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A Survey on Human Activity Identification using Machine Learning and Deep Learning Approach

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Abstract: ***Human activity recognition (HAR) is very interesting and active area of research era from past one or two decades. HAR is also an impotent research topic in computer vision field. It is extensively utilized in various fields such as remote monitoring, person to person interaction system, health care monitoring, robotics and so on. The major motivation of this survey paper is to introduce various human activities in the series of video utilizing different postures video done by the people. Creation of data is done by the utilization of static kinetic and wearable sensor devices which are collect the data using accelerometer, magneto meter and gyroscope. Analysis of human activity is to carry out using machine learning and deep learning techniques named SVM, Logistic regression, KNN, Random Forest, Navie Byes, CNN, LSTM and so many. In this paper, monitoring of activities is possible by the use of modern available Kinetic, accelerometer and gyroscope sensor device with GPS and vision based technology.***

Keyword: Human Activity recognition, Accelerometer, Gyroscope, Artificial intelligence, Machine learning, NNN

1. Introduction

Recognizing different proactive activities executed by people to achieve their everyday living assignments alludes to Human Action Recognition (HAR). A HAR framework can distinguish subject exercises to give specialists important data to perform explicit activities [1]. Various sensors are accessible for recording exercises, including an assortment of physiological movement sensors, surrounding sensors, infrared movement identifiers, and attractive sensors [2], RADAR [3], acoustic sensors [4], reverberation, regular items, and camcorders. Video - based HAR frameworks are well known because of their various genuine applications, yet they likewise represent numerous protections and natural limitations in certain conditions.

The goal of the HAR framework is to recognize genuine human exercises and order them. Human movements are profoundly convoluted and varied, which makes precise movement recognition a test in PC vision.

Prior examinations in HAR frameworks consider action identification as a run - of - the - mill design ID issue [5]. Support vector machines (SVM) were used in early HAR methods. Later examination in this field has moved towards AI. Conventional AI procedures, also known as shallow learning, include heuristically driven highlight extraction from information that primarily relies on human master information for a specific space, limiting the engineering intended for one climate to outperform the issue of another area [6].

The study of human activity recognition is currently very popular. Automatic recognition of activities, such as jogging, fast walking, stair climbing, etc., is feasible. According to new research, there will be more elderly people on the planet by the year 2060. As a result, there will be more elderly people living alone at home who will require intense care from the family. The government will have greater hurdles in creating appropriate and effective health policies for elderly people as well as updating its technologies to support elderly people in caring for those types of disabled people. Applications which can watch over older people and offer good assistance with everyday activities are required in Word [7]. We have improved

There are a variety of domains to identify human activities. A brief summary is given below [8]

Deep learning and computer vision approaches to identify human physical activity
1) Using machine learning and sensory data
2) Using wearable sensors and deep learning approaches
3) Using image processing concept with sensors data
4) RFID approach to detect activity using machine learning

1.1 Sensor [9] [10]

In many of the locations we live, including offices, residences, cars, etc., sensors are used. By turning on the lights, regulating the thermostat, detecting smoke, sounding an alert in a dangerous location, cooking delectable cuisine, opening doors, etc., they make our lives easier. Sensors are used to carry out all automated tasks. Sensors transform the input from physical objects into output signals. There are many different types of sensors available; each is designed to carry out a certain function.

1.2 Classification of Sensor [11]

Authors and experts in this field regularly classify sensors in various ways. Detection, conversion, and signal properties are used to classify data.

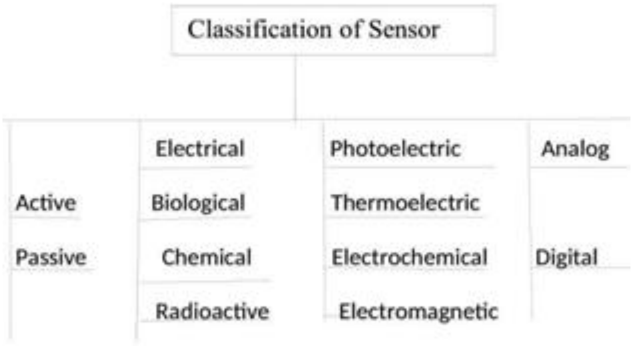

Figure 1: Classification of Sensor

1.3 Human Action Recognition (HAR) [12]

Human action is the process of picking out a certain activity among a wide range of activities. It is also known to group a specific activity with other activities. According to some authors, it is the process of anticipating everyday regular individual action like jogging, rapid running, and normal strolling.

1.4 Different Approaches Used in HAR [13]

Because sensor technology is relatively inexpensive, human activity recognition is a hot topic in AI and ML engineering. Due of the wide range of applications for HAR, various techniques to sensory datasets have already been used [14]. This section discusses all of the strategies employed in the past as well as prospective strategies and future trends related to HAR. Three categories—actions - based, motion - based, and interaction - based human activity recognition—have been used by several authors to discuss the topic. It has been divided into three categories named "device - free environmental - based method, " sensor - based approach, " and "vision - based approach.

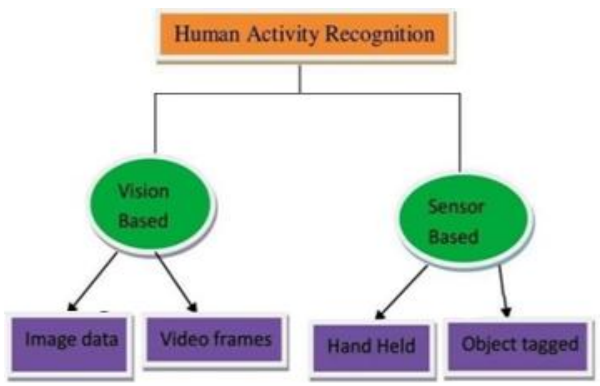

Figure 2: Classification approaches of Human Activity Recognition

1) Video Based HAR [15]:
This method identifies activity in specific video frames. Using a video approach, computer vision algorithms, and image processing principles for segmentation and video framing, identify human action. The three primary types of activity recognition are crowd - based activity with anomalous activity recognition, multiple - person - based particular human activity recognition, and single - subject activity recognition. The worlds of entertainment and surveillance both use this domain. The fundamental element of this strategy is object segmentation, which is followed by feature extraction and classification procedures.

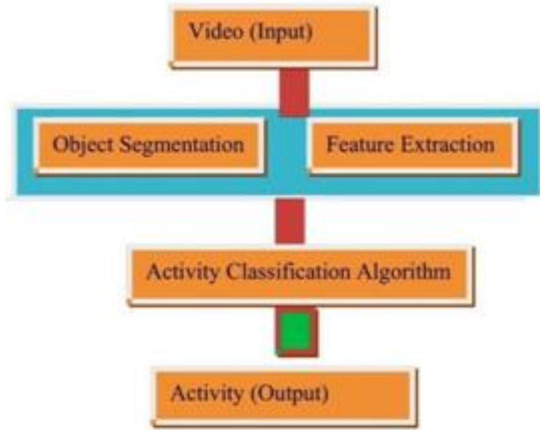

Figure 3: Basic Diagram of Video based Human Activity Recognition

2) Sensor Based HAR [16]:
On the human body, an embedded sensor system is utilized to record or capture the dataset and monitor the subject's activity. It is required to manage numerous complex operations using high - intensity cameras in order to track the high - quality photos of human objects in light of the many challenges. Additionally, sensor systems have the benefit of being portable and easily bound to objects. We have been surrounded by sensor thanks to modern technology, which offers IOT and sensor - based gadgets like phones, watches, and goggles but not portable items like cars, walls, and furniture [8–10].

1.5 Applications of HAR [17] [18] [19]

A wide range of physiological activity sensors, environmental sensors, infrared motion detectors, magnetic sensors, RADAR [8, acoustic sensors, Echo, commonplace objects, and video cameras are all accessible for recording activities. Due to their many practical uses, video - based HAR systems are widely used, but in smart environments, they also present a number of privacy and environmental concerns.

Due to the numerous applications it has across numerous disciplines, the problem of labeling actions is one that is of interest. Recognizing individual and group activity has applications in many fields, including surveillance, medicine, sports, entertainment, gaming, robotics, video indexing, and video annotation, among others. [20]. Network - based surveillance systems offer cooperative, immediate observation as a result of the widespread use of security cameras, enhancing human productivity and throughput [21]. Improved searching is made possible by content - based video analysis and logical video clip labeling [22]. Activity recognition can facilitate greater natural language understanding in human - computer interaction, which can assist us in developing computers with better speech recognition [23]. Finally, home care technology that can recognize daily living activities can be created, lowering the expenses.

Lighting, heating, electricity, and all other domestic appliances are controlled by smart home technology, which also monitors activity of all occupants. When it comes to creating the next generation of technologies that can enhance healthcare and the security of smart homes, vision - based human activity recognition in smart homes has grown to be a serious problem. Lighting, heating, electricity, and all other domestic appliances are controlled by smart home technology, which also monitors activity of all occupants. When it comes to creating the next generation of technologies that can enhance healthcare and the security of smart homes, vision - based human activity recognition in smart homes has grown to be a serious problem.

A unique CNN architecture for extracting features after a series of convolutional and pooling layers has been presented [24] [25], taking advantage of automatic feature extraction and leveraging large - scale datasets of deep learning methods. In this context, DMLSmartActions, a video dataset of actual human action, has been utilized [26].

2. Literature Review

Authors [27] have developed a computational for analysis of human motion recognition through the CNN approach. In this research paper classify the human activites. Authors have achieved better accuracy of model and also evaluated measuring parameters such as precision; recall and F1 score including low time complexity and reduced execution time of model

Authors [28] have conducted a Meta analysis of numerous survey papers to determine their bias. The findings indicate that 11% of the study publications were found to be bias. This work adds to the discussion of the equilibrium number of records in datasets relating to human activities. Movements of all kinds should be in the proper equilibrium numbers if we want to achieve quality results.

In substitute of 2D - LDA, author [29] has developed a new method called general tensor discriminant analysis (GDTA) for the preprocessing stage. They tested their suggested method using human gait, and GobarD, GobarS, and GobarDS were employed for picture decomposition. The suggested strategy had produced great and improved results.

The wave change strategy [30] plans and supports the human identification approach. The intended strategy is assessed and contrasted with the quality HG recognition method that does not involve wave change using the Chinese Academy of Sciences (CASIA). Model - based and model - free techniques are being tested for the anticipated HG recognition. Options within the planned HG recognition technique include second - stage separate wave remodel (DWT) and second - stage lifting wave remodel (LWT) level one decomposition. The intended technique also uses the HAR basis performance of wave transformation for feature extraction. Experimental outcomes using CASIA information differ from those using the quality technique in terms of chromosomal improvement and accurate classification performance.

Author [31] has investigated what the sensor plan's implications are on the accuracy and quality of its information collection. Four tasks were thought to be particularly relevant to heart rate, breathing rate, hand signal recognition, gulping observation, and stride analysis. It is implied that the design and wiring of the sensor affect the accuracy and quality of the information captured.

One of the dynamic evaluation regions in PC vision for situations like security surveillance, medicinal services, and human PC connection is human activity recognition [32]. The report examines three categories of advancement detection, including wearable technology, depth sensors, and RGB cameras. It also looks at the benefits and drawbacks of the mentioned detecting breakthroughs. The results showed that depth sensors and wearable technology are more popular in HAR research than RGB cameras.

One of the most cutting - edge approaches to understanding human actions, deep learning successfully employs the image structure to reduce the search space of the preparation model, beating other "non - deep" art of the states procedures and producing outstanding results. The most recent advances in movement acknowledgment using sophisticated learning models are briefly discussed in this study. Additionally, they looked into the advantages, disadvantages, and productivity of cutting - edge deep learning models for action recognition.

Action recognition's goal is to identify information designs hidden inside the series of images from a given demonstration film. Act acknowledgment is used in a variety of contexts, such as observation frameworks, medical diagnostics, sports video information analysis, interpersonal communications, and technological devices. Creators have examined various acknowledgment systems.

Authors considered [33], which is in any case a challenging task in an unlimited number of environmental factors, despite ongoing advances in the field. In this study, we focus on a few of the most current research studies that explore the range of activity acknowledgment strategies. Three common methods for detecting movement are included in the work: specifically vision - based (using present assessment), wearable technology, and cell phone sensors. We shall briefly evaluate the correctness of the aforementioned applied sciences as well as some of their advantages and disadvantages. The discoveries will also show how the vision - based approach is currently becoming a well - liked method for HAR [34] questions.

Table 1: Table of relevant paper review summaries

S. No.	Author's name	Methods/Techniques	Concept discussed	Future work
1.	Wenchuan [Wei, W., McElroy, C., & Dey, S., 2018] [35]	Learning based personalized treatment system for Parkinson disease.	Support Vector Machine (SVM) technique	A recommendation system can be proposed, who will suggest future treatment for any patients based on its feedback

2.	ShimaBahrami Z. S. et al. [Shima Bahrami, 2017] [36].	A comparative study between Lumbar Spinal stenosis and Lumbar intervertebral disc degeneration.	Duty factor from both two LSS and LIDD had evaluated with gait analysis.	Enhance accuracy of model with the use of AI, ML and DL domain in LSS and LIDD identification.
3.	Omar Costilla - Reyes et al. [Omer Costilla - Reyes, 2016] [37]	By using machine learning model and feature engineering, human gait can be predicted with the help of footprint images.	Creation of dataset human of walking in 10 different ways of different (757 counts) times. It covers normal gait, slow walk gait side gait etc. Check best performance of model.	The choice of walking manner can be further refined and adding some walking manners like Gait with hands on stomach, hands on head.
4.	Sachin settyet al. [Sachin Setty, 2016] [38]	SVM based Machine Learning technique using gait analysis.	SVM machine learning technique has helped to identify Parkinson which affects human walking.	Differentiate Parkinson and two other neuro - degenerative diseases.
5.	Chen et al. [Chen, 2016] [39]	Hypergraph partition approach.	3D tensor gait features. Created 120 subjects multi - gait dataset with 2 - 4 participants.1440 videos walking alone and two viewpoints assume: frontal, lateral.	
6.	Nandy et al. [Nandy, 2016] [40]	Statistical gait energy image (GEI).	Statistical shape features from GEI edge contour and OU - ISIR treadmill dataset, covariates clothing condition.	

3. Proposed Methodology

Hyper tuning is very important to get best and fit model for ML and DL techniques [26 - 30]. We have shown a basic approach to train and test model. Main part of this work is as follows

1) To address the importance of data preprocessing and feature extraction.
2) To address hyper tuning impact on getting normalized neural network.
3) To upgrade the accuracy of model to predict human activities.

Figure 4: Basic Diagram of proposed methodology

4. Expected outcome of the study

1) Based on recorded data (Dataset), we will apply classification technique to identify about Normal/Abnormal gait (Binary classification).
2) If we found abnormal gait, then our model will try to find out disease like Parkinson, Paralysis etc.
3) Comparative study will be verified by applying some available tools

5. Conclusion

There has been a great deal research done human activity recognition. There is even more work yet to completed in the area of human activity recognition. A proposed model will be anticipating high accuracy to classify human activity. A more spotlight on numerical verification as well as exploratory step examination by utilizing AI methods or machine learning deep learning human activity based examination.

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