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A Review On Human Activity Recognition Based On I-O-T And Deep Learning Approaches

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Abstract- Human Activity Recognition (HAR) has been treated as a typical classification problem in computer vision and pattern recognition, to recognize various human activities. HAR is mostly dominated by vision-based approaches that typically focus on action recognition using monocular RGB videos, which make it hard to comprehensively represent actions in 3D space. With the rapid development of low-cost 3D data capture devices like Kinect and Asus Xtion Pro Live cameras. Human activities play a significant role with respect to activities related to environment, aquatic life, I-O-T (Internet Of Things) etc.

Keywords - Human Activities Recognition, Sensor based HAR, Deep Learning, Video Surveillance, I-O-T.Introduction

I. INTRODUCTION

Humans engage in a wide range of activities in their daily lives. The recent advancement in technology and data from Closed-Circuit Television (CCTV) and sensors has enabled the detection of anomalies as well as the recognition of daily human activities for surveillance [1,2]. The term anomaly refers to abnormal or unusual behavior or activity [3]. Human Activity Recognition (HAR) has been treated as a typical classification problem in computer vision and pattern recognition, to recognize various human activities [4]. HAR based on visual and sensory data has a huge number of potential applications and has piqued the interest of researchers due to rising demand. There is also an ongoing debate about the effectiveness of sensor-based HAR techniques versus vision-based HAR techniques. Currently, HAR has been utilized in diverse widespread use of HAR applications has significantly improved human safety and well-being all over the world [6]. Several surveys have been conducted in this literature to highlight the recent progress in the research area of human activity recognition.

The existing surveys focused on different approaches including the areas of deep learning machine learning, sensor, and vision for human activity recognition. Wang et al. [7] reviewed the existing literature for HAR considering the deep learning models, sensor modalities, and application perspectives. Although this review demonstrated different architectures and datasets, it lacks some important aspects of HAR including technical details of the type of activities, and performance measures for deep learning architectures. Additionally, the details description of the location and orientation of sensors in the datasets is not properly analyzed in this review.

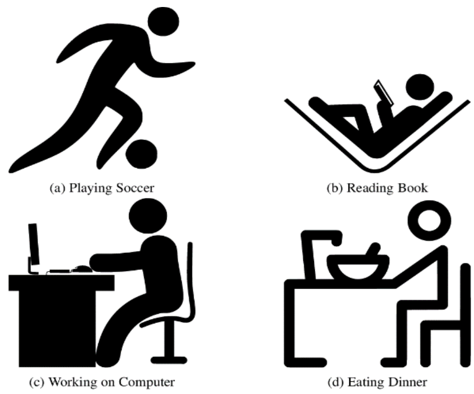

Fig.1 Various human activities performed at different places

The task of HAR has been performed under varying granularity, from simple day-to-day activities like sitting, standing, walking to other complex activities like recognizing shots in sports, preparing meals etc. [8]. Two common approaches for HAR are using (i) wearable inertial sensors and (ii) external devices like video cameras. Wearable inertial sensors based on HAR systems use sensors like gyroscope, accelerometer, etc. whereas camera-based HAR systems use RGB, RGB-D, thermal cameras, etc. to recognize activities from video data [9]. Apart from the vision and inertial sensors, environmental and acoustic sensors are also used to infer activities from the interaction of the user with its environment. However, environmental and acoustic sensors are less preferred for HAR [10]. This paper focuses on the works that use vision (RGB, RGB-D, and Skeletal), wearable inertial sensors, and a combination of these two for HAR.

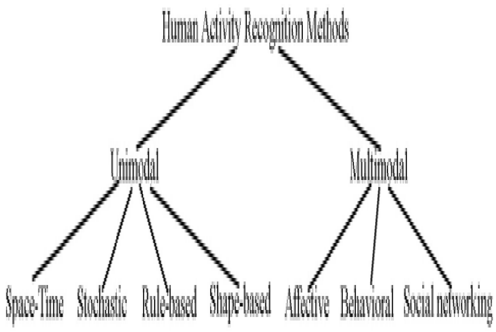

Fig.2 Proposed hierarchical categorization of human activity recognition methods.

HAR is mostly dominated by vision-based approaches that typically focus on action recognition using monocular RGB videos, which make it hard to comprehensively represent actions in 3D space. With the rapid development of low-cost 3D data capture devices like Kinect and Asus Xtion Pro Live cameras, newer research is more focused on 3D action recognition [11].

There exist many detailed surveys for RGB-D based HAR. Notably, [12] surveyed HAR approaches that include skeleton joints, depth maps, and other hybrid methods, using RGB-D sensors and also stated their advantages and limitations. In [10], depth signal processing-based HAR techniques are reviewed and give details on a method based on the temporal pyramid of key poses evaluated on the MSR Action3D[13] dataset. The camera-based sensors are good for presetting areas but have some limitations such as activity cannot be determined if the user is not in the visible range of the camera and it raises issues regarding the user's privacy. Additionally, the light, clutter, and occlusion may also affect recognition performance. [14]

II. LITERATURE REVIEW

(Ghayvat, H et. al., 2019)[1]Background: Ambiguities and anomalies in the Activity of Daily Living (ADL) patterns indicate deviations from Wellness. The monitoring of lifestyles could facilitate remote physicians or caregivers to give insight into symptoms of the disease and provide health improvement advice to residents; Objective: This research work aims to apply lifestyle monitoring in an ambient assisted living (AAL) system by diagnosing conduct and distinguishing variation from the norm with the slightest conceivable fake alert. In pursuing this aim, the main objective is to fill the knowledge gap of two contextual observations (i.e., day and time) in the frequent behavior modeling for an individual in AAL.

Each sensing category has its advantages and restrictions. Only a single type of sensing unit may not manage composite states in practice and lose the activity of daily living. To boost the efficiency of the system, we offer an exceptional sensor data fusion technique through different sensing modalities; Methods: As behaviors may also change according to other contextual observations, including seasonal, weather (or temperature), and social interaction, we propose the design of a novel activity learning model by adding behavioral observations, which we name as the Wellness indices analysis model; Results: The ground-truth data are collected from four elderly houses, including daily activities, with a sample size of three hundred days plus sensor activation. The investigation results validate the success of our method. The new feature set from sensor data fusion enhances the system accuracy to (98.17% ± 0.95) from (80.81% ± 0.68). The performance evaluation parameters of the proposed model for ADL recognition are recorded for the 14 selected activities. These parameters are Sensitivity (0.9852), Specificity (0.9988), Accuracy (0.9974), F1 score (0.9851), False Negative Rate (0.0130).

(Gupta, N et al., 2022) [2]Human activity recognition (HAR) has multifaceted applications due to its worldly usage of acquisition devices such as smartphones, video cameras, and its ability to capture human activity data. While electronic devices and their applications are steadily growing, the advances in Artificial intelligence (AI) have revolutionized the ability to extract deep hidden information for accurate detection and its interpretation. This yields a better understanding of rapidly growing acquisition devices, AI, and applications, the three pillars of HAR under one roof.

There are many review articles published on the general characteristics of HAR, a few have compared all the HAR devices at the same time, and few have explored the impact of evolving AI architecture. In our proposed review, a detailed narration on the three pillars of HAR is presented covering the period from 2011 to 2021. Further, the review presents the recommendations for an improved HAR design, its reliability, and stability. Five major findings were: (1) HAR constitutes three major pillars such as devices, AI and applications; (2) HAR has dominated the healthcare industry; (3) Hybrid AI models are in their infancy stage and needs considerable work for providing the stable and reliable design.

Further, these trained models need solid prediction, high accuracy, generalization, and finally, meeting the objectives of the applications without bias; (4) little work was observed in abnormality detection during actions; and (5) almost no work has been done in forecasting actions. We conclude that: (a) HAR industry will evolve in terms of the three pillars of electronic devices, applications and the type of AI. (b) AI will provide a powerful impetus to the HAR industry in future.
(Dhiman, C et al., 2019) [3]The concept of intelligent visual identification of abnormal human activity has raised the standards of surveillance systems, situation cognizance, homeland safety and smart environments. However, abnormal human activity is highly diverse in itself due to the aspects such as (a) the fundamental definition of anomaly (b) feature representation of an anomaly, (c) its application, and henceforth (d) the dataset. This paper aims to summarize various existing abnormal human activity recognition (AbHAR) handcrafted and deep approaches with the variation of the type of information available such as two-dimensional or three-dimensional data. Features play a vital role in an excellent performance of an AbHAR system. The proposed literature provides feature designs of abnormal human activity recognition in a video with respect to the context or application such as fall detection, Ambient Assistive Living (AAL), homeland security, surveillance or crowd analysis using RGB, depth and skeletal evidence. The key contributions and limitations of every feature design technique, under each category: 2D and 3D AbHAR, in respective contexts are tabulated that will provide insight of various abnormal action detection approaches. Finally, the paper outlines newly added datasets for AbHAR by the researchers with added complexities for method validations.

(Dang, L.M et al., 2020)[4]Human activity recognition (HAR) technology that analyzes data acquired from various types of sensing devices, including vision sensors and embedded sensors, has motivated the development of various context-aware applications in emerging domains, e.g., the Internet of Things (IoT) and healthcare. Even though a considerable number of HAR surveys and review articles have been conducted previously, the major/overall HAR subject has been ignored, and these studies only focus on particular HAR topics. Therefore, a comprehensive review paper that covers major subjects in HAR is imperative.

This survey analyzes the latest state-of-the-art research in HAR in recent years, introduces a classification of HAR methodologies, and shows advantages and weaknesses for methods in each category. Specifically, HAR methods are classified into two main groups, which are sensor-based HAR and vision-based HAR, based on the generated data type. After that, each group is divided into subgroups that perform different procedures, including the data collection, pre-processing methods, feature engineering, and the training process. Moreover, an extensive review regarding the utilization of deep learning in HAR is also conducted. Finally, this paper discusses various challenges in the current HAR topic and offers suggestions for future research.

(Beddiar, D.R et al., 2020) [5]Human activity recognition (HAR) systems attempt to automatically identify and analyze human activities using acquired information from various types of sensors. Although several extensive review papers have already been published in the general HAR topics, the growing technologies in the field as well as the multi-disciplinary nature of HAR prompt the need for constant updates in the field. In this respect, this paper attempts to review and summarize the progress of HAR systems from the computer vision perspective. Indeed, most computer vision applications such as human computer interaction, virtual reality, security, video surveillance and home monitoring are highly correlated to HAR tasks. This establishes new trend and milestone in the development cycle of HAR systems. Therefore, the current survey aims to provide the reader with an up to date analysis of vision-based HAR related literature and recent progress in the field. At the same time, it will highlight the main challenges and future directions.

(Chen, K et al., 2021) [6]The vast proliferation of sensor devices and Internet of Things enables the applications of sensor-based activity recognition. However, there exist substantial challenges that could influence the performance of the recognition system in practical scenarios. Recently, as deep learning has demonstrated its effectiveness in many areas, plenty of deep methods have been investigated to address the challenges in activity recognition. In this study, we present a survey of the state-of-the-art deep learning methods for sensor-based human activity recognition. We first introduce the multi-modality of the sensory data and provide information for public datasets that can be used for evaluation in different challenge tasks. We then propose a new taxonomy to structure the deep methods by challenges. Challenges and challenge-related deep methods are summarized and analyzed to form an overview of the current research progress. At the end of this work, we discuss the open issues and provide some insights for future directions.

(Y. Wang. al., 2019) [7]Increased life expectancy coupled with declining birth rates is leading to an aging population structure. Aging-caused changes, such as physical or cognitive decline, could affect people's quality of life, result in injuries, mental health or the lack of physical activity. Sensor-based human activity recognition (HAR) is one of the most promising assistive technologies to support older people's daily life, which has enabled enormous potential in human-centred applications. Recent surveys in HAR either only focus on the deep learning approaches or one specific sensor modality. This survey aims to provide a more comprehensive introduction for newcomers and researchers to HAR. We first introduce the state-of-art sensor modalities in HAR. We look more into the techniques involved in each step of wearable sensor modality centred HAR in terms of sensors, activities, data pre-processing, feature learning and classification, including both conventional approaches and deep learning methods. In the feature learning section, we focus on both hand-crafted features and automatically learned features using deep networks. We also present the ambient-sensor-based HAR, including camera-based systems, and the systems which combine the wearable and ambient sensors. Finally, we identify the corresponding challenges in HAR to pose research problems for further improvement in HAR.

(ZhouH. et. al., 2020) [8]Due to the prevalence of social media sites, users are allowed to conveniently share their ideas and activities anytime and anywhere. Therefore, these sites hold substantial real-world event related data. Different from traditional social event detection methods which mainly focus on single-media, multi-modal social event detection aims at discovering events in vast heterogeneous data such as texts, images and video clips.

These data denote real-world events from multiple dimensions simultaneously so that they can provide comprehensive and complementary understanding of social event. In recent years, multi-modal social event detection has attracted intensive attentions. This paper concentrates on conducting a comprehensive survey of extant works. Two current attempts in this field are firstly reviewed: event feature learning and event inference. Particularly, event feature learning is a pre-requisite because of its ability on translating social media data into computer-friendly numerical form. Event inference aims at deciding whether a sample belongs to a social event. Then, several public datasets in the community are introduced and the comparison results are also provided. At the end of this paper, a general discussion of the insights is delivered to promote the development of multi-modal social event detection.

III. HUMAN ACTIVITIES AND ENVIRONMENT

The Environmental and internal microbiome session of the workshop mentioned above aimed at opening a window on the microbiota in a OneHealth/EcoHealth perspective, leaning on their potential ecosystem services for human and environment health and on their potential disturbance by various factors. We also discuss the ways in which human activities are distorting these microbiotas and creating risks to human, animal and plant health. Finally, we suggest research priorities, and propose administrative and educational measures that can help to stop this damage to our microbial environment. [15]

IV. HUMAN ACTIVITIES AND AQUATIC LIFE

The factors affecting aquatic biodiversity and resources in the Yangtze River Basin include overfishing, habitat loss, fragmentation and destruction, invasive species, and so forth. These activities that are closely related to human activities, have made contributions to the economic development of the Yangtze River Basin, but have also had negative impacts on the aquatic biodiversity of the Yangtze River.[16] Habitat loss, fragmentation, and destruction due to Human Activities.

V. ADVANTAGES AND DISADVANTAGES OF DEEP- LEARNING BASED HAR [17]

Compared to conventional machine learning, deep learning-based HAR generates better results and helps recognize more complex human activities. The merits of deep learning HAR approaches are as follows:

(1) Deep learning extracts more robust features using massive data. Though human-expert knowledge helps us design effective hand-crafted features for HAR, these features may not hold good generalization ability when confronting data under dynamic environments or more complex human activities, such as gym exercise that contains a series of irregular human motions. Deep learning methods learn the feature space that mostly contributes to the task automatically by novel network architectures and back-propagation, which overcomes the shortcomings of hand-crafted features [17].

(2) Deep learning can still learn representations in an unsupervised manner. Recent progress on unsupervised learning based on mutual information and contrastive learning tackles the problem of the requirement of a large amount of well-annotated data that is costly [17].

Nevertheless, in real-world applications, deep models still encounter challenges:

(1) Deep learning models still require sufficient labeled HAR data to obtain a good classifier. In practice, such data is either expensive to annotate or hard to collect [17].

For device-free HAR, the dynamic and complex environments can degrade the deep learning performance. Even though deep learning features are robust, statistical learning approaches still follow the assumption that the training and testing data are independent and identically distributed. This might be broken when the environmental dynamics change the HAR data distribution. For example, in visual HAR, the training samples mostly come from the ideal condition with good illumination conditions and clear human targets, but in the real world, the testing scenario might be at night and the targets are severely occluded [17].

VI. APPROACH TO USE HUMAN ACTIVITY IDENTIFICATION [18]

Human activity recognition's primary objective is to accurately describe human actions and their interactions from a previously unseen data sequence. It is often challenging to accurately recognize humans' activities from video data due to several problems like dynamic background and low-quality videos. In particular, two main questions arise among various human activity recognition techniques: "Which action is performed?" – which comes under the action recognition task, and "Where exactly in the video?" is the localization task. The sequences of images are referred to as frames. Thus, the primary objective of an action recognition task is to process the input video clips to recognize the subsequent human actions.

Human activity mimics their habits; therefore, every human activities are unique, which turns into a challenging task to recognize. Moreover, developing such a deep learning-based model to predict human action within adequate benchmark datasets for evaluation is another challenging task.

A Types of HAR System

There are two main categorizations of the HAR system based on the equipment:

B Vision-based HAR

Static cameras installed at various places for surveillance purpose record the videos and store at servers. These camera feeds or recorded videos are then used for monitoring purposes. For example, (Htike et al. 2014) performed human posture recognition for video surveillance applications using one static camera. This type of HAR is used for road safety, public security, traffic management, crowd monitoring, etc. Figure 1 shows the typical steps of a vision-based human activity recognition system.

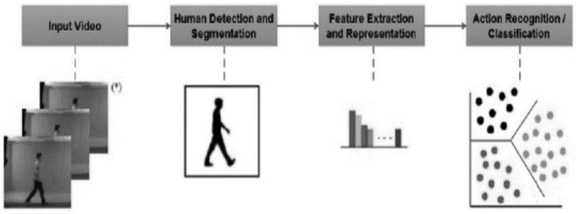

Fig.3 A typical human activity recognition system[18]

C Sensor-based HAR.

Smartphones have become a global communication tool and, more recently, a technology for studying humans. Built-in sensors of smartphones can capture continuous information about human activities. Wan et al. (S. Wan et al. 2020) performed the identification of human activity using smartphone sensors. In this approach, data is retrieved from the smartphone's in-built accelerometer and gyroscope sensors, and then machine learning techniques were applied to recognize human activity. This type of HAR is helpful for patient monitoring systems, an individual player's activity monitoring during sports, etc., but cannot be applied to the broad application of human activity recognition for security at home/public places, monitoring, etc. [18]

D. Video Surveillance based on Deep learning approach [19]

Human action recognition is one of the most crucial tasks in video understanding. This field has a wide range of applications, such as video retrieval, entertainment, human-computer interaction, behavior analysis, security, video surveillance, and home monitoring. In detail, we want to find handshake events in a movie or offside decisions in a football match and the results are returned automatically. The goal of human action recognition is to recognize automatically the nature of an action from unknown video sequences.

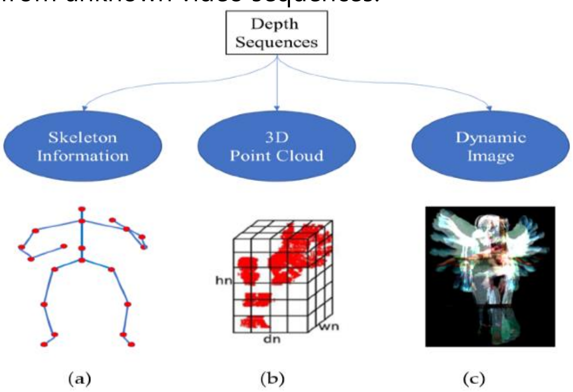

Fig.4 Different techniques to encode the depth sequence into a spatio-temporal image; (a) skeleton, (b) point cloud, and (c) dynamic image from depth sequence.

Background is easy to recognize than an action that is recorded in a cluttered or dynamic background. In addition, lighting conditions or viewpoints contribute to increase or decrease of the accuracy of recognition. The next problem is intraclass and interclass variations. A human action recognition method must be able to generalize an action over variations within a class and distinguish between actions of different classes. For examples, people have different speeds when they run or walk. The occlusion problem is a hard issue in action recognition because some body parts of humans are disappeared temporarily. For example, some body parts cover other parts or a subject, or a person is hidden behind another person. Temporal variations are also an important challenge because actions are happening for a long time.

Deep learning methods have achieved state-of-the-art results on various problems of computer vision, especially human action recognition. Convolutional neural networks (CNNs) are the neural network that uses convolutional operator in their layers. Convolutional network is used for computing a grid of values such as images while recurrent neural networks (RNNs) are a type of neural network for processing sequential data, such as text and video. In this survey, we focus on proposed methods for human action recognition using deep learning techniques.[19]

E Suspicious Human Activities Based on Internet-of-Things

In recent years, ever-increasing technological advances have made automated human activity recognition a common research subject. Video surveillance has a wide range of applications. These applications include normal and suspicious activities such as gaming, human-computer interaction, exam invigilation, detecting chaos, analyzing sports, predicting crowd behavior, etc. It is an important safety aspect for indoor and outdoor environments [20].

Innovations are occurring rapidly, and since there is a large amount of video data to process, manual intervention is not feasible and is error-prone. Additionally, it is exceedingly challenging to monitor public spaces constantly. Hence, it is necessary to install intelligent video surveillance that can track people's movements in real time, classify them as routine or exceptional, and provide alerts [21].

Human activity detection relies on sensors like radar, cameras, and cell phones to identify abnormalities in human behaviour. They are being used for human-computer interaction, surveillance, monitoring suspicious activities, and other security purposes [22, 23]. The majority of today's systems rely on video gathered from CCTV cameras. If a crime or act of violence occurs, this footage will be utilized in the investigation. It would be preferable, however, to build a system that might identify an anomalous or unexpected circumstance beforehand and notify the authorities [24, 25].

In recent years, ever-increasing technological advances have made automated human activity recognition a common research subject. Video surveillance has a wide range of applications. These applications may include normal and suspicious activities such as gaming, human-computer interaction, exam invigilation, detecting chaos, analyzing sports, predicting crowd behavior, etc. It is an important safety aspect for indoor and outdoor environments [26, 27].

Currently, innovations are occurring at a rapid pace. The most popular exploration topic these days is robotized human activity recognition. Since there is a large amount of video data to process, manual intervention will not only be tiring but also cause omissions, making the system effective and error-prone. Automatic video surveillance has tacked on this issue. It is impossible to monitor CCTV events manually. Whether the event has already occurred or not, searching for the desired event through recordings is extremely time-consuming. However, a system that automatically senses any irregular or abnormal condition in advance and alerts the appropriate authorities is more appealing. It can be used in indoor and outdoor settings [28].

Different efficacious algorithms are used for automatic activity recognition on roads, airports, educational institutions, offices, etc. Computer vision has provided machines with humanlike vision. Large datasets are accessible and can be trained with GPUs' to help make future predictions. Computer vision technology has a few stages, like taking input from surveillance cameras, separating the frames, classifying and labeling the activity, and writing its description. Normally, two types of classification techniques are used in computer vision. Supervised and unsupervised; supervised classification requires manual labeling whereas unsupervised is completely computer-based and does not need computer intervention [28].

Deep learning is the most exemplary architecture that learns difficult tasks among other architectures. It extracts features from images automatically and portrays significant information about the image. Since it extracts features automatically, it makes it more convenient to use. CNN learns visual patterns directly from pixels [28]. Long short-term memory (LSTM) models can be used for videos as they can recall things for a longer time. The proposed work implemented the YOLOV4 for detecting the different activities related to surveillance and for recognizing the activities, 3D CNN is used. Multiple cameras are connected to the centralized system via IoT (Internet of Things) protocols. Ethernet communication creates a local server to access each camera feed through its specific IP address used in the centralized GPU for prediction [28].

F Human-activity-recognition- Military Restricted areas

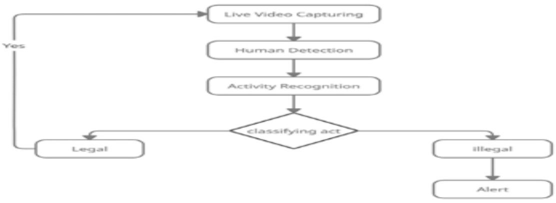

Fig.5 Human Activity Recognition-System Architecture

The recognition and analysis of daily human activities is an attractive area for the researchers due to its effectiveness and wide applications in various domains. Human activity recognition (HAR) aims to provide information on physical activity and to detect simple or complex actions in real world . Human activity recognition is an active research area in last decades due to its applicability in various fields and increasing need for home automation and convenient service for elderly ones. Human activity recognition has been revolutionized in various domains such as healthcare, sports, entertainment etc. It involves behaviour and environment monitoring, activity modelling, data processing and pattern recognition. We use IoT technologies to monitor in real time or to get sensitive data to be analyzed for security purposes. Artificial intelligence is one of them which is used to detect a human activity and is trendy nowadays.

Artificial intelligence aims towards building machines that are capable to think like humans. It refers to systems or machines that mimic human intelligence to perform tasks and can continuously improve themselves based on the information they collect. An Artificial Neural Network (ANN) in the field of Artificial intelligence attempts to mimic way nerve cells work in the human brain. It makes understanding of computers easy to make decisions similar to a human-brain. The artificial neural network is trained to behave like interconnected brain cells by programming computers. It utilizes computer software programs that analyse the audio and images from videos in order to recognize humans, vehicles, objects, attributes, and events. It has been proven a very useful technology to detect illegal occurrences to avoid threats and maintain security.

Recognition of human activity is an ability to look over the movements/gestures of the human body and to determine human action/activity. If the majority of routine human tasks can be identified by activity recognition systems, they can either be made simpler or mechanised. The main objective of HAR framework is to observe and analyze human behaviours efficiently, understand the human actions and then to retrieve and process the relative data. Abnormal activity recognition is another area of research for public safety. In public sectors CCTV cameras are used to monitor the crowd activities and track the motion of suspicious activities. HAR has attracted a great amount of attraction in past decades due to its great value in wide range of real-world applications.

In this study we have proposed a HAR system that collects data and uses ANN for classification in military restricted areas. For compound security, a military system must be able to identify specific human behaviours. To secure military installations or other critical infrastructure, early identification of human activity that suggests a potential danger is required. The variety of human actions makes their automated recognition a real issue.

There are activities that are performed by person such as running, fighting, picking up an item, exchanging items, digging, entering restricted area etc. The area of human action recognition is related to other ways of research that analyze human actions from images and video. We focus on actions and do not explicitly consider context such as the environment, interactions between persons or objects. Moreover, we consider only full-body movements. The system must be able to represent each of these components in order to be able to recognize a wide range of human actions. To identify the focus of attention, the person is distinguished from the rest of the scene. Based on the position of key points system can generate alerts in real time when potential assault is in progress.

VII. CONCLUSION

We have shed light on various types of Human Activities and its recognition. We have reviewed on (i) wearable inertial sensors and (ii) external devices like video cameraswhich are the two common approaches for HAR. The biodiversity in Yangtze River Basin has been seriously affected due to the reason that the rapid population and economic growth requires lots of resources, and the intensity of development in the Yangtze River Basin continues to increase. High intensity human activities, includes water pollution, damming, wetland reclamation, channelization, and so forth, result in the habitat loss, fragmentation, and destruction of aquatic organisms .Hence it is concluded that human activities play a significant role with respect to activities related to environment, aquatic life, I-O-T (Internet Of Things) etc.

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