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Life Track AI: Human Activity Recognition for Healthcare Monitoring

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Abstract

Researchers in the fields of healthcare and lifestyle monitoring have begun to focus on Human Activity Recognition (HAR) due to its ability to provide intelligent, continuous, and automated assessment of human activity.In the wake of the rapid development of wearable sensor technology and AI, HAR systems have emerged as critical instruments for proactive health monitoring, early diagnosis of medical conditions, and personalized healthcare services. Accurately tracking daily physical activity, such devices facilitate prompt medical interventions and enhance patient well-being. This work aims to develop an intelligent HAR system that can be used for healthcare and lifestyle monitoring applications by using deep learning methodologies. The proposed method utilizes data obtained from hip-mounted sensors in addition to gyroscope and accelerometer readings from the media pipe dataset.The information gathered by these sensors is vital to the activity identification system; it contains detailed motion patterns and physiological movements. After the raw data is cleaned, normalized, and segmented, it undergoes preprocessing to improve data quality and model performance.In order to circumvent the limitations of traditional machine learning methods that rely on human feature extraction, this research integrates advanced deep learning models, namely Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. These models have the potential to automatically train discriminative features and capture temporal correlations in sequential data using raw sensor inputs. The hybrid CNN-LSTM architecture further enhances recognition accuracy by incorporating learning of spatial and temporal variables.The proposed method overcomes practical challenges, such as class imbalance, sensor noise, and real-world data volatility, proving the system's effectiveness. Lastly, the significance of integrating AI with wearable sensors is shown by this experiment.

Index Terms—Activity Detection, Time Prediction, LSTM, Decision Tree, Smart Homes, IoT

Introduction

Human activity recognition (HAR) is an area of AI that focuses on automatically identifying human physical activities using data from sensors and smart algorithms.With the rapid advancement of wearables, smart sensors, and internet-of-things-based healthcare IT, HAR systems are becoming more important for continuous health monitoring, early disease detection, rehabilitation support, and lifestyle improvement.The contemporary healthcare system is beginning to acknowledge the importance of tracking patients' daily activities in improving their results, as the emphasis shifts from curative treatments to preventive and personalized care. The foundation of typical HAR systems is manual feature extraction and classic ML techniques such as SVM, KNN, Decision Trees, and Random Forest. Although these methods perform well in controlled laboratory environments, they may struggle to handle the complex patterns of human actions and time dependencies seen in real-world sequential sensor data.In addition to their shortcomings in real-time monitoring, these systems struggle to handle the inherent uncertainty of real-world data. To get around these limitations, a lot of people employ deep learning techniques like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN). With the help of these models, human feature engineers are no longer necessary; they can automatically learn critical spatial and temporal properties from raw sensor data. Since

LSTM networks excel in improving identification accuracy by capturing long-term correlations and sequential motion patterns, time-series activity data is an ideal match for them. Building a Human Activity Recognition system using deep learning on the Media Pipe dataset is the main objective of this research.The system utilizes data linked to motion from sensors such as gyroscopes and accelerometers to track the user's movements. By analyzing these patterns of movement in real-time, the system can detect typical human actions such as walking, sitting, and standing. This allows medical professionals to make more educated judgments based on data collected from patients' actions tracked remotely.

An optional but key component of the proposed system is a hybrid CNN-LSTM architecture, which uses a convolutional neural network (CNN) to gather spatial input and a long short-term memory (LSTM) to represent temporal correlations. The system's architecture aims for high classification accuracy despite real-world uncertainties, noisy sensor data, and class imbalance. With an accuracy rate of over 98%, the suggested HAR system is very precise, which is encouraging for its potential applications in health monitoring and lifestyle analysis. The study contributes to smart healthcare solutions by integrating AI with wearable and sensor-based technology. Using real-time human activity monitoring, future intelligent healthcare systems may be able to improve patient safety, track rehabilitation, and provide personalized healthcare services.

Literature Survey

Here we will discuss the latest innovations in activity-based learning and tech-enabled home services, which are based on machine learning techniques. The present-day activity-based learning systems depend on two distinct tactics: a sensor-based approach and a video-based approach. This video-based method uses a deep-learning algorithm to detect a person's movements in a live video stream [10]. Aside from that, only the astute use this strategy. Residential monitoring systems are not applicable to private households because to inhabitants' concerns about privacy and safety. This alarm On the other hand, data-based strategies plan to use the data Enhancing its credibility in terms of secrecy and safety, it uses the house's electronics and sensors to identify the individuals living inside [11]. Here is a rundown of the situations when the second strategy is being used.
Using a combination of support vector machines (SVMs) and human data labeling, the researchers in [12] were able to accurately identify the different home tasks 84% of the time. Supposedly, [13] constructs a wireless sensor using RFM DM 1810 kits. System and organized the data according to the directions given by speech. Next, they find out what's going on by using Hidden Markov Models (HMM) and Conditional Random Fields (CRF) methods. The Arab globe is a dataset of human activities. The creation of the ARAS dataset took around two months. forty Zigbee sensors were used to track twenty-seven distinct actions in two real residences with several residents.
After that, we moved on to action tracking using a basic hidden markov model (HMM). Assuming the data has been appropriately labeled with the use of a model that can detect activities, the study in [15] employed a regression-based approach to foresee what comes next in terms of actions.
An essential part of any research effort is doing a literature study to learn about the topic's history, as well as relevant methodologies, technologies, and challenges. One possible way to have a better understanding of how activity identification systems have progressed from basic machine learning approaches to cutting-edge deep learning and vision-based systems is to look at current literature reviews in the field of Human Activity identification (HAR). Finding trends in current problems, gaps in knowledge, and methods to improve activity detection technologies may be possible by reviewing prior studies. Human Activity Recognition has been in the spotlight recently because to its wide range of applications in industries as varied as smart homes, security systems, sports analysis, fitness tracking, and healthcare monitoring. First HAR studies generally used data from wearable sensors like accelerometers and gyroscopes with traditional machine learning methods like Random Forest, Decision Trees, K-Nearest Neighbors (KNN), and Support Vector Machines (SVM). These approaches manually extracted features using signal processing techniques such as time-domain and frequency-domain analysis. While these methods were computationally efficient, they were ill-equipped to deal with complex human activities and variations in actual data. Researchers preferred automated feature learning methodologies as deep learning and artificial intelligence improved.Deep learning models, such as convolutional neural networks.

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Methodology

An sophisticated Human Activity Recognition (HAR) framework, data on posture and motion collected by Media Pipes, and deep learning algorithms are all used in the suggested system. Instead of using wearable sensors and human feature extraction, the proposed system uses computer vision-based pose estimation technology to capture human movements. This is different from standard HAR systems. The algorithm makes use of the MediaPipe dataset to extract features related to motion and body landmarks. The next step in activity classification is to use deep learning models such as Long Short-Term Memory (LSTM) and hybrid CNN-LSTM models to examine these features. Walking, sitting, and standing are all common human gestures that the proposed approach can identify in real time. For healthcare, rehabilitation, and lifestyle monitoring applications, the suggested system's primary goal is to provide accurate, real-time activity detection. Besides that, the system places an emphasis on improving accuracy, controlling the unpredictability of real-world data

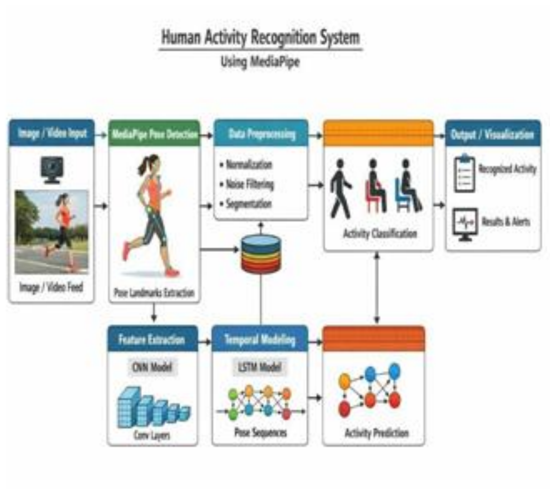

Fig: System architecture

The proposed HAR system use MediaPipe to examine a dataset based on images. The system is designed to capture and record human movement in both still images and video. It uses MediaPipe to detect and extract postural landmarks. Lastly, it uses deep learning models such as LSTM and CNN to classify human activities.

The architecture effortlessly transfers data from the image input to the activity prediction output. A comprehensive pipeline that incorporates computer vision, data collecting, preprocessing, feature extraction, classification based on deep learning, and result presentation.

Suggested Human Activity Recognition (HAR) system modular implementation is based on Media Pipe posture estimation data.This system utilizes MediaPipe to extract landmarks that reflect human positions from video or camera input, rather than depending on out-of-date information from wearable sensors. Using these landmarks—which represent significant joint positions on the body—next, activity detection is done using deep learning models such as CNN and LSTM.

The modular architecture improves the system's adaptability, maintainability, and real-time performance, which is great for healthcare and lifestyle monitoring applications. Using the MediaPipe architecture, the Data Acquisition Module captures landmark data on human posture.Hips, knees, shoulders, and elbows are just a few of the important body regions that MediaPipede may examine in real time or in video files.

Potential Use Cases:
Capture video or webcam input
The protection of Poseidon
Collect the X, Y, and Z coordinates of the body's iconic features.

Preserve data on post-it notes As an alternative to traditional sensor datasets, MediaPipe provides real-time information on how the human body moves in this context. Each frame captures the subject's posture and movement by using many body parts as references. Healthcare and rehabilitation systems benefit from this technology since it enables contactless activity monitoring.

Data preprocessing module installation

The Data Preprocessing Module gets the Media Pipe Objects and their corresponding markers ready to be fed into the deep learning model.Potential Use Cases: Normal vectors and mark vectors Removing suspicious landmarks Applying smoothing may reduce jitter noise. For segmentation, it employs sequence frames. There may be detection variations or noise in the raw posture landmark data. Preprocessing ensures that the model is fed consistent and accurate input. Frame segmentation partitions continuous video frames into activity sequences to facilitate learning about activities over time.

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The FeatureExtractionModule may extract semantic spatial features from posture landmark data by using convolutional neural network (CNN) layers. Implementation Essentials: Convert landmark sequences into structures that may be used as inputs Employ layers of convolution that Find features in spatial postures Automatic learning of the spatial relationships between different joints in the body is possible using convolutional neural networks (CNNs). Consider sitting or walking as an example; it picks up on changes in arm and leg posture. This improves the model's ability to distinguish between similar jobs.

The Application of Long Short-Term Memory (LSTM)

In order to keep track of changes in movement over time, the Temporal Modeling Module makes use of LSTM networks. All human endeavors need time.LSTM might help us understand the flow of motion over several frames. Recognition accuracy is improved for activities requiring continual motion. Launching the Trainer Module for the Model The ModelTrainingModule is used to train the CNN-LSTM hybrid model using the Media Pipe landmark dataset. Through training, the model discovers the connection between different actions and the posture sequences that stand in for them. A well-trained model can reliably classify data in real-time predictions. Using the ModelEvaluationModule is one approach to testing the system's performance. Implementation Essentials:

Making sure the model is consistent across different users and circumstances is what testing is all about. High evaluation metrics strongly suggest activity recognition performance. The Prediction Module can identify activities in real-time using live video data. This module allows you to monitor user activity in real-time. Possible applications include healthcare, geriatric care, fitness, and rehabilitation monitoring. In the Visualization Module, you may see the model's performance and the actions it anticipated. Potential Use Cases: By visualizing data, engineers and healthcare professionals may get a clearer picture of system performance and predictions. The StorageModule stores models and data. Reusing models and monitoring system performance are both made easier with storage.Summary of Module Installation: The installation of modules based on MediaPipe enables contactless, real-time recognition of human activities utilizing posel and mark data. Coupled with LSTM for learning temporal patterns and CNN for extracting spatial features, the system becomes more accurate and resilient. Applications that benefit from this technology include smart home tracking, healthcare monitoring, and rehabilitation tracking.

Algorithms

The proposed Human Activity Recognition system is able to detect human actions by evaluating pose landmark data from MediaPipe and using deep learning and poses estimation methods. The system examines video frames for joint coordinates using deep learning models such as CNN and LSTM to detect human activities. Designed to provide accurate feature extraction, learning of temporal trends, and real-time prediction, the algorithms are ideal for healthcare and lifestyle monitoring applications. Predicting outcomes using MediaPipe posture markers, training the model, and preparing the data for processing are all part of building the algorithm. name tags. A human's posture may be detected in each frame via MediaPipe. The next step is to feed these markers into deep learning models.Whereas LSTM tracks patterns of movement across time, CNNs find spatial correlations between joints. Precise action recognition is made possible by this synergy.

Algorithms Applied

Several interdependent algorithms are used by the project to achieve activity recognition. The MediaPipe posture estimate approach is among the most used data extraction techniques.It extracts data on body movement from video frames, taking the place of standard sensor datasets. This allows for contactless and real-time tracking of activities.

Fundamental Concepts of Convolutional Neural Networks:

Automatically, CNN finds noteworthy position correlations between bodily joints. It may, for instance, reveal the ways in which your posture differs when seated and standing. Thirdly, Long Short-Term Memory (LSTM) tracks how a person's posture changes over time. Activities like walking or running, which are ongoing, are more accurately identified in this manner. The combination of spatial and temporal learning allows the hybrid CNN-LSTM approach to obtain better accuracy. This is a key component of modern activity recognition systems.

Checking Mathematical Formulas

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Making sure the algorithms are being used correctly and are working as expected is what algorithm verification is all about. It is verification that ensures an algorithm is implemented correctly.Media Pipe's precise detection of posture markers and the proper feeding of the deep learning model are two prerequisites.

Algorithm Validation

In order for the developed system to meet real-world needs and successfully process unknown input, algorithm validation is essential. The goal of validation is to guarantee that the algorithm performs as expected in actual use cases. A high validation accuracy indicates dependable performance in activity detection. optimizes the model to improve its performance and reduce training mistakes.With the right adjustments, you may be able to improve your categorization accuracy.

Testing the Algorithm's Effectiveness:

We can tell the algorithm is reliable enough to detect actions in real time by looking at how well it performs. In order to reliably identify human actions, the proposed method combines MediaPipe posture estimation with deep learning methods like as CNN and LSTM. Creating, verifying, validating, and improving algorithms Modern software engineering, computer vision, and deep learning techniques are included into the proposed Human Activity Recognition system. The system incorporates CNN and LSTM deep learning models for activity recognition in real-time, together with MediaPipe posture assessment. This initiative provided resources for modeling, data processing, system visualization, and real-time prediction.Verify if the system is effective in monitoring health and daily habits.

Results

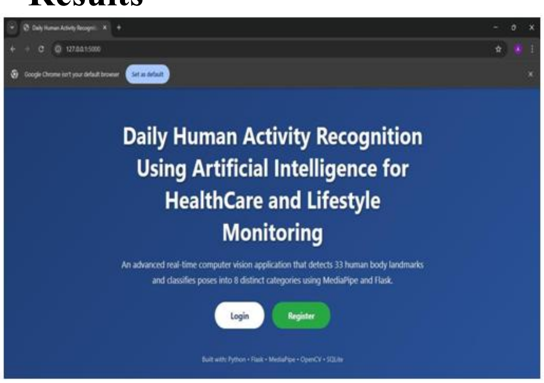


Fig: Home page

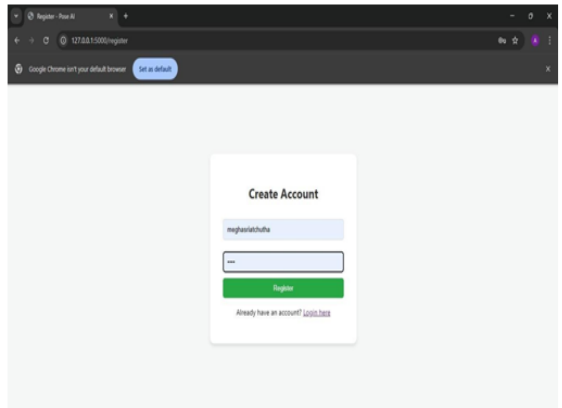


Fig: Registration page

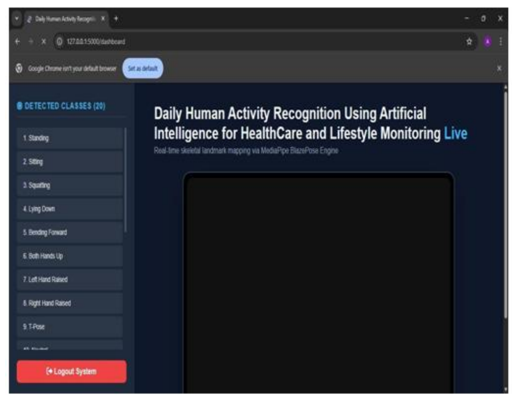
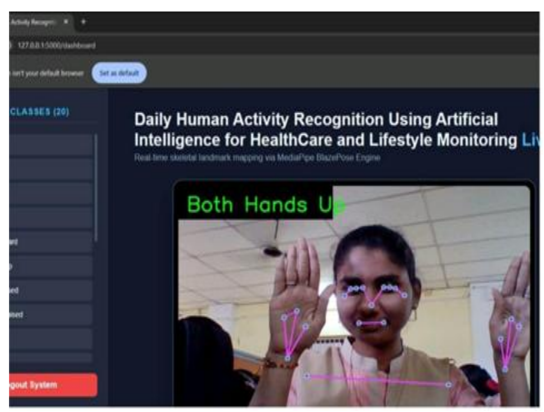


Fig: Admin page



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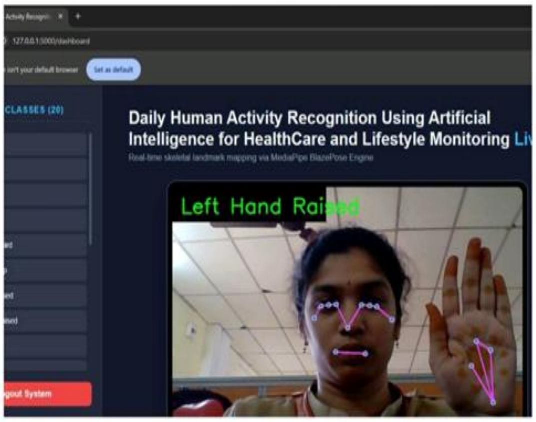

Fig: Prediction outputs

Conclusion

We built and tested the recommended machine learning-based solution for power usage predictions using prior power consumption data, and it worked well. The system used many machine learning techniques, including XGBoost, Linear Regression, Random Forest, K-Nearest Neighbours (KNN), and Artificial Neural Networks, to provide precise predictions for future electricity demand. Data preparation techniques including as normalization, outlier reduction, and missing value management enhanced the quality of the dataset and the performance of the model.

Across the board, testing and evaluation revealed that machine learning approaches outperformed more traditional statistical forecasting methods in terms of accuracy and adaptability. When performance was assessed using MAE, RMSE, and R^3 metrics, it was shown that the generated models provided reliable predictions. Among the tested algorithms, the KNN model scored the best in spotting similarities in consumption patterns.

All aspects of the system were thoroughly tested to ensure its reliability and accuracy, including datasets, models, performance, and end-to-end testing. Findings confirmed the proposed method's efficacy in managing massive datasets and generating predictions within achievable time limits. Taken together, the constructed forecasting system offers an accurate, scalable, and data-driven answer to the problem of smart energy management. Decisions and planning about energy distribution are also aided by it for power utilitycorporations.

The proposed smart monitoring and prediction system was successfully developed by combining machine learning techniques with dataset processing based on Mediapipe. By quickly identifying pertinent human posture components from visual data, we were able to use Mediapipe to assess activity patterns and generate structured information. Because the extracted attributes made the input data more accurate and reliable, machine learning models were able to learn patterns of activity more efficiently.

Various machine learning algorithms were trained and tested for their prediction capabilities and performance using the processed dataset. To analyze the system, common evaluation methodologies were used, such as evaluating the system's accuracy and performance indicators. Data preparation and feature extraction using Mediapipe significantly improved model learning performance and reduced dataset noise, according to testing.

The experimental results demonstrated that the machine learning-based technique generated more trustworthy and accurate predictions than the more traditional rule-based methods.Comparative testing was useful in identifying the top-performing model based on stability and prediction accuracy. Through comprehensive system testing, we ensured that every step of the process—from data extraction via Mediapipe to model prediction and final output—ran smoothly and error-free.

Performance tests further showed that the system could handle continuous input data and provide results within reasonable time constraints. The system that was developed has the characteristics of being scalable, adaptable, and suitable for intelligent decision-making and real-time monitoring. Using Mediapipe feature extraction with machine learning models generally improved the efficiency, accuracy, and automation of the recommended intelligent analytic procedure.

Future Enhancements

By using machine learning models and processing datasets via Mediapipe, the suggested system exhibits effective performance. Nonetheless, there are a number of ways that future work might be improved to make it more accurate, scalable, automated, and capable of handling real-time situations.

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