Skystrm: An Activity Monitoring System to Support Elderly Independence Through Smart Care Homes

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***Abstract*—Ageing contributes to a lack of independence on the part of the elderly, whether in their own homes or care settings. The world is looking into alternative ways to increase the independence of the elderly. However, there are many risks associated with the independent living of the elderly. This paper presents an activity monitoring system which uses computer vision techniques to monitor the activities of vulnerable older people. The algorithms used in the system can detect their movements and track their activities which can build their activity profile. Once a deviation from their daily pattern is detected, the system can alert caregivers and family members. The proposed system has the potential to be a building block for remote elderly care services, in which they can live independently yet will have the attention of caregivers, if needed. Further trials are underway in the United Kingdom and South Africa, which will help to generalise the results of this research.**

***Index Terms*—Activity recognition, remote monitoring, elderly care, internet of things, computer vision**

I. Introduction

The recent World Health Organization statistics shows that the world population is ageing. By the end of this decade, every sixth person will be above 60 years worldwide [1]. This trend will not fall soon, and by 2050 there will be over 2 billion people over the age of 60 years. At the start of the 21st century, the ageing trends were only associated with developed and high-income countries. However, recent projections show that ageing also occurs in low and middle-income countries. By 2050, almost 80% of the over 60 years older people will be in low and middle-income countries [1].

So, is the ageing population a bad thing? Should we not be happy that people are living longer than before? Well, there is no simple answer to this, and first, we have to understand the advantages and challenges associated with the ageing population and then focus on their potential solutions.

A. Advantages of Ageing Population

A longer life means more opportunities for the person, his family, and society. In these additional years, people can pursue further education, a new career, and even realise their long-neglected passions. Older people can contribute to their families and communities based on their experiences and lessons learnt. However, these opportunities and contributions depend on their health [1].

B. Ageing Populations Challenges

The ageing population has to cope with many medical conditions like eyesight and hearing loss, loss in reflective actions, mobility, back pain, depression, diabetes, and dementia. Sometimes, people face more than one disease at a time [2]. All these can result in overall thinking that older people are less valuable and burden the economy.

C. Potential Solutions for Ageing Population

Evidence suggests that if ageing people live in good health and supportive environment, their abilities add value to do things they like will remain almost the same compared to their younger days. Good habits like daily exercise, a healthy diet, no smoking and positive behaviour contribute to a healthy lifestyle. The supportive social and physical environments can also enable people to healthy ageing despite loss in their capacity to do things.

The technology-assisted environment is considered one of the potential solutions for healthy ageing. Many technological solutions are contributing positively to the lives of older people. Therefore, good health manners, supportive environments and technological solutions can be considered potential solutions for healthy ageing [3].

D. Research Gaps

The United Nations (UN) General Assembly declared 2021–2030 the UN Decade of Healthy Ageing. The UN has emphasised the need to come up with solutions that aid to ageing and independence of the elderly [1]. Much work is going on in the medical domain related to this topic. Although technological advances are helping some areas of active ageing, there is a need to develop innovative ideas to promote independence among the elderly [4]. The recent Covid-19 crisis has highlighted that elderly care systems are vulnerable even in developed countries. Many older people in care settings died due to a lack of care and monitoring [5]. Remote monitoring would have helped in this situation to give them proper care. Another problem is ensuring adequate staff is the real point with all care settings worldwide. The most significant challenges are ensuring enough staff to monitor the number of people in care and keeping them safe.

All these challenges can be mitigated through innovative monitoring systems, which could provide remote monitoring to monitor individuals to ensure they have not been harmed.

E. Proposed Solution

Our research team at The Centre of Excellence in Mobile and Emerging Technologies (CEMET) always tries to develop emerging technology-based solutions for real-life problems. Considering the needs of the older people and recent Covid-19 crisis, remote monitoring would have helped in taking care of the older people living alone at home or in the care settings. Therefore, the research team, with consultation from the elderly care industry, came up with the idea to develop a system that can anonymously monitor a person's movements, learn their routines, and notify family or carers if there are any concerns. The proposed system was tested through a pilot study that generated efficient results. Further testing sessions are underway to generalise the results for the proposed system in two countries.

II. Literature Review

The ageing-related challenges have motivated many researchers and companies to develop technological solutions that can add to the independence of older people. Especially in the last two decades, much work has been carried out in this field of research.

One of the earliest works comes from a research team from the USA, who developed a real-time visual surveillance system in the year 2000 with the idea to detect and track multiple people. Their system used an infrared camera, monocular grey-scale video imagery, and shape analysis to track people and their body parts. The system could determine whether there were multiple people in the frame and if they were carrying any objects. However, due to the technological capabilities at that time, the system could not issue real-time alerts or messages [6].

Another USA-based research team developed a real-time system for in-home activity monitoring and functional assessment for elder care. The proposed system efficiently extracts silhouettes. The collected silhouette features were analysed, and experimental data demonstrate that the proposed system performed efficiently [7].

Researchers from Spain and France developed an automatic fall detection and activity monitoring system considering the independence of older people. The system comprises a mobile module worn by the user and a call centre to analyse and save the information. The authors claimed that trials conducted with the elderly showed a 90% accuracy for falls detection [8].

In 2010, a research team proposed an activity monitoring system to achieve older people's behaviour analysis. The proposed system consists of an approach combining heterogeneous sensor data to recognise activities at home. This approach connects data provided by video cameras with data provided by environmental sensors attached to house furnishings. The system collected data from nine residents living in an experimental apartment. The research team compared the behaviour profile of the nine residents. Overall, the results were good, with few false alarms [9].

The Homecare project, which is part of a research project in 2014, experimented with a multi-sensor monitoring system for the elderly with cognitive disabilities in a care unit. The system consists of a motion sensors network deployed in different care unit areas and an electronic patch worn by the subject to identify him and detect falls. System testing resulted in seven correct and one false alarm. The system used a web application which helped the nursing staff with the generated alerts [10].

Many researchers used accelerometer-based activity monitoring systems [11]. Although such systems have given positive results, the output of an accelerometer varies at different positions on a subject's body. Also, accelerometers need to be attached to the subject body, which makes them impractical for long-term use. To overcome this challenge, another research team experimented with a single triaxial-accelerometer-based activity recognition system that significantly reduces the high within-class variance and allows subjects to carry the sensor freely in any pocket without its firm attachment. The system performed well; however, the subject still has to carry it in their jacket or pocket [12].

From the literature, it is evident that there has been a lot of work going on for the activity monitoring of the elderly and to improve their independence. State-of-the-art shows that most researchers developed systems that either use sensors or wearable devices. A recent study about wearable devices concluded that research is equivocal about whether they are valid and reliable methods to specifically evaluate physical activity and health-related outcomes in older adults since they are mainly designed and produced considering younger subjects' physical and mental characteristics [13].

Additionally, wearable devices can be a problem for older people to use for extended periods. Therefore, solutions which involve installed devices like cameras have the potential to mitigate this challenge. We do understand that cameras can be taken as violating someone's privacy. That's why the proposed system in this study uses computer vision and image processing techniques to analyse the movements of the elderly without compromising their privacy through video feeds.

III. RESEARCH METHODOLOGY

This study followed a participatory co-design process involving a team of researchers, developers, care industry experts and end-users throughout the research process [14].

A. Requirements Workshops

The research process started with multiple requirements workshops between the research team, care industry experts and the end users to understand the care industry needs. The workshops helped scope the project, and the research team developed a MoSCoW. This process determines the Must's, Should's, Could's, and Wont's of the project. The MoSCoW is generally created with a high level of abstraction and is later broken down into detailed user stories.

B. Prototyping Approach

The objective of this research project was to develop a working system called (Skystrm) that provides a way to demonstrate the possibilities of applying computer vision techniques within the care industry. Based on the nature of this study, the prototyping approach was best suited for the system development. This approach was applied with the help of agile methodology, which involved multiple research and development sprints. The prototyping and agile combination allowed the involvement of experts and end-users throughout the research process.

C. Data Collection Process

The data to test the performance of the Skystrm was collected through a pilot study to record a person's movements in a predefined scenario. The data was captured with the help of cameras and infrared sensors, which monitor an individual's movements. The pilot study data will act as a first step to determine the suitability and efficiency of the Skystrm.

D. Data Analysis

The pilot study data received data analysis using computer vision techniques. The pilot study results demonstrate how computer vision techniques such as frame differencing can detect motion and generate activity logs using video data. The correct implementation could improve the experience of both care home residents and staff members.

IV. THE SKYSTRM SYSTEM PROTOTYPE

This section describes the development of Skystrm with its main functionalities. The current version of the Skystrm is developed for Windows. However, the same system can be implemented for other operating systems easily.

A. Development Plateform Selection

The platform selected was Windows Presentation Foundation (WPF). WPF is an updated Windows Forms version that can develop desktop applications with visually stunning user experiences. Given that the end goal of this project is data visualisation for activity monitoring, opting for the best User Interface (UI) experience available was a fitting choice. Visual Studio is used used to develop the environment for this project.

B. LiveView Software Flow Diagram

The flow diagram outlines the basic functionality of the Skystrm activity monitoring system, i.e. 'MonitorView' as shown in Fig. 1. The diagram shows a step-by-step process for activity monitoring, data collection and updating activity logs.

C. The Settings Screen

The settings screen is relatively simple but requires users to define which video files they want to play, along with their corresponding room names. Video files can be selected by clicking the purple button next to the file path. This will open a windows dialogue box allowing users to navigate to their desired directory and select a file.

There are four parameters in total that can be tuned.

- Activity Update Rate: The activity update rate defines how often activity events are logged. This value can range between 1 and 60 seconds.

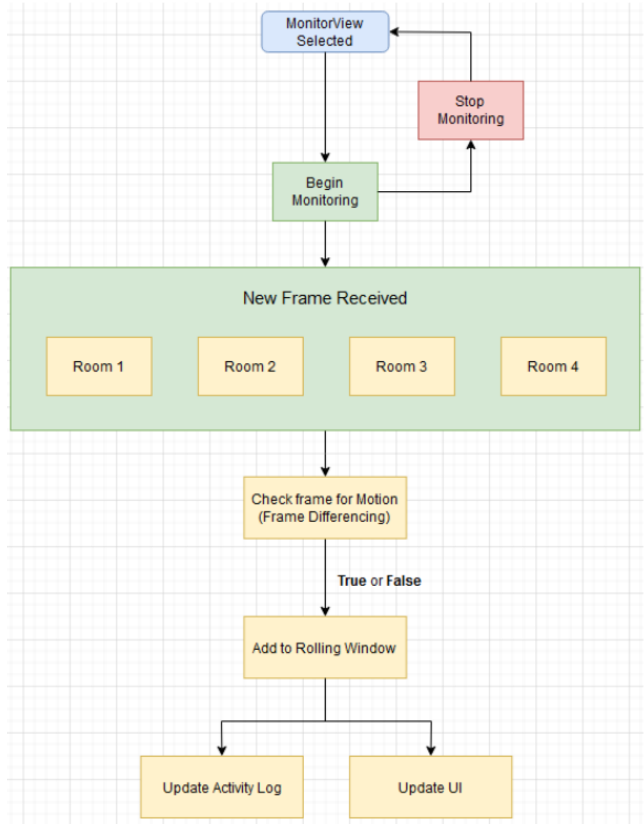

Fig. 1: Software Flow Diagram.

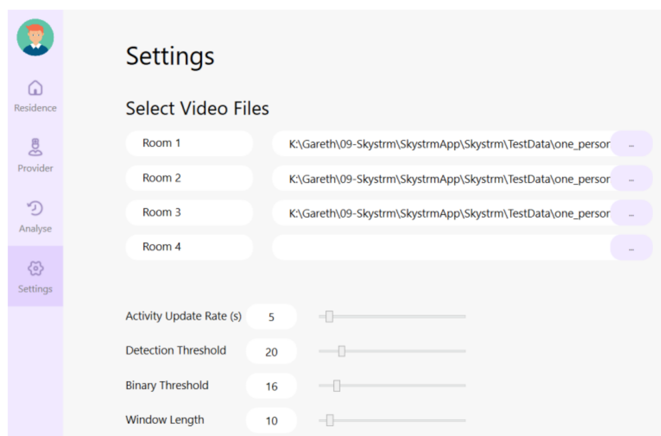

Fig. 2: The Settings Screen.

- Detection Threshold: The detection threshold defines the number of contours that determine motion to exist. This value can range between 1 and 125. This parameter can effectively be used to tweak the motion detection sensitivity (1 being sensitive, 125 being less sensitive). This can be tuned in real-time while the application is running.
- Binary Threshold: Thresholding is one of computer vision's most common segmentation techniques. It allows

the separation of the foreground from the background in an image.

- Window Length: The window length parameter was introduced to increase the system's confidence when determining the presence of motion. The system considers multiple frames (of Window Length) instead of determining motion frame by frame. The optimal window length for this particular scenario was 10. The Length parameter can be increased in real-time but not decreased. The algorithm creates a sum of the elements in an array of motion values. Every time a new frame is processed the resulting motion value '0' or '1' is added to the array and the entire array is shifted by an index of -1. If the sum of the array is greater than five, we can confidently say that motion does exist.

V. MONITORING, DATA COLLECTION AND ANALYSIS

This section describes the pilot study done for this project and how data was captured and analysed.

A. The Pilot Study Settings

MonitorView is the core of this application, containing the computer vision and motion detection system. To access MonitorView, double-click any Residences on the Residence page.

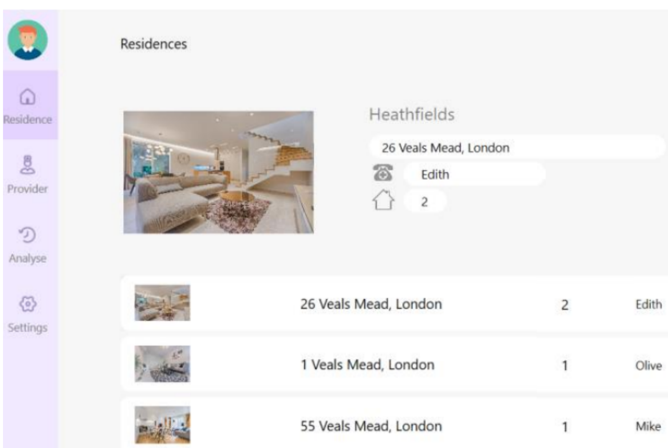

Fig. 3: Monitor View.

After double-clicking on the desired residence, the user will be taken to the MonitorView. Before progressing any further, ensure that the user has first navigated to the settings page and selected the desired video files for testing. When the files have been selected, click the green play button in MonitorView. This will begin the scenario and activate the motion detection system.

B. Data Collection and Analysis

The system will begin monitoring, and the current 'Motion Active' room will be displayed in the 'Overview' tab. The Overview tab quickly lets the user digest key information about the occupant and their activity. The donut chart illustrates a breakdown of how much time has been spent in each of the rooms. The activity log displays a more detailed breakdown of the room activity and corresponding timestamps. This is very useful for the AnalysisView where we can view the data after it has been stored locally in a JSON file.

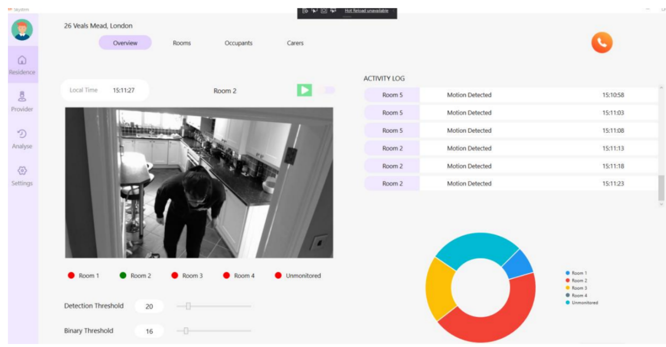

Fig. 4: The Motion Detection System.

To view all the rooms simultaneously, click on the 'Rooms' tab. The small green circle beside the room name can identify the active room. These small activity indicators update in real time due to the moving average window.

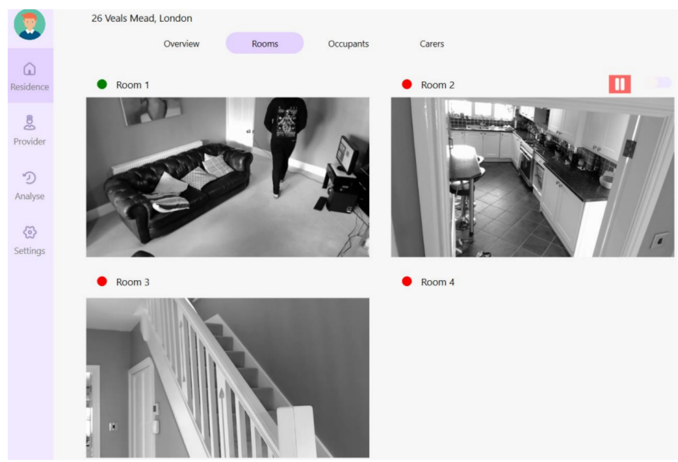

Fig. 5: Different Rooms Through Video.

In both the 'Overview' and 'Rooms' tabs, the selector switch next to the play/pause button can be toggled to switch between the raw camera feed and the real-time frame differencing video. This was most beneficial for testing, but it can also be useful for demonstration purposes and potentially anonymising the video data in future. Figure 6 shows that the care home residents' video will not be shown to the users; motion will be captured, and only their activities will be visible.

C. The Occupants and Carers Tabs

The 'Occupants' and 'Carers' tabs are excellent features in this application. Navigating these tabs allows the users to add/remove/update information about a carer or an occupant.

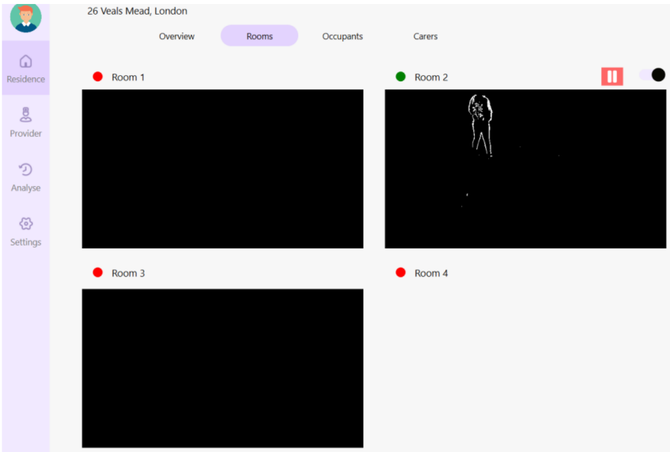

Fig. 6: Motion Detection in Different Rooms.

This feature is more about information related to the occupants and their caregivers, which can be helpful in any events happening.

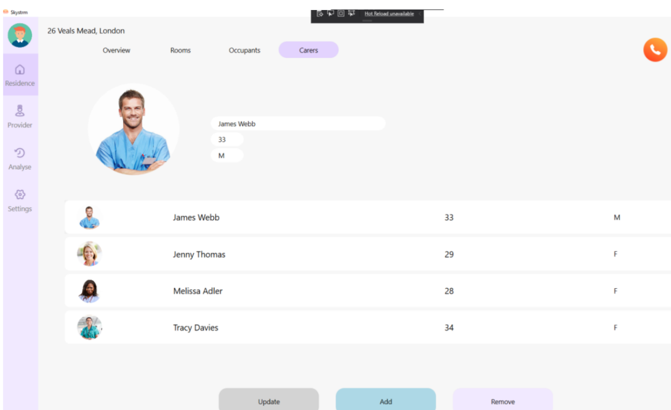

Fig. 7: The Carers Tab.

D. System Working

The current system uses cameras, and infrared sensors, which monitor an individual's movements. The Skystrm system uses AI to learn their routine and then inform family or carers if there is a reason for concern. The system can watch the person, get to know their movements, where they may be, and their routines, and build a picture of what's normal for them. This can include things such as how the person walks, whether they are moving slower than usual, how much time they are spending in each room, when they are visiting the kitchen, and, for example, it'll know that, for example, a person lying on a bed is average for them, but lying next to the bed is out of the ordinary.

Understanding the privacy concerns, the data collected by the system is anonymised to ensure that any individual cannot be identified. The system will monitor images of the individual, but then that data is 'black-boxed' so it becomes anonymised for end-users. It works by using a 'stickman' image of the person being monitored and then uses what it has learned from their past movement to see if things are normal, or if the system needs to notify a carer or family member of any issues. It can work in seconds. If a person falls or is not where they are expected to be and perhaps can't raise the alarm, the system's algorithm will be able to respond to that within just a few seconds.

E. Analysis View

AnalysisView is a separate part of the application that lets the users analyse activity data after a live scenario has ended. This could be data from a previous day or a particular date in real-world data. On the first click on AnalysisView, it will appear empty. To populate AnalysisView, the user can import data that has been automatically recorded from MonitorView by clicking the 'Load Data' button. A windows menu will pop up, asking the user to select a file. Navigate to the following directory (the same directory you used to launch the application). Open the 'SavedData' folder. Inside this folder, the user will find JSON files containing the data from any scenarios that have been run inside the application. This folder also contains data for any of the ListView's such as provider data, residence data, etc. The file name will always be '$activitylog$' followed by a $date/time$ stamp of the following format: '$YYYY - MM - DD - HH - MM - SS$'.

The most recent file saved should be at the bottom by default. Select the file the user wants to use and click 'open'. From here, the user can adjust the slider at the bottom of the screen to select data between two timestamps. Users can also drag the slider around to select a different data window. After selecting desired time window, press the 'Update' button. The UI will update and show all the relevant information for that particular time window. Each time the user drags the slider to a different location, press 'Update'. After importing the data and selecting a window of time, the user should be able to analyse the activity data.

Figure 8 shows the data analysis view of the Skystrm system along with different options. The analysis view provides a donut chart breakdown, precisely like the real-time chart provided in MonitorView. However, it also provides a line graph showing a distinct record of the occupant's activity for the specified period.

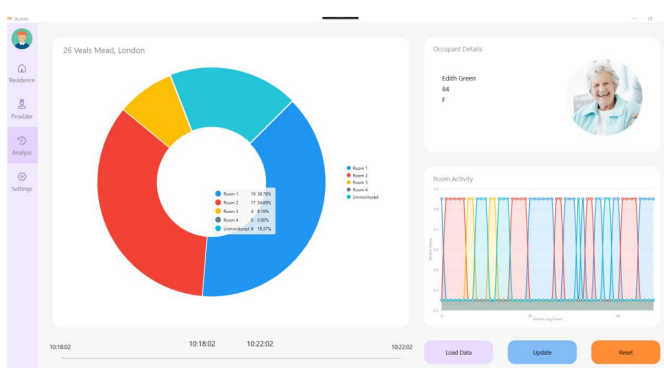

Fig. 8: Data Analysis View.

For this project, the main challenge was trying to determine motion in raw video data solely using computer vision techniques. Using raw image data requires extensive data cleaning and pre-processing techniques (see figure 9). The diagram below shows the data cleaning and pre-processing process from start to finish. This process required lots of experimentation to ensure optimal results whilst still providing the user with enough flexibility and control over the process.

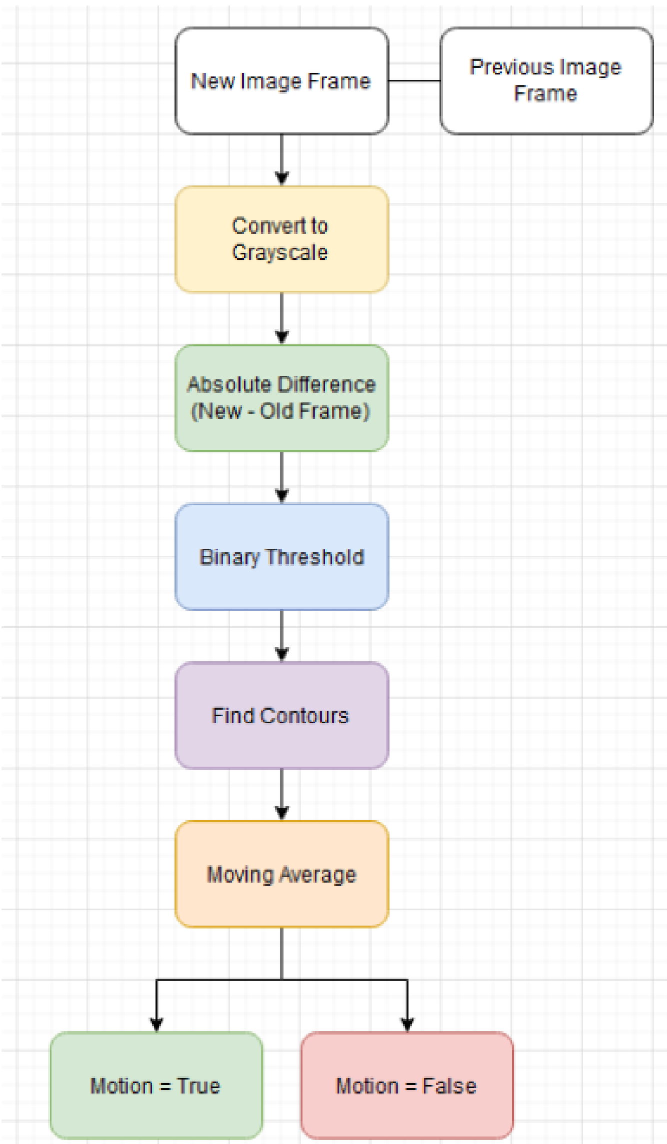

Fig. 9: Data cleaning and Visualisation.

Visualising data is considered one of the best ways to absorb data quickly. There are many different types of data visualisation available, but for this particular project, given the nature of real-time updates, the donut chart seemed best suited to the application. A donut chart presents the activity data excellently, giving an immediate overview of the most frequently visited rooms within the last n period (n = user-defined parameter). This should be very valuable to build an activity profile for occupants living alone. This can be extremely useful for building anomaly detection models to detect abnormal behaviour on any given day.

Similar to the donut chart, the graph presents the same activity data in a different visual format. The graph plots motion status over time. The motion status can either be true or false (i.e. 1 or 0). The most insightful feature of the line graph is that it also shows the transitions between rooms.. Given that our test data was a pre-recorded scenario, we essentially had a script to compare the system logs and the expected output directly. The output logged above is the actual output expected when watching through the footage manually. The Skystrm system resulted in 91% efficiency for the activities and alerts recorded in the pilot study. This proves that the Skystrm motion detection system functions correctly and is a great foundation to build on in the future.

Currently, the system can monitor four rooms at a time. However, this functionality can be easily enhanced to add more rooms, even to add multiple places at the same time. Motion detection is done using computer vision techniques, and no live or recorded video feed is visible to anyone. Thus, the system does not violate the privacy of the residents where this system is being used.

Much work has been carried out in this field using camera-based systems to help older people. A team of researchers have used a video camera for fall detection using an Exponentially Weighted Moving Average based on Support Vector Machines (MEWMA-SVM). However, the system is challenging to install in older homes and compromises privacy [15]. Another study used Pi Camera to monitor and detect a person's fall-like movements. The Pi Camera can watch the movements of the person. It can generate alerts in an emergency [16].

Considering the limitations of the existing systems, this research has tried to use cross-cutting technologies and techniques to improve the efficiency and reliability of the activity monitoring system. The researchers believe it can be a step forward to realise the potential of activity monitoring systems for the elderly without compromising their privacy and without wearable devices that, as per literature, can negatively affect the elderly in the long term.

VI. FUTURE CONSIDERATIONS

With sufficient data, there is potential for implementing advanced deep-learning classification systems for activity monitoring and fall detection in the long term.

A. Integration with the Cloud

One of the challenges faced during this project was intensive real-time processing. When running neural network models such as facenet on real-time video, it would cause delays and issues with the asynchronous nature of the WPF development process. One potential solution is to offload all processing and data storage to the cloud. Given that the long-term goal is to have live video feeding into this application, it makes sense to go down this route.

B. Train Anomaly Detection Model

One immediate improvement opportunity for this project is to use an anomaly detection model. Anomaly detection models are not as complicated as deep neural networks, meaning they are slightly easier to train and do not require as much data. Anomaly detection models are typically best suited to situations where conditions/variables are consistent. The idea is to build up a profile of a particular pattern/behaviour and classify it as a "normal" operating condition. Then, anything that falls outside of this "normal" operation would be considered an anomaly. This type of machine learning model has the potential to be a fitting solution for monitoring an occupant who lives alone.

Assuming a care home occupant has a daily routine, it would be fair to say that the daily graph produced by the occupant would be reasonably similar each day. After collecting a sufficient quantity of daily activity data for individual occupants, we should be able to build a data profile for each of them. An anomaly detection model could then be trained to detect any behaviours that fall outside the "normal" profile, which can also be achieved in real-time. To explore this further, we will monitor one occupant for seven days, collate all the data, and then explore the feasibility of this anomaly detection approach.

C. Added Functionality

From our internal and external testing feedback, there are a few ways the Skystrm system functionality could be improved. The system is currently limited to a single window for displaying all the data. It might be worth exploring options where each application section can become modular in a live environment with multiple monitors. This would give the user complete control over the most significant UI elements and allow for the UI's expansions over multiple displays.

The system currently uses 'LiveCharts' for WPF to plot donut charts and live graphs. This library was selected for its functionality and development support. Using a pre-existing library was also a realistic option, given that this is the prototype system. This library is useful for data visualisation; the library's functionality is limited. For complete control over live graphs and to build-in additional functionality, we can create a LiveCharts fork or develop our custom version.

Another helpful tool that could be integrated into this system is Open Pose. This is another open-source library that attempts to estimate posture detection in real-time, which could prove helpful in attempting to detect falls. The primary benefit of this library is that it does not require pre-existing data.

D. Integrating Artificial Intelligence for People with Dementia

Dementia is one of the most significant challenges that are a direct result due to the ageing population [17]. Our research team has already worked on many technological solutions for people with dementia. We have proposed a software-based solution to help people with dementia in their daily activities, a travelling tutor application to assist them in independent travel and a reminders system to remind them about medication, prayer and weather warnings [18] [19]. In continuation of our support for people with dementia, we plan to add artificial intelligence into the Skystrm system. As the current system learns from data, we can train it to monitor the activities of people with dementia and on deviation; the system can generate alerts to the caregivers. Such a feature will help highlight when a person has forgotten to eat, exercise, walk or take medication.

E. Internet of Things for Smart Care Homes

Finally, we propose integrating internet of things (IoT) concepts in a future version of the Skystrm activity monitoring system. The IoT integration will help expand such systems' capabilities beyond a single home/care home. This combination can help create chains of smart care homes where hundreds of residents can get monitored and supported simultaneously. This will save money and time but also resolve the issue of staff shortages in the care homes sector.

VII. Conclusion and Future Work

This paper presented Skystrm an activity monitoring system intending to aid the independence of older people living alone or in care settings. The Skystrm system is designed using a co-design approach and tested through a pilot study. The system uses cameras and infrared sensors to collect activity data and generate the activity profile of the individual. On detecting a deviation from the individual's daily activities, the system generates alerts for the caregivers or family. The performance of the prototype system shows that it has the potential to assist in the independence of the elderly and can aid in healthy ageing. Additionally, this paper has proposed many future research directions that can be useful to achieve the fundamental capabilities of the activity monitoring systems like the Skystrm.

However, the current work is based on the activity monitoring system tested through a single case study. There is a need for more testing to generalise the results of this study. The research team is conducting multiple testing sessions with people living in care settings in the UK and South Africa.

Acknowledgment

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