, prevalence, risk factors and consequences among older persons, *Age Ageing* 37 (1), 19–24.
[6] R. Igual, (2013). Challenges, issues and trends in fall detection systems, Biomed. Eng. Online 12 (1) 1.
[7] M. Mubashir, (2013). A survey on fall detection: principles and approaches, *Neurocomputing* 100, 144–152.
[8] J.T. Perry, (2009). Survey and evaluation of real-time fall detection approaches, high-capacity optical networks and enabling technologies (HONET), in: 2009 6th International Symposium on, IEEE, , pp. 158–164.
[9] T.N. Gia, (2016). Iot-based fall detection system with energy efficient sensor nodes, in: Nordic Circuits and Systems Conference (NORCAS), IEEE, pp. 1–6. IEEE, 2016.
[10] F. Bonomi, R. Milito, J. Zhu, S. Addepalli, (2012). Fog computing and its role in the internet of things, Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing, 13–16. ACM.

[15] D. Chen, W. Feng, Y. Zhang, X. Li, T. Wang, (2011). A wearable wireless fall detection system with accelerators, Robotics and Biomimetics (ROBIO), in: 2011 IEEE International Conference on, IEEE, pp. 2259–2263.

[16] O. Biros, (2014). Implementation of wearable sensors for fall detection into smart household, Applied Machine Intelligence and Informatics (SAMI), in: IEEE 12th International Symposium on, IEEE, 2014, pp. 19–22.

[17] S.Z. Erdogan, T.T. Bilgin, (2012). A data mining approach for fall detection by using knearest neighbour algorithm on wireless sensor network data, *IET Commun.* 6, 3281–3287.

[18] F. Wu, H. Zhao, Y. Zhao, H. Zhong, (2015). Development of a wearable-sensor-based fall detection system, *Int. J. Telemed. Appl.* 2015, 2.

[19] Y. Li, (2012). Accelerometer-based fall detection sensor system for the elderly, in: IEEE 2nd International Conference on Cloud Computing and Intelligence Systems, vol. 3, IEEE, 2012, pp. 1216–1220.

[20] C. Shuo, (2015). Fall detection system using Arduino Fio, in: Proceedings of the IRC Conference on Science, Engineering and Technology, Singapore, p. 13.

[21] Y. Cheng, C. Jiang, J. Shi, (2015). A Fall Detection System Based on Sensortag and Windows 10 Iot Core.

[22] R. Freitas, M. Terroso, M. Marques, J. Gabriel, A.T. Marques, R. Simoes, (2014). Wearable sensor networks supported by mobile devices for fall detection, Sensors 2246–2249. IEEE, IEEE, 2014.

[23] S.G. Pease, R. Trueman, C. Davies, et al., (2018). An intelligent real-time cyber-physical toolset for energy and process prediction and optimisation in the future industrial Internet of Things, Future Generat. Comput. Syst. 79 (Part 3) 815–829.

[24] Gad I. Doreswamy, B.R. Manjunatha, (2018). Multi-label Classification of Big NCDC Weather Data Using Deep Learning Model, En: Soft Computing Systems. Springer, Singapore, pp. 232–241,

[25] P. Probst, B. Bischl, A.-L. Boulesteix, (2018). Tunability: Importance of Hyperparameters of Machine Learning Algorithms, arXiv preprint arXiv:1802.09596.

[26] H. Salehinejad, S. Sankar, J. Barfett, E. Colak, S. Valaee, (2017). Recent Advances in Recurrent Neural Networks, arXiv preprint arXiv:1801.01078.

[27] W. Bao, J. Yue, Y. Rao, (2017). A deep learning framework for financial time series using stacked autoencoders and long-short term memory, *PLoS One* 12 (7).

[28] C. Y. Hsieh, C. N. Huang, K. C. Liu, W. C. Chu, C. T. (2016). Chan, A machine learning approach to fall detection algorithm using wearable sensor, in: Proceedings of the International Conference on Advanced Materials for Science andEngineering (ICAMSE), IEEE, Tainan, Taiwan, November 2016, pp. 707–710.

[29] D. Ajerla, (2018). A Real-Time Patient Monitoring Framework for Fall Detection, Queen's University, Ontario, Canada, 2018. M.Sc. project, http://cs.queensu.ca/~farh ana/assets/Sample_ MSc_Project.pdf.

[30] P. Preethi, R. Asokan, N. Thillaiarasu, T. Saravanan, (2021). An effective digit recognition model using enhanced convolutional neural network based chaotic grey wolf optimization, *J. Intell. Fuzzy Syst*, (Preprint) 1–11.