INFORMATICS INSTITUTE OF TECHNOLOGY

In Collaboration with

ROBERT GORDON UNIVERSITY ABERDEEN

Multimodal Fall Detection System For Elderly Persons

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Submitted in partial fulfilment of the requirements for the BEng/BSc in Artificial Intelligence and Data Science degree at the Robert Gordon University.

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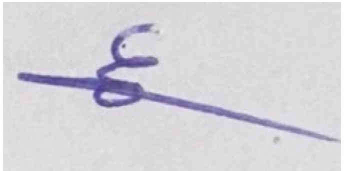
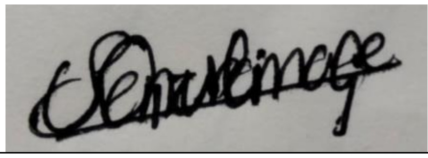
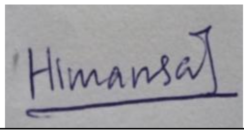
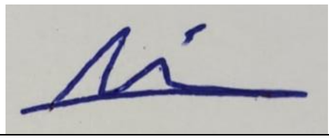
Declaration

We hereby certify that this project proposal and all the artifacts associated with it is our own work, and it has not been submitted before nor is currently being submitted for any degree program.

Student Name	Student ID (IIT)	Signature
Modarage Ethan Christoff Perera	20221812	
Senuli Laknara Wickramage	20220950	
Himansa Wathsiluni Jayasuriya	20230903	
Mevinu Induwara Gunaratne	20232429	

I have read the project proposal, and it is in accordance with the approved university project proposal outline.

Signature of supervisor: ___________________ Date: _________________

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Section 1

1.1 Introduction

Regarding what the project is, we intend on introducing a sophisticated fall detection system that can detecting/predict whether a person is in the process of falling or simply about to fall. It was found that an alarmingly notable rate of elderly persons (over the ages of 65) are left in isolated conditions in homes where they are left to care for themselves. A result of this has led to devastating mortality rates due to the risks causing falls that have damaging effects that are retained unto them. Given the feeble state of most elderly people they are seen as to being individuals that are not fit/capable of looking after themselves as most of them tend to experience elongated issues such as joint aches. Arthritis, etc. Given this "disabled" state that the target populi lie in, we believe that the availability of an automated caring system that can prevent falls is an adequate solution to address this issue. So, in terms of how we intend on achieving this, we believe that the use of the "Internet of Things" may prove to be quite resourceful in this aspect as it provides us with complete access into monitoring a user's movements and status in the absence of a more capable individual. To summarize the content to be viewed in this document, we intend on documenting and explaining how our fall detection system is to work and be developed such that its users may be prevented from falling while alerting the proper authorities of their fall.

1.2 Problem Domain

Addressing the problem domain, it has been found that elderly populi within the range of 65+ have experienced fall related injuries that have rapidly increased the mortality rate of individuals as such given the fact that these injuries are almost always fatal. A study was carried out to develop a "Low-cost fall detection system" and it was found that an estimated 684,000 individuals die from falls each year from adults over the age of 60 suffering the highest number of fatal falls (Fitriawan, et al., 2024). Furthermore, regarding how these injuries are caused it has been found that these individuals are often left in isolated conditions as to where they have little to no supervision over what they do and where they are because the availability of an individual as such is not always present and is often seeing as to being quite costly. Individuals that offer support as a service tend to overcharge users given their requirements, thereafter it was found in a study that more and more of the elderly populi are experiencing issues in funding long term healthcare solutions given their limited income (RIVLIN, 1988).

Furthermore, even if the user may be able afford a service as such it would not mean that these individuals would be present in their wake for every moment and place that they move into, rather they may instead be present in open spaces where they are not preoccupied with another task. So, given these persons preoccupied states it is seen as to being almost impossible to always accompany these elderly individuals such that they are never posed with the potential of falling. In terms of the more reserved details as to why elderly individuals tend to fall more than younger individuals it may be broken down into the following categories.

- 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 1: 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.

2. 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.

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, 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 2: 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. **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	LO1

	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.	
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 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

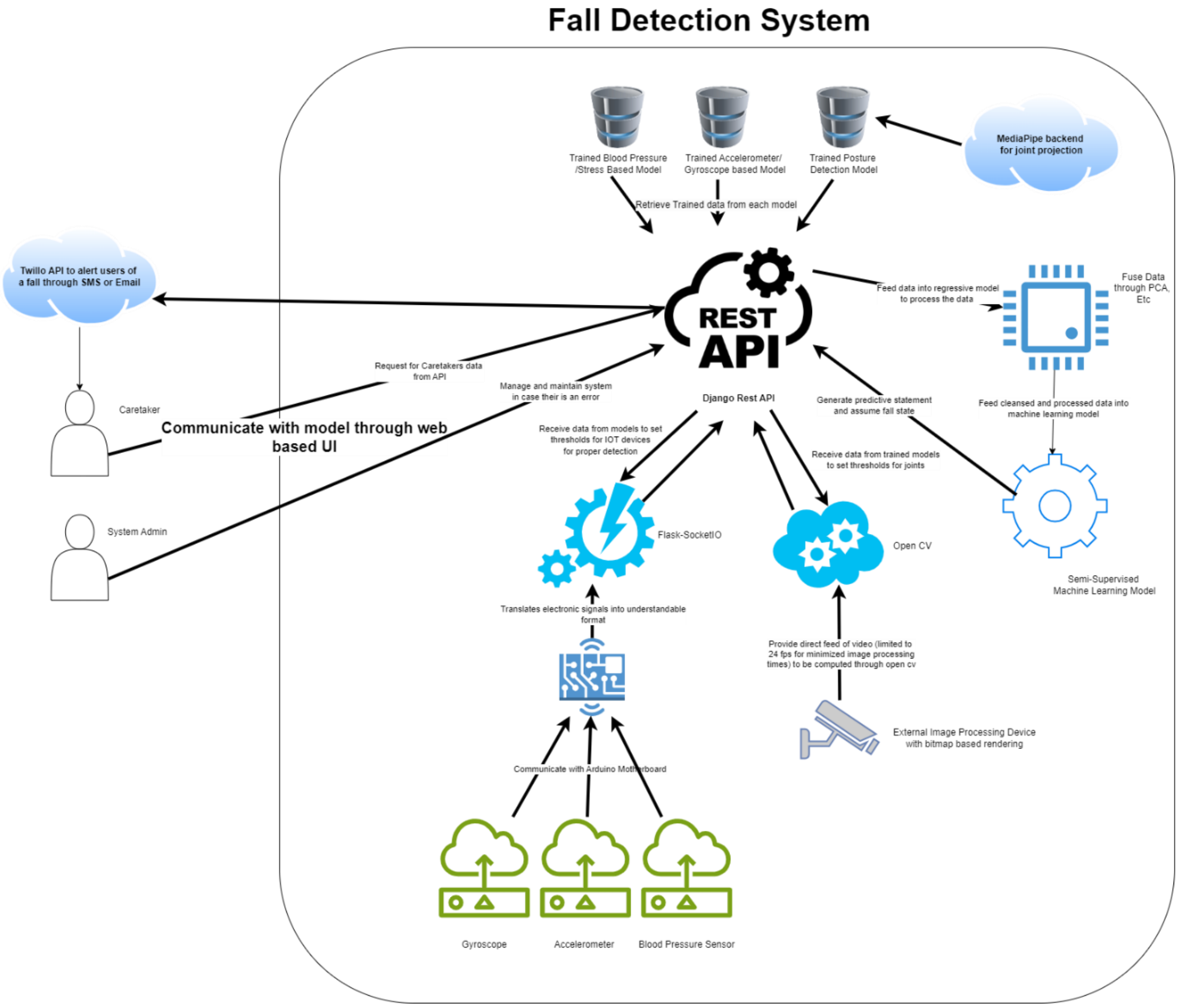

Figure 1: Feature Prototype Design

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

Section 2

2.1 Research Methodology

Research Philosophy	The author of the research has selected positivism as the research philosophy. Positivism is a research philosophy that focusses on using observable and quantifiable facts in developing knowledge. This method emphasizes testing the theories and hypotheses through data collection and analysis and then reaching object conclusions. This lines with the principles of science. In this study, the detection and prediction of falls relies on real-time sensor data. The prioritization on quantifiable data, and the results being based on measurable evidence rather than subjective interpretation make this approach adequately felicitous for this study.
Research Approach	We will adopt a deductive approach, starting with a hypothesis that factors such as posture, blood pressure, motion speeds, and angular velocities can predict falls. This hypothesis will be tested through data collection and analysis from sensors and monitoring devices. The approach is suitable as it allows for testing pre-established correlations between variables and drawing conclusions based on measurable evidence.
Research Strategy	We intend on using interviews (qualitative data gathering), questionnaires and forms (quantitative data gathering) for our research.
Research Choice	Multi Method – In order to consider both the qualitative and quantitative components of the study we intend on regarding the multi-method approach as it takes into consideration the factors that require an in-depth analysis (such as ethical constraints)
Time Zone	We will be using a cross-sectional Time zone for our research as we intend on having this occur in a single point in time

2.2 Development Methodology

In terms of the type of methodology we are to use, the project is to refer to a "**scrum**" based approach as to where it utilizes an iterative and incremental agile framework (type of framework where the project is faced with iterative procedures where it goes through multiple assessments and revisions to maximize its accuracy, etc) for managing the projects development. The key benefit of using Scrum as our development methodology is the fact that it breaks the project down into smaller tasks called "**sprints**" where the workload is mitigated into smaller and more feasible tasks that minimize time consumption and maximize productivity. Furthermore, scrum refers to the use of an **"Object Oriented Analysis and Design"** (OOAD). This is since Scrum has a modular approach to task management as it breaks down the project into smaller and more manageable tasks while maintaining incremental and iterative development processes. In terms of the project developments life cycle to be regarded for the project we believe that the use of a spiral model is appropriate given its current nature. The given PDLC is an iterative life cycle model where the project is developed in small incremental iterations as to where its iterations are like a sprint from a scrum methodology. Besides that, using a spiral management system we may be able to detect and mitigate issues before they could occur such that the risk of a total failure is avoided. To conclude, the idea is scalable and compatible with an Object-Oriented Analysis and Design approach.

2.3 Project Management Methodology

2.3.1 Deliverables

Deliverable	Date
Semester 1	
Literature Review Submission to supervisor	Week 3
Literature Review Submission Final	Week 3
Project Proposal Submission to supervisor	Week 4
Project Proposal Submission Final	Week 5
Software Requirements Specification Submission to supervisor	Week 8
Software Requirements Specification Submission Final	Week 9
Semester 2	
Prototype Implementation	Week 14
Testing And Evaluation	Week 19
Documentation and Final report submission	Week 23

Table 5: Deliverables table

2.3.2 Resource Requirements

2.3.2.1 Hardware Requirements

- ***Processor:*** Core I7 (13 gen) or greater for minimized bottle caps in processing large data loads
- ***Storage:*** 128GB~256GB of storage for large datasets
- ***Memory:*** 8GB~32GB of RAM to host multiple processes that run parallel to each other
- ***GPU:*** GTX 1650 Ti or greater for the machine learning model developed through TensorFlow
- ***Peripherals***: An accelerometer, gyroscope and blood pressure sensor

2.3.2.2 Software Requirements

- ***Python*** – The primary language used to code in the entire model and proposed project
- ***Vscode/Intelij IDEA*** – Code editors referred to develop project on
- ***HTML*** – To structure the web page
- ***CSS*** – To design and beautify the web page for ease of access
- ***JavaScript/TypeScript*** – To automate certain processes and include form submissions
- ***MS Word*** – For developing the documents for the entire project
- ***Github Desktop*** – For version control and data logging

- ***TensorFlow & OpenCV & MediaPipe*** – For training and processing each data set
- ***Windows Based Operating System*** – Used to host the entire application
- ***Arduino IDE*** – For programming Arduino board sensors and peripherals to follow algorithms
- ***Flask-SocketIO*** – API used to translate communications made between the Arduino Board and python
- ***Django (Rest API) Framework*** – Used to host and manage the entire project such that it is accessible online, etc.
- ***Twillio*** – API used to message caretakers of the user's status through SMS or email

2.3.2.3 Skills Requirements

- Time management
- Thorough understanding of Python fundamentals, etc
- Fundamental understanding of machine learning concepts
- Fundamental understanding of what Principal Component Analysis is
- Thorough understanding of how to document and log data
- Thorough understanding of GIT and Version control etiquette
- Fundamental understanding of web development and Django's Rest API

2.3.2.4 Data Requirements

In addition to using a dataset from a public hospital in Sri Lanka to study blood pressure among the elderly, we will enhance fall detection accuracy by incorporating factors such as BMI (Body Mass Index), weight, age, gender, and BPM (Beats Per Minute). These variables provide a comprehensive view of how physiological factors influence fall risk. The dataset will also include posture detection through joint projection to analyze how different physical conditions contribute to fall events. The primary target demographic is individuals aged 65 and older.

2.3.3 Risk Management

Risk	Severity	Frequency	Mitigation Plan
1. Data Privacy and Security	9	5	Use strong passwords and secure networks.
2. Accuracy of Fall Detection	8	8	Test often, adjust the system regularly.
3. Hardware Failure	6	6	Check devices frequently for any issues.
4. Latency in Real-Time Processing	9	3	Make sure the system runs efficiently.
5. Usability for Elderly Individuals	5	7	Keep the design simple and user-friendly.
6. Limited Scalability	7	5	Use flexible software that can adapt.

7. Sensor Calibration Issues	8	4	Set reminders to recalibrate regularly.
8. Legal Liability	9	3	Include clear terms and easy-to-read warnings.
9. High Cost of Implementation	6	6	Start with basic options and expand later.
10. Environmental Constraints	7	4	Test in different spaces to ensure it works.

Table 6: Risk Management Table

2.3.4 Gantt Chart

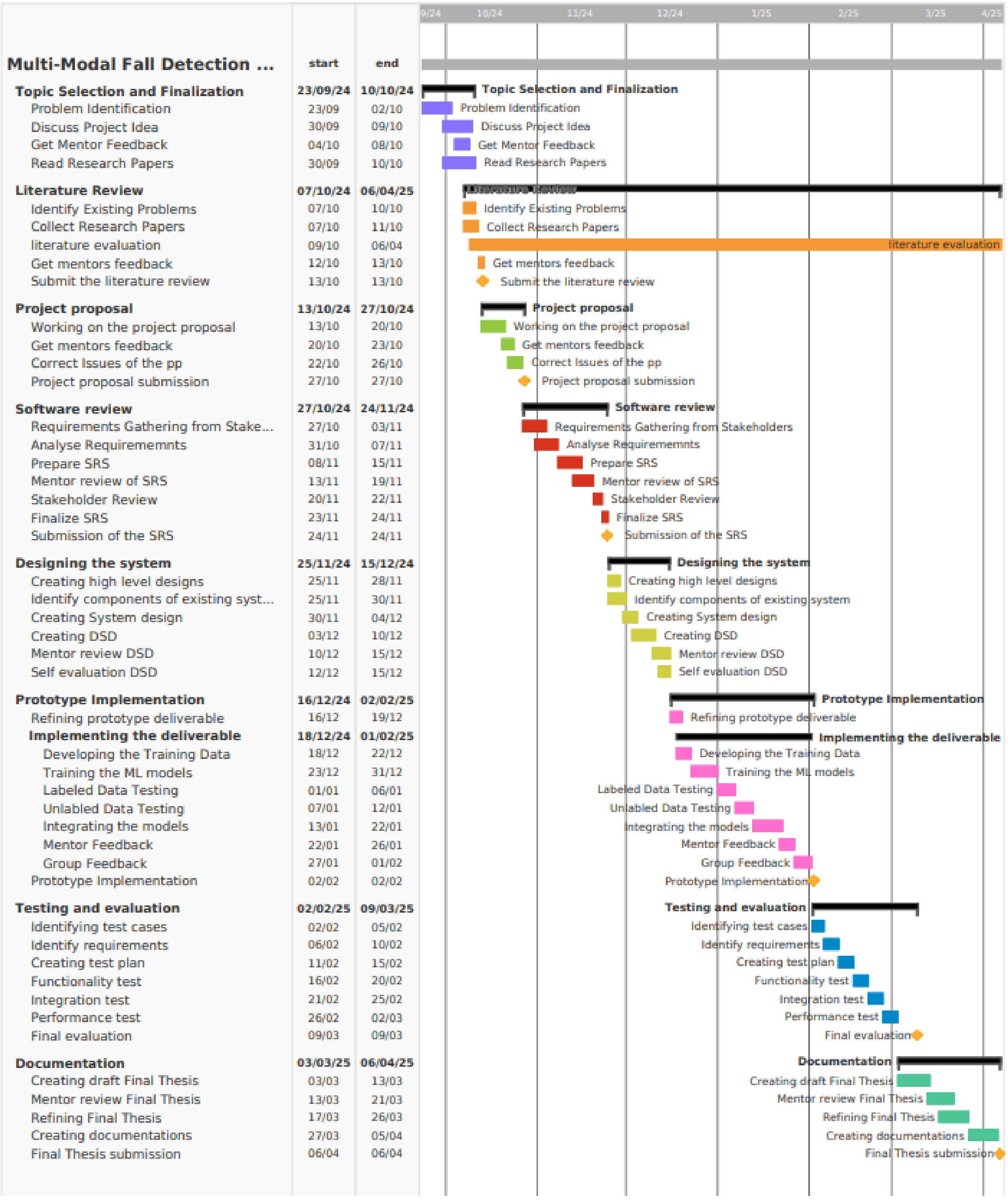

Figure 2: Gantt Chart Diagram for deliverables, etc

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