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# Multimodal Fall Detection System For Elderly Persons

Group 20 Project Proposal Document by:

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# 1.0 Introduction

## 1.1 Chapter Overview

We aim to introduce a sophisticated fall detection system capable of predicting and detecting falls or near-fall events. Many elderly individuals, especially those over 65, are often left in isolated conditions, leading to high mortality rates due to falls and their lasting effects. Given their vulnerable state, including issues like joint aches and arthritis, many elderly people struggle with self-care.

Our proposed solution is an automated system that prevents falls and ensures timely assistance when needed. By leveraging the Internet of Things (IoT), we can effectively monitor user movements and status, even in the absence of a caregiver. This document outlines the development and functionality of our fall detection system, which aims to prevent falls and alert appropriate authorities promptly.

## 1.2 Problem Domain

Elderly individuals aged 65 and above are particularly vulnerable to fall-related injuries, which have significantly contributed to increased mortality rates in this age group, as such injuries are often fatal. A study on a "Low-cost fall detection system" revealed that an estimated 684,000 individuals die from falls each year, with adults over 60 experiencing the highest number of fatal falls (Fitriawan, et al., 2024).

The causes of these injuries are closely tied to the isolation many elderly individuals face, with little to no supervision over their activities due to the absence or high cost of caregivers. Support services, while available, are often expensive, placing a financial burden on users. According to a study, many elderly individuals struggle to fund long-term healthcare solutions due to limited income (RIVLIN, 1988).

Even for those who can afford caregiving services, it is not feasible to ensure constant supervision. Caregivers may not always be available during critical moments or locations, as they often need to attend to other tasks. This gap in continuous monitoring leaves elderly individuals vulnerable to falls.

The increased risk of falls among elderly individuals compared to younger people can be attributed to several factors, which will be further explored in this document.

- Physical Decline due to aging as joints and muscles no longer function the same
- Chronic health problems such as arthritis can cause falls as well
- Sensory impairments such as a detachment from their sight could lead to walking into objects unexpectedly, hence causing them to fall
- Medical Side Effects may be another cause given the potency and severity of the drugs consumed by the target populi

Some of the consequences experienced by these individuals may be permanent and could quite potentially lead to a death inducing injury, so to prevent the possibility of such a process occurring a solution where the individual is closely monitored is required.

## 1.3 Problem Definition

Elderly individuals over 65 face a high risk of falls due to physical decline, sensory impairments, and chronic conditions. Living alone increases their vulnerability, often leading to serious injuries or death. Caregivers are costly and not always available, making a real-time IoT-based fall detection system a reliable, cost-effective solution for improving safety and independence.

## 1.4 Research Motivations

This research is motivated by the need to address falls among the elderly, a leading cause of injury often disregarded and overlooked in existing solutions. By developing an enhanced, cost-effective system that combines real-time fall detection, prediction, and prevention through advanced data analysis and joined models, we aim to significantly reduce fall incidents. Our goal is to empower elderly individuals to live more independently and safely, providing timely interventions, minimizing injury risks, and offering peace of mind to families while improving their overall quality of life.1.5 Literature Review

*Table 1: Table for Literature Review*

| **Citation** | **Technology/Algorithm Used** | **Dataset** | **Advantages** | **Limitation** | **Metric** |
|---|---|---|---|---|---|
| **Posture Detection using Image Processing API for fall detection** | | | | | |
| (KANDAGATLA, 2022) | Makesense.ai utilized to create labels for each move made in the dataset such that each image has a label appended to it | Fall_dataset | Can be utilized to develop a complex fall detection system using the | Due to the poor joint mappings because of poor visibility for some joints, | Number of non-falls: 3124<br><br>Number of falls: 3784 |

| | | | | | |
|---|---|---|---|---|---|
| | | | provided dataset | there may be some false positives | |
| **Use of Accelerometers and Gyroscopes along with ML models for fall detection** | | | | | |
| (Li, et al., 2009) | A threshold-based fall detection algorithm using tri-axial accelerometers and gyroscopes. Divides human activities into static postures and dynamic transitions. | The dataset includes activities of daily living (ADL), fall-like motions, and different types of falls (e.g., forward, backward, on stairs) | Reduces false positives and negatives. Low computational cost and real-time response. | Difficulty distinguishing between jumping into bed and falling against a wall with a seated posture. | Sensitivity: 91% Specificity: 92% |
| **Real-Time Data Analysis for Event Prediction in Fall Detection** | | | | | |
| (Nguyen, et al., 2024) | Non-vision-based (wearable sensors) vs Vision-based (image sequences, skeleton modeling). YOLOv3-tiny (for real-time object detection) and DeepSORT (for human tracking). AlphaPose for high-accuracy skeleton | RGB-D images and skeleton sequences captured by Kinect sensors. | High detection accuracy with YLOv3-tiny and DeepSort<br><br>Preprocessing reduces false positives | RNNs used struggle with long sequences<br><br>Falls lasting 400 to 1600ms require precise timing | over 99% accuracy on both standard and custom datasets for fall detection. |
| **Monitoring Blood Pressure to Predict Fall Risk** | | | | | |
| (Hermida, et al., 2012) | ABPM for hypertension diagnosis | Data on adult hypertension and cardiovascular risk | Establishes best practices for diagnosing hypertension and identifying cardiovascular risks | Focuses on diagnosis rather than direct fall risk | Accuracy in predicting hypertension progression |

## 1.6 Research Gap

Existing fall detection systems typically rely on a single data stream, such as motion sensors or posture detection, which limits their ability to predict falls with high accuracy. These systems primarily focus on detecting falls after they occur and often lack the capability to foresee potential fall risks. Our project aims to address this gap by integrating multiple data streams, including real-time posture detection and motion sensors (gyroscope and accelerometer) for immediate fall detection, and abnormal blood pressure level monitoring to assess fall risks.

By combining these streams, the system can predict potential fall events based on factors like high or low blood pressure levels, while also providing rapid detection through sensor data. Additionally, user-provided data such as BMI, age, gender, weight, and heart rate (BPM) will further enhance the accuracy of fall risk predictions. This approach creates a more comprehensive and proactive fall prevention solution. Our project uniquely addresses this gap by considering multiple modes of input to achieve higher accuracy and fall prediction capabilities that existing research has not yet accomplished.

## 1.7 Contribution to the body of knowledge

### 1.7.1 Domain Contribution

Our model will be trained to deliver a comprehensive, multilayered solution capable of detecting and predicting falls with greater accuracy. The domain contribution can be broken down into the following points:

1. Enhanced Accuracy

The combination of three main models—fall detection through posture analysis, sensor data (gyroscope and accelerometer), and monitoring of abnormal blood pressure levels—leads to improved system accuracy. This approach reduces false positives and false negatives, making the system more reliable and effective in real-world use.

2. Fall Prediction and Prevention

The system offers a novel approach by predicting potential falls based on physiological data like blood pressure levels. While vision data and sensor data detect falls, abnormal blood pressure measurements, such as unusually high or low readings, signal the risk of a fall. This allows the system to notify caregivers or medical professionals, enabling preventive measures to be taken before a fall occurs, which adds a critical layer of early fall prediction and prevention. This aspect has not been thoroughly explored in previous systems.

3. Broader Involvement in Elderly Care Systems

Given that falls are one of the leading causes of injury among the elderly, the implementation of such a comprehensive system can have a significant impact on improving safety for this vulnerable population. By offering real-time monitoring and predictive alerts, our system empowers caregivers and healthcare providers with valuable information, enabling them to make better decisions regarding the care and well-being of elderly individuals.

Additionally, the project contributes to the field of data science by promoting the use of multimodal systems. With models that integrate posture detection, sensor data, and physiological measurements, our project supports the development of hybrid models, which remains a broad and actively researched area in data science today.

### 1.7.2 Technological Contribution

The key technological contribution lies in the multi-modal integration of different input streams, from posture detection to sensor data (gyroscope and accelerometer), combined with blood pressure monitoring. This integration enhances the system's ability to predict and detect falls with greater accuracy.

By assessing the user’s physiological state (specifically through blood pressure levels) along with physical postures and movements, our system introduces an innovative approach to fall detection. To summarize this segment, even though fall detection is a well-established field, the following points highlight our project's unique contributions to the technological domain:

- Multimodal data integration
- Accurate and immediate real time fall detection
- Hybrid Model Development

## 1.8 Research Challenges

### 1.8.1 Data Fusion and Synchronization

Synchronizing data from multiple sources (posture detection, motion sensors, blood pressure monitoring) with different sampling rates is challenging. Proper data fusion is crucial to ensure accurate real-time performance.

### 1.8.2 Real-Time Processing and Computational Load

Handling multiple data streams in real time can strain system resources, particularly on mobile or wearable devices. Optimizing for speed and accuracy without overwhelming the system is a significant challenge.

### 1.8.3 User Variability and Adaptation

User differences in movement patterns and blood pressure responses require models that adapt to individual needs. Designing a flexible system to handle this variability adds complexity to the development.

### 1.8.4 False Positives and False Negatives

Balancing sensitivity and specificity are critical to reducing false positives (incorrect fall alerts) and false negatives (missed falls), ensuring reliable and accurate fall detection.

### 1.8.5 Privacy and Security Concerns

Continuous monitoring raises privacy concerns. The system must securely handle sensitive physiological and movement data while maintaining user trust.

## 1.9 Research Questions

1. How can real-time data from sensors and monitoring devices be effectively integrated to ensure the accuracy and timeliness of fall detection and prediction?
2. To what extent could cuffless-blood pressure analysis reliably predict an individual's likelihood of falling in comparison to other risk factors?
3. How will the system differentiate between fall-related movements and non-critical activities to minimize false alarms in everyday scenarios?
4. What methods will be used to assess the effectiveness of the system in a real-world setting, and how will the results be measured to ensure reliability and scalability?

## 1.10 Research Aim

To conclude what our research's aim is, it is to simply attain a system that is capable of detecting and predicting a fall that a user is to experience before they can experience it such that they are instead saved from it, this solution is also to be a more cost effective and friendly one such that it is more inexpensive when compared to regular healthcare.

## 1.11 Research Objectives

*Table 2: Table for research objectives*

| Research Objective | Explanation | Learning Outcome |
|---|---|---|
| Problem Identification | **RO1:** Develop a multimodal fall detection system integrating motion sensors, posture detection, and blood pressure monitoring for comprehensive fall detection and prediction.<br>**RO2:** Enhance accuracy in fall detection and prediction by fusing multiple data streams, reducing false positives and negatives.<br>**RO3:** Enable real-time processing and alerts to caregivers or emergency services for timely intervention.<br>**RO4:** Incorporate ambulatory blood pressure monitoring (ABPM) to predict falls based on blood pressure-induced risks.<br>**RO5:** Ensure user adaptability by learning individual movement patterns and health conditions for personalized detection.<br>**RO6:** Address privacy and security concerns through secure data storage and transmission.<br>**RO7:** Provide a cost-effective IoT-based solution as an alternative to full-time caregiving, improving accessibility for elderly individuals. | LO1 |
| Literature Review | The literature review aims to cover already explored and covered research's that have been carried out over our project, inclusive of them following similar ideas and concepts. Having listed these similar works out, we also intend on pointing out useful documents and articles that cite and prove certain facts and claims our study makes within the domain of elderly people (age 65 +) falling. Finally, to address ethical constraints, we intend on referring to papers that explain how we may tackle these issues and limitations such that they are properly addressed and dealt with, etc. | LO1 |
| Data Gathering and analysis | Interviews with medical professionals with the fields of physiotherapy and elder care to understand their needs and probabilities into how they are to fall<br>Questionnaires on how useful this may be to isolated elders to see how useful the project is to be<br>Data for research papers are to be collected from IEE Data Port, Google Scholar, etc<br>Journal, Articles, Books published within 2021 to 2024 | LO2, LO3 |
| Research Design | Quasi-experimental design – since randomization is not possible due to ethical and logistical constraints, and we are comparing the outcomes of pre-existing groups to evaluate the effectiveness of different fall detection algorithms in elderly individuals. (Scribbr, 2024) | LO3, LO4 |
| Implementation | 1. The implementation of a web-based UI to handle and manage interactions with the system is to be expected<br>2. Implementation of a machine learning model to take in new data without relying on trained data is to be expected as well<br>3. Develop a real-time multimodal fall detection and prediction system by integrating posture detection, motion sensors, and monitoring data streams into a unified machine learning model. | LO2, LO3, LO4 |
| Testing and Evaluation | Surveys and questionnaires will be used to gather feedback from end-users, caregivers, and healthcare professionals regarding the usability, effectiveness, and reliability of the fall detection system, alongside pilot testing to evaluate its performance in real-world scenarios (QuestionPro, 2024) | LO2, LO4 |

## 1.12 Project Scope

### 1.12.1 In scope

| No | Description |
|---|---|
| 1 | Predict if a person is about to fall |
| 2 | Monitor the users' vitals such that they are not put at a risk |
| 3 | Alert the proper authorities when such an event |
| 4 | Monitor the user's blood pressure, body position using the gyroscope and accelerometer, and posture through the camera |

*Table 3: In-scope project elements*

### 1.12.2 Out scope

| No | Description |
|---|---|
| 1 | Make the web UI available on all kinds of devices with all kinds of language support |
| 2 | Make an application instead of a web-based UI for better performance and quality in terms of user engagement |
| 3 | Amend the model to develop medical reports of the user with the ability to pinpoint potential medical conditions as well |
| 4 | Train the model such that it can detect long term illnesses as well while making amends to the hardware such that it may be used for a longer time |

*Table 4: Out-scope project elements*

### 1.12.3 Feature Prototype

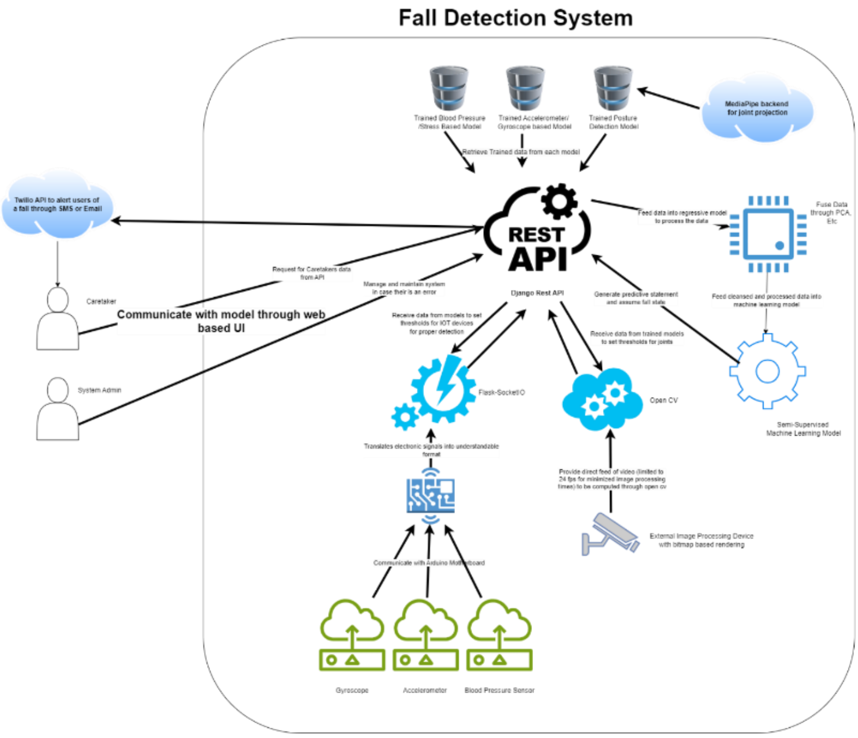


*Figure 1: Feature Prototype Design*

#### *1.12.3A Process Breakdown*

In terms of the process taking place in the diagram above, regard the following steps to understand the general workflow:

1. The device is mounted onto the user and the sensors begin collecting data of the user the device is mounted onto.
2. The data is then passed through each API (Flask SocketIO and Open CV), each of which translates the inputted signals and images into a processable format.
   - Flask-SocketIO : API used to translate communications made between IOT devices and python
   - Open CV: Framework utilized to compute images and videos into numerical formats while supporting the use of MediaPipe based frameworks for joint projection
3. After the data is passed into Django it is then pushed through into the data pre-processing module where it is broken down into its key components
4. Django then retrieves the known data from the trained models and passes it onto the machine learning model to have the system compute whether the user is in the process of falling
5. The machine learning model is tasked with unifying and fusing all the data streams together through models such as TensorFlow to process the general outcome of a person that may fall
6. If the system returns a positive, an alert is sent to the caretaker who interacts with the system (through an API such as Twilio) to alert them of the user falling

## 1.13 Resource Requirements

Refer to the following to see the fundamental requirements of the project in terms of the mentioned components:

### 1.13.1 Hardware Requirements

- **MPU6050** – Combined Accelerometer and Gyroscope sensor for movement processing and tracking
- **Logitech BRIO Ultra HD Webcam** – Relatively cheap camera (alternates may be used as long as it’s a webcam) for posture analysis
- **Arduino UNO board** – For the sensors to interface with the application

- **CPU (Intel Core i7 10th generation processor or higher)** – A better processor may be ideal for optimal performance given its processing capabilities
- **16Gb ~ 32Gb of DDR4 RAM** – For processing heavy loads in the training process of each model
- **Storage (64Gb~128Gb) as a minimum** – To store the datasets and models in

### 1.13.2 Software Requirements

- **Python** – Main language used to process the entire model/dataset
- **C++ -** For Arduino's component management
- **HTML, CSS, JS** – For the frontend web development used to maintain and develop the web application used to interface with the user
- **ReactJS** – To implement a more dynamic and interactive web application
- **PHP** – For the backend storage of important credentials the user may store (e.g. Age, height, etc)
- **Intelij/Vs Code** – Code spaces utilized to execute the code and carry out model training, etc
- **MS Word** – Used for documenting important notes and report-based files for the project
- **Obsidian** – Used for Markdown based notes for quick error annotations
- **GITHUB** – Utilized for version controlling and regulated submission for the code, etc
- **Windows Operating System (10 or greater)** – Main operating system utilized to host all the mentioned applications, etc. Optimal and simple to understand

### 1.13.3 Data Requirements

- The main requirements in terms of the project's dataset include the following in terms of each model:
  - Images that depict persons falling that may be used for training purposes for the image processing/pose estimation segment of the application
  - Average blood pressures for adults over the age of 50 which include details such as heart rate, height and age
  - Falls detected based on erratic movements picked up from devices such as gyroscopes and accelerometers such that they may optimize the current model further
- The focus of the dataset is to be distributed amongst the mentioned features given the fact that there are three main models to the application

### 1.13.4 Skill Requirements

- Intuitive though processing abilities
- Time management
- Rudimentary problem-solving skills
- Report Writing
- Critical Thinking
- Fundamental knowledge of coding and version control

## 1.14 Chapter Summary

To summarize the chapter, all it covers is an introduction to the concept of the project such that its stakeholders, vision and purpose are listed out with an additional list of what the functional and non-functional requirements of the project are. The applications hardware, software and skill requirements are marked out as well to project what the financial costs of the project may be (in vague detail). Thereafter, the challenges experienced by the project (as well as the actions taken to handle them) are explained to convey how the project overcame some shortcomings it was to experience.

# 2.0 Bibliography

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