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**Title: Webcam Application for High-Risk Independent Resident**

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# Abstract

This display the development of a webcam application that are designed to monitor the resident under high risk or other venerable situations which could lead to injury or potential hazards. It will combine with local weather information support and Convernutionary Neuron Network (CNN) for image recognition to help user to identify the situation and status of high-risk residents.

This report will provided full process of its development and the theory of key elements. Although the project partially achieved many of the design goal for a monitor application, this project provided a clear idea of what are the key elements for a monitor application for this type of tasks. It provides a potential pathway for a comprehensive and a mature monitor application for the smart devices and IoT.

# Acknowledgements

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# Chapter 1 – Introduction

## 1.1 Background

Traditional healthcare and monitoring systems have long relied on human supervision and warden. Even in professional environments such as nursing homes, constant individual supervision is not always feasible. Furthermore, there have been reported cases of neglect or even abuse in residential care facilities. On the other hand, many high-risk individuals, including elderly people, live alone without immediate access to assistance. In the UK alone, there are 3.3 million pensioners who live independently (Office for National Statistics, 2023) and are at risk of possible injuries or unconsciousness at any moment. The possibility of such an event would only increase with age. Delays in medical response due to undetected falls can lead to severe health deterioration or even death (WHO, 2021). Moreover, as extreme weather conditions become more frequent than ever before, vulnerable individuals who live on their own may refuse to use heating or cooling appliances, often due to cost or personal habits. This has caused casualties of illnesses related to temperatures like hypothermia or dehydration every year.

The demand for technologies that assist high-risk individuals who are living independently is increasing with more reliable and more powerful tools and equipment as the technologies have improved in terms of computational power and networking for the past decades. This project aims to address that need by developing a prototype webcam monitor application system for detecting whether a person has fallen using computer vision techniques and machine learning. By using a camera, the system captures images at a rate of two frames per second, processes them using a Convolutional Neural Network (CNN), and classifies the user’s pose to determine whether a fall has occurred.

If a fall is detected, the system will automatically notify a pre-configured contact, enabling a timely response. Falls are one of the leading causes of injury-related death among adults in many countries. Additionally, another module provides health-related feedback based on temperature and humidity, helping ensure that the resident is living in safe conditions.

## 1.2 Project Aims and Objectives

The core objective is to design and implement a real-time fall detection system using images captured by a webcam and analysed via a CNN-based pose estimation model. The secondary objective is to provide environmental advice based on sensor data.

Primary Objectives:

* Capture webcam images at a consistent frame rate.
* Train and deploy a CNN to classify human poses.
* Determine if a set of poses indicates a fall.
* When a fall is detected, pass the message to relevant contactor.

Secondary Aspirations: (Implementation subject to time and complexity constraints)

* Provide a text-based advisory system based on environmental conditions.
* Record daily activity time
* Log medication intake times.
* Deliver personalized alerts or reminders based on behavioural patterns.

## 1.3 Scope and Constraints

This project is developed under academic constraints and does not extend to clinical or regulatory compliance for medical-grade devices. The system is intended as a prototype to demonstrate feasibility rather than a commercialised product. While the application is designed to operate on consumer-grade hardware (laptop and webcam), and is not designed for multi-camera setups or advanced motion tracking.

Due to the incident during training of the model, this application is tested and trained on a CPU-based system. Hence, the CNN model complexity and the speed of image processing are limited.

## 1.4 Ethics Review

This monitoring system does not store or process personally identifiable information beyond what is necessary for fall detection and alert generation. The project has received ethics approval (Reference: TETHIC-2025-110551) from the Technology Faculty Ethics Committee, confirming that it involves no physical, psychological, or environmental risks.

## 1.5 Report Structure

This report is structured as follows:

Chapter 2 - Literature Review: Critical analysis of relevant studies in the fall detection, pose estimation, and ambient health monitoring.

Chapter 3 – Methodology: Justification of the development approach, neural network design, and system structure.

Chapter 4 – Requirements: Functional and nonfunctional requirements.

Chapter 5 – Design: Detailed system architecture, data flow, and model selection.

Chapter 6 – Implementation: Description of key components including webcam interfaces, CNN training, and alert mechanism.

Chapter 7 – Testing and Evaluation: Verification of results against requirements and performance benchmarks.

Chapter 8 – Conclusion and Future Work: Summary of findings and potential improvements.

# Chapter 2 – Literature Review

## 2.1 Introduction

This chapter presents a critical review of the technologies and techniques that support fall detection in high-risk individuals, particularly those living alone. The main areas of discussion include:

1. Sensor-based fall detection mechanisms – List the current fall detections and their disadvantages.
2. Pose estimation through computer vision – Discuss a few popular approaches for getting the pose of a person from the image.
3. The use of CNNs in human activity recognition – Discuss what is CNN and how will this monitor application system’s CNN work.
4. The effect of the environmental monitoring – Why does the monitor application also need to evaluate the environment for high-risk individuals.

Outline of each technique of these topics will be discussed and the key points and basic requirements of this monitor application will be drawn. The limitation of existing systems will also be discussed, leading to rationale for using RGB image-based CNN classification in the proposed solution.

## 2.2 Fall Detection in High-Risk Residents

Falls are one the most serious health threats to older adults, commonly resulting in fractures, trauma, or ling-term hospitalisation. According to the U.S. Centres for Disease Control and Prevention (CDC), falls are a leading cause of traumatic brain injuries and prolonged recovery demands on healthcare systems (CDC, 2019).

Currently, there are hardware devices have been developed or under developing to detect fall of a person. These fall detection method each has its own advantages and disadvantages.

* Wearable Sensors: Devices which are designed to be worn on the residents on different part of the body. Some are just like watches on the arm, some of them need to be placed on the main body. These types of devices using accelerometer to identified the motion and the high-risk residents’ condition. However, these devices must be worn at all time and can produce inaccurate results if the devices are worn at different places or shift position on the body (Singh et al., 2020). This limit the place and scenario of the device being used.
* Ambient Sensors: This type of devices collect the information from the environment to identifies falls.
* Acoustic Sensors: Classify the sound of fall as well as other sounds from the surrounding. However, this type of device’s accuracy is affected by background noise. Even the presents of large pets will lead to inaccurate results.
* Floor Pressure Sensors: This type of sensor is still under development in the lab environment. It detects vibrations from the fall impact. However, the performance varies based on floor material and body weight. Another approach is to put the pressure sensor around the bed to detect the fall around the bed only (Huan-Wen Tzeng, 2010). This type of fall detection has very limit of use in terms of the area it will be able to cover.
* Infrared, Radar, Ultrasonic Sensors: These types of sensors offer contactless monitoring by placing them in a carefully selected place. However, these require precise setup and specialised equipment that are not typically common in households.
* Image Sensors: These use cameras to visually detect falls. While accurate, many reply on cameras with special functions like 3D camera or depth camera, which are expensive and not typically common to our ordinary life. Additionally, privacy concerns arise when capturing live video streams or photos has risk of leak to the social media.

[Insert Table 1: Comparison of Fall Detection Technologies – Sensor Type, Cost, Accuracy, Limitations, Real-world Usability]

## 2.3 Computer Vision and Pose Estimation Techniques

Pose estimation aims to localise key body joints in images or videos. Popular frameworks such as OpenPose, BlazePose, and MediaPipe are capable of reconstructing a full human skeleton for motion analysis. These models often use multiple camera angles or RGB-D inputs to infer pose in 2D or 3D space. However, most state-of-the-art pose estimation frameworks have high demands for hardware requirements like depth data or high-resolution camera. Otherwise, technical issues like occlusion or low-light would occur leads to incorrect body skeleton model (Mehta et al., 2016). These will also demand more computational power for a real-time application like our monitor application.

[Insert Figure 2.3.1: Example of keypoint detection in OpenPose and RGB-only visual classification]

Nonetheless, existing pose estimation models/software are mutual and many of them have a high accuracy rate than typical CNNs-based pose estimation. This project will select Y

## 2.4 CNNs in Human Activity Recognition

Convolutional Neural Network (CNN) is a class of deep learning models designed for image-based pattern recognition. CNNs have been widely adopted in human activity recognition (HAR) due to their ability to detect statical features from raw image data. A typical CNN architecture includes:

* Input Layer: Fixed-size RGB image will be received at this layer at beginning.
* Convolutional Layers: This layer applies filters to extract visual features such as edges, shapes, or patterns.
* Activation Layers: Using functions to introduce non-linearity into the model. Typical activation functions include ReLU, SoftMax, and Tanh etc.

[ Insert Figure2.4.1: Different activation functions]

* Pooling Layers: This layer reducing the sampling rate to reduce overfitting and training time. Two typical pooling layers are Max Pooling and average Pooling.
* Fully Connected Layers (Output Layers): This layer will combine features to classify the input image.

Currently, many HAR software use CNN as a primary structure to build their models. Back to 2016, researches in this filed has already developed a “binary sensor network” enhanced by CNNs. It was able to identify daily human activities that claimed accuracy rate of at least 94.7% with test samples (Liu et al., 2016)

In the monitor application system, we will be trying to train a CNN for HAR with a typical CNN structure. However, due to hardware constrain, a degraded, simpler CNN with less channels and convolutional layers were considered. Given the limitations with the custom CNN model, the monitor system will adopt the pre-trained YOLO11n-pose model. This model is developed by Ultralytics was able to detect 17 human key points and make pose estimation based on the key points (Ultralytics). Allowing our monitor application system to have a more reliable core HAR system to achieve the primary objective.

[Insert Table 2.4.2: CNN Architecture – Layer Name, Filter Size, Output Shape, Activation Function]

## 2.5 Environmental Sensing in Elderly Monitoring

Temperature and humidity are critical for elderly welling. High indoor temperatures are associated with heat exhaustion and dehydration, while cold environments increase the risk of hypothermia (WHO, 2018). Smart monitoring systems often include sensors that trigger alerts when ambient conditions fall outside safe thresholds. In this project, the monitor application includes a secondary module that provides text-based advice derived from local environmental data. This lightweight approach is suitable for resource-constrained systems and avoids the need for expensive multi-sensor arrays.

[Insert Figure 2.5.1: Diagram of temperature/humidity-based advisory logic used in the system]

## 2.6 Research Gaps and Design Justification

Many existing fall detection systems have achieved high accuracy. Yet, there are still limitations in each of those systems:

1. Sensor-heavy.
2. Hardware specified for a particular detection method.
3. Low cost-effective.
4. Rarely integrated.

Adhikari et al. (2017) proposed a CNN-based method using both RGB and depth data for indoor fall detection. However, their system depended on Kinect-like devices and requirement for depth camera. Inspired by his team’s research, this project seeks to replicate its effectiveness using only readily accessible RGB webcams. The aim of this project is to develop a prototype of a system that covers simplicity, affordability, and extensibility that other fall detection application systems unable to achieve.

## 2.7 Summary

This chapter reviewed the evolution of fall detection technologies, pose estimation models, and CNNs-based image recognition. Key design decisions, such as using RGB only inputs and avoiding expensive skeleton estimation models and depth camera, are justified through both technical and practical considerations. The literature supports a strong case for the development of a light-weight, real-time, webcam-based solutions to monitor vulnerable individuals living independently.

# Chapter 3 – Methodology

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## 3.1 Introduction

This chapter outlines the methodology and approaches to developing the Monitor Application for High-Risk Independent Residents. The system’s core functionality revolves around real-time webcam-based image capture and pose detection. Initially, a custom CNN-based pose detection model was developed. However, due to its low testing accuracy (~33%) and high validation loss (~1.2), this approach was replaced with a pre-trained pose estimation model from Ultralytics YOLO. This transition ensured a more robust and dependable core for the system.

## 3.2 Overall System Development Approach

The core of the monitor application, pose estimation is divided into 3 subsystems: real-time webcam feed, pose estimation and fetch pose to webpage. The application was built using an interactive development methodology for software development. This modular structure allowed for parallel development and the ability to substitute components if technical issues arose, such as the switch from a custom CNN to a pre-trained model.

## 3.3 Data Acquisition and Preprocessing

### 3.3.1 Data Source

The application captures real-time data from a standard consumer-grade webcam. Due to hardware constraints and a focus on accessibility, the system captures images at 2 frames per second (FPS) by taking screenshots rather than streaming video continuously. During testing, frame rates above 4 FPS led to corrupted “snowy picture” displays on the web interface. Although the root cause remains unclear, reducing the capture rate significantly mitigated the issue. Each frame is saved locally and processed for pose estimation.

### 3.3.2 Preprocessing Steps

Captured images are pre-processed before being passed to the pose estimation model module:

* Resizing: Each frame will be resized to 640x640 pixels to match the input for the pose estimation model. A typical webcam resolution is 1920x1080 (Full HD). Although there is no formal requirement for CNN image input to ensure high accuracy, and to balance the image resolution and process time, about 20% of the full HD is set as the default size.

[Insert Figure: Data Preprocessing Pipeline]

## 3.4 Pose Estimation Model Integration

The initial plan was to develop a custom CNNs-based pose detection model to detect 6 basic human poses as output with a lightweight structure and faster process speed with minimal computation power. However, during the development, the final custom CNN model achieved over 1.2 loss on the validation dataset and only a 33% test accuracy rate. Due to the time constraint, a pre-trained model was adopted to ensure the monitor application system meets its functional requirements.

The selected YOLO11n model from Ultralytics was chosen for its balance between accuracy, computational efficiency and real-time inference capability. The model detects 17 human key points to estimate complicated pose analysis (Ultralytics, 2023). Integration was achieved using the Ultralytics Python library, which allows loading pre-trained weights and applying pose detection to static images. The model processes each frame and outputs key points, which are passed to a custom rule-based detector (RuleBasedFallDetector) to infer human posture.

[Insert Code Snippet: Model Loading and Initialization]

## 3.5 Fall Detection Logic

The fall detection logic is implemented using the RuleBasedFallDetector module. This module evaluates the spatial relationships between the 17 detected keypoints to classify poses.

* Angel Calculation: Computing angles between key points to detect abnormal postures.
* Position Analysis: Assessing the relative positions of key points to determine if the subject is lying on the floor.
* Motion Patterns: The model monitors transitions from upright poses (standing/sitting) to prone (lying) over time to confirm a fall.

If a “Lying” pose is detected and no fall alert was recently triggered, an email is sent to a designated contact, with a 10-minute cooldown to prevent spamming.

[Insert Figure: Fall Detection Rule-Based Flowchart]

## 3.6 Environmental Advisory System

Apart from the fall detection system in the monitor application system, the application also monitors environmental parameters (temperature and relative humidity) to provide advisories feedback. An OpenWeatherMap API was used to obtain environmental parameters based on the user’s geographical location (latitude and longitude). These values are then passed to a lightweight neural network defined in comfitness.py, which returns text-based health advice. The neural network was trained on labelled environmental data and achieved a validation loss as low as 0.08, ensuring reliable outputs.

[Insert Table: Environmental Parameters and Advisory Thresholds]

## 3.7 Tools and Technologies

The development utilised the following tools and libraries:

| **Tool/Library** | **Purpose** |
| --- | --- |
| **Python 3.8** | Core development |
| **Flask** | Running the web-based interface |
| **OpenCV** | Webcam image capture |
| **Ultralytics** | Pose estimation model (YOLO11n-pose) |
| **NumPy** | Image array manipulation and numerical processing |
| **Matplotlib** | Visualizing training loss (for CNN) |
| **smtplib & email** | Sending alert emails |
| **Threading** | Running parallel tasks for real-time frame handling |
| **OpenWeatherMap API** | Environmental data acquisition |

## 3.8 Constrains and Limitations

The monitor application system’s performance is subject to certain constraints:

* Lighting Conditions: Poor lighting can affect pose estimation accuracy.
* Occlusions: Partial obstruction of a person may prevent accurate pose estimation.
* Image Artifacts: Static images or posters showing people may falsely trigger fall alerts.
* Hardware Limitations: Performance depends on CPU capacity; slower devices may drop frames.
* Internet Dependency: API calls for weather data and email alerts require an active internet connection.

## 3.9 Summary

This chapter presented the step-by-step methodology for building the Monitor Application for High-Risk Independent Residents. It covered the rationale for selecting YOLO11n-pose over a custom CNN, the design of a rule-based fall detection engine, and the integration of an environmental advisory system. The use of lightweight, open-source tools ensures broad compatibility and ease of deployment.

# Chapter 4 – Requirements

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## 4.1 Introduction

This chapter