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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 sensor-based fall detection, pose estimation through computer vision, the use of CNNs in human activity recognition, and the effect of the environmental monitoring. This chapter also highlights the limitation of existing systems, 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]

## 2.4 CNNs in Human Activity Recognition

CNNs are 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.

( please talk about the model and architecture this report will be using briefly)

[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.