

# A Decision Tree Based System for Real Time Fall Detection in Geriatric Population

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**Abstract**— This paper presents a Decision Tree based system for detecting “falls” in geriatric population. Falls in elderly people are leading cause of physical injury, mental trauma and death. It can also put huge economic burden on society and can adversely affect FQOL (Future Quality of Life) of elderly. This paper proposes an AIoT (Artificial Intelligence of Things) system for detecting falls in elderly people. In the unfortunate event of “Elderly Fall”, an AIoT based system can be used to request caregiver’s attention in an automated manner and help mitigate the harmful consequences of such falls. We used SensorTile.Box Pro IoT kit to create a TinyML system for detecting fall events. Proposed system can discriminate between different causes of fall (forward, backward, lateral, slip, trip, faint etc.). This system can use BLE (Bluetooth Low Energy) based connectivity for connecting to an Edge Gateway device, for triggering cloud and/or smartphone-based applications to alert caregivers and medical professionals and request their prompt response.

**Keywords**— Fall accidents, Fall prevention, Fall Detection, Machine Learning, Artificial Intelligence, Decision Trees, AIoT, STAIoT craft, ST Edge AI, TinyML, Edge Computing

## I. INTRODUCTION

A fall may be described as the event in which an individual, involuntarily comes to rest on a surface having lower elevation than the surface on which he/she was resting previously [1]. They can be caused by either intrinsic events like dizziness, loss of balance, blackouts etc. or extrinsic such as slips etc. [17] Elderly Fall Detection has attracted a lot of attention from researchers in this field. There are two main reasons for this phenomenon.

Firstly, advancements in medical science have increased the life expectancy of people around the world and most people can expect to live well into their sixties and seventies. It is expected that the population of people living in their sixties will grow to 2.1 Billion in 2050 [2]. Secondly, multiple socio-economic factors (e.g. preferring economic prosperity over large family size, marrying later in life, availability of contraceptive technologies, improvement in overall healthcare system etc.) have contributed to lower birth rates in many countries and there are fewer young individuals available to care for the elderly. Therefore technology assisted solutions for detecting and preventing falls can reduce the severity and count of falls

for elderly. This paper proposes a cost effective solution for detecting falls in geriatric population.

The rest of the paper is organized as follows: Section II gives a general outline of broad strategies which can be employed to handle fall related events in elderly. Section III introduces readers to relevant technological landscape. In section IV a possible categorization of various “fall detection and verification systems” is presented. Section V explains various aspects of our fall detection system in detail. In section VI discusses research methodology followed by the author. Finally, section VII draws conclusions from this research.

## II. HANDLING FALLS IN OLDER ADULTS: FALL DETECTION AND FALL PREVENTION

Fall detection in elderly people has been studied well in literature [3], [27], and many different strategies have been used to detect and correct falls in older adults [26]. Literature suggests fall detection and fall prevention as two major strategies for tackling the problem of elderly fall [4], these approaches have been studied in detail in the last few years. While fall detection aims to detect the event of fall once it has occurred, and its goal is to “alert” the caregivers and medical staff so that necessary assistance can be arranged for the elderly in the shortest possible time. Fall prevention, on the other hand, deals with preventing the occurrence of “fall” in older adults either by estimating the probability of fall in advance, or using other preventive strategies like physical exercise etc.

### A. Fall Detection

“Fall detection systems” focus on detecting the occurrence of fall events once they have occurred. This can avoid the situation of “long-lie” which can result in further complications like Blood clots, pressure sores, dehydration and malnutrition. In some cases, the ‘mental trauma’ of falling can also lead to fear-of-falling and can impact mobility of the old-adults for the rest of their lives. The alert generated by a fall detection system can trigger actions which can result in notifying the caregivers and medical professionals. Optionally, these alerts can contain contact and location related information of the “fallen elderly” so that caregivers can immediately contact the victim and assess if an immediate support team should be sent.

## B. Fall Prevention

Fall Prevention also known as “Pre-Impact Fall Detection” includes exploiting gait information of pre-frail old adults to assess the likelihood of a fall in near future. Some researchers have also reported that using a Multi System Physical Exercise (MSPE) to improve Health Related Quality of Life (HRQOL) in pre-frail adults [18]. In our experiments we restrict ourselves to the study of fall detection methodologies only, therefore Fall prevention strategies will not be discussed hereafter in this article.

## III. RELEVANT TECHNOLOGICAL LANDSCAPE

The Internet of Things (IoT) paradigm proposed for the first time by Kevin Ashton in 1999 [9] has gained significant attention from researchers and software developers in the previous two decades and has successfully helped in providing efficient solutions to problems in diverse application domains like remote monitoring, personalized medicine, traffic monitoring etc. In 2012 Krizhevsky et. al. [10] demonstrated a significant improvement in ImageNet classification [11] using a convolutional neural network. This not only attracted significant attention from researchers across the globe but also inspired the research community to explore Data Science based approaches to solve complex pattern recognition problems. As a result, almost all aspects of contemporary human life have been revolutionized by this technology.

Computations done during training and inference phase of AI models require large amounts of input-data and transmitting this data over the Internet to remote cloud servers can have significant economic and environmental costs (power consumption). In cases where user identity, location or some other type of sensitive information is being used, privacy concerns also act as an impediment to sending data over the network. Additionally, Latencies involved in transmitting sensor data to remote servers, and fetching the results back to the originating device can result in ‘delays’ that can make such an approach unfeasible. Supervised ML techniques like Deep Neural Networks, Decision Trees, K-Nearest Neighbors, SVM have been extensively used for detecting falls. In particular, Optimized Random Forest algorithm has shown promising results for computational resource constrained devices [28].

Therefore, Edge Computing [13] emerged as a preferred data processing paradigm for analyzing large quantities of locally generated sensor data on a real time basis. As cost of these devices is an important consideration, Edge devices are characterized by low computing and memory resources.

Various Primary focus of state-of-the-art ML models is to achieve highest possible computational accuracy with no regard to computational and environmental costs involved while running the inference phase. As a result, specialized efforts are required to adapt various ML algorithms for resource constrained devices and microcontrollers. The sub-branch of Machine Learning which focuses on reducing the resource requirements of ML algorithms is called TinyML [15]. MLOPS (Machine Learning Operations) platforms like ST-Edge AI Suite [16] and Edge-Impulse [14] provide tooling required for deploying ML algorithms on resource constrained devices.

This paper proposes an AIoT System (Artificial Intelligence of Things) which combines the sensing and machine learning capabilities in remote sensor nodes [8], [9], with complex business logic running on cloud servers for detecting falls. Taking such an approach to manage the aftermath of falls can greatly decrease the response time of caregivers when such events occur.

## IV. DIFFERENT TYPES OF FALL DETECTION AND PREVENTION SYSTEMS

There are many approaches which can be used to categorize fall detection systems. In our opinion the most relevant categorization can be done from the point of view of the user of the system. Here

### A. Intrusive Fall Detection Systems

These fall-detection systems are based on collecting vision and/or audio sensor data for monitoring the elderly people inside their local environment like homes or other such premises. These systems require the elderly person to be constantly under the “surveillance” of electronic sensors. Data captured by these sensors can be used by inference-phase of AI models to detect the fall-event. There are two main disadvantages of this strategy: Firstly, most people do not like being “watched” by surveillance cameras [23]. Clearly, such a system can have privacy implications even if the captured data is not used reproduce the picture/audio, and all people may not feel comfortable in using these systems. In addition, processing video and audio data requires more complex data processing (and hence more computational resources which increases cost of equipment) in comparison to processing other type of time-series data.

### B. Ambient Fall Detection Systems

These systems are based on detecting the “fall” event by using multiple ambient sensors like floor pressure monitors, thermal sensors, electromagnetic waves [24] etc. These sensors must be installed in the local environment of elderly people, which limits the efficacy of such systems to a limited geographical area. Such installations may require significant cost which makes them less preferable.

### C. Wearable Fall Detection Systems

Wearable Fall Detection systems are based on using inertial sensor-based data collected by a wearable device attached to the body of an elderly person. They are less privacy-intruding than vision and audio sensor-based devices and can be easily embedded in wristbands and smartphones these days. However, it is possible that some people may still feel uncomfortable wearing these devices. Moreover, their affordability also makes them more attractive.

After carefully considering the pros and cons of all three approaches mentioned above, author selected an accelerometer-based approach for building fall detection system. For this research, we focus on wristwatch like wearable devices, as they offer a reasonable compromise between privacy, cost and comfort, while solving the fall detection problem.

## V. FALL DETECTION SYSTEM OVERVIEW

In this section we describe the hardware and software aspects of creating Fall Detection System that we used for this study. Detecting the event of “Fall” is central problem in designing a fall-detection system for old adults. Low power consumption is critical requirement for such nodes as users expect such devices to work without recharge for several days.

Therefore, it is imperative that a device selected to create AIoT node should have low power requirements.

. STMicroelectronics’s MLC core engine can be used to detect specific “fall” events and can communicate such occurrences to the MCU (micro-controller unit) when such an event is detected. IoT kits like SensorTile.Box Pro have on-board BLE (Bluetooth Low Energy) device which can communicate the occurrence of “Fall” to an edge-gateway which can support always-on connectivity to a cloud application which can trigger caregiver attention in a timely manner.

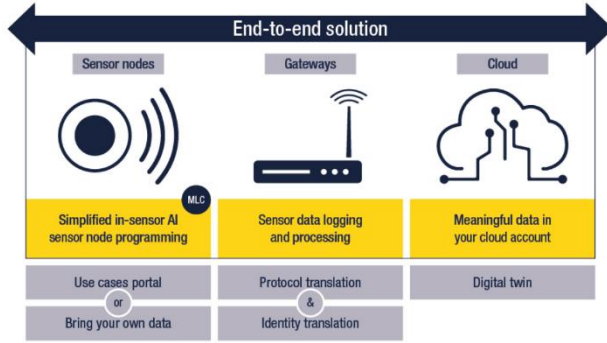


Fig. 1. End-to-end system using SensorTile.Box Pro and Edge Gateway (Adapted from STMicroelectronics [24])

As we are using a Decision Tree based Machine Learning approach to build such system, it is imperative that the ease of data collection, data visualization, data labelling, model training and model deployment aspects are of highest priority for us. In addition, our hardware choices are motivated by considerations like compact design and low-power consumption.

### A. Hardware Overview

Primary goals for fall detection AIoT node are low latency and low power requirements. Both requirements are satisfied by ST’s (STMicroelectronics’s) SensorTile.box Pro HW platform (shown in figure below). It is a ready-to-use programmable toolkit for building sensor based IoT applications [19], it is a palm sized, battery powered device containing an all-in-one sensor node. Our Fall Detection algorithm is based on LSM6DSV16X 6-axis IMU (Inertial Measurement Unit) sensor which has embedded Machine Learning Core processing engine for enhanced response time of Edge-AI applications. It can be accessed using STBLESensor app which is available for both Android and iOS devices.

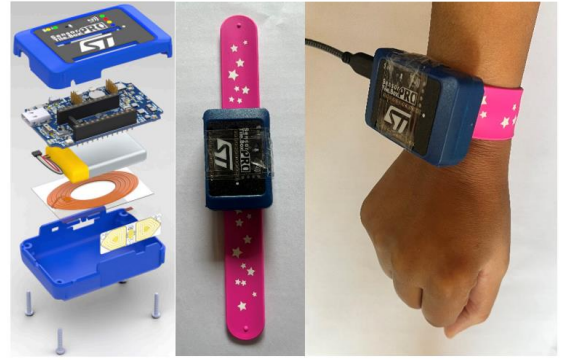


Fig. 2. From Left to right (1) STMicroelectronics SensorTile.Box PRO device. (Courtesy of STMicroelectronics [25]) (2) Device attached to a wrist band (3) Wristband used for data collection

### B. Software Overview

Our choice of software platform is influenced by the hardware platform selected to build fall detection devices. *ST Edge AI Suite* is a set of software tools for creating Artificially Intelligent IoT system using ST’s hardware devices. This technology suite contains several software tools like NanoEdge AI Studio, HandPosture ToF, STAIoT Craft, STM32Cube.AI, MEMS Studio etc. which can be used to create TinyML applications under two paradigms namely: *Bring your Data* and *Bring your Model*. Focus of *bring your model* paradigm is to optimize and deploy a pre-trained ML model on STM32 microcontroller to minimize the processing power requirements and memory footprint of these models during inference phase. *Bring-your-data* tools, however, can be used to create end-to-end solutions by using minimal software setup.

From available options in ST-Edge AI suite, we selected *ST AIoT Craft* online toolchain for developing AIoT solutions using SensorTile.box Pro kit. ML practitioners can use this toolchain, to collect, visualize, and label data. Once this process is complete, she can use the same tool to train and deploy ML model directly on the target device.

This toolchain helps in deploying a Decision Tree based ML application on Embedded MLC (Machine Learning Core) engine present in LSM6DAV16X six axis IMU (Inertial Measurement Unit).



Fig. 3. STMicroelectronics AI and IoT Craft landing page. (Courtesy of STMicroelectronics [26])

There is also a possibility to use it for deploying a cloud application based on the deployed firmware application, however for this study we have not dwelled into cloud application development, and it is subject of future research.

## VI. RESEARCH METHODOLOGY

This work started with a careful review of available research papers on the topic of “Elderly Fall Detection and Prevention”, and we searched for relevant research papers on MDPI, Google-Scholar and IEEE Xplore digital library platforms. In addition, we also referred to online statistics shared by WHO (World Health Organization) and some Governments. Pre-existing datasets for Fall Detection and ADLs (Activities of Daily Living) were also examined. The author studied data collection methodologies adopted by UP-Fall Detection [21] and SisFall Dataset [20]. One important decision while doing this work was to decide on the number and type of “Falls” which we wanted to focus on. Author studied primary reasons and types of falls based on the “elderly fall” related incidents reported in the literature mentioned in [20], [21], [27]. It was found that mainly three types of falls can occur while performing simple activities of daily living, namely: Forward, Backward, and Lateral Fall. Moreover, each of these falls can happen because of a slip, trip or faint. The following types of activities/falls were simulated in laboratory conditions by young adults in the age group of 25-45 years.

Fall/Activity Type	Activity Context	Reason	Label
Forward Fall	Walking	Slip	FF_W_S
Forward Fall	Walking	Trip	FF_W_T
Forward Fall	Walking	Faint	FF_W_F
Backward Fall	Walking	Slip	BF_W_S
Backward Fall	Walking	Trip	BF_W_T
Backward Fall	Walking	Faint	BF_W_F
Lateral Fall	Walking	Slip	LF_W_S
Lateral Fall	Walking	Trip	LF_W_T
Lateral Fall	Walking	Faint	LF_W_F
Forward Fall	Sitting on Chair		FF_SC
Backward Fall	Sitting on Chair		BF_SC
Forward Fall	Getting up from Chair		FF_GUC
Backward Fall	Getting up from Chair		BF_GUC
Walking	Walking on a flat surface		WLK_FS

Fig. 4. Types of activities/falls under Study and corresponding Labels

Kindly note that the Label column present in above table is used as target (dependent variable) for ML training algorithm, and it is also used to refer to the class of fall in various charts that are shared in this paper. The first two letters in the Label correspond to fall direction (FF: Forward, BF: Backward, LF: Lateral), third letter corresponds to the activity being done when data was collected (W: Walking, S: Sitting, GUC: Getting up from chair). When the fourth letter is ‘W’, sixth letter codifies the the reason of fall (S: Slip, T: Trip, F: Faint). Moreover WLK\_FS labels is used to represent “Walk on Flat Surface”.

### A. Data Collection and Labelling

Data collection was done by using a SensorTile.Box Pro IoT kit and STAIoT Craft online toolchain. This toolchain offers

capability to label data on-the-fly when it is being collected and thus greatly simplifies data collection phase of any accelerometer based TinyML project. This toolchain was used to collect data for each of the above mentioned categories. It is very important that data collected for any machine learning project should be balanced among all the target labels so that model can learn each of the target labels correctly and is not unfairly biased towards any particular category. Below diagram shows the distribution of data among various labels:

Classes distribution:



Fig. 5. Percentage of Data present for each label/class

As can be seen, most of the target labels were equally distributed in our dataset.

### B. Model Training Phase

A Decision Tree based ML model was trained using the in-house developed dataset. STAIoT toolchain model training algorithm can detect whether all the labels are represented in the equal data. In addition, each target label must have accelerometer data available for at least five seconds. Initial data collection process failed to satisfy “five seconds” constraint, and hence we collected additional data for such labels. Once sufficient data was available for model training, a Decision Tree based ML algorithm was trained. A training accuracy of 98.18% was achieved in the experiments that we performed. Following figure shows model training workflow in STAIoT Craft toolchain:



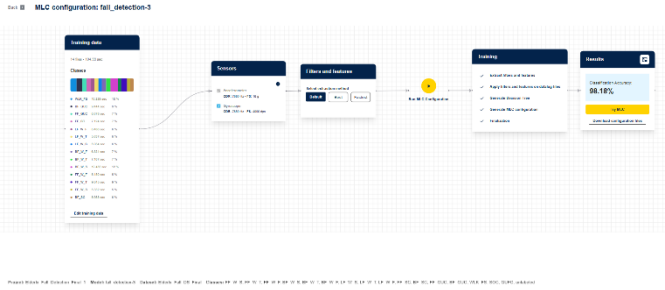


Fig. 6. Pre-processing and Training using STAIoT Craft

STAIoT Craft tool also displayed a confusion matrix which can be used to understand how different classes are being interpreted by machine learning model.

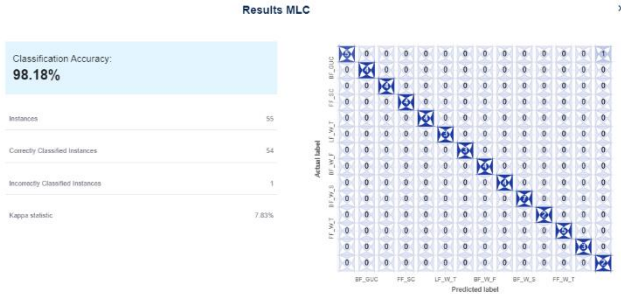


Fig. 7. Confusion Matrix

### C. Validation on SensorTile.Box Pro IoT Kit

Data collection and model training phases are followed by validation of the TinyML algorithm on target device (SensorTile.Box Pro). In this phase real time simulations were conducted to verify that ML algorithm is providing correct inference. The following diagram shows result of running some inference on the device.

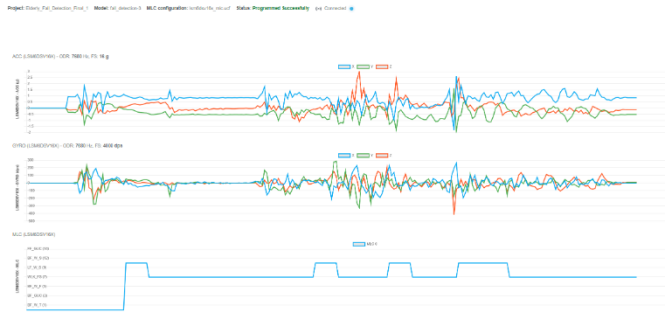


Fig. 8. Validation on target (SensorTile.Box Pro IoT Kit)

## VII. CONCLUSION

This research demonstrates that:

1. A Decision Tree based AI algorithm can effectively detect and discriminate between different types of "falls" in elderly.
2. MLC engine embedded in SensorTile.Box Pro has sufficient computational power to run this tree

algorithm to detect and discriminate between various types of elderly falls (as defined in Figure 4).

3. ST AIoT Craft online toolchain provides an intuitive interface to program MLC engine embedded in many of ST's MEMS inertial sensors.

Such systems can be deployed in the field by connecting them to a cloud-based application which can run additional services for alerting caregivers and healthcare professionals. These systems can greatly reduce the scope of physical injury, mental trauma and economic cost faced by older adults living independently.

As stated earlier, an efficient cloud and smartphone integration is essential for effective-deployment of fall-detection-systems in the field, and this problem remains a subject of future research. In addition, this system can be further extended to assess the health and vital signs of older adults by incorporating classification for ADLs (Activities of Daily Living).

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