Daily Human Activity Recognition Using Artificial Intelligence for Healthcare and Lifestyle Monitoring

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ABSTRACT

A crucial part of contemporary healthcare and lifestyle monitoring systems is human activity recognition. This study offers a non-invasive, real-time method for identifying routine human actions using computer vision and artificial intelligence algorithms. The method extracts skeletal markers that reflect human body movements using MediaPipe Pose Estimation and a typical webcam. To detect behaviours like sitting, standing, raising one's left hand, etc., these characteristics are examined. A Flask-based web application is created to offer activity visualisation, live video streaming, and safe user authentication. The suggested method is inexpensive and easy to use since it does not require wearing sensors. Results from experiments show dependable performance in real-time settings. Applications for lifestyle analysis and healthcare monitoring have a lot of promise with this method.

KEYWORDS: Human Activity Recognition (HAR), Artificial Intelligence, Media Pipe Pose, Computer Vision, Healthcare Monitoring, Lifestyle Monitoring, Flask Web Application

INTRODUCTION

Human Activity Recognition is a significant field of artificial intelligence research that focusses on recognising and evaluating everyday human actions for lifestyle and medical monitoring. A person's health, mobility, and general well-being can all be better understood by regularly monitoring their physical activity. Conventional activity monitoring techniques mostly rely on wearable sensors, which can be expensive, unpleasant, and inappropriate for continuous usage. Vision-based activity recognition utilising computer vision has drawn a lot of interest as a solution to these problems. This research uses MediaPipe Pose Estimation in conjunction with Artificial Intelligence and Computer Vision algorithms to identify human body movements in real-time video taken with a normal camera. To identify everyday actions including sitting, standing, walking, and exercising, the extracted skeletal markers are examined. The goal of creating a non-invasive, affordable, and real-time activity recognition system employing AI technology replaces the issue of intrusive and hardware-dependent monitoring systems. Secure user authentication, real-time activity detection, and visualisation are all provided by a Flask-based web application. In conclusion, the suggested approach provides a practical and effective way to monitor lifestyle and heath without the need for wearable technology.

LITERATURE REVIEW

The authors of the work "Human Activity Recognition by Sequences of Skeleton Features" demonstrate the usefulness of skeletal data for activity detection by proposing a vision-based algorithm that uses human skeleton pose estimation to extract features from video images and classify multi-frame activities like falls using benchmark datasets and conventional machine learning techniques.

In "Human Pose Estimation Using AI/Machine Learning Algorithms," Muhammad Sahal et al. examine a variety of posture estimation methods, highlighting its function in locating human body locations for applications including activity detection and fitness tracking. The contribution of AI and machine learning to precise pose analysis, which forms the basis for more advanced activity identification systems, is highlighted in this work.

RELATED WORK

Several studies have explored vision-based human activity recognition using artificial intelligence and pose estimation techniques. In the paper “Real-Time Human Pose Estimation and Activity Recognition”, the authors utilized MediaPipe and deep learning frameworks to detect skeletal landmarks and classify physical activities, demonstrating high accuracy in distinguishing actions like walking and sitting. Another study.

“Vision-Based Human Activity Recognition Using Pose Features”, employed computer vision and machine learning models such as CNN and SVM to extract pose-driven features and recognize complex daily activities from video frames, highlighting the robustness of skeleton-based approaches over traditional pixel representation methods.

EXISTING METHOD

Wearable sensors like accelerometers, gyroscopes, and smart gadgets are primarily used for activity monitoring in current human activity detection systems. Users of these systems must wear gear all the time, which can be cumbersome and uncomfortable for long-term monitoring. Certain vision-based methods are susceptible to illumination, background noise, and camera angles because they employ conventional image processing or machine learning algorithms that depend on manually created features.

To obtain acceptable accuracy, many current approaches require controlled conditions and considerable computational resources. Furthermore, the majority of systems lack user-friendly interfaces and real-time implementation. Because of this, current approaches are frequently expensive, hardware-dependent, and unsuitable for routine healthcare and lifestyle monitoring.

PROPOSED METHOD

The suggested system uses computer vision and artificial intelligence to provide a real-time, non-invasive method of identifying human activities. The device records live video of the user using a normal webcam rather than wearing sensors. Key skeletal markers of the human body are identified and extracted using MediaPipe Pose Estimation. To identify everyday activities including sitting, standing, walking, and exercising, these stance characteristics are examined. Activity identification, user authentication, live video streaming, and dashboard visualisation are all integrated into a Flask-based web application. Through login and signup modules, the system maintains efficiency and user-friendliness while guaranteeing secure access. This method offers a practical and affordable way to monitor lifestyle and healthcare.

SYSTEM ARCHITECTURE

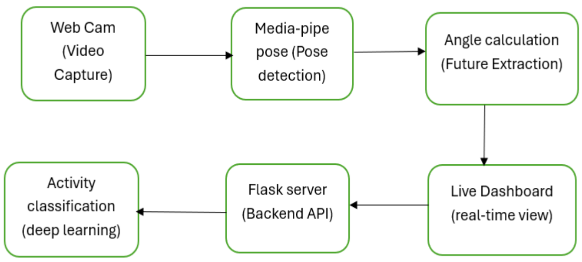


Fig 1: Architecture

METHODOLOGY DESCRIPTION

Video Capture: The system uses a standard webcam to capture live video of the user in real time. The video stream is continuously processed to enable uninterrupted activity monitoring.

Frame Preprocessing: Each captured frame is resized and converted into an appropriate format to ensure consistent input quality. This step helps reduce noise and improves pose detection accuracy.

Pose Estimation: Media-Pipe Pose Estimation is applied to each video frame to detect key human body landmarks such as shoulders, elbows, hips, knees, and ankles. These landmarks represent the skeletal structure of the human body.

Feature Extraction: Spatial relationships and movement patterns between skeletal landmarks are extracted. These features describe body posture and motion, which are essential for identifying different human activities.

Activity Recognition: The extracted features are analysed using rule-based logic or AI-based classification techniques to recognize activities such as sitting, standing, walking, and so on.

Web Application Integration: A Flask web application manages real-time video streaming, activity analysis, and user interaction. It includes modules for login, registration, and secure session handling.

Data Storage and Visualization: Recognized activities and user-related information are stored in an SQLite database. The system displays real-time activity results on a user dashboard for healthcare and lifestyle monitoring.

System Output: The final output presents the recognized human activity clearly on the dashboard, supporting healthcare monitoring and lifestyle analysis applications.

RESULT& DISCUSSION

Fig 2: Main Page

The main page contains the options to login in and make registration which is the first page that will be displayed after pasting the URL in the web browser

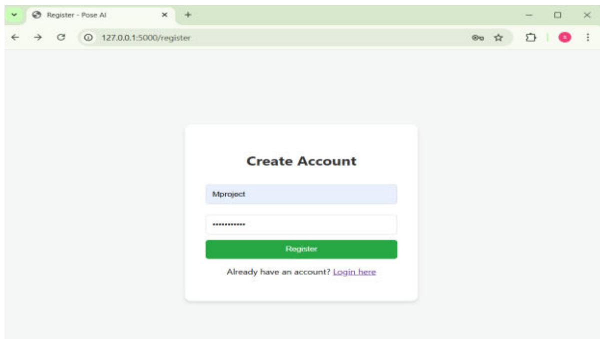
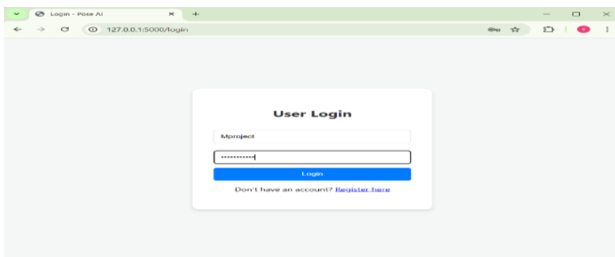


Fig 3: Account creation page

Here we need to create the account to make to make the login and enter into the main



page for performing the required activity

Fig 4: Login page

This Login page contains the user login who have already made their registration for the application entering their details will make them login into the main page.

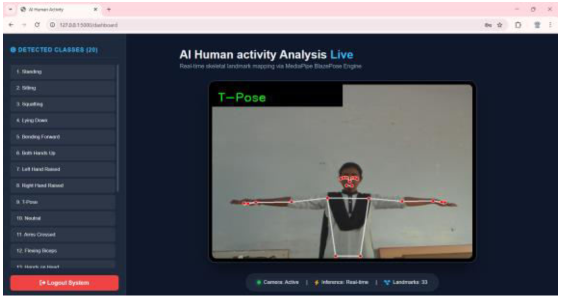


Fig 5: Activity Detection Page

This page detects the activity which is performed.

CONCLUSION&FUTURE ENHANCEMENT

This project presents a real-time, non-invasive system for daily human activity recognition using artificial intelligence and computer vision. By utilizing MediaPipe Pose Estimation and a standard webcam, the system accurately identifies common daily activities without the need for wearable sensors. The integration of a Flask-based web application enables secure user access and real-time activity visualization. The proposed solution is cost-effective, user-friendly, and suitable for healthcare and lifestyle monitoring. In the future, advanced deep learning models such as CNN-LSTM or Transformer-based architectures can be integrated to improve accuracy. Activity history tracking and analytics can provide deeper behavioral insights. Cloud and mobile deployment will enable scalable remote monitoring. Personalized health alerts and recommendations can further enhance system effectiveness.

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