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In Collaboration with

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**Multimodal Fall Detection System**

**For Elderly Persons**

Group 20 Project Proposal Document by:

Modarage Ethan Christoff Perera – 20221812 | 2331419

Senuli Laknara Wickramage – 20220950 | 2330973

Himansa Wathsiluni Jayasuriya – 20230903 | 2330903

Mevinu Induwara Gunaratne – 20232429 | 2330893

Supervised by

Mrs Vishmi Embuldeniya

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Table of Contents

[List of Tables iii](#_Toc188957023)

[List of Figures iii](#_Toc188957024)

[1.0 Introduction 4](#_Toc188957025)

[1.1 Chapter Overview 4](#_Toc188957026)

[1.2 Problem Domain 4](#_Toc188957027)

[1.3 Problem Definition 5](#_Toc188957028)

[1.4 Research Motivations 5](#_Toc188957029)

[1.4.1 Research Motivation - Ethan 5](#_Toc188957030)

[1.4.2 Research Motivation – Senuli 5](#_Toc188957031)

[1.4.3 Research motivation-Himansa 5](#_Toc188957032)

[1.4.4 Research Motivation – Mevinu 5](#_Toc188957033)

[1.5 Literature Review 6](#_Toc188957034)

[1.6 Research Gap 8](#_Toc188957035)

[1.7 Contribution to the body of knowledge 9](#_Toc188957036)

[1.7.1 Domain Contribution 9](#_Toc188957037)

[1.7.2 Technological Contribution 9](#_Toc188957038)

[1.8 Research Challenges 10](#_Toc188957039)

[1.8.1 Data Fusion and Synchronization 10](#_Toc188957040)

[1.8.2 Real-Time Processing and Computational Load 10](#_Toc188957041)

[1.8.3 User Variability and Adaptation 10](#_Toc188957042)

[1.8.4 False Positives and False Negatives 10](#_Toc188957043)

[1.8.5 Privacy and Security Concerns 10](#_Toc188957044)

[1.9 Research Questions 10](#_Toc188957045)

[1.10 Research Aim 11](#_Toc188957046)

[1.11 Research Objectives 11](#_Toc188957047)

[1.12 Project Scope 12](#_Toc188957048)

[1.12.1 In scope 12](#_Toc188957049)

[1.12.2 Out scope 12](#_Toc188957050)

[1.12.3 Feature Prototype 13](#_Toc188957051)

[1.13 Resource Requirements 14](#_Toc188957052)

[1.13.1 Hardware Requirements 14](#_Toc188957053)

[1.13.2 Software Requirements 14](#_Toc188957054)

[1.13.3 Data Requirements 15](#_Toc188957055)

[1.13.4 Skill Requirements 15](#_Toc188957056)

[1.14 Chapter Summary 15](#_Toc188957057)

[2.0 Bibliography 16](#_Toc188957058)

[2.1 References 16](#_Toc188957059)

# List of Tables

[Table 1: Table for Literature Review 5](#_Toc188953123)

# List of Figures

[Figure 1: Feature Prototype Design 14](#_Toc188953239)

# 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, particularly those over 65, face a high risk of falls due to age-related physical decline, sensory impairments, and chronic conditions like arthritis. These factors, combined with medication side effects, significantly increase their vulnerability. Unfortunately, many elderly people live alone, often without access to immediate help when they fall, leading to serious injuries or even death. Falls are a leading cause of accidental injury deaths among this age group, with long recovery times or permanent disability being common outcomes.

While caregivers provide some relief, they are costly and not always available. Family members also can’t always be present, leaving these individuals at risk. A reliable, cost-effective solution that can monitor and predict falls in real-time, such as an IoT-based system, could allow elderly individuals to live independently while reducing the risks associated with falls, improving their safety and quality of life.

## 1.4 Research Motivations

### 1.4.1 Research Motivation - Ethan

Seeing as to how falls with the elderly populi are regarded as an underdeveloped topic, I believe it as to being a domain that we could expand on and provide them with the ability to take care of themselves without the need to have a third-party take care of them (given the fact that it may be demeaning and maybe even insulting). Besides that, we hope to provide these persons with a cost friendly and inexpensive solution to preventing them from falling.

### 1.4.2 Research Motivation – Senuli

Falls are a leading cause of injury, especially among the elders and individuals with certain medical conditions. Although there are many existing systems, our system aims to develop an enhanced fall detection system with the addition of fall prediction and prevention, with improved accuracy through joined models. We hope this will significantly reduce fall incidents in elderly populations.

### 1.4.3 Research motivation-Himansa

Building on the need for accurate and immediate detection, our system focuses on real-time capabilities to not only detect but also predict potential falls. By utilizing advanced data analysis techniques, the system aims to provide timely responses and interventions, enhancing safety and minimizing injury risks for the elderly.

### 1.4.4 Research Motivation – Mevinu

The motivation behind this project stems from a genuine desire to improve the quality of life for elderly individuals, who are often left vulnerable to falls due to age-related factors. Falls can have devastating consequences, and existing solutions can be costly or ineffective. By combining technology and a deep understanding of health indicators, we aim to create a more accessible and reliable system for fall detection and prevention. This project is about providing peace of mind for families and empowering elderly individuals to live more independently and safely.

## 1.5 Literature Review

Table : Table for Literature Review

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
| **Citation** | **Technology/Algorithm Used** | **Dataset** | **Advantages** | **Limitation** | **Metric** |
| **Posture Detection using Image Processing API for fall detection** | | | | | |
| (Lin, et al., 2022) | Object Detection API using neuromorphic computing hardware and cameras | N/A | Able to accurately detect whether a person has fallen or is about to fall given the fact that it utilizes "emulated' brain tissue elements | **False Alarms**: Occlusion, especially when the subject's skin is blocked by clothing or background elements, leads to **false positives** | Fall Detection Rate: 91.01%  False Detection Rate: 0.3% |
| (Ogundokun, et al., 2022) | Utilizes  Convolutional Neural Networks (CNNs) Which is normally used for human posture detection due to their ability to extract multiscale high-level visual representations. | MPII Human Pose Dataset | By using image data augmentation, the model reduces overfitting issues typically seen in deep learning when training on small datasets. | Deep CNN models like AlexNet and VGG16 require significant computational resources and time due to the millions of parameters involved making it cost inefficient |  **AlexNet:**   * **Accuracy: 91.2%**    **VGG16:**   * **Accuracy: 90.2%**    **CNN:**   * **Accuracy: 87.5%**    **MLP:**   * **Accuracy: 89.9%** |
| **Use of Accelerometers and Gyroscopes along with ML models for fall detection** | | | | | |
| **Invalid source specified.** | 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% |
| **Invalid source specified.** | Sensor and Image Data - Deep Convolutional Neural Network (CNN) for feature extraction and SVM (Support Vector Machine) for classification of falls and non-falls​ | validated using the UR Fall Detection (URFD) dataset | The integration of sensor data and video analysis makes the system more effective. System has reduced fall positives and negatives. | The processing and joining of image and sensor data needs more computational power and speed. | accuracy of **99.81%** on the UR Fall Detection dataset  high sensitivity and specificity |
| 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  Preprocessing reduce false positives | RNNs used struggle with long sequences  Falls lasting 400 to 1600ms require precise timing | over 99% accuracy on both standard and custom datasets for fall detection. |
| (Liu & Shi, 2024) | MoveNet for 2D human pose estimation and LSTM for temporal sequence modelling. | UR Fall Detection dataset | Real-time performance  Efficient pose    estimation  High accuracy | Limited to 2D pose estimation  Future work needed:  needs validation in multi-scene, multi-view, and multi-fall scenarios | MoveNet achieves superior frame rate performance (2.68x faster than OpenPose) with a significantly reduced number of parameters (27% of Open Pose's). |
| **Monitoring Blood Pressure to Predict Fall Risk** | | | | | |
| (M.D, 2016) | Ambulatory Blood Pressure Monitoring (ABPM) | N/A | Real-time monitoring of blood pressure variability, useful for detecting stress-induced fall risk. | Limited to elderly subjects, may miss transient events | N/A |
| ‌  (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 project offers a novel approach to addressing the well-documented issue of fall detection, providing an enhanced and more refined solution within the domain of healthcare technology. It introduces a new practice in fall detection by integrating multiple data streams. The system detects falls through posture detection and sensor data analysis, while also assessing fall risk based on abnormal blood pressure levels, such as high or low values that may contribute to the likelihood of a fall.

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.

1. Fall Prediction and Prevention

Our 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.

1. 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, our 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

In terms of the technological advancements our project offers, it integrates several components that are already well-documented but introduces novel improvements in their application. 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

Given the features and benefits of this project, it can be seen that the domain of healthcare systems in fall detection may be greatly improved through the various components present in this project. This includes its accuracy and reliability, as the image processing device does not require a clear line of sight and can monitor users' conditions through a blood pressure sensor. Additionally, their linear acceleration (in the x, y, or z axis) is measured using the accelerometer, while the gyroscope assesses the users' angular velocity. If the system detects movement toward a threshold that indicates a potential fall, it will be initiated.

## 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 : Table for research objectives

|  |  |  |
| --- | --- | --- |
| Research Objective | Explanation | Learning Outcome |
| Problem Identification | **RO1: Development of a Multimodal Fall Detection System**: The project successfully designs and implements a multimodal fall detection system that combines data from motion sensors, posture detection, and blood pressure monitoring, offering a comprehensive approach to detect and predict falls among elderly individuals.Top of FormBottom of Form  **RO2:** **Improved Accuracy of Fall Detection and Prediction**: The system demonstrates enhanced accuracy in both fall detection and prediction through the fusion of multiple data streams, reducing false positives and false negatives in comparison to existing fall detection systems.  **RO3:** **Real-Time Processing and Alerts**: The system achieves efficient real-time data processing, allowing for timely alerts to caregivers or emergency services when a fall is detected or predicted, improving response times and potentially preventing serious injuries.  **RO4:** **Integration of Blood Pressure Monitoring for Fall Prediction**: The inclusion of ambulatory blood pressure monitoring (ABPM) successfully predicts potential falls by detecting blood pressure-induced risks, adding a predictive layer to the system’s capabilities.  **RO5:** **User Adaptability and Customization**: The system is designed with adaptability in mind, allowing it to cater to individual users by learning their unique movement patterns and health conditions, leading to more personalized fall detection and prevention.  **RO6:** **Addressing Privacy and Security Concerns**: The system ensures that user data, including motion and health metrics, is securely stored and transmitted, addressing privacy concerns associated with monitoring elderly individuals in their homes.  **RO7:** **Cost-Effective Fall Prevention Solution**: The project demonstrates that an IoT-based fall detection system can be implemented as a cost-effective alternative to full-time caregiving services, making it accessible to a wider range of elderly individuals living independently. | 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 * Questionnaires on how useful this may be to isolated elders to see how useful the project is to be * Data for research papers are to be collected from IEE Data Port, Google Scholar, etc * 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 2. Implementation of a machine learning model to take in new data without relying on trained data is to be expected as well 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 : 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 : Out-scope project elements

### 1.12.3 Feature Prototype

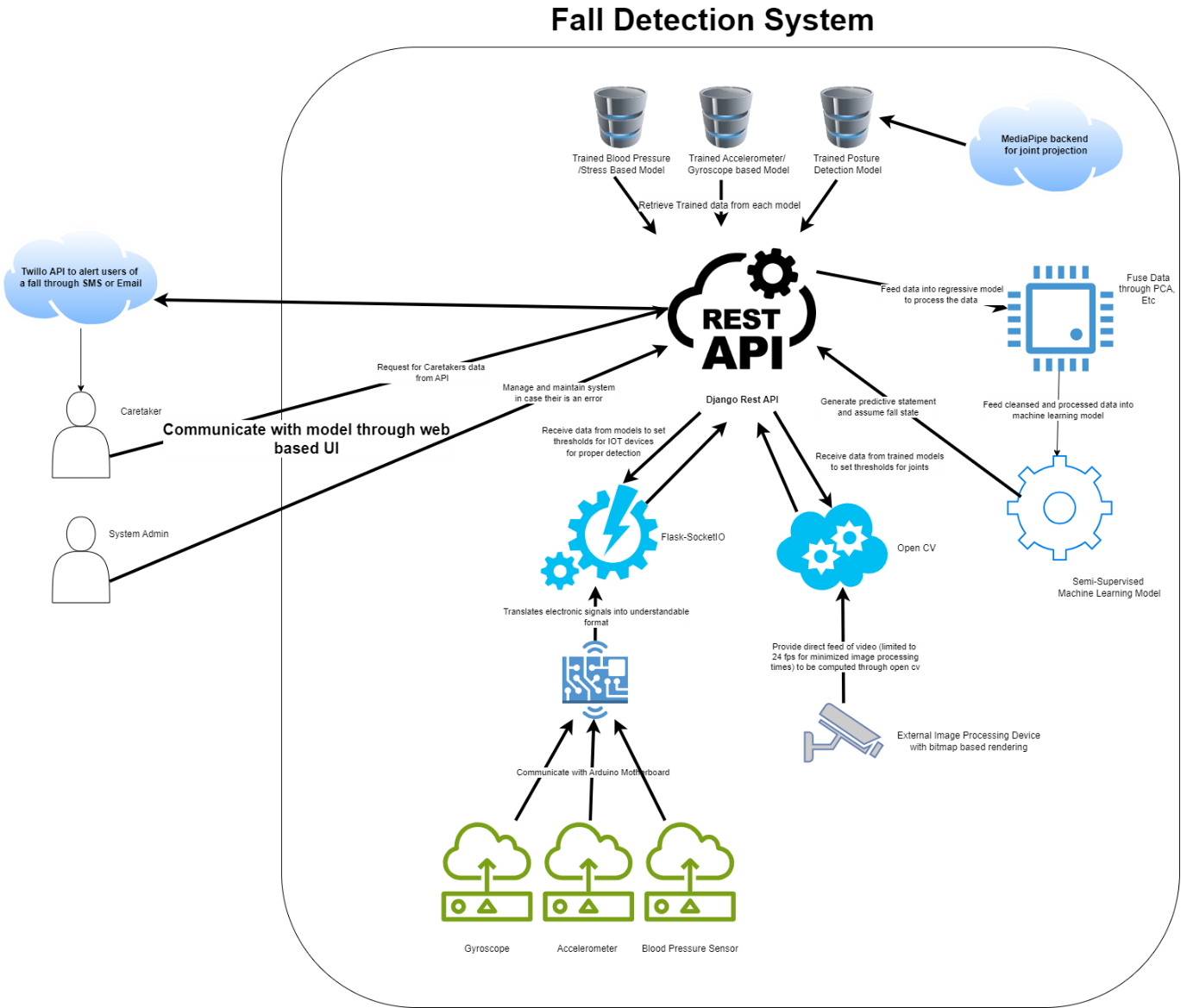


Figure : Feature Prototype Design

#### **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.

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