Health Monitoring System for Senior Citizens

Project Team

Javairia Rehman	19P-0020
Matti Ur Rehman	19P-0048
Muhammad Mohsin Raza	19P-0072

Session 2019-2023

Supervised by

Dr. Hafeez Ur Rehman

Department of Computer Science

National University of Computer and Emerging Sciences
Peshawar, Pakistan

June, 2023

Student's Declaration

We declare that this project titled "*Health Monitoring System for Senior Citizens*", submitted as requirement for the award of degree of Bachelors in Computer Science, does not contain any material previously submitted for a degree in any university; and that to the best of our knowledge, it does not contain any materials previously published or written by another person except where due reference is made in the text.

We understand that the management of Department of Computer Science, National University of Computer and Emerging Sciences, has a zero tolerance policy towards plagiarism. Therefore, We, as authors of the above-mentioned thesis, solemnly declare that no portion of our thesis has been plagiarized and any material used in the thesis from other sources is properly referenced.

We further understand that if we are found guilty of any form of plagiarism in the thesis work even after graduation, the University reserves the right to revoke our BS degree.

Javairia Rehman	Signature: ________________
Matti Ur Rehman	Signature: ________________
Muhammad Mohsin Raza	Signature: ________________

____

Verified by Plagiarism Cell Officer
Dated:

Certificate of Approval

The Department of Computer Science, National University of Computer and Emerging Sciences, accepts this thesis titled *Health Monitoring System for Senior Citizens*, submitted by Javairia Rehman (19P-0020), Matti Ur Rehman (19P-0048), and Muhammad Mohsin Raza (19P-0072), in its current form, and it is satisfying the dissertation requirements for the award of Bachelors Degree in Computer Science.

Supervisor

Dr. Hafeez Ur Rehman Signature: ________________

____

Zeshan Khan

FYP Coordinator
National University of Computer and Emerging Sciences, Peshawar

____

Dr. Hafeez Ur Rehman

HoD of Department of Computer Science
National University of Computer and Emerging Sciences

Acknowledgements

Your acknowledgements here

Javairia Rehman

Matti Ur Rehman

Muhammad Mohsin Raza

Abstract

Human action recognition (HAR) is considered as one of the most promising assistive technology tools to support elderly's daily life by monitoring their cognitive and physical function through daily activities. Due to competitive fast changing technologies, people need assistance for their elderly people in their absence. In previous approaches in HAR the proposed system were able to recognize activity from offline videos. We propose a complete healthcare monitoring system with a skeleton-based approach for elderly people in which they will be continuously monitored using camera such as Kinect 360. The system uses IndRNN a variant of RNN which is trained on 12 health-sensitive activities to recognize the activity of elderly people such that if health-sensitive activity occurs and is recognized by our model it will instantly notify users or doctors through app so immediate actions can take place. The outcomes show that the trained algorithm can be used to identify HAR, which is very encouraging.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

The health monitoring system recognizes health sensitive activities of senior citizens using sensors. Then it will inform hospitals or relatives. So using this system we can monitor the health of senior citizens without any involvement of humans. These types of systems depend on sensor data, cloud, mobile applications and deep learning algorithms. This has been done either using wearable sensors or using cameras. There are some challenges that need to be addressed such as if senior citizens do not wear wearable sensors, data of health-sensitive activities, privacy issues and many other challenges.

1.1 Deep Learning

To classify which action is performed in the sequence of images we have to extract features from the frames and then feed them to our model. Initially, feature extraction was done by hand [5]. This process was very time-consuming because all work is done by humans. The prediction from videos is also a very time-consuming process. So if we extract features by hand and then feed them to the model it will be very time-consuming ultimately it will be not useful.

New research results in deep learning.The Convolutional Neural Networks (CNN) [2] are used for feature extraction for images then these features will be fed into a model which is also a deep neural network. So, the raw data comes from the sensors and give this raw data to the neural network that will extract the features combine them and classify the human activity.

1.2 Sensors

The sensors are used to provide the data in case of activity recognition it is human activity. As time passes by new technologies are being introduced. So human activities can be monitored by the sensors easily. Vision-based and sensor-based [1] are the two approaches that are used to capture the activity. These sensors can be used to monitor health-sensitive activities so there is no need to see the doctor or if you have to see the doctor using these sensors doctor will also monitor the patient.

1.2.1 Vision Based Sensors

The process of classifying the action from a sequence of images is called vision-based action recognition [6]. In vision-based sensors, there are many challenges [14] such as privacy issues, not giving good results in dark light, inter and intra-class differences, occlusion and many more. The vision-based approach is easy to implement but one has to tackle these issues. It is also harder to classify complex activities as compared to normal activities. It is also harder to classify activities in a group of people where everyone is doing their respective activity.

1.2.2 Sensor Based Sensors

According to the survey, [1] and due to difficulties in the vision-based approach, people are doing more research on the sensor-based approach than the vision-based approach. One reason is the low cost of these sensors than cameras. In the sensor-based approach, sensors are categorized but we will talk about wearable sensors. Wearable sensors are placed on the body for example the smart watch etc. These sensors continuously take the reading and send it to the app or where it is needed.

Chapter 2

Review of Literature

2.1 Deep Learning

Deep learning is used in human activity recognition so feature extraction is not done by using traditional techniques in activity recognition there is continuous monitoring of a human so a large amount of data is generated if we use traditional approaches it will be very time-consuming so activity will not be timely recognized. To automate the process of feature extraction and activity recognition deep learning is used [8]. Deep learning is used in both vision-based human activity recognition as well as sensor-based human activity recognition [3].

2.1.1 Vision based

2.1.1.1 CNN

In survey [8], Authors discuss action recognition using deep learning methods emphasising using CNN. Also, discuss some of the problems that we face during activity recognition. The main problem that they discuss was pre-processing. People skip this part so activities will not correctly classify. They also discuss various publicly available datasets for human action recognition. The authors conclude this survey by saying pre-processing has been ignored and deep learning is mostly used in action recognition and pose detection, especially CNN because it solves different problems such as occlusions, lighting issues and so on.

2.1.1.2 3D CNN

Initially, 2D CNN was used but it uses only spatial features. To classify the activity in motion temporal features are needed. So 3D CNN [7] uses both temporal and spatial features. It gives much better results than 2D CNN. Testing on the KTH dataset which is a publically available dataset of human activities shows an average accuracy of 90% using 3D CNN which is the maximum accuracy of previously used methods. The activities in which 3D CNN gives the best performance were cell to ear, object put and pointing.

2.1.1.3 RNN

RNN is considered to be the best deep neural network for video classification than CNN. Because of its multiple recurrent networks, [12]. But due to this feature of RNN, it has to face the gradient vanishing problem. So its updated version Long short term memory (LSTM) was proposed it has also drawbacks. So, Independent RNN [9] has been proposed in which In neurons are independent of each other within the same layer but connected across layers.

2.2 Action Recognition Systems

The action recognition from RGB videos is very complex due to illumination issues. It is sensitive to illumination so the videos will affect by this and data will be corrupted which results in classifying the wrong activity. For example, if there is no light in the room the RGB camera will not be able to capture the activity and also not be able to continuously monitor the elderly people. So 3D skeleton [4] based action recognition for elderly people is purposed in which RGB-D images sequence are used. As you can see in 2.1 skeleton image. Using depth sensors such as Microsoft Kinect sensors we can easily get rid of illumination issues. It uses depth images which are affected by distance from the sensor to the object (human). From depth images, body features are extracted, combined with all features, and fed to an extremely randomized tree algorithm. They have used Microsoft's dataset. But it misestimates the body poses due to some wrong points in the dataset. It was able to classify normal activities.

A proposed IoT-based health monitoring system [10] in which the authors compare previous methods. IoT was used so that the data from the sensors arrived over the network. Finally, they state that SVM and Random Forest are the best algorithms so far, with an accuracy of 99.89%. The main drawback of this system was that its model predicted offline activities.

A health monitoring system for elderly people [13] was proposed. The author discusses their approach and compares the results with the proposed approaches. They have used 2D CNN with skipping 2 layers of convolution neural network. The main goal of this system was to use surveillance video to assist the activities of elderly people. They get high accuracy on their own dataset and other publicly available datasets as compared to models that classify images. The main flow was it was able to detect normal activities like walking, standing, walking etc.

Another health monitoring [12] was proposed rather than using raw data from videos they used skeleton images in which they use 20 joints. The authors used independent RNN [9] for classifying the activity and triggering the alarm. But there is still a challenge, for example, elderly people have sensitive health issues like asthma if there is nobody is present in the house except the elderly person then if it continuously monitors the health successfully and triggers the alarm it will be of no use because nobody is there to help the elderly people. There should be a proper mechanism in which the doctor or children of elderly people see the health condition if they found any health-sensitive activity they should inform their children or user of the app.

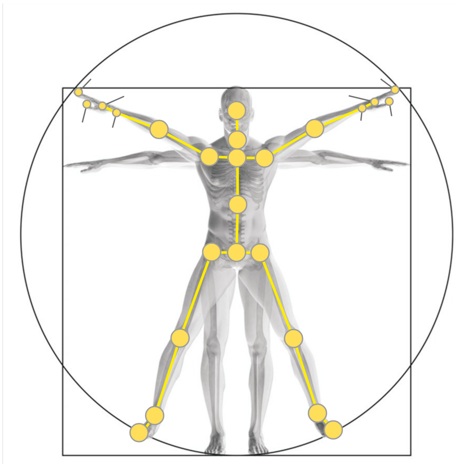

Figure 2.1: Skeleton Image [11]

Chapter 3

Project Vision

3.1 Problem Statement

In this modern era of the world. Almost everyone is busy with their work kids are busy with their studies, adults are busy with their work and if they work physically not from home then their parents or senior citizens will be alone at home. Most likely they have some health-related issues that require 24/7 monitoring of their health conditions. Senior citizens also do not feel comfortable in hospitals. Even if you hire a nurse that takes care of your senior citizens it is not possible for a nurse to take care 24/7 also there will be some trust issues with the nurse and doubts about how a nurse will behave with your senior citizens.

3.2 Business Opportunity

We are making a full product which includes vision-based sensors and an app so if elderly people are uncomfortable having a caretaker the camera is still there to monitor and classify their activity. The mobile application is also developed to see real-time data coming from the cloud. So doctors or users of the app will able to see the current readings of sensors.

3.3 Objectives

The main objectives of our project are as follows:

- Detection of health-sensitive human activities
- Alert relatives/attendants/doctors.
- Keep activity analytic.

3.4 Project Scope

Our main goal is to assist in human action recognition in the healthcare field using vision. Using cameras without disturbing the privacy of elderly people our system will be able to detect health-sensitive activities. The final deliverable will be IOT based system in which a camera is installed in the room. The data will be sent to a server if the activity is normal in the mobile app the status of the patient will be normal if not then the alert will occur showing the name of the activity and the status of the patient will be updated to the abnormal. so immediate action can take place to help elderly people.

3.5 Constraints

The three main constraints are time, money and scope. If you do not balance them you are going to face many problems during the software development life cycle. If you increase the scope of your project you also have to increase time and money to balance them. So, we also don't want to face problems that's why seeing the scope of the project we use iterations in our life cycle in order to successfully accomplish our task.

3.6 Stakeholders Description

The stakeholders in our project are as follows

1. Our team
2. Supervisor
3. Users

They are one of the best assets in the software development life cycle.

3.6.1 Stakeholders Summary

Stakeholder feedback at any time during the software development life cycle will be very beneficial. As they give input to our project that's why they are very useful. If our developed system has any flaws and our testing is not able to detect any kind of error the stakeholders will help by giving time-to-time input.

3.6.2 Key High-Level Goals and Problems of Stakeholders

The high-level goal is to have a project that adds some value to their life, that is helpful for them. The Project Manager is responsible to manage stakeholders in such a way that it meets the constraints of the project and successfully makes a project that adds value to them. The project manager has to take wise decisions such that it does not affect the stakeholders and the project.

Chapter 4

System Analysis and Design

This chapter will have the functional and non-functional requirements of the project.

4.1 List of Features

4.1.1 Well designed and functional

The end product is designed well. According to the plan, all components are tested separately and then combined to make them function properly.

4.1.2 Fully responsive(platform independent)

The app front-end is designed on react-native which is a complete platform-independent language. We can use apps on any Operating System.

4.1.3 User friendly

The app front-end is designed in basic English. All options are understandable for any layperson. Avoid using jargon.

4.1.4 Easy to register

After purchasing the product. The user will get a username and password scanned from the camera and the user would be able to log in just from single click

4.1.5 Accessibility of patients status

After connecting to the internet user can view the status of the patient continuously on his smartphone

4.1.6 Safe time and money

Reducing human efforts can save time as well as money. If we introduce this product in our room rather than in nurses we can save both time and money easily.

4.1.7 Alert to health sensitive activity through notification

Notification is one of the big advantages, the user might be busy with his/her tasks. Notification will give him an alert that someone is needed his/her attention.

4.2 Functional Requirements

ID	Requirments	comments
FR001	User should get correct username and password scanned from their camera	from the place they buy product
FR002	User can log in by entering a correct username and password	if registered
FR003	A website must have a main page after login verification	-
FR004	Main screen must contain patient status	normal or abnormal
FR005	Camera must be fixed and on	light must be on
FR006	User can see the name of sensitive activity from popup notification on display	on uncertain condition
FR007	Website must take the status of the patient on the main screen through cloud	If the Internet is connected
FR008	Website takes sensitive activity name on the main screen through cloud	If the uncertain condition occurs

Table 4.1: Function Requirments of Health Monitoring System for Senior Citizen

4.3 Non-Functional Requirements

ID	Requirements
R001	The system must be secure from hackers
R002	Login and passwords must be real and unique
R003	System should cost between $150 to 170$
R004	Information on the cloud must be secure in a proper way
R005	IOT devices connectivity must be done properly
R006	System must be scalable on the basis of cost
R007	If the system goes done there must be some recovery method to recover it within days
R008	On year software warranty should be given
R009	APP should be platform independent

Table 4.2: Non-Function Requirments of Health Monitoring System for Senior Citizen

4.4 Use Cases/ Use Case Diagram

4.4.1 Use Case

The use case diagram shows the behaviour of our system. How our system is going to behave when end users interact with our system. The use case diagram is simple. It does not contain any kind of complexity. Our proposed use case diagram for the health monitoring system is given in 4.1.

4.4.2 Main Scenario

The user gets a username and password when he purchases the product. When the user login app, the first app will verify the user. After the verification process, the main screen will appear with the current status of the patient detected by the camera. If the camera is placed fixed and in the correct position relevant to the patient. It will give skeleton points of the patient to model and the model will predict the status of the patient. The status component will show if patients are normal or abnormal. If the camera shows any health-sensitive activity from the patient, the user will get a notification from the app through a popup with the activity name.

Figure 4.1: Use Case Diagram of Health Monitoring System for Senior Citizen

4.5 Use Case Description

4.5.1 Login

Description	**Details**
Goal	Successful Login
Precondition	User must enter username and password
Successful End	Login and moves to display screen
Failed End	Unable to login and moves to login screen again
Primary Actors	User
Secondary Actors	Database
Trigger	Login Button
Main Flow	User enters credentials.And authenticated move to display screen
Alternative Flow	User enters credentials.And not authenticated then do not allow to login

Table 4.3: Use Case Description for Login

4.5.2 Getting Username and Password

Description	**Details**
Goal	Successful Login
Precondition	User must get correct username and password where he buys product
Successful End	if he enters username and password he could move to display screen
Failed End	Unable to get correct username or password
Primary Actors	User
Secondary Actors	shopkeeper
Trigger	Login Button
Main Flow	User gets credentials.User login from that username and password.display screen appears
Alternative Flow	User enters credentials.incorrect username or password.try again message appears

Table 4.4: Use Case Description for SignUp

4.5.3 View Status Of Patient

Description	**Details**
Goal	View either status is normal or not
Precondition	Successful Login
Successful End	After successful login user can view status of patient
Failed End	Unable to view status of patient
Primary Actors	User
Secondary Actors	IOT Devices
Trigger	-
Main Flow	After successful login.the user reaches the main page. user can view the status of the patient as normal
Alternative Flow	After successful login.the user reaches the main page. user views the status of the patient as abnormal

Table 4.5: Use Case Description for View Status of Patient

4.5.4 View Health Sensitive Activity Name

Description	**Details**
Goal	view View Health Sensitive Activity Name when something uncertain happens
Precondition	status goes abnormal or uncertain condition detected through cameras
Successful End	if something uncertain happens user can view the name of that activity
Failed End	uncertain condition happened but cannot viewed name on screen
Primary Actors	User
Secondary Actors	Cloud
Trigger	-
Main Flow	After successful login.The user reaches the main page. if something uncertain happens display the name of that activity
Alternative Flow	After successful login.The user reaches the main page. if something uncertain happens cannot displays the name of that activity

Table 4.6: Use Case Description for View Health Sensitive Activity Name

4.5.5 Get Notify

Description	**Details**
Goal	getting popup notification on phone if uncertain condition happens
Precondition	something uncertain happens or status becomes abnormal
Successful End	popup notification
Failed End	no notification on uncertain condition
Primary Actors	User
Secondary Actors	Cloud
Trigger	-
Main Flow	After successful login.The user reaches the main page. if something uncertain happens display the name of that activity. Get popup notification on phone
Alternative Flow	After successful login.The user reaches the main page. if something uncertain happens display the name of that activity. cannot get popup notification

Table 4.7: Use Case Description for Get Notify

4.6 Sequence Diagram

The sequence diagram shown in 4.2 shows the flows of all possible activities that will be happened in our system. This diagram explains how our system will go to work. How different components will behave in different conditions? This diagram will deeply explain the flow of our system

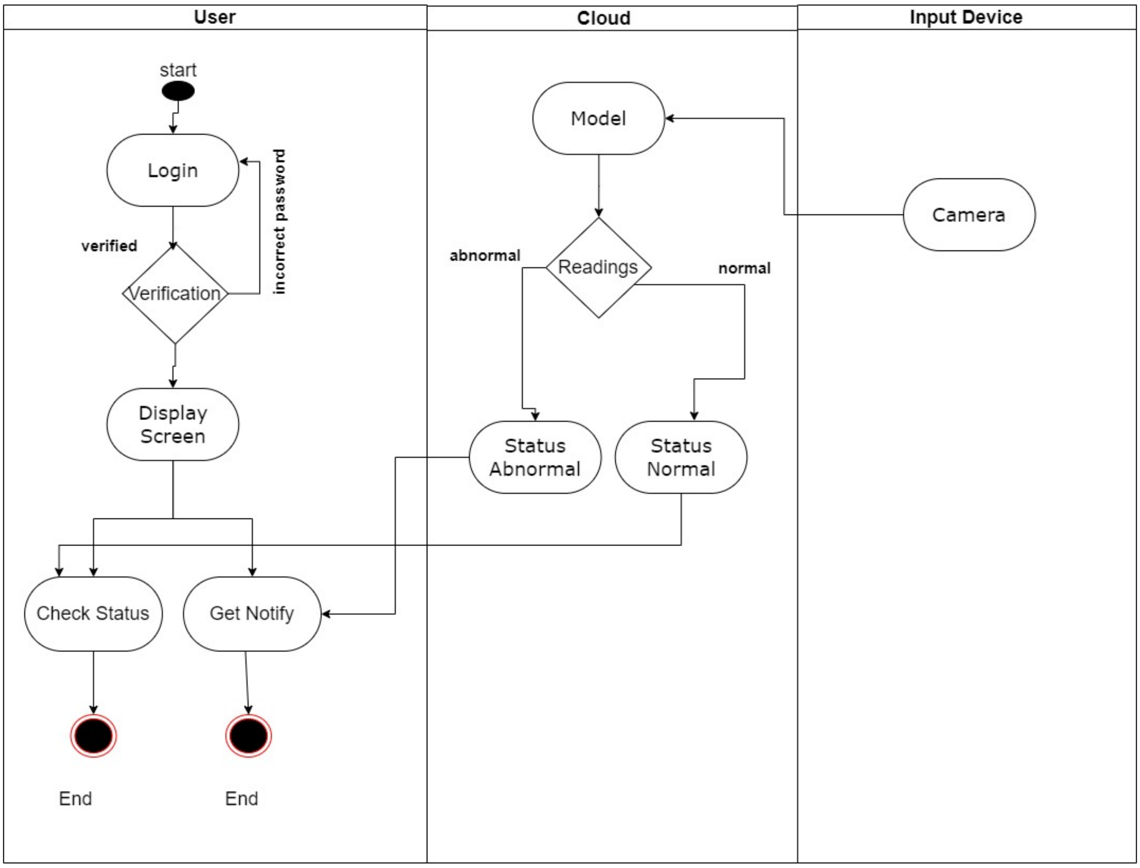

Figure 4.2: Sequence Diagram

4.7 Software Development Plan

4.7.1 App functionality

1. Home page with login and button.

2. Login page.

3. Main screen has the following component.

   - **Patient Status:** User can view the status of the patient on the main screen from the cloud whether it is normal or abnormal.

4.7.2 Models Functionality

4.7.3 Product Users

People	Usage
patient	continuously monitored through app
attendant	Can monitor patient continuously
attendant	Can get notification alerts on uncertain conditions

Table 4.8: Product Users details

4.7.4 Product Management

ID	Tools	comments
01	any python compiler for model building	-
02	Visual studio for react native	-
03	Cloud services azure or aws	May cost
05	Kinect Camera	100 dollars

Table 4.9: Project Management

4.7.5 Advantages Of Using This Product

- Remote accessibility
- Cost friendly(installation fee only)
- Authentic information(skeleton points based prediction)
- Notification alert
- Reduction of human burden
- Caring for a patient

4.7.6 Issues in Product

- If it goes down attendant cannot get a notification
- Installment fee
- Machine error
- Electricity issue

4.7.7 Conclusion

The project is based on readings of the model (camera skeleton points detection) designed to notify the health-sensitive activity of patients. It saves money and human time. This is designed with a user interface which can be used by any person easily. Best for people who have their loved ones waiting at home and need them for health care.

This chapter is used to describe the iteration plan of the project. How will try project proceeds to complete all the requirements? The chapter will guide the modules of the project and the development of those modules.

4.8 Plan

4.8.1 Planing Strategy

In this chapter, we have shown that we will be using agile methodology while developing our final year project. Our project is divided into 4 spans of time i-e

- FYP 1 MID
- FYP 1 FINAL
- FYP 2 MID
- FYP 2 FINAL

In the figure below we have shown how we have divided our work in this time spam. This planning can be changed according to the situation. A detailed explanation of these modules will be done in the coming chapter

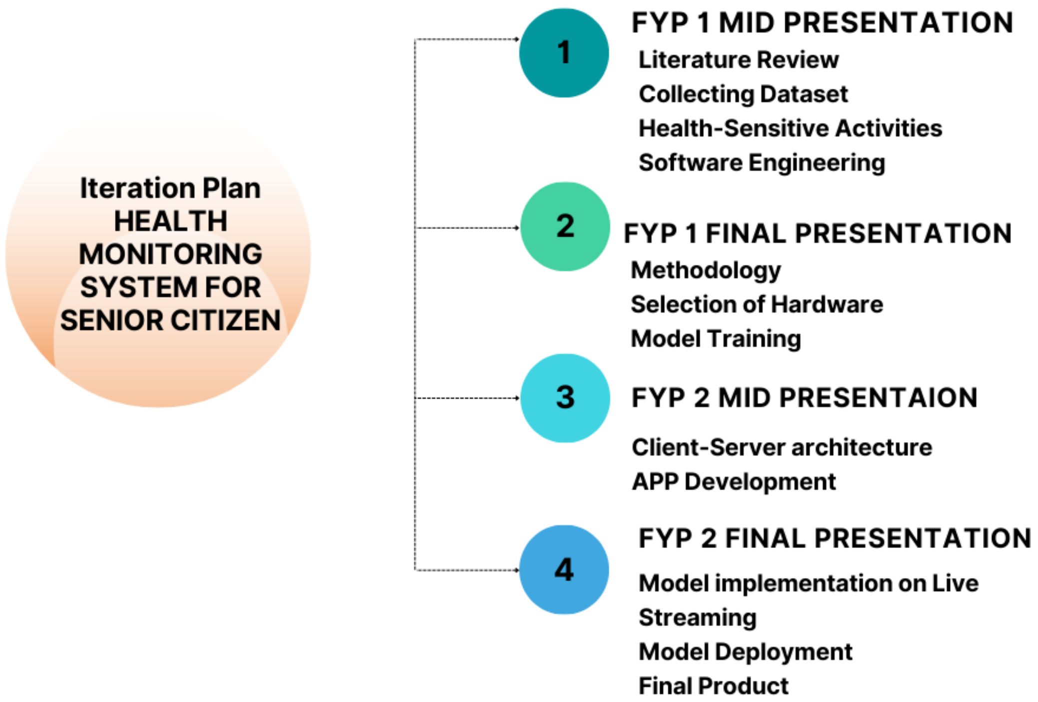

Figure 4.3: Planning

4.8.2 FYP 1 MID

The things that we will cover in FYP 1 mid are given below:

- Literature Review
- Collecting Data set
- Health-sensitive activities
- Software Engineering

4.8.3 FYP 1 Final

In FYP 1 Final we will cover the following things:

- Methodology
- Selection of Hardware
- Model Training

4.8.4 FYP 2 MID

- Client-Server architecture
- App Development

4.8.5 FYP 2 FINAL

- Model implementation on Live Streaming
- Model Deployment
- Final Product

4.9 Iteration 1

4.9.1 Data set

Collecting data sets was quite challenging because of the privacy issues of people. We have downloaded the data set from roselab .Data set length is 11412 in which we have 12 classes. Each class have 4 videos. We have got skeleton points for each video in a data set.

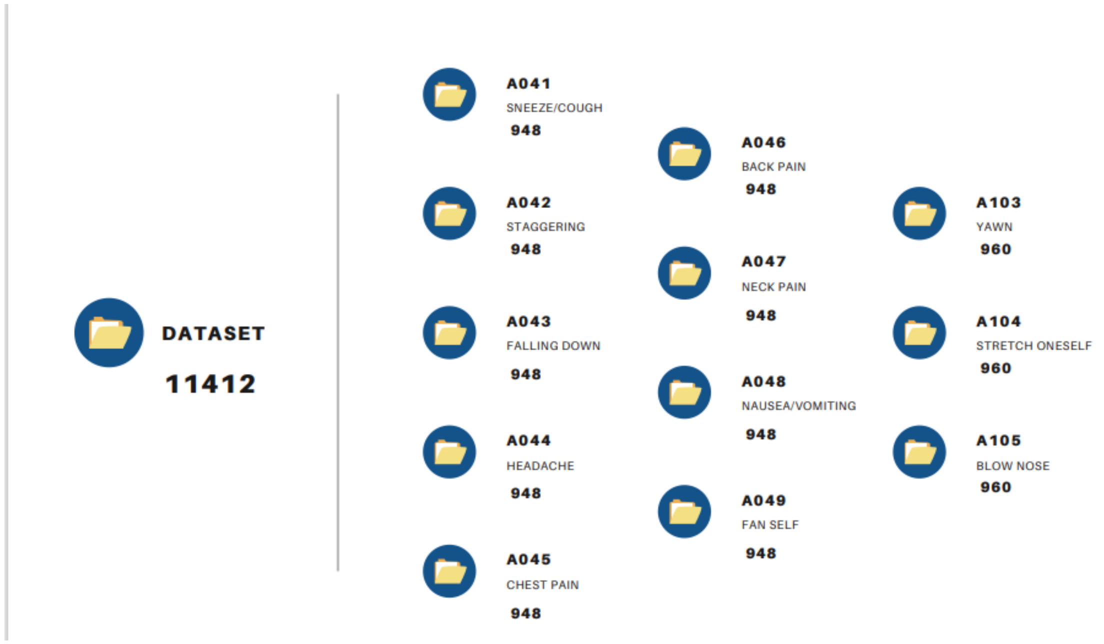

Figure 4.4: Data set

4.9.2 Health Sensitive Activities

Before training of data. We need to classify some activities as "train data set" and some as "test data set".In this project, we are using some activities listed below as training data sets. Our model will be able to classify these only sets of activities. After training the model, we will perform the algorithm on live streaming.

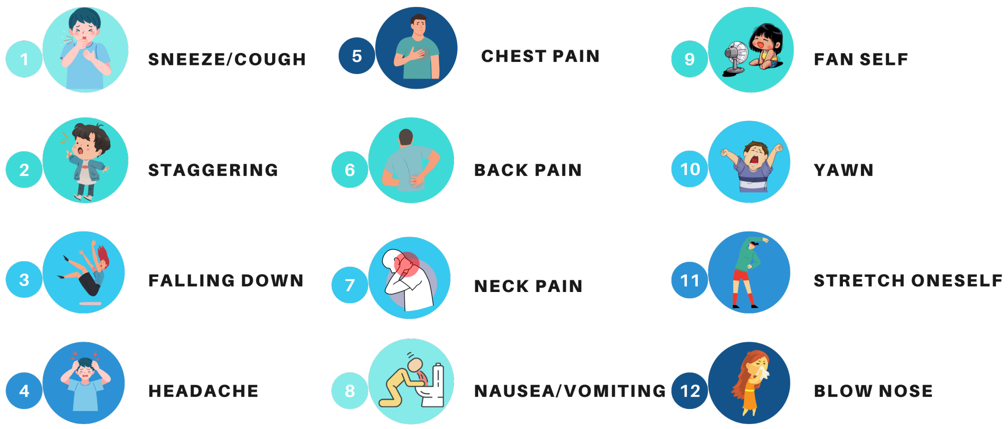

Figure 4.5: Sample From Videos

4.10 Iteration 2

4.10.1 Activity Diagram

The activity diagram is designed to describe the complete flow of project development during this time span This is a part of the activity diagram which we covered in this iteration.

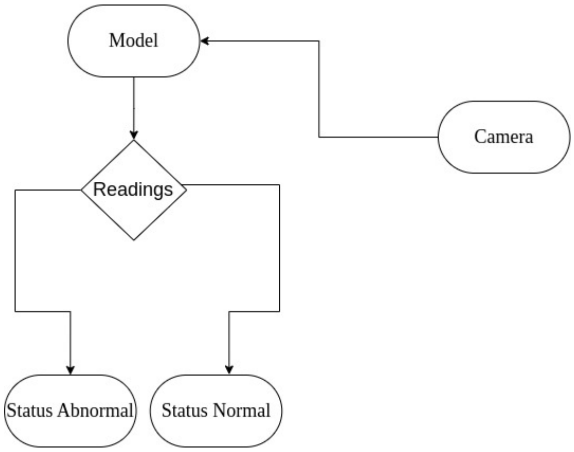

Figure 4.6: Activity Diagram

4.10.2 Methodology

We are using Kinect 360 through which we are getting skeleton joint points which will be fed into our model. Before feeding joints into the model key frames are extracted from a large amount of frames. We are using a variant of RNN which is independent RNN to classify health-sensitive activity. When the model classifies health-sensitive activity it will instantly notify user through an app that will be installed in their smartphone so that immediate action can take place. The basic methodology is explained in 4.7. The skeleton joints are explained in 4.8 you can easily understand that we are getting 20 body joints. All of them have a unique number.

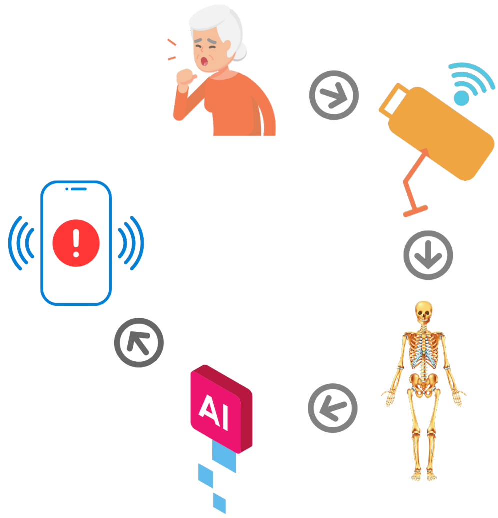

Figure 4.7: Methodology

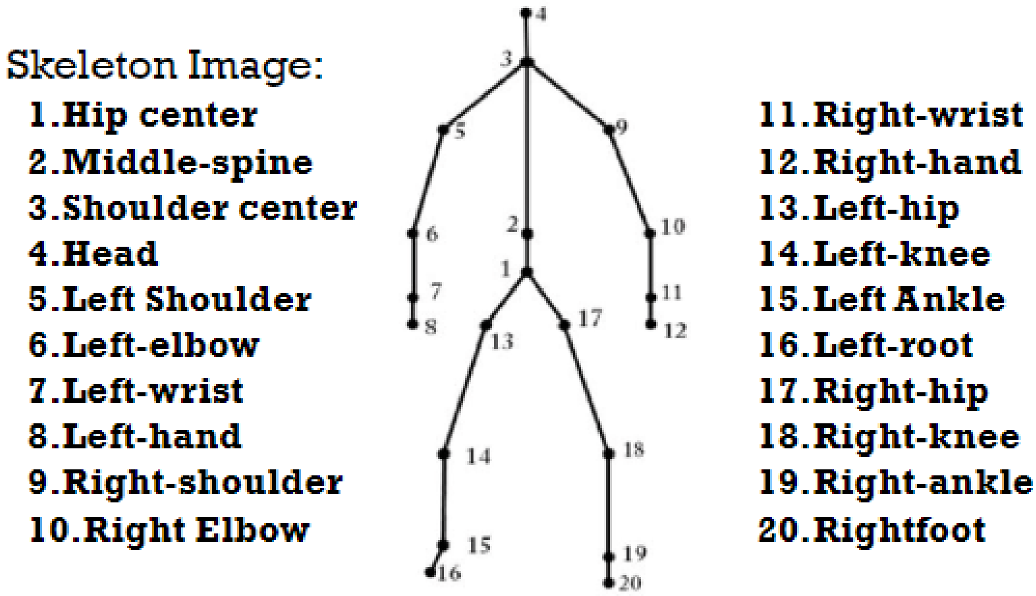

Figure 4.8: Skeleton Points

4.10.3 Sliding Window

We included the sliding window concept in our project to avoid any errors or misconceptions. The basic concept is that rather than moving the image block by block, we use sliding windows because, in the block-by-block method, we may miss the activity on the edges. However, the sliding window size of the window will be fixed and it will move accordingly without missing a single second. Its detailed explanation can be found in 7.2

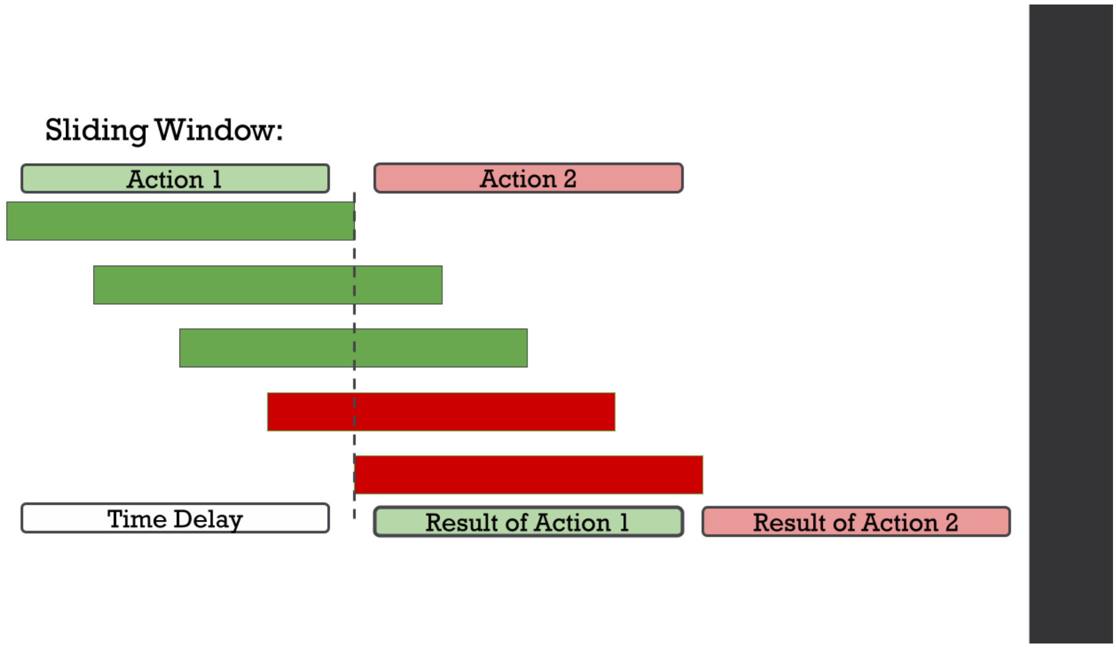

Figure 4.9: Sliding Window

4.10.4 Hardware

After a lot of research, we found that by using a Kinect sensor we will get skeleton points of the body easily. So we used Kinect 360 for this purpose. You can see in 4.10 skeleton points of one frame of video that is recorded by Kinect 360.And its skeleton image can be seen in 4.11 which is drawn using python library matplotlib.

```
[[-1.632375e-01, -2.719418e-01,  3.793614e+00],
 [-1.610523e-01,  4.210661e-02,  3.846833e+00],
 [-1.581150e-01,  3.500930e-01,  3.886799e+00],
 ...,
 [-1.258912e-02, -6.452508e-01,  3.676026e+00],
 [ 5.057659e-02, -9.741414e-01,  3.607743e+00],
 [-5.858317e-04, -9.986490e-01,  3.480269e+00]],

[[-1.623635e-01, -2.719830e-01,  3.793427e+00],
 [-1.605287e-01,  4.207006e-02,  3.846594e+00],
 [-1.578705e-01,  3.500673e-01,  3.886553e+00],
 ...,
 [-1.237373e-02, -6.445345e-01,  3.676000e+00],
 [ 5.025174e-02, -9.735253e-01,  3.607689e+00],
 [-7.577874e-04, -9.980372e-01,  3.480130e+00]],

[[-1.615281e-01, -2.718283e-01,  3.795125e+00],
 [-1.601908e-01,  4.162662e-02,  3.847232e+00],
 [-1.577816e-01,  3.489477e-01,  3.886734e+00],
 ...,
 [-1.206885e-02, -6.445941e-01,  3.675985e+00],
 [ 5.155781e-02, -9.734418e-01,  3.607960e+00],
 [ 3.340404e-02, -1.042716e+00,  3.525048e+00]],
```

Figure 4.10: Skeleton Points

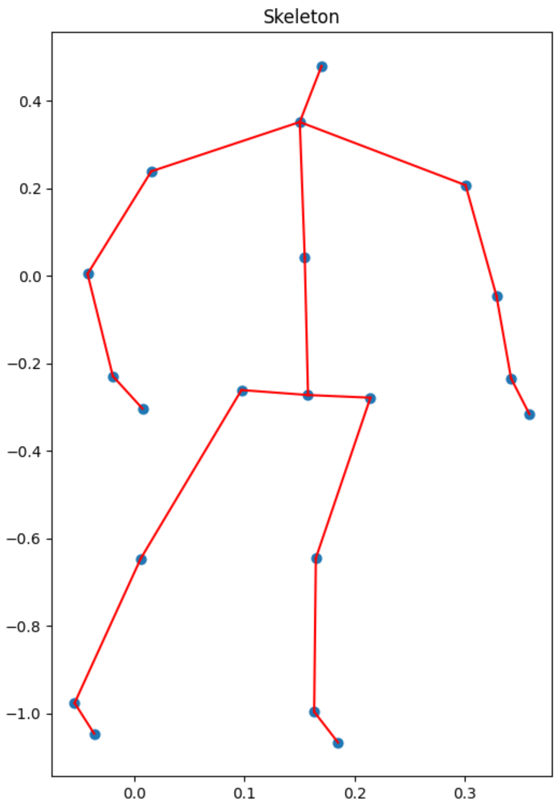

Figure 4.11: Skeleton Image

4.11 Iteration 3

4.11.1 Client-Server architecture

In order to send points from the patient's room to the model we designed a client-server architecture. We implemented it using

- Python 2
- Python 3
- Sockets

We are using Kinect 360 which supports Python 2 so we wrote a client code for that and on the server side we used Python 3. The client sends each frame point if the body is detected and sends it to the server then from the server it is fed into the model.

4.11.2 Activity Diagram

In the previous iteration, we make a pipeline in which the model was getting points from the camera. To alert the user of health-sensitive activity we make an app in this iteration. You can see in the activity diagram 4.12. In the real world users basically, scan a QR scan to sign up for a device in the app such as a CCTV app. But in our case, we have only one device so we register the user instead of scanning. When a user logs in they will able to see two activities status of patient and activity name alert when health-sensitive activity occurs.

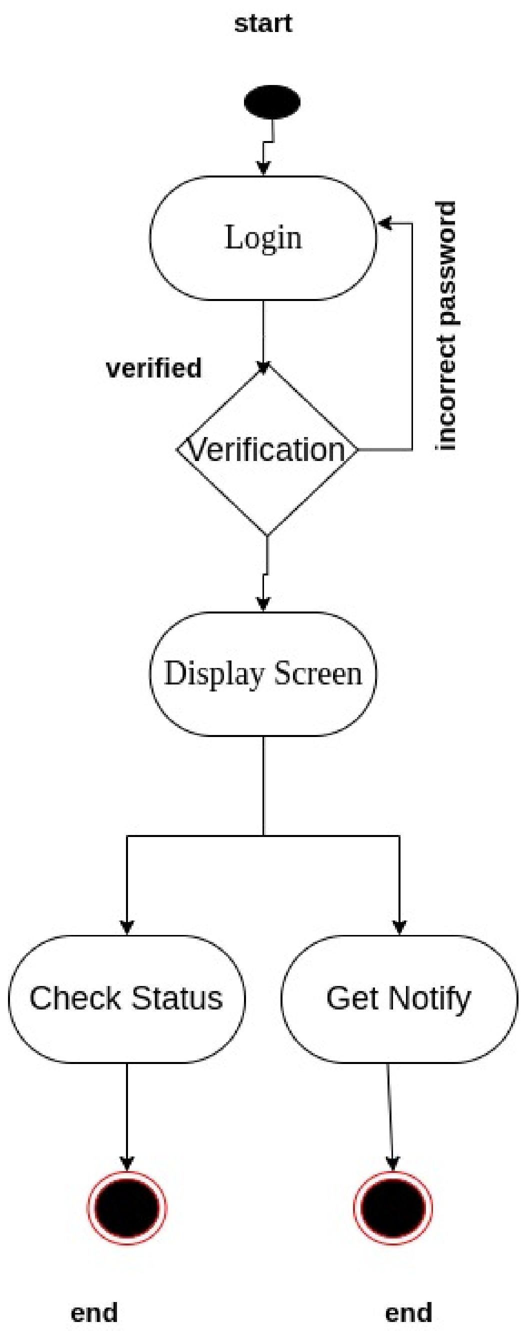

Figure 4.12: Activity Diagram

4.11.3 Prototype 1

In the following figures, you will see interfaces of our health monitoring system app from launcher activity to altering the health-sensitive activity.

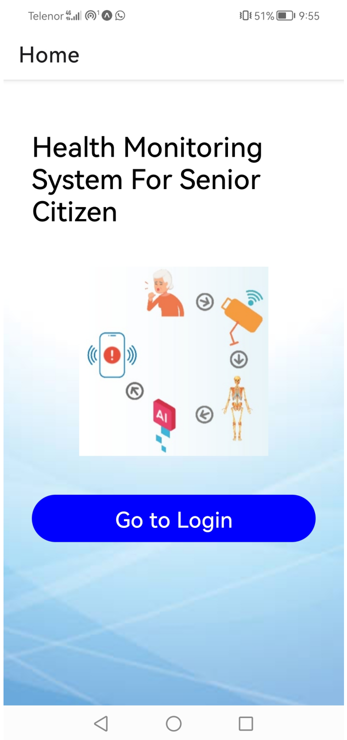

Figure 4.13: Launcher Activity

Here user can log in to the app to see the status and other things. In case the user enters the wrong credentials . He or She will not be able to log in.

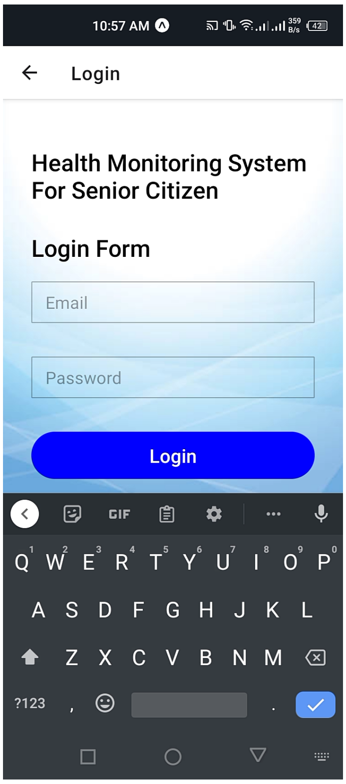

Figure 4.14: Credentials Activty

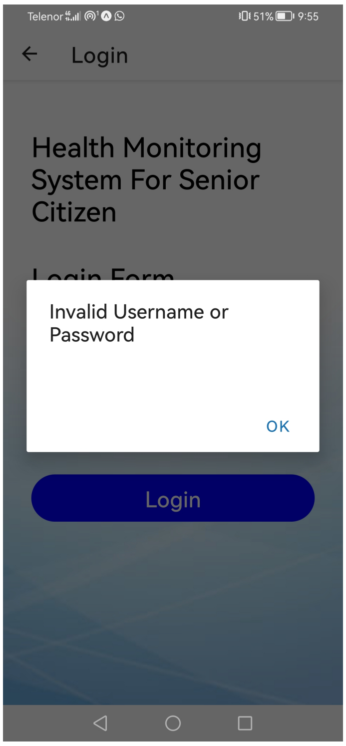

Figure 4.15: Checking Credentials of users

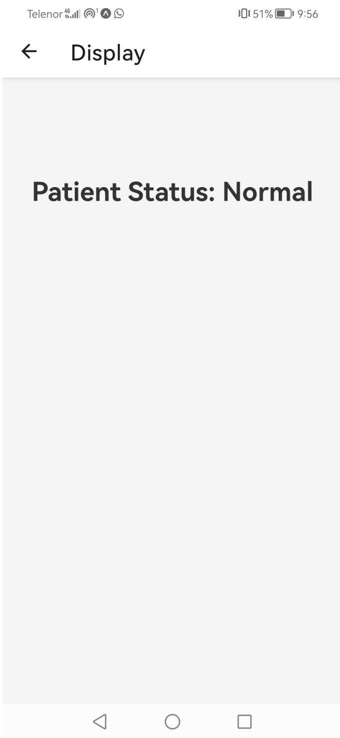

Figure 4.16: Patient Status Activity

Figure 4.17: Alert Activity

4.11.4 Testing

As you can see in 4.17 when health-sensitive activity occurs our app was able to alert instantly to the user with the name of that activity.

4.12 Iteration 4

4.12.1 Activity Diagram

Finally in this iteration, we have completed our project by connecting the pipelines. we integrate our model with the app and the full system was able to detect live health-sensitive activity and alert the users.

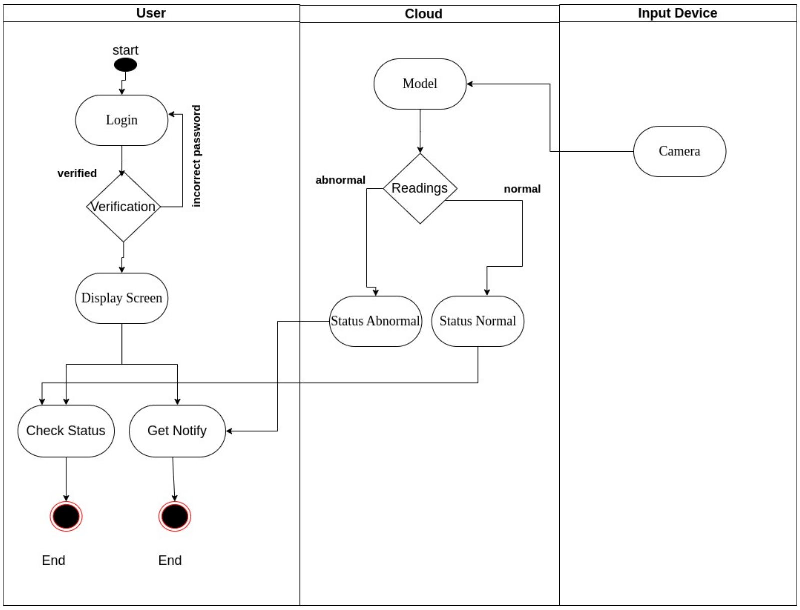

Figure 4.18: Activity Diagram

Chapter 5

System Implementation

5.1 Flow Diagram

The flow diagram represents the flow of the system from start to end. The basic flow of our system can be found in 5.1. At the start, the camera will be installed in a room where elderly people spend at least 90% of their time. That camera will monitor the 24/7 activities of elderly people and send the skeleton points to our model. Before points fed into a model, we implemented a sliding window approach (more detailed in 7.2). After that input is given to the model and the model starts outputting activities if they are health-sensitive activities our system will notify the users using an alert notification through an app which is installed in their mobile.

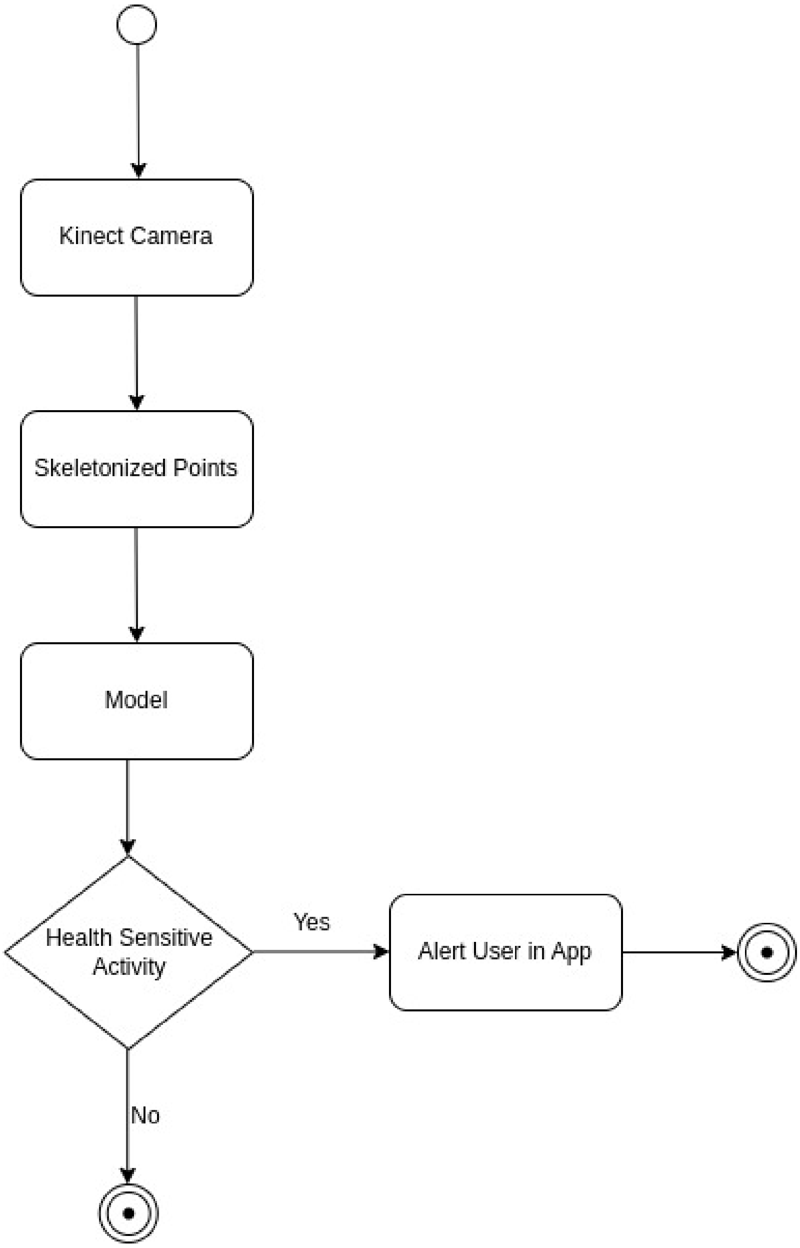

Figure 5.1: Flow Diagram

Chapter 6

Results

In 6.1 you can see as epochs increase the loss decrease on both training and testing datasets.In 6.2 you can see the accuracy of the model increases as epochs increase. Our model performed well as compared to previous approaches because previous approaches used RNN or CNN they both have drawbacks but in independent RNN gradient, the vanishing problem has been resolved. The model was evaluated on a test set of 2280 videos. We got an accuracy of 69%. The model was trained using the Adam optimizer with a learning rate of 0.01. The model was trained for 100 epochs on a dataset of 9100 sequences.

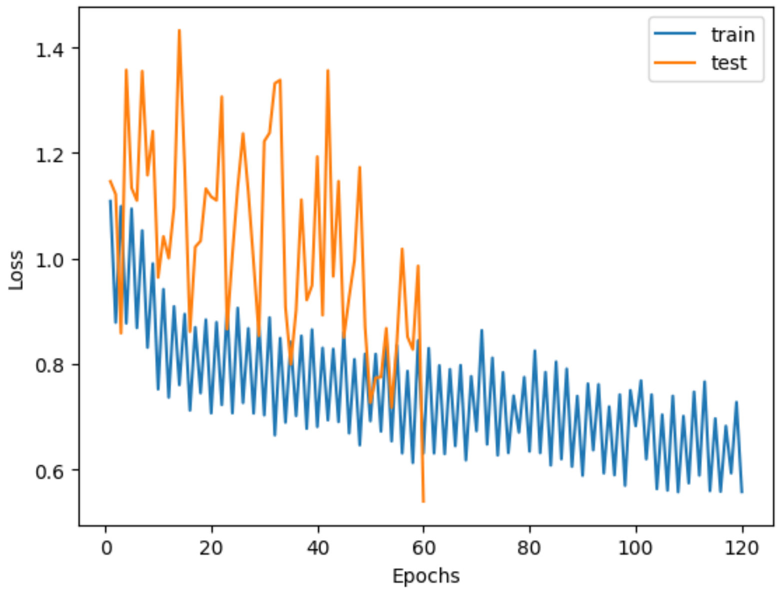

Figure 6.1: Learning of Model

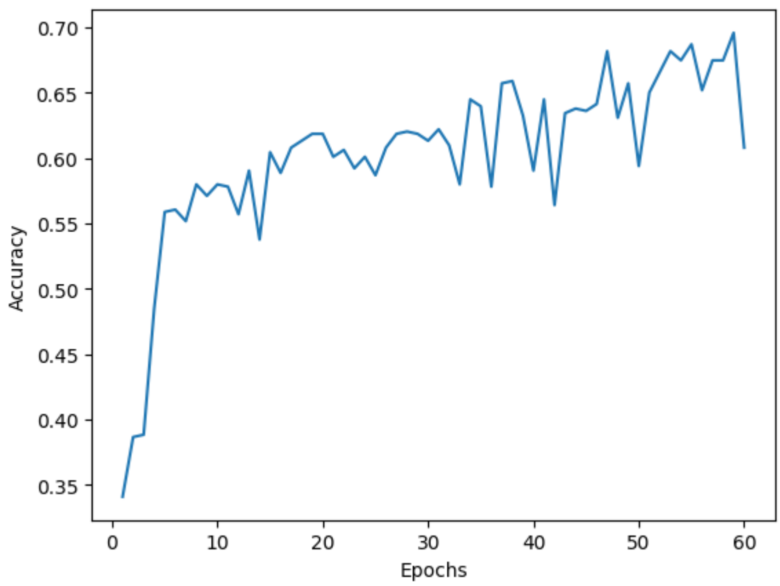

Figure 6.2: Accuracy of Model

Chapter 7

Implementation Details

In this section, we will describe the model that we used for our experiments. The model is an IndRNNModel with 100 epochs, a batch size of 128, and 3 layers with 256 hidden units each. The input dimension is 60 and the output dimension is 12.

7.1 Architecture of Model

The IndRNNModel is a type of recurrent neural network that is well-suited for sequence prediction tasks. The network consists of 3 layers, each with 256 hidden units. The first layer takes the input sequence and produces a hidden representation of the sequence. The second layer takes the hidden representation from the first layer and produces a new hidden representation. The third layer takes the hidden representation from the second layer and produces the output sequence

7.2 Architecture of Sliding Window

The sliding window technique is a method for processing sequences by dividing them into overlapping windows. The window size is the number of frames in each window and the stride is the number of frames to slide the window. In our experiments, we used a window size of 80 frames and a stride of 20 frames. The sliding window technique was used to process the input sequences in our experiments. The output of the sliding window technique was used as input to the IndRNN model.

Chapter 8

User Manual

You just have to set a camera in a room where the elderly people spent most of their time then scan the QR code from the hardware then you will be registered. Then you will be able to log in to the app after successful login the app you will be able to see the patient status either normal or abnormal and you will be notified when health-sensitive activity occurs.

Chapter 9

Conclusions and Future Work

The number of elderly people living alone is increasing day by day and there is no way to monitor their health so we developed a product which users install in the room of elderly people and if health-sensitive activity occurs it will notify users using the app. The main issue in these kinds of problems is to propose a solution without disturbing privacy. So, we use a skeleton-based approach our final product was able to detect a finite set of health-sensitive activities it can be expanded to detect more health-sensitive activities. The model got an accuracy of probably 69%. Live streaming is missing because we have used Kinect 360 no proper documentation is available on the internet that helps us to implement live streaming.

Bibliography

[1] Liming Chen, Jesse Hoey, Chris D Nugent, Diane J Cook, and Zhiwen Yu. Sensor-based activity recognition. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 42(6):790–808, 2012.

[2] Leon O Chua and Tamas Roska. The cnn paradigm. *IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications*, 40(3):147–156, 1993.

[3] L Minh Dang, Kyungbok Min, Hanxiang Wang, Md Jalil Piran, Cheol Hee Lee, and Hyeonjoon Moon. Sensor-based and vision-based human activity recognition: A comprehensive survey. *Pattern Recognition*, 108:107561, 2020.

[4] Youssef Hbali, Sara Hbali, Lahoucine Ballihi, and Mohammed Sadgal. Skeleton-based human activity recognition for elderly monitoring systems. *IET Computer Vision*, 12(1):16–26, 2018.

[5] Samitha Herath, Mehrtash Harandi, and Fatih Porikli. Going deeper into action recognition: A survey. *Image and vision computing*, 60:4–21, 2017.

[6] Zawar Hussain, Quan Z Sheng, and Wei Emma Zhang. A review and categorization of techniques on device-free human activity recognition. *Journal of Network and Computer Applications*, 167:102738, 2020.

[7] Shuiwang Ji, Wei Xu, Ming Yang, and Kai Yu. 3d convolutional neural networks for human action recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35(1):221–231, 2013.

[8] Muhammad Attique Khan, Mamta Mittal, Lalit Mohan Goyal, and Sudipta Roy. A

deep survey on supervised learning based human detection and activity classification methods. *Multimedia Tools and Applications*, 80(18):27867–27923, 2021.

[9] Shuai Li, Wanqing Li, Chris Cook, Ce Zhu, and Yanbo Gao. Independently recurrent neural network (indrnn): Building a longer and deeper rnn. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5457–5466, 2018.

[10] Jose K Reena and R Parameswari. A smart health care monitor system in iot based human activities of daily living: a review. In *2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon)*, pages 446–448. IEEE, 2019.

[11] Amir Shahroudy, Jun Liu, Tian-Tsong Ng, and Gang Wang. Ntu rgb+ d: A large scale dataset for 3d human activity analysis. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 1010–1019, 2016.

[12] Han Sun and Yu Chen. Real-time elderly monitoring for senior safety by lightweight human action recognition. In *2022 IEEE 16th International Symposium on Medical Information and Communication Technology (ISMICT)*, pages 1–6. IEEE, 2022.

[13] K Vijayaprabakaran, K Sathiyamurthy, and M Ponniamma. Video-based human activity recognition for elderly using convolutional neural network. *International Journal of Security and Privacy in Pervasive Computing (IJSPPC)*, 12(1):36–48, 2020.

[14] Ying Wu and Thomas S Huang. Vision-based gesture recognition: A review. In *International gesture workshop*, pages 103–115. Springer, 1999.