AI-Enabled Sensor-Based Human Activity Recognition for Automated Surveillance

Dr. Rajeev Shrivastava[1], Dr. Anurag Shrivastava[2]
[1]Post Doctoral Researcher, [2]Supervisor
[1](pdf.rajeev@lincoln.edu.my), [2](anuragshri76@gmail.com)
Lincoln University College, Petaling Jaya, Selangor Darul Ehsan-47301, Malaysia
[2]Department of Electronics & Communication and Computer Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, Tamil Nadu, India

Abstract- A Raspberry Pi microcontroller and a mobile application for real-time tracking and reporting of specified human activities were chosen in light of the activities' vital importance. In order to provide immediate rescue assistance, aged and sick individuals were observed using a camera installed to cross-communicate changes in their postures on the bed over a wireless network. Because they lack intelligent real-time capturing and reporting technologies, the conventional methods of keeping an eye on the aforementioned individuals using cameras or other people prove to be ineffectual. Notifications are sent to the mobile application by the video recorders. Modern computer vision and artificial intelligence techniques, which enable highly accurate human posture detection and recognition, fuelled the system's intelligence. To extract hidden information from photographs, the system was trained using Convolutional Neural Networks on the Common Objects in the Context dataset. This system uses mobileNet, Posenet, and Single Shot Detection to track human positions in real time and estimate postures.

Keywords- Raspberry Pi microcontroller, mobile application, real-time tracking, rescue assistance, real-time capturing and reporting technologies.

I. INTRODUCTION

Many cameras have been installed or mounted during the past few decades to prevent crime, watch over situations and activities and acquire evidence. Population growth and demographic shifts have created significant problems for society, including longer life expectancies and a high dependency rate. As a result, there is a substantial need for self- monitoring services and support systems, resulting in an increase in life expectancy. linked machine learning, transfer learning, and vision sensor-based activity recognition under one roof for human activity recognition [1]. An intelligent gadget that combines deep learning and computer vision to gather video feeds of a scene, analyze it, forecast various behaviours, and report when commanded to do so thus, the artificial intelligence-enabled multi-function human activity monitoring and reporting system. To build an intelligent computer that carries out activities better than humans is the broad field of artificial intelligence (AI). This is divided into a number of categories, including computer vision, deep learning, and machine learning, which uses structured data to create predictions[2]. Deep learning as a subfield of AI that makes use of neural networks to simulate how the human brain functions, this doesn't require organized data, like machine learning, it functions with both text and images. An AI-enabled multi-function activity and monitoring system are created in order to monitor multiple actions and events at once. Given the current security concerns in both homes and hospitals, the inability to monitor and report on multiple activities at once without human intervention or mounting a wearable device on the human body necessitates the development of the multifaceted system using deep learning approach. Health and other relevant conditions cannot be recorded or reported in offices, residences, or public spaces because there is no AI-enabled multi-activity system to do so. One of the most frequently reported problems in society is banditry, which calls for an AI-enabled self-reporting and monitoring system. Although there isn't a recognized use case for deep learning for activity monitoring with a self-reporting solution, an alternative approach was discovered for tracking the movements of elderly people utilizing sensor and kinematic data. The purpose of this paper is to develop and put into use a multi-functional activity monitoring and reporting system based on artificial intelligence (AI), with the following goals: to create an activity tracking and reporting system with different functions, to develop a centralized database architecture with storage options, and a mobile application for managing observed and reported human activities. An AI-enabled multi-function activity recognition monitoring and reporting system was used in this research paper to phase out the manual activity monitoring and reporting system. Health and security systems are two potential industries that this research could help. With this suggested technique, patients' posture status could be tracked without the assistance of medical personnel. Similarly, employing an AI-enabled multi-functional activity monitoring and reporting system, several insurgencies and bandit actions could be efficiently observed and reported without physical interventions 3]-[4].

II. HUMAN ACTIVITY MONITORING AND REPORTING SYSTEM

The Pi Camera module and Raspberry Pi 3 controller were adapted to create a system for monitoring and reporting activities to suits the design needs. Raspbian Operating System, the most popular operating system for the raspberry pi controller, was installed as the default operating system to promote speedy operation and integration of the controller with the Pi camera module. This section contains comprehensive information on data preparation and acquisition, video feed acquisition, activity detection and recognition, and reporting channel.

(i) Data Acquisition and Preparation- The gathering of data was the first step in the training process for this machine learning model. Although the process could frequently be automated, in this training situation but high- quality photographs were collected, noise was removed, and the data was supplemented by personally collecting and processing the information. Nearly a thousand samples were obtained for this study's training and testing [5].

(ii) Video Feed Acquisition- This was a crucial stage in this research work, video feeds are sourced from households and hospitals. For hospital scenario, getting video of the patient was the objective whereas for homes, acquiring a video of an elderly person was another objective. Frame by frame, this video was processed using computer vision algorithms to allow for processing and analysis. The flowchart in figure 1 details the video acquisition [6].

(iii) Activity Detection and Recognition- Mobilenet as one of the fastest machine learning models was largely created, scaled, and optimized for low-level devices, and this was implemented for recognizing activities in this research work. The mobilenet builds thin deep neural networks using depth-wise separable convolutions and the coco dataset, consisting of classes with more than 100 objects, was used to customize the mobilenet SSD for this research work. With this capability, the system instantly recognizes more than 100 items from the experimented video feed, however it was configured to only recognize and locate individuals for home and hospitals. The pose estimation model uses a pre-trained model and a custom neural network with just three classes lying, standing, and sitting.

(iv) Data Acquisition Validation System- The acquired data from the camera were manually connected to train the posture detection model as in Figure 1. and lying down. A total of 1720 pictures were acquired for the training, and it recognizes sitting, standing, and lying down poses. 344 images were kept aside for testing while 1372 were used to train the proposed model. The Coco and pascal Voc datasets were utilized for motion detection based on the original mobilenet SSD model. These allow the accurate detection of a person in the hospital bed and at home through the video feed, which is a great avenue for motion detection. Data was acquired through accelerometer and mobile device sensors as, whereas data in this research work were visual and acquired via a camera sensor and utilized already existing public dataset, Coco and Pascal voc.

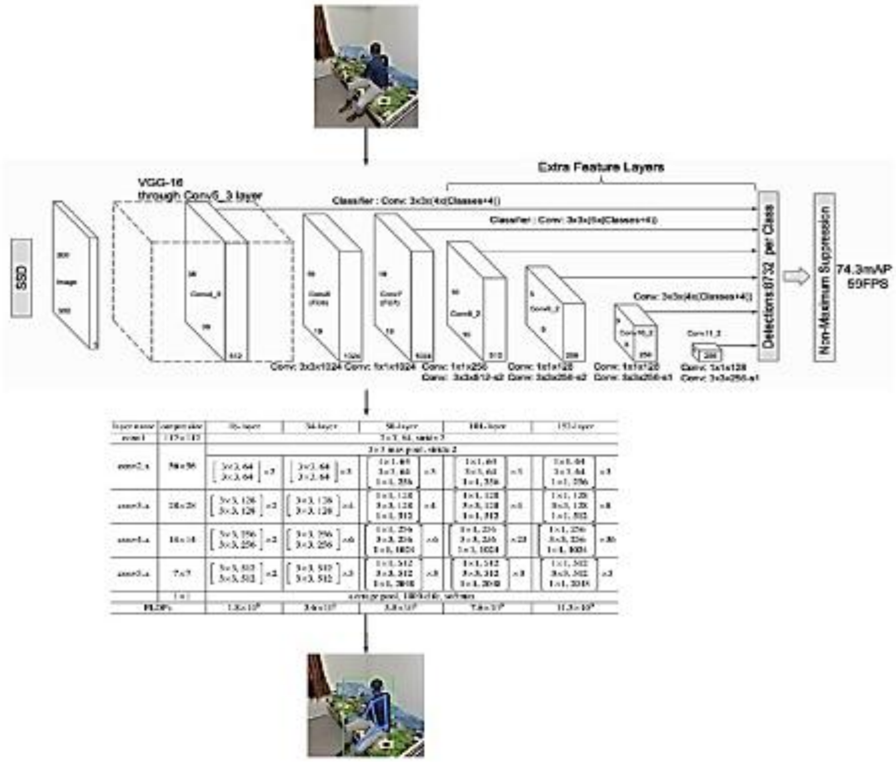

Figure 1- Data Acquisition Scheme for human Posture detection

III. RESEARCH METHODOLOGY

The system design and development process use materials, methods, instructions, and algorithms to achieve the intended home and hospital human activity recognition as the outputs of this research work. Security, surveillance, and other industries could benefit from the use of artificial intelligence in activity detection and monitoring systems[9]-[10]. An AI-based multi-function activity monitoring and reporting system with a mobile application acting as a gateway for system interaction was developed using MobileNets, SSD pose estimation, and internet of things (IoT) processes. Consequently, tools and techniques for implementing a multi-functional activity monitoring and reporting system based on AI was deployed:

(i) Materials- Software and hardware components were utilized in this research. OpenCV library, TensorFlow, MediaPipe, Firebase, Python, React Native, and Proteus are among the software components whereas the Raspberry Pi 3, and Pi Camera were the components of the hardware.

(ii) Methods- AI-based multi-function activity monitoring and reporting system was achieved using Object detection and recognition algorithms in synergy with pose estimation models to detect and recognize human activities in homes and hospitals [7]-[8].

(iii) Model Formulation for the Posture Detection System- AI-based multi-function activity monitoring and reporting model is depicted in Figure 2, block diagram. Artificial intelligence (AI) techniques based on computer vision was used to recognize and classify different physical activities of human in hospital and home scenario, such as sitting, standing, walking, and on motion using camera sensors. The proposed system collects data from the camera sensor in the form of a video stream and analyzes the data using AI algorithms.

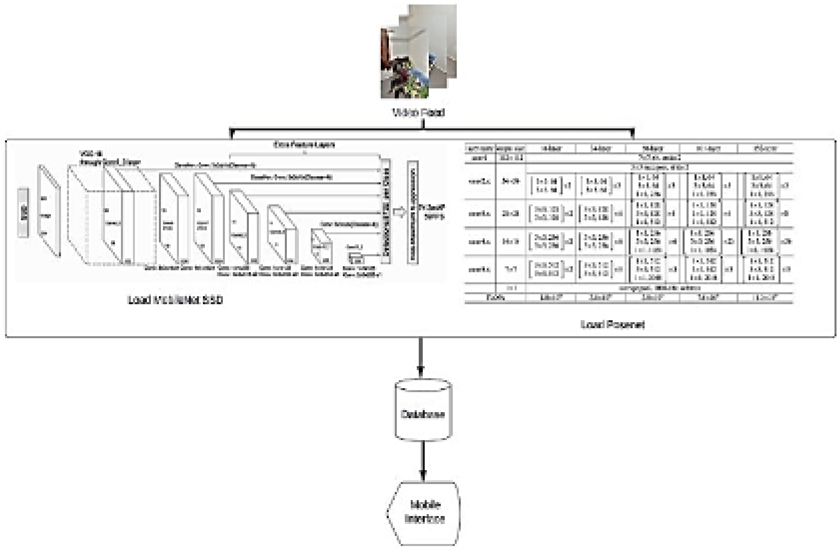

Figure 2- AI based multi-function activity monitoring and reporting system

(iv) Convolutional neural network (CNN)- this techniques were used to train the algorithm on a decent amount of dataset of labelled images, where each activity was annotated with a label indicating whether the person was sitting, standing, or walking. During the training, the AI algorithm learnt to identify the features that distinguish these activities from each other, such as the angle of the person's legs or the movement of their arms. After training, the algorithm was deployed in the activity monitoring and reporting system to analyze camera sensor data in real-time. The design Pseudo Code is given below.

Figure 3- Motion detection directly from testing the Pi Camera on desk

Figure 4- Motion detection from Raspberry Pi Camera placed at the top

START
Declare *activities_name_lists!*
Get *activities!*
    Initialize *Models*
    Initialize *Detected*
For *activity in activities:*
Append *activity name to Activities_name_lists*
While *true:*
Start *Video feed*
Get *current_time*
Start *Models*
For *object in detected objects from Models:*
If *object classID is recognized* ***then***
    Draw a rectangle around detected objects
If *object name exists in Activities_name_lists* ***then***
Get *start time and end_time for the activity.*
If *start time and end time are both infinity or if current_time is within start time and end time:*
Send *Report Else: Abort Else:* ***Continue***
End
End if

IV. RESULTS AND DISCUSSION

Analyzes and assesses the outcomes of the methodology used in the implementation of human activity recognition and monitoring system for homes and hospitals. These serve to assess the system's performance and evaluation template where level of service was given the initial provided criteria to function. The system was tested in Keffi, Abuja, and Minna to validate its functionality.

(i) Human Activity Monitoring and Reporting system for Home and Hospitals- This system as designed detected activities using still images and live video streams. The video streams featured scenes from hospitals and homes in Keffi, Abuja and Minna were created to test the systems' accuracy from all positions. The room's center and top were both where the camera was placed, and the results varied in terms of accuracy. While the accuracy level for motion detection was nearly identical across all camera locations, for other activities, placing the camera in the middle yielded a better and more precise prediction. A Raspberry Pi controller and a 1080P Pi camera were used to carry out this experiment, and the results are shown in Table 1. The Raspberry Pi had a 5% tolerance and was made to run at 5 volts (4.75 - 5.25 volts). Whenever the supply to the Raspberry Pi was less than the required 5 volts, the system controller won't switch ON. The software component of this research processes the up to 30 frames per second feed acquired from the Pi Camera[11]-[12].

Table 1: Performance of the A.I at different positions	Position	Activities	Success Rate
Hospital	Top	Motion	90%
Home	Center	Motion	95%
Hospital	Top	Posture	45%
Home	Center	Posture	70%

Table 1- Performance of the AI at different positions

(ii) Motion Detection- The Raspberry Pi Camera captures images and the controller uses the MobileNet technique to detect and locate objects within the frame. As illustrated in figures 3 and 4, the system is able to draw a rectangle around the detected objects. The user-set timer in the mobile interface governs the detection operation, allowing for customization of the detection period. Additionally, the system updates in real-time to reflect any changes detected.

(iii) Posture Recognition- The posture recognition function was used to distinguish between activities like lying down, sitting, and standing. When the subject's full body is visible to the camera, this system performs better. Furthermore, capturing the subject's face improves the system's dependability by giving a vital indicator for identifying other keypoints and precisely recognizing human activities in both homes and hospitals. Figure 5 demonstrates this.

Figure 5- Body Posture Detection of a person sitting down

(iv) Home Screen for managing monitored and reported activities- The home screen of the mobile application offers users the capability to view activity reports and graphical representations of statistical data, such as the bar chart shown in Figure 6. This page displays information on recently recorded activities, including date, time, and percentage. Access to this page is restricted to authorized users who have completed the login validation procedure[13]-[14].

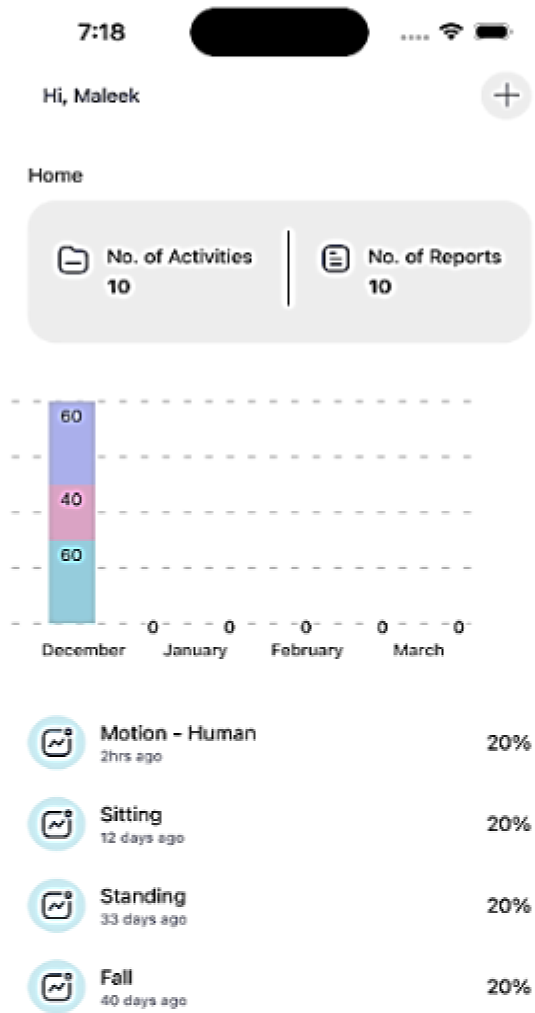

Figure 6- Home Screen

COLCLUSION

The multi-functional activity monitoring and reporting system that leverages the capabilities of Artificial Intelligence (A.I) was developed through the deployment of Deep Neural Network (DNN) algorithms, namely MobileNetSSD for motion detection and PoseNet for posture recognition, the system was able to detect and recognize human activities with high accuracy. This was accomplished through the integration of the OpenCV library and the Firebase platform, which facilitated the creation of a centralized database architecture and a user-friendly mobile application built with React Native. It is worth noting that this system has the potential to revolutionize the way we monitor and report activities, particularly in domains such as security and surveillance. By automating the process, the system reduces the dependence on human involvement, thus alleviating the associated stress and workload. However, there is still room for improvement. Future work could focus on enhancing the system's robustness in challenging lighting conditions and supporting low-quality cameras, as well as incorporating a night vision camera to enable the activity identification model to operate in low-light environments. Furthermore, the mobile application could benefit from providing live video feeds and the ability to switch between cameras

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