Wait, You'll Trip! A Real-time Fall-prevention Wearable System

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Abstract

Falls remain a prevalent issue in the healthcare industry. Hundreds of thousands of unintentional deaths happen yearly because of falls. This is especially true with the elders, as they are the most prone to falls. To solve this, fall-detection systems have been developed to detect when a person has fallen. Generally, fall-detection systems are capable of detecting when a person has fallen and landed on the floor, but there has been a lack of research on preventing falls altogether. This study aims to solve this by developing the first fall-prevention system. This system will be built on a Jetson Orin NX 8 GB board with 3 RGB cameras for object detection and a ToF camera for depth measurement. This study introduces a novel fall-prevention system that is capable of preventing falls that happen from tripping entirely, which, in turn, will lessen the amount of unintentional deaths that happen yearly.

Keywords

Fall-Prevention, Wearable Device, Visual-based Device

1. Introduction

Aging is a natural occurrence in which individuals can experience a change in their emotional, physical, and cognitive abilities that will require additional support. According to recent statistics [1], people 65 and older in the UK are predicted to have a long-term limiting physical or mental health condition for more than half of their remaining years, which will increase their need for care and support. In fact, about 30% of women and 20% of men in this age bracket currently require assistance with at least one activity of daily living (ADL). According to current projections, the absolute number of older people with low or high reliance will increase by more than a third by 2035, making it more difficult to meet their care and support needs. According to the World Population Prospects 2019 report, elderly people will account for roughly 16.5% of the population by 2050.

In the Philippines, the number of elderly persons is growing at a faster rate than the country's overall population. By 2025, 10.25% of the Filipino population were predicted to be elderly people [2]. According to a 2017 Population Division report by the United Nations Department of Economic and Social Affairs (UNDESA), the Philippines was predicted to rank among other nations with an aging population, which means that by 2032, at least 7% of the Filipino population would be 65 years or older, and by 2069, at least 14% of the Filipino population would be of that age. According to the Philippine Statistics Authority (PSA) 2020 survey, 11.31% of the 109,035,343 Filipino population were 60 years or older, exceeding the 10.25% predicted by 2025 [2]. This indicates that the number of older Filipinos is growing rapidly, which could lead the Philippines to be classified as an aging or elderly society even before the projected years.

The demand for health care and related support is rising as the number of older people rises as the elderly often need more interactions with healthcare providers, have several medical issues, and/or require multiple maintenance drugs. Among the elderly population, osteoarthritis and hypertension were the most prevalent conditions, followed by visual impairment [2]. In addition, elderly Filipinos suffer from mental health conditions such as depression, dementia, and anxiety disorders, as well as

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sensory impairments like vertigo, hearing loss, cataracts, and sleep difficulties, with 22% struggling to complete at least one of the seven activities of daily living (ADL) (i.e., bathing and grooming, dressing and undressing, preparing meals and eating, functional transfers, safer use of a restroom, maintaining and maintaining continence, ambulatory ability, care and stimulation of memory) [2].

Unintentional falls for elderly people aged 65 years or older has been a prevalent issue in the healthcare sector, sometimes resulting to fatal injuries. To put the problem more into perspective, the World Health Organization [3] stated in an article that there are estimated 684,000 fatal falls that occur each year, making it the second leading cause of unintentional deaths, only second to road accidents. Fall detection systems are an effective way to alleviate the consequences of falls as they would inform any person capable of helping and would effectively reduce the time a victim spends lying on the floor. These systems can fall under one of three categories: wearable device-based, ambient sensor-based, and camera (vision) based. Wearable device-based sensors are meant to be worn by a person, wherein built-in sensors are used to detect the location and motion of a person. The most common devices used for these sensors are accelerometers, gyroscopes, and magnetometers. Ambient sensor-based sensors, on the other hand, are sensors that make use of vibrational data to detect falls. Lastly, camera-based sensors use visual sensors such as RGB and RGB-D cameras to detect falls through a person's activity.

The problem that exists with fall-detection systems is that these systems are only capable of detecting when a fall has already occurred. Fall detection systems are only able to reduce the time to rescue a victim after falling, but are unable to prevent injuries from happening [4]. These systems will only be able to notify a caregiver after the fall, taking care of the injury that has already been afflicted. With this, fall-detection is only the first step in protecting the elderly, with the final goal being to completely prevent and protect the elderly from falling [4]. Despite this, there has been little research on focusing on preventing falls from actually happening; most research has been focused on only detecting when a fall occurs, predicting a fall before a person falls (person is already in the act of falling), or making elders take precautionary measures through activities that may lessen the chances of them falling. This study, on the other hand, will focus on developing a system that would prevent falls entirely. Since there are numerous reasons as to why a person fall, this study will only focus on preventing one of the biggest causes for falls, which are hazards on the floor that people trip on. Extrinsic fall risk factors, such as hazards on floors, are usually overlooked in fall detection and fall prevention systems [5]. It was encouraged to discover and develop new technologies that will be able to reduce the risk of falling due to these factors [5]. By answering the question, "How may we prevent falls from happening by preventing people from tripping?", this study will introduce a novel approach to prevent falls from completely happening by these factors.

The system that will be developed for this study is a fall-prevention system prototype that makes use of an application utilizing the YOLOv8 framework to efficiently detect and warn any potential fall hazard. In addition, this study will also create a dataset of a small sample size of 5 classes of potential fall hazards. This prototype will be built on a Jetson Orin NX 8 GB board, with the use of three RGB cameras for object detection, an Arducam ToF camera for depth measurement, and a vibration motor that will warn the user. This study will be using two YOLOv8 models that are trained on different sets of data. The first model will be pre-trained on specific classes of the COCO dataset, while the other model will be trained on the dataset this study aims to develop. When a fall hazard gets detected by the system, haptic feedback made through vibrations on the vibration motor will be given in order to warn the user. In addition, this study also aims to provide a novel dataset consisting of images of potential fall hazards by creating a small dataset of potential fall hazards. The dataset will consist of 5 classes of 100 images each. It is good to note that the system is still conceptual. The novel dataset still lacks sufficient data, and the software has yet to be tested on the Jetson Orin NX board.

By developing the fall-prevention system, this study will introduce a novel approach aimed at completely preventing falls, which will be beneficial to Philippine HCI research concerning older adults, especially given the local increase in their population. Fall detection and fall prediction systems are only capable of detecting and warning falls that have already or are about to occur, and cannot prevent injuries from happening [4]. These systems are often built with wearable or visual-based sensors, such as accelerometers, gyroscopes, magnetometers, and RGB-D cameras, and are either worn around parts of their bodies (for wearable devices) [6] [7], or placed around rooms (visual-based devices) [8]. Wearable devices often utilize data such as the acceleration and orientation of the person [6], while visual-based devices often extract key features from the body to detect the activity the person is doing (and if the person is in the act of falling) [8] [9]. The fall-prevention system of this study builds upon this idea by aiming to prevent falls from occurring altogether by warning the user of any potential fall hazards while also addressing the privacy concerns associated with visual-based devices, as the fall-prevention system requires no third-party observer. This innovative approach not only enhances user safety but also empowers individuals to maintain their privacy while receiving crucial alerts. This design is based on electronic travel aids that assist visually impaired people in unknown environments. Electronic travel aids use a mixture of cameras and sensors to visualize and notify the user of any obstruction in their environment, and are used to navigate to a designated location [10]. An electronic travel aid used an RGB camera and an ultrasonic sensor (on a torch that is held by the user) to detect and notify the user of all objects (and their distance from the user) along a path [11]. Instead, this study builds on this idea by designing the system to detect and alert users about potential fall hazards along a path. It also emphasizes accessibility by being worn around the hips with a belt bag while being simple to use.

2. Review of Related Literature

2.1. Fall-Detection

2.1.1. Fall-Detection Systems

Earlier work on this field relied on wearable sensors to detect falls. Research was usually done with an accelerometer or a gyroscope, or a mixture of both, to develop a fall-detection system. These devices take into account the rotation and motion of which the body is moving and uses this information to detect a fall. These systems were often attached to parts of the body when research on this field was at its early stages [7]. Wearable devices relied on acceleration-based systems, and used it to get kinetic data from the motion of the body. Technology has since advanced, with modern smartphones now having built-in accelerometers, gyroscopes, and magnetometers, all of which can be used for fall-detection systems.

Most research done in this field that uses a wearable device utilized accelerometers, where in a study it was found that out of the 20 key papers that used a wearable device, 19 out of 20 used accelerometers [12]. A tri-axial accelerometer built into a smartphone was used in one study [6], and tested their device with three different methods while placing the device on the subject's chest. Another study made use of the built-in tri-axial accelerometer and magnetometer of a smartphone, and developed a threshold fall detection algorithm that detects four key features which are extracted from the signal vector magnitude (SVM) to detect falls [7]. They extracted the base length of the triangle, the SVM peak value, the residual movement and post-impact velocity as the four key features. They also added the vertical acceleration as another feature in order to detect falls better. In order to differentiate falls from activities of daily living (ADL), the researchers made use of three features. The base length of the triangle, the SVM peak value, and the post-impact velocity were used to differentiate falls from walking, jumping, and falling. While conducting their study, they found out that these three features were not enough to differentiate falls from running. To solve this problem, they added residual movement and vertical acceleration as features.

Visual-based devices became a good alternative to wearable devices. These devices are cheap and effective, and is why it is an attractive alternative. Research on this type of system usually uses RGB-D cameras such as Kinect, and infrared sensors as their preferred devices. As soon as Microsoft launched the Kinect camera, research on this field saw a shift from RGB cameras to RGB-D cameras. Reason being is Kinect cameras have built-in RGB cameras, depth sensors and multi-array microphones, and created a trend in 3D data collection and analysis [12].

A study developed a fall-detection system using Kinect [8]. They developed a method to extract features from the human body then classify whether a fall was detected through an SVM. The researchers were able to garner an accuracy of 92.05% on the Telecommunication Systems Team fall detection dataset V2, which is deemed better than other methods.

Sensor fusions are a mixture between different sensors, and usually involve sensors among the three sensors mentioned: visual-based, wearable, and ambient devices. Sensors are fused together in order to address the issues of different types of sensors, and by mixing the strengths of the combined sensors, the system would generate better results. In terms of visual-based approaches, there has been a study done that has tried to fuse signals from RGB and RGB-D cameras and have effectively showed better stability and robustness by reducing false alarms caused by occluded falls [9]. Another study made use of Kinect sensors and smartphones to develop a more robust system [13].

Most of the previous studies in this field focus on fall-detection systems. These systems are only programmed to detect when a person has fallen and fails to prevent falls from happening. By introducing a fall-prevention system aimed at preventing people from tripping on fall hazards, we introduce a novel approach to prevent falls from completely happening.

2.1.2. Datasets for Fall-Detection

Fall-detection datasets usually consist of data obtained through sensors such as accelerometers, gyroscopes, and magnetometers, as well as through cameras such as the Kinect camera. There have been notable datasets in the field that researchers utilize in their datasets to measure the effectiveness of their fall-detection systems. One of which is the FARSEEING (FAll Repository for the design of Smart and sElf-adaptive Environments prolonging Independent livinG) dataset [14] that contains 208 verified real-world fall events that are available for analysis. All recorded data contain measurements taken from accelerometers with 58% of the data being recorded with additional gyroscope and magnetometer data. The verified dataset currently consists of 94 fallers with an average age of 76.1 years.

One notable benchmark video dataset for fall detection is FallVision, a dataset that is mainly comprised of video recordings of people falling and doing other activities of daily living [15]. There are three categories of falls that were conducted: falls from a bed, standing position and from a chair. There are a total of 11,732 videos obtained from willing participants, 6,002 of which are videos of people falling, and 5,730 of which are no-fall videos.

There exists datasets that utilize a mixture of sensors and cameras for fall detection. The UP-Fall Detection dataset consists of data that have been measured using wearables, context-aware sensors, and cameras [16]. To be more specific, 5 Mbientlab MetaSensor devices were placed in five various places around the body to collect various raw data. This sensor is capable of measuring 3-axis accelerometer values, 3-axis gyroscope values as well as the ambient light value. An additional electroencephalograph (EEG) NeuroSky MindWave headset was attached to each participant to measure EED signals from the head. The environment in which the participants performed the various activities also contained six infrared sensors and two Microsoft LifeCam Cinema cameras placed in various ideal places.

All aforementioned datasets utilize data specifically for fall-detection. With this knowledge, there exists no dataset in the field that aims to detect potential fall/trip hazards. By introducing the novel dataset of potential fall hazards, we will introduce a dataset with the sole purpose of preventing falls from completely happening.

2.2. Electronic Travel Aid

One of the systems most comparable with the fall prevention system that this study is aiming to develop is an electronic travel aid. An electronic travel aid is a piece of technology that aims to help visually impaired people navigate through a terrain or environment. It can help people avoid obstacles and reach their designated locations. Without external assistance, it seems impossible to navigate and orient oneself in an unfamiliar situation. In this regard, a system that can reliably and precisely locate a visually impaired user in an urban setting is essential. The most common travel aids are guiding dogs and white canes. However, it does not offer all the information necessary for perception and control of movement during navigation, such as object speed, volume, and obstacle distances, which are typically obtained through the eyes [10], hence the need to develop electronic travel aids.

A study developed an AI-based handheld electronic travel aid for visually impaired with the use of an RGB camera and an ultrasonic sensor [11]. Their system acts as a torch that people will carry that is in charge of detecting any obstacles along the walk path. In more detail, the system uses a monocular camera, an ultrasonic sensor, a Raspberry Pi board, and an earphone to communicate with the person. The system uses a pre-trained SSD MobileNet v3 algorithm to detect 80 outdoor and indoor objects. The MobileNet algorithm was trained with the MS COCO dataset that contains 80 different classes consisting of an estimated number of 2.5 million labeled images. The authors used MobileNet as it is capable of achieving fast speeds and good accuracy due to its use of convolution filters instead of bounding boxes to detect images.

To measure the distance between the obstacle and the person, the ultrasonic sensor of the system was utilized [11]. Once an object has been detected, the ultrasonic sensor will calculate the time it takes for sound to reflect back to the sensor. Depending on the measurements taken by the sensor, if the distance of the object is less than 1 meter from the person, the person will be alerted of an incoming danger. Otherwise, if the object is 1 meter away from the person, the person will instead be warned through the earphone with the title of the obstacle along the path.

Similarly, this study aims to utilize the YOLOv8 object detection model to efficiently detect any potential fall hazards present in the cameras. Instead of utilizing the object detection model to detect as much obstacles/environmental hazards as possible, this system will instead be focusing on detecting potential fall hazards, and warning if the fall hazard gets too close to the user.

2.3. Accessibility of Assistive Devices for Older Adults

Assistive devices generally provide older persons with vital support for aging in place, independent living, and health management, enabling them to preserve their independence while taking care of everyday medical needs or chronic illnesses [17]. Although the elderly are benefiting from health-related technologies, fewer of them accept and use them than the general population [18]. This is generally due to the security and privacy issues surrounding digital technologies, with a group of older adults having limited knowledge of these systems [17], and with systems having access to sensitive information [19]. With this, it is important to understand and answer the specific needs and challenges of older adults in order for them to adopt these devices.

Over the past few decades, AAL (Active and Assisted Living) technologies have advanced quickly. Common home automation sensors, such as contact sensors on doors, motion detectors, and pressure mats on mattresses, as well as wearable sensors, have served as the basis for monitoring systems designed to help people and improve their well-being. However, when complex scenarios need a more thorough awareness of the environment and an individual's activities, the usefulness of binary sensors is suboptimal. In these situations, combining visual sensors with machine learning and pattern recognition techniques can provide complex insights regarding the people and the surroundings. The increasing use of computer vision technology for assisted living solutions is fueled by this synergy [19]. However, with the increased usage comes the issues surrounding privacy, especially when they are used in private places and bystanders are involved.

The Video Monitoring System (VMS) is a privacy protection mechanism that employs filters to the person being monitored (for visual-based AAL devices) to circumvent the privacy issues regarding the use of cameras [19]. The filter will then be removed once a fall has been detected in order to make the caretakers aware of the type of assistance needed. This was met with mixed reviews by older adults they interviewed with some saying that the mechanism benefits them since they remain anonymized while still knowing that if needed, there will be people intervening immediately. Some of them accepts the use of the mechanism as it allows them to remain independent while being assured that there is something that can help them in case of an emergency. An older adult gave a positive remark about the mechanism's ease of use as she did not need to do anything. Despite this, a psychologist stakeholder still remarked that the mechanism still gives them an impression of being watched as there are cameras monitoring them, raising privacy concerns.

The fall-prevention system of this study solves the privacy concerns surrounding visual-based devices by removing the need for it to be monitored as it is operated. It works remotely without outside observation, having software that warns the user of a potential fall hazard. In that regard, operating the system is simple, as the user will be able to utilize the system by turning it on.

3. Methodology

To develop the fall-prevention system, this study will undergo three phases: the data collection, prototype building, and prototype testing phases. In addition, the prototype testing phase will be divided into two parts: calibration and usability testing. The data collection phase will be utilized to collect all necessary images for the small dataset of potential fall hazards. Once this study enters the prototype building phase, all the necessary equipment and software will be gathered and developed. Lastly, the prototype testing phase will be used to test and evaluate the effectiveness of the system.

3.1. Data Collection

Two object detection models will be used throughout the duration of this study. One model will be trained on the dataset this study will create, and the other model will be pre-trained on the COCO dataset that will only detect the possible fall hazards (not all 80 classes present in the COCO dataset will be detected). The dataset that this study will create consists of 5 common and uncommon objects that are not seen in the COCO dataset. The created dataset will only consist of 100 images for each object class, and an additional 100 images as the background image class (for training). This dataset is used to test the viability of the system utilizing a relatively small set of data.

The created dataset will consist of images posted by people on the Internet that are available for public use. In addition, this study will collect screenshots of video recordings that focus on walking / traveling in malls, indoor buildings, and outdoor environments. The screenshots that will be collected will be frames in the videos that contain the trip hazards of the proposed dataset. These images will include objects of the following types: rugs, boxes, pillows, wet hazard signs (since it indicates a wet floor), and clothes.

For the prototype to detect objects more commonly found such as round objects, toys, and pets, this study will utilize a pre-trained model that is trained on a portion of the COCO (Common Objects in Context) dataset. The COCO dataset is a large-scale object segmentation, detection, and captioning dataset that contains classes such as an airplane, apple, kite, laptop, motorcycle, and many more. More specifically, the dataset contains more than 330,000 images with 80 object classes [20]. Since this study will focus on fall hazards, the pre-trained model will only be trained on 45 classes present in the COCO dataset.

3.2. Prototype Building

Once the data are collected, the wearable prototype and its accompanying software will be developed. To ensure that the system is robust and effective, this study will utilize a wearable prototype with a Jetson Orin NX 8GB board that contains an Arducam ToF Sensor and 3 UGREEN 2K resolution web cameras (has a FOV of 80 degrees), with software that will detect and warn any potential fall hazards.

The prototype will be attached to a belt bag, where the Jetson Orin NX 8GB and its power supply will be placed inside the bag. The belt bag will be worn the other way around, where the bag of the belt bag is located on the back of the person. The three RGB cameras will be placed in front of the person while attached on the strap of the belt bag. The first camera will be attached on the middle part of the strap. When worn by a person, the camera will be located around the middle area of the hip. The remaining two cameras will be placed around 2 - 5 cm from the left and right hips of the person, protruding towards the front area of the person. Both of these cameras will be able to view the left and right surrounding areas of the user. A visualization of the worn prototype can be seen in Figure 1.

The front facing camera will be tilted around 30 - 45 degrees from the ground depending on the height of the user. Upon testing, the ideal distance of which the front facing camera can see is 1.6 meters from the person. This is based on the average stride length of a person (distance between when the same foot touches the ground again). The average stride length of a male was recorded at 1.37 meters while the average stride length of a female was recorded at 1.26 meters [21]. 1.6 meters is a comfortable enough distance to warn the user 2 steps ahead of the fall hazard.

If the system is worn by a taller person, the tilt angle will be adjusted to a lower angle to have a maximum viewing distance of around 1.6 meters. By having a maximum distance of 1.6 meters, the camera's bottom view will be roughly around 0.4 - 0.6 meters from the person (depending on the height), which is an ideal length based on the average length of a person's step. A viewing distance of 0.4 - 1.6 meters will be sufficient to warn the person ahead of time. Lastly, the ToF sensor will be placed on the right side of the front-facing camera, tilted at the same angle, while the vibration motor will be placed on the left side of the front-facing camera.

The camera placed on the middle part of the strap will have a front view perspective with a viewing distance of around 0.4 meters from the person to a maximum viewing distance of around 1.6 meters. Once an object enters the view of this camera, an initial warning will be communicated to the person through vibrations. The initial warning will consist of a one- time vibration. Following this, a "step threshold" will be placed around the middle of the viewing angle of the front-facing camera. This has an estimated distance of around 1 meter from the person. When an object has reached this distance, the application will create a repeated warning to the person by means of multiple repeated vibrations. These warnings signify that the person is approaching the detected fall hazard/s.

The remaining 2 cameras have a viewing angle of the area surrounding the left and right sides of the person's feet. If a fall hazard was detected in any of these 2 cameras, repeated warnings will be communicated to the person (there are no thresholds for the repeated warnings). This is because if a person is to turn towards any of the two directions, he/she will take a step to either the right or left side, and if a potential fall hazard is cluttered around any of these areas, the person may trip.

Lastly, the ToF sensor will be used to observe if a detected fall hazard is placed on a chair or table. If fall hazards were to be placed on a chair or table, the system must not warn the user of a potential fall hazard as there is no risk of tripping on an object that is on top of a chair or table. To accomplish this, the program will initialize a variable with the distance of the ToF sensor from the ground once the object detection application starts running. A static value can not be placed inside this variable as the height of the users vary. Once the ToF sensor returns a negative change in distance value of at least 0.4 meters (the average height of a chair or small table), the program will trigger an if statement that would cease it from warning the user as long as this condition is true.

We understand that there are fall hazards that have a height of 0.4 meters or taller (big dogs, for instance). Due to this reason, the software will also be programmed to check if the increase in height captured by the ToF sensor is caused by a fall hazard. This is done by checking the object detection model if the object detected was a dog, or any other hazard that could have a height of 0.4 meters or taller. If this case was true, the system will still warn the user. On the other hand, if a small dog were to be on top of a chair, couch, or table, the viewing angles are set-up in a way that most features of a small dog will not be seen and will not be enough for the object detection model to detect.

3.3. Prototype Testing

In order to test the effectiveness and viability of the system in real scenarios, this study will conduct two types of tests: calibration and usability testing. Calibration tests will be conducted in a controlled environment with small sets of hazards per willing participant. Usability tests, on the other hand, will be conducted in a private and public indoor environment, more specifically, a house and a mall, where

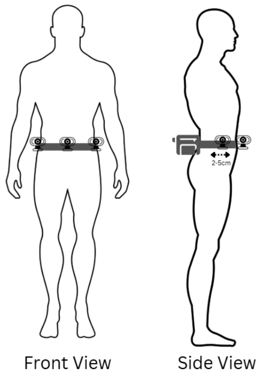

Figure 1: Visualization of worn prototype.

participants will walk for 30 minutes while wearing the prototype.

Before testing the usability of the system in real-time scenarios, the study will first test the robustness of the system through a series of calibration tests that will detect if the system is working accordingly. Four participants that are 18 years or older will be asked to participate in the calibration of the system. We understand that there exists a risk in tripping over these fall hazards, and to take precautionary measures, an additional person will assist and act as a "spotter" of the participant. The spotter will walk behind the participant as the participant conducts the tests. The spotter will not bother the participant and will only act when the participant has tripped. When the participant trips, the spotter will assist the participant by catching the participant as he/she trips. This is to ensure that the participant does not fall.

The participants for the calibration tests will be asked to perform 10 tests in a span of 30 minutes to an hour. The researcher will be placed on the corner of the room, monitoring the system with a laptop. The camera footage will be recorded and saved for every test to ensure proper evaluation of the robustness of the system. Once the tests have been concluded, the researchers will review the footage and will label each recording as the following: true positive, false positive, and false negative. A true positive in this research represents when the system correctly detects a potential fall hazard with its respective warning. A false positive indicates that the system warned the user without any fall hazard. A false negative on the other hand, represents scenarios where a fall hazard appeared in the viewing range of the system, but failed to warn.

This study also aims to evaluate the real-time efficiency of the system. The latency performance will be noted to evaluate the real-time efficiency (recorded in milliseconds). Latency performance is tested by recording the time it takes for the system to detect a potential fall hazard from the first time it enters the system's field of view. In addition, the distance between the fall hazard and the user when the first warning occurred will also be measured (to be measured in meters).

There will be a total of 10 tests that will be performed by the participants. This group will be performing all the tests in a room with the layout in Figure 2. As seen in the figure, the room contains three hazards: round objects, clothing, and a wet hazard sign. Each participant will have different sets of hazard types. Since there are a total of 2 object detection models trained on different data, one of the participants' tests will consist of only the hazards seen in this study's created dataset: rugs, boxes, pillows, wet hazard signs, and clothes. During this set of calibration tests, the model trained on the created dataset will be used. This is to test the viability of the model trained on a small dataset. Hazards are strategically placed in a triangle formation as this is important to test the system's effectiveness. Each test will examine the robustness of the system in different sets of scenarios.

Lastly, this study will be asking for 6 willing participants of varying heights and ages to take part in the usability testing portion of the study. 4 of the 6 willing participants will be of ages 18-64 years old, while the remaining two participants will be of ages 65 years and older. All 6 of the participants will be placed into two separate groups.

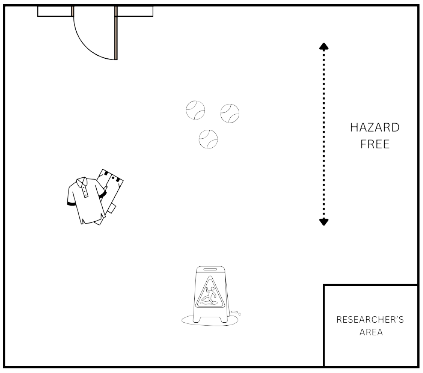

Figure 2: Room layout for calibration tests.

Since these tests involve real-life scenarios, only the YOLO v8 model pre-trained on the COCO dataset will be used. 3 participants will be asked to walk for a total of 30 minutes (the elder is only asked to walk for 15 minutes) around a well-lit house while wearing the prototype. This experiment is to simulate a real-life scenario of a person walking inside their respective homes. At random intervals, random fall hazards will be cluttered (and de-cluttered) around the house. Participants will be asked to walk towards any fall hazard of their choice but avoid it once he/she reaches the fall hazard. All video footage will be recorded and saved for final evaluation.

Despite the fact that trips from fall hazards usually occur in enclosed private spaces such as rooms [22], it is still useful to test the usability of the fall-prevention system in public indoor environments. The remaining 3 participants will be asked to walk around a mall for 30 minutes (the elder is only asked to walk for 15 minutes). This is to test the usability of the system when used in a public enclosed environment such as the mall. All video footage will be recorded and saved as well for final evaluation.

There are no tests to be conducted in outdoor environments since the usual fall hazards that can be found in outdoor environments are uneven surfaces and potholes, which is not in the scope of this study.

Final evaluation will be similar to how the prototype was evaluated during the calibration tests. The researchers will manually review the footage and will count the number of true and false positives, as well as the number of false negatives. In addition, the real-time efficiency will also be evaluated.

4. Conclusion

Falls remain a prevalent issue in society and are more prevalent in the elderly population. It is considered the second leading cause of unintentional deaths, only behind road accidents. To mediate this issue, researchers have developed fall-detection systems to detect whenever a person has fallen, either through wearable devices, cameras, or a mixture of both. Once a person has been detected to have fallen, the systems will notify any assigned caregivers that the person has fallen and is in need of assistance. However, this solution does not prevent falls entirely from occurring. The system will only generate warnings once a person has fallen, which means that the person has already suffered the injuries from the fall that has occurred [4]. With this knowledge, this study aims to prevent falls from happening. Since falls occur for various reasons, this study will focus on preventing falls that happen from tripping on fall/trip hazards.

In order to prevent falls that happen from tripping on fall/trip hazards, a system will be created for this study. The system will use a Jetson Orin NX 8GB board along with three RGB cameras and one ToF sensor to efficiently detect and warn users of potential fall hazards. Once a potential fall hazard is detected inside the viewing range of the system, the system will warn the user accordingly. To properly evaluate the effectiveness of the system, calibration and usability tests will be conducted. The calibration tests are designed to evaluate the robustness of the system in various controlled tests, while the usability tests are designed to evaluate the effectiveness in real-life scenarios.

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