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Artificial Intelligence-Enabled Multi-Function Activity Monitoring and Reporting System

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Abstract*-There are critical times in life when human activities require close monitoring, these crucial moments (an elderly-aged at home where wrong body posture or positioning may affect the person's health status, and an ill-health patient in a hospital bed on account of orthopedical admissions) prohibit humans from changing its position on the bed without the caregivers' approval. The traditional ways of monitoring the aforementioned persons by fellow human or camera recording prove ineffective in that it lacks intelligent real-time capturing and reporting systems. Considering the activities' critical nature, a Raspberry Pi microcontroller and a mobile app for real-time tracking and reporting of stated human activities were adopted. Aged-elderly and ill-health persons were monitored with a camera mounted to cross-communicate the change in positions on the bed through a wireless network for prompt rescue service. The video recorders push notifications to the mobile application. The system's intelligence was powered by cutting-edge computer vision and artificial intelligence algorithms, which make it possible to detect and recognize human posture with high accuracy. Convolutional Neural Networks were used to train the system on the Common Objects in the Context dataset to extract hidden information from photos. This system deploys Single Shot Detection, mobileNet, and Posenet to estimate postures and track human positions in real time. The result shows that the system detects sitting, standing, lying down, and motion activities via the camera feed using posture recognition. This study highlights the potential solution for advancing human activity recognition and provides the foundation for further research.

***Keywords*--**Artificial Intelligence, Computer Vision, Convolution Neural Network, Human Activities, Single Shot Detection, Object Detection

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. [1] linked machine learning, transfer learning, and vision sensor-based activity recognition under one roof for human activity recognition. An intelligent gadget that combines deep learning and computer vision to gather video feeds of a scene, analyze it, forecast various behaviors, and report when commanded to do so thus, the artificial intelligence-enabled multi-function human activity monitoring and reporting system. To build an intelligent computers 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 [3]. 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

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solution, an alternative approach was discovered for tracking the movements of elderly people utilizing sensor and kinematic data [4].

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.

II. Review Literatures

Artificial intelligence would find use in object placement in real-time across multiple regions utilizing object detection techniques in activity tracking monitoring employing location detection. Some of these methods can locate an object even in an obscured place. However, a number of studies on machine learning, computer vision, convolutional neural networks, SSDs, mobileNets, and model designs were taken into consideration in this study.

A. Single-shot Detector (SSD) and it's functionalities in Human Activity Recognition System

SSD as a well-known algorithm, was created by Google Inc. find its application in object detection and VGG-16 skeleton was used for computations [5][6]. SSD concept are straightforward and simple to set up as a result, figure 1 illustrates the VGG 16 SSD model in use. A collection of predetermined boxes was transferred through numerous feature maps in a convolutional manner. If the identified object belongs to one of the object classifiers or not, a score is determined during the prediction phase. The geometry of the object was altered to fit within the confines of the localization box. The anticipated shapes of the boxes using the data increases the level of confidence in these predictions [7][8]. This was accomplished by comparing the real boxes to the default boxes produced by the training process. Layers that are totally connected are discarded by SSD architecture. By summing the weighted sums of the confidence loss and localization loss, the model loss was determined. The distance between the anticipated box and the actual box was measured by localization loss.

A system's level of confidence in a predicted object's reality was a measure of confidence. Because SSD eliminates the need for feature resampling and consolidates all processing into a single network, MobileNets are simple to train.

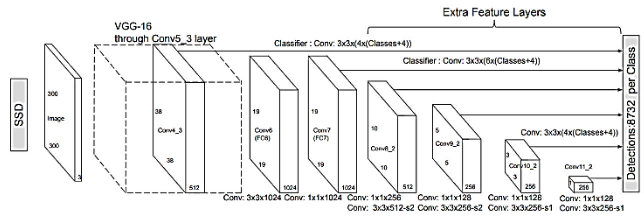

Fig. 1. VGG-16 SSD Model [9]

SSD does explicit region suggestions and pooling more fast and effectively than YOLO (including Faster R-CNN) [9].

B. MobileNets in Computer Vision and Deep Learning for Human Activity Recognition

Researchers have been hard at work creating techniques of identifying driver distraction and fatigue to reduce the frequency of fatal accidents caused by these states. As it has in many other disciplines of study, the effectiveness of deep-learning-based algorithms for driver status identification was increased [10][11]. Despite decades of research in the field of driver status recognition, the visual image-based driver monitoring system has not yet been widely used in the automotive industry, this is because the system requires strong CPUs and has a hierarchical design, which allows failures in one step to negatively impact succeeding steps [12][13].

[14] recommended that to resolve the issue of human activity recognition, Mobilenets techniques could be used, because of its capabilities and efficiency to operate on medium to low-end devices like raspberry Pi.

C. Application of Computer Vision in Human Activity Recognition System

Object detection, tracking, and classification are all possible using computer vision, this technology relies primarily on cameras to learn details about certain objects [15]. The use of cameras for object recognition and addressing infractions was a noteworthy example of how this technology is being applied. [1] cameras could capture and record information about human activity and are widely used with acquisition tools like smartphones and video cameras, human activity recognition has many applications. The use of deeply hidden information for reliable detection and its interpretation has been revolutionized by developments in artificial intelligence, despite the steady growth of electronic devices and the applications they support. This results in a deeper understanding of the three pillars of human activity recognition acquisition devices, AI, and applications, all of which are rapidly expanding. This approach communicates this information for proper documentation on the specified network and allow monitoring of the observance of multiple functions without human intervention [16]. Furthermore, computer vision considerably improves the dependability of the monitoring system by reducing the number of techniques for determining an object's parameters that require human interaction to apply in order to gather the relevant data. This would enable automated data collection and processing on the infrastructure under study, as well as complete digitalization of the monitoring cycle for such assets. [17] [18][1], developed a vision home system that allows elderly and disabled individuals to live independently at home while receiving care and safety services via vision-based monitoring without a reporting system. The ability to recognize human movements due to the importance of posture in sports health, the inertial sensor technology could distinguish between four postures: dribbling, passing, catching and shooting in the case of basketball. Some axis inertial sensors that are worn on the arm could help gather the data. After smoothing and normalizing, the time domain and frequency domain features are retrieved, the principal component analysis dimensionality reduction, and eigenvectors were created, and the support vector machine approach is utilized to detect posture. The experimental findings, the features identification accuracy as the support vector machine input is notably high after principal component analysis dimensionality reduction. The average recognition accuracy, which confirms the dependability, was higher than the back propagation neural network's recognition accuracy[19].

This proposed system considers both monitoring and reporting techniques to mitigate the earlier mentioned deficiency. The experimental results of the behavior recognition method show great performance, support for multi-view circumstances, and real-time execution, both of which are required to deliver the proposed services.

D. Application of Artificial Intelligence (A.I) in Human Activity Recognition Systems

Convolutional neural networks (CNNs) and deep learning are two rapidly developing technologies capable of evaluating enormous amounts of data much faster and with greater accuracy than humans. A human researcher would be overwhelmed by the vast amount of data generated every day, but AI programs effectively sort through this data and extract insightful information using machine learning. Currently, one of AI's main limitations was found to be the high expense of processing the enormous amounts of data required for AI algorithms [20][1][21]. To create and develop a machine learning system for vehicle detection and tracking, [22] used a decision tree and support vector machine technique, both of which were written in the Python computer language. This tool monitors a range of operations and generate in-depth information about the system. Their article offered a theoretical framework for integrating machine learning into a company. [12][4] examined the use of Deep Learning to address some of the most urgent problems in big data analytics, including the extraction of complicated patterns from big datasets, the standardization of data tagging, the speeding of information retrieval, and the simplification of discriminative tasks. Big data has arisen as a crucial tool for addressing difficulties in domains as diverse, such as national intelligence, cyber security, automobile detection, fraud detection, marketing, and medical informatics as both public and private institutions has started gathering enormous amounts of domain-specific data. Adopting this area for home and hospitals could further extends the area of application of this system model.

In human-to-human and human-to-object contact and interpersonal relations, human activity recognition is essential. [4]stated that an automatic recognition of human behavior has paved the way for the creation of a smart society when combined with powerful deep learning algorithms and advanced hardware technologies. A crucial component of comprehending and forecasting human behavior was termed Human Activity Recognition. This concept develops and recommended systems to track levels of health, track levels of lifestyle habits, and estimate levels of sedentary behavior. Numerous researchers have used the inertial measurement unit as an input tool to explore the field of human activity recognition. Recent years have seen a wide range of uses for the recurrence plot technique. The feature vectors could be extracted manually or automatically from the recurrence plot. This work assessed and verified the viability of using recurrence quantification analysis, a customary technique [23].

Channel State Information (CSI) was employed by [16]for effective device-free human activity recognition using deep learning. The cumulative effects of environmental changes are stored in the CSI, and this stored pattern was used to identify various human actions including walking, standing, and sitting. Previous research on activity recognition mainly distinguished between human activities by designating one entire sequence as an activity. Although the categorization is based on short-term activity samples rather than the entire activity series, these algorithms need enormous datasets to provide reliable findings in real-time applications.

In this proposed research, little number of datasets without designating an entire sequence of activities were required to train the model for detection and recognition.

Most of the reviewed literature in this research work, adopts the use of wearables and accelerometers to determine the angle and positions for the recognition of certain human activities which brings inconvenience to the user. On the other hand, this system uses camera and computer vision with deep learning techniques to detect and recognize human activities without human intervention as an enhanced approach for human activity recognition system in homes and hospitals.

More so, the use of Radio Frequency (RF) transmissions does not predict high accuracy of human activities and lacks a reporting and monitoring system on a real-time basis with mobile interface for the interchange of different activities to be monitored. Although the researchers [16] carried out several reviews on different machine and deep learning algorithms but without implementation in simulated environment nor real-life scenarios.

The advent of epidemic makes telehealth and remote patient monitoring attract significant interest and gain popularity, unlike before. Obtaining patient data and giving patients high-quality care at an affordable price was simple without another human physically contacting the patient. It was suggested that monitoring patient activities and vital signs performances should be based on installed sensors' interaction with the device's Internet. This was created utilizing machine learning models to track the patient's activities, such as jogging, sleeping, walking, and exercising. Other vital signs were also monitored, including their heart rate, body temperature, and breathing pattern. In order to track the patient's various actions, machine learning models were proposed to list the patient's varied activities and evaluate the patient's respiratory health during those activities. Only healthy breathing and coughing were currently detected by machine learning models. The data uploaded by the suggested devices were tracked by a web application [24].

Recent developments in the Internet of Things have paved the way for widespread connectivity and encouraged the gathering and sharing of information about humans with health challenges. The most recent IoT trend connects several technologies to make it possible to connect physical items with digital tools for wise and intelligent decision-making. It has been suggested that recent developments in Machine Learning and other related Artificial Intelligence algorithms could be made to potentially collect, analyze, and interpret this unprecedented amount of IoT sensory information for efficient health and well-being monitoring. As the number of IoT sensing devices in healthcare increases, it also raises doubts about properly analyzing this large volume of data.

In this sense, this study seeks to summarize the research, focusing mostly on AI-enabled IoT devices for human supervision in hospitals for sick persons and homes for elderly persons[25].

With the use of wearable technology, the breathing patterns of people engaged in daily activities were observed. The system shows how effective the framework for tracking breathing patterns while performing daily tasks for possible usage in healthcare contexts. The suggested multimodal-based system offers fresh perspectives on how breathing functions during exercise and offers a cutting-edge method for monitoring one's health[26].

As a platform for next-generation computing, combining conventional clothing with flexible electronics is an intriguing idea. In this innovative platform, the issue of user authentication is still not fully understood. This work accomplishes user authentication by tracking human posture with flexible sensors. Four stretch sensors are placed around the shoulder, and one is placed on the elbow to record human movement patterns. The long short-term memory fully convolutional network, which checks the compatibility of user-predefined movement patterns with noisy and sparse sensor data was introduced. Even when significant intrapersonal variances exist, the approach may recognize a user by matching movement patterns. The dependencies between dynamic time warping and authentication accuracy[26].

The researcher suggested a posture identification approach that combines joint point information with a convolutional neural network to address the current algorithm's low accuracy and weak robustness based on manual features. The method employs deformable convolution to enhance the stacked hourglass model and enable accurate extraction of the location of the human joint point. The convolutional neural network structure was built to extract the inherent relationship between the human body's joint point and the joint point's position information and confidence. The pose category was then determined using the softmax classifier. The Willow data set experimental verification was conducted, and the results show that the recognition precision displays the efficiency and superiority of the improved concept [27].

Recognizing human body postures has become one of the most crucial research areas in the world of computer vision, with applications in intelligent monitoring, detection and rescue, and other fields. Their major objective was to analyze different human body regions, extract posture information, and then recognize human body position using computer vision technology. The research focuses mostly on video sequences, but the video-based human body posture identification approach cannot accommodate all possible application scenarios since it requires a sufficient number of continuous frames. Consequently, recognizing human body posture from static images also has significant study significance. Due to considerations including changes in viewing angle, the human body, and other variables, accurately determining human posture was a highly difficult task.

The need for aged patient monitoring systems in the healthcare industry is significantly rising. The research community has turned to computer vision and image processing to design and implement new systems for monitoring the elderly in the authors' society and transforming their living homes into smart environments due to the growing elderly population, patient privacy violations, and the cost of elderly assistance. A new skeleton-based method was

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proposed to describe the spatiotemporal aspects of a human activity sequence using the Minkowski and cosine distances between the three-dimensional joints by utilizing recent developments and the low cost of three-dimensional depth sensors like Microsoft Kinect. On the Microsoft MSR 3D action and MSR Daily, the collected data were used to train and validate their methodology[28]. The study revealed that device-free Human activity recognition using a Wi-Fi device could make use of Human activity recognition as an essential component of a human's healthy life. Sensor-based Human activity recognition with miniaturizing devices will show the ground for opportunities in healthcare applications, especially remote care, and monitoring. The study concluded by offering suggestions that will broaden the perspectives of new researchers and aid them in extending the scope of Human activity recognition in various areas with emerging AI frameworks for ensuring a healthy quality of life for people.

Video-based posture analysis utilizing a biomechanical model is gaining popularity for ergonomic evaluations. A human posture simulation method for calculating various spinal loads and postural angles from a video record was developed to expedite ergonomic assessments. Three levels of trunk flexion, two levels of lift asymmetry, three viewing angles, and three trial repetitions were used as experimental parameters in a repeated measures study design to evaluate the method. A computer-generated humanoid's ability to accurately portray both one's own and other people's lifting postures was tested in two sections of the study and under identical lifting conditions, the approach exhibited excellent repeatability, which reduced simulation error[29].

In this research work, CNN, computer vision, and a mobile app as the user interface for smart monitoring and reporting were among the resources identified for the development of an AI-enabled multi-enabled activity monitoring and reporting system. The monitoring and reporting system with the database and storage infrastructure serves as an avenue for keeping track of monitored activities. Using a convolutional neural network, images are processed, recognized, and objects are found and segmented. The CNN builds a network using a hierarchical architecture that resembles a funnel. After that, it creates a fully connected layer where all neurons are interconnected, and the processed output were displayed, CNN is therefore essential to the development of this system.

III. 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. 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:

A. 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.

B. 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.

i. Model Formulation for the Posture Detection System

AI-based multi-function activity monitoring and reporting model is depicted in Figure 2's 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.

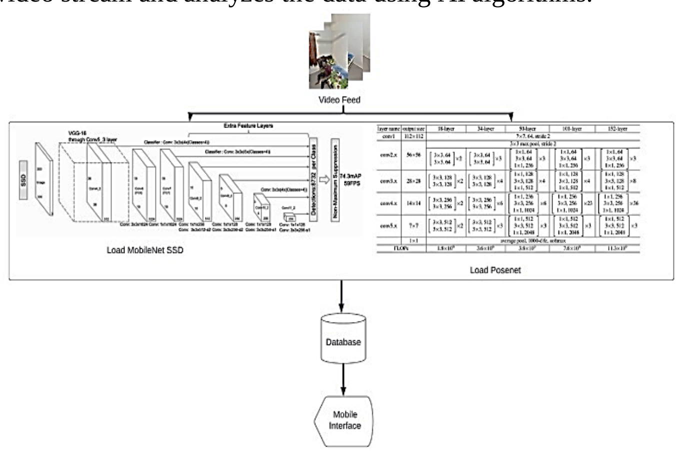

Fig. 2. *AI based multi-function activity monitoring and reporting system.*

Convolutional neural network (CNN) 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.

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

The operational algorithm deployed follows the following steps: the first approach was to initialize the list of detected objects and then make some changes to the loop that processes the detected objects. The check was also carried out to confirm when the detected object's class ID was recognized, and then the system draws a rectangle around the detected object. Whenever the detected object's name exists in the list of activity names, its retrieves that activity's start and end times. The check was carried out to know whether the current time was within the start and end times (or if both times are infinity) for the system to send in its report if any. If the object name is not in the list of activity names, the system continues with the next detected object. Lines of code were added to get the current time and initialize the detected object list before starting the loop.

i. Human Activity Monitoring and Reporting system for Home and Hospitals

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.

a. 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.

b. 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 3 details the video acquisition.

c. 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.

d. Data Acquisition Validation System

The acquired data from the camera were manually connected to train the posture detection model as in figure 3.

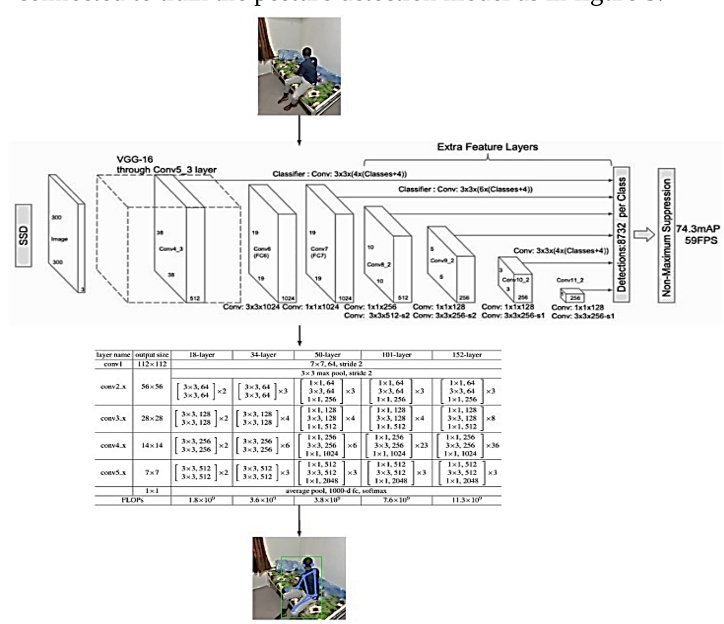

Fig. 3. Data Acquisition Scheme for human Posture detection

The postures detected in this work were sitting, standing,

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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 in [8], whereas data in this research work were visual and acquired via a camera sensor and utilized already existing public dataset, Coco and Pascal voc.

ii. Database Architecture with Storage Scheme for Human Activity tracking and Reporting system

For this paper, Firebase services, which are renowned for their usability and scalability, were adapted to build a centralized database with a storage capacity.

a. Firebase Firestore Database

Database hosted in the cloud was used to provide real-time data updates from the mobile interface to the controller and vice versa. Data was saved as JavaScript Object Notation (JSON) and synchronized in real-time to the controller. The controller and mobile interface share a Realtime Database instance, ensuring that the device always has access to the most recent data. The firestore database stores activities, camera information, and tracking information for home and hospitals human activity recognition and monitoring system.

b. Firebase Cloud Storage

Cloud storage for firebase was adopted giving it is a reliable, convenient, and reasonably priced object storage solution for this research work. The firebase Software Development Kits (SDKs) for Cloud Storage provides Google standard security for file uploads and downloads for this research work regardless of network conditions. This serves as a central repository for all videos captured as part of the design and offers a publicly available link to access the video from anywhere in the world.

iii. Mobile Application for Managing Monitored and Reported activities

For controlling observed and reported actions, a fully-fledged mobile interface for iOS and Android was provided in this design.

a. Expo

Expo has made the process of setting up for mobile development simple and quick as such deployed as toolchain for building on React Native for this research work. It offers a number of tools for the process of developing and testing Native React apps, as well as the user interface and service components that are typically featured in third-party Native React Native components. Additionally, it provides the Expo SDK which applies to several regional mobile features, such as barcode scanning, map viewing, image picking, etc. This was modified for use in this research as the framework to launch the mobile interface for recognizing and monitoring human activities.

b. React Native Chart Kit

In this research, data was also visualized using a bar chart, as a graphical representation of information. This as a well-known chart framework presents data in an interesting way and was adopted for visualizing tracked activities. The visualized data in this research work was presented using a stacked bar chart in figure 7.

c. React Navigation

The Mobile navigator oversaw deciding how different displays are displayed and switched between screens for home and hospital human activity recognition and monitoring system. React Navigation displays stack navigation and tabbed navigation patterns on both Android and iOS, providing a straightforward navigational solution.

iv. Evidence of AI development in this research work

Data samples of a person sitting, standing, and lying down was collected from home and hospitals from the camera. The data samples were labeled to depict sitting, standing, and lying down. Each of the data sampled was categorized and separated into testing and training purposes. A pose estimation model using PoseNet was utilized for training the acquired data to detect poses as labeled. A low latency, low-powered model, mobilenet SSD was utilized to detect motion by determining when the person exists within the video frame.

A multi-thread system was now created to run these two models in synergy. The thread was watched from the camera video feed such that whenever the person's motion was detected, it showed that motion was detected. In the contrary, whenever the pose indicates sitting, standing, or lying, the posenet model detects and recognizes the pose and indicates the same through the artificial intelligence algorithm. The Artificial intelligence aspect of this system was the adoption of the pose estimation model (poseNet) and the classification/detection model (mobilenet SSD), where the poseNet was programmed to recognize sitting, standing, and lying poses, whereas mobilenet SSD detects the motions and transmit same to the caregiver's platform for prompt attention.

IV. Result and Discussion

This section 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.

A. 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.

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%

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.

i. 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 4 and 5, 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.

Fig. 4. Motion detection directly from testing the Pi Camera on desk

Fig. 5. Motion detection from Raspberry Pi Camera *placed at the top*

ii. 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 6 demonstrates this.

Fig. 6. Body Posture Detection of a person sitting down

B. Database Architecture with Storage Scheme for Human Activity tracking and Reporting system

Real-time communication was essential since the hardware prototype and mobile interface had to be quickly synced. To demonstrate this functionality, a database schema was used to keep track of activities created and observed using the Firebase Firestore database. Furthermore, the captured videos of tracked actions, limited to a storage capacity of 1GB, were securely stored in the cloud.

i. Firebase Firestore Database

The firestore database system was used in this study to create a well-structured database schema. Three different collections made up this schema: tracked, cameras, and activities. Information about the actions carried out by specific users was saved in the activities collection. The cameras collection contained all the data from the active cameras as well as the associated actions that the cameras were designed to record. The tracked collection was created to serve as a notification collection as well as a repository for activity data, providing essential data for the system's efficient operation.

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ii. Firebase Cloud Storage

The Firebase Cloud Storage served as the main repository for data storage in this project. The generated link was utilized by both the database and mobile interface to display the recorded tracks once the videos were securely stored in the cloud.

C. Mobile Application for Managing Monitored and Reported activities

A cross-platform mobile application was created and evaluated to enable interaction with the hardware prototype. The app was designed to work on both Android and iOS operating systems and provides a user-friendly interface. The architecture of the system required the creation of several interfaces with defined functions and operations.

i. 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 7. 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.

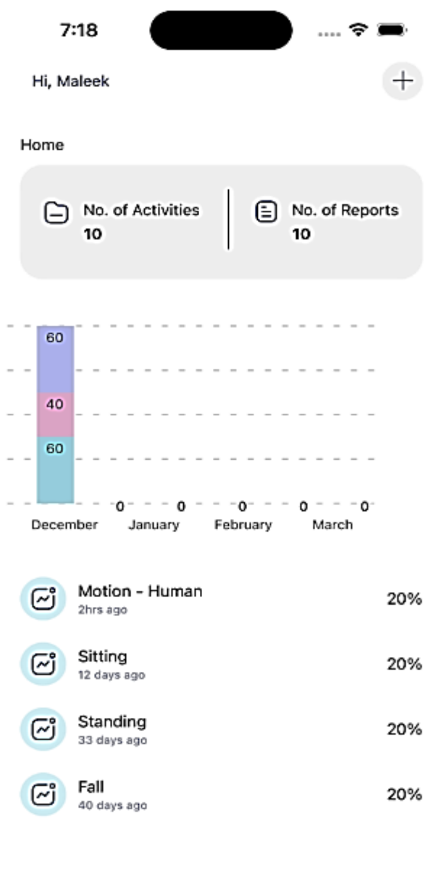

Fig. 7. Home Screen

ii. Activity Screen for Creating and Monitoring Activities.

This constitutes the tracking interface for the activities displayed in Figures 8 and 9. The user is able to specify the activity to be tracked, determine an optional duration, and select a reporting channel. The designated time period limits the tracking of activities to the selected interval.

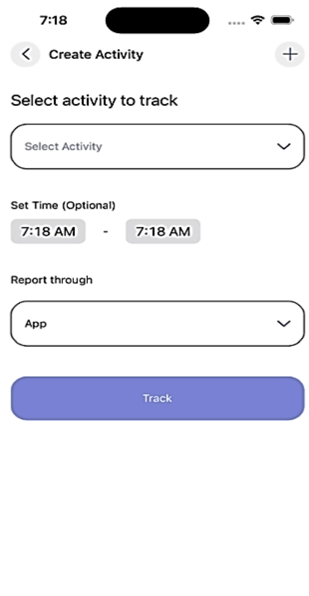

Fig. 8. Create Activity. Inactive Screen

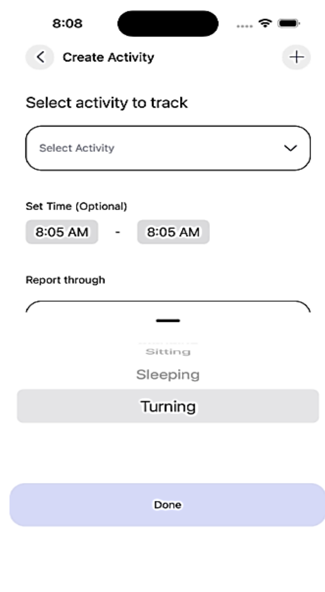

Fig. 9. Create Activity Active Screen

D. Summary of Result and Discussion

This research seek to develop an AI-powered multi-function activity recognition and monitoring system. The system utilized a combination of Single Shot Detection (SSD) and PoseNet for detection and recognition of human activities. The MobileNet technique was utilized to locate objects and draw bounding boxes, while the PoseNet model was used to estimate human poses from the video feed for the detection of human activities in homes and hospitals.

The system was implemented with a hardware prototype and a mobile application built with React Native. The results demonstrate the effectiveness of the proposed system in accurately detecting, recognizing, and monitoring human activities.

V. Conclusion

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.

In summary, this research demonstrates the potential of A.I. to augment the monitoring and reporting of human activities, providing a step towards a more efficient and automated future.

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