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Review On Human Body Action Recognition System Using ELM Algorithm

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Abstract: Human action recognition is the field of research that has gained importance in the recent years because of its wide range of applications spread across different fields. Human action recognition plays a crucial role in human-to-human interaction and also interpersonal relations as it provides the information about the identity, personality and psychological state of the person. The human ability to recognize other person's activities is one of the major subjects of study of the scientific areas of computer vision and machine learning and because of this research many applications such as video surveillance systems, human-computer interaction, control free gaming systems, etc. require multiple action recognition system. Human action recognition also has a very significant use in security systems installed in public places to track any suspicious activity or threat. This project aims to develop an algorithm which can recognize actions such as jogging, bending, bowling, jumping, kicking, running etc. from the input video sequences. The multiple actions in the video sequence will be detected with each passing frame of the video sequence.

Keywords: Human action recognition, computer vision and machine learning.

I. INTRODUCTION

Human Action Recognition (HAR) basically refers to the task of analyzing the video sequence in order to recognize the activity or action that is taking place in that particular video. Detecting human activities in detail is very beneficial in areas which are particularly human centric such as home care support, abnormal activities, exercise and fitness, etc. Most of the human's daily task can be automated if such actions are recognized by HAR system. According to the complexity, the human actions are categorized into: atomic actions, gestures, group actions, human to object or human to human interactions, events and behaviors. Atomic actions refer to the movements of a person which describes certain motions that may be the part of more complex activities. Gestures are basic movements of the body part that corresponds to particular action of the person. The activities that involve two or more persons or objects are called as human to object or human to human interactions. The activities that are performed by group of persons is called as are called as group actions. Events refers to the high-level activities that describes social actions between individuals. Human behavior means the physical action that are related with the personality, emotions and psychological state of the individual. HAR systems are usually based on unsupervised or supervised learning. Unsupervised system has set of rules during its development whereas supervised system requires training using labelled data sets. In supervised method, the computer is provided with example inputs that are labelled with their desired outputs. In the unsupervised method, the data is unlabeled. As the technology is rising up the use of internet and smart phone are increased. The action recognition in the personal videos has become an important research topic due to its wide applications such as automatic video tracking and video annotation. Human action recognition has also its wide use in the area of security surveillance. Any suspicious activity can be identified with the use of human action recognition and it can help in security concern.

II. LITERATURE SURVEY

A With respect to our problem statement, we have referred research papers related to our project human body action tracking and recognition using ELM algorithm. This section summarize the various research papers on human body action tracking and recognition using ELM algorithm.

A Survey on Human Activity Recognition and Classification: This paper was proposed by Abhay Gupta, Kuldeep Gupta, et al., which focused on recent research papers based on various methods of activity recognition[1]. They mainly conducted their survey on three popular methods of activity recognition, namely smartphone sensors, wearable devices and vision based or using pose estimation.

Human Action Recognition Based on Skeleton and Convolutional Neural Network: In 2019, Yusi Yang, Zhuohao

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Cai, et al., have proposed the method which is based on data preprocessing using human skeleton information to recognize human action through Convolutional Neural Networks [2]. The authors have presented a Convolutional Neural Network (CNN) based automatic human action recognition method, which automatically learns the spatial and temporal characteristics of the data in order to improve the performance of recognition. In this paper interframe difference method is used to extract the key frames.

Subject Identification using Walking Posture: In 2019, Mihaela Hnatiuc, Mirel Paun, et al., have proposed amethod to recognize the posture during walking with the help of leg inclination [3]. This system uses deflection sensor and mobile phone tilt sensor. The mobile phones are attached at the back side of the foot above and below the knee. The flex sensor is positioned on the foot. The system identifies the subject after the walking posture.

Human Action Recognition using Deep Neural Networks: This project was designed by Rashmi R. Koli, Tanveer I. Bagban in 2020 to develop a platform for a hand movement recognition which recognizes the hand gestures [4]. Human action recognition in other words is human gesture recognition. Gestures are nothing butthe movement of body part that convey some meaningful message. In this project, they have used CNN algorithm as an interpreter that interprets the gestures and it builds a statement from the video. The statement or text is the meaning of those gestures.

An Overview of Extreme Learning Machine: Extreme Learning Machine (ELM) is one of the most important topics in the field of artificial intelligence in recent years. ELM has been widely used in human action recognition, multiclass classification and other fields. ELM provides efficient learning framework for regression, classification, feature learning and clustering [5]. It has much faster learning speed compared to traditional Support Vector Machine (SVM). In recent years the ELM applications have increased rapidly.

Human Activity Recognition Based on Evolution of Features Selection and Random Forest: In 2019, Christine Dewi and Rung-Ching Chen have proposed a study on dataset for Human Activity Recognition (HAR)which is based on four methods Support Vector machines (SVM), K-Nearest Neighbors (KNN), Random Forest (RF) and Linear Discriminant Analysis (LDA) with the different features to select the best classifier among the models to test the dataset [6]. From the experiments and analysis on different dataset it was concluded that among this four the RF is the best classifier method.

Action Recognition by Dense Trajectories:(Heng Wang, Liu Cheng-Lin, Alexander Klaser, Cordelia Schmid) In this paper a very effective and efficient way to extract the dense trajectories is discussed. Using the optical flow fields the densely sampled points can be tracked and then the associated trajectories can be obtained. The scaling of these tracked points is done in much easier manner due to pre computation of denser flow fields. Moreover, the imposition of global smoothness constraints over the points involved in dense optical flow field also results in more robust trajectories unlike matching or tracking of points separately. These dense trajectories are denser and more robust to that of the trajectories of KLT tracker

A very usual problem occurred in this process of tracking is drifting. During the process of tracking the trajectory drifts a bit, usually from its original location. So, to avoid the very occurrence of this problem the length of trajectory is limited to L frames. If the trajectory has greater length than L it is excluded from the process of tracking. These dense trajectories are assessed on standard datasets like Hollywood2, YouTube, KTH and UCF sports. The datasets used are very diverse in nature and can track the activity in different kinds pf scenarios. Also the implementation of KLT tracker is done from OpenCV to compare the dense trajectories with standard KLT tracker.

Behaviour Recognition via Sparse Spatio-Temporal Features: (Piotr Dollar, Garrison Cottrell, Vincent Rabaud, Serge Belongie) This paper presents the work of doing behavior recognition by characterizing the behavior according to spatiotemporal features. They have presented a new spatiotemporal interest point along with analysis of many cuboid descriptors. Due to the use of these cuboid prototypes, an efficient as well as much robust behavior descriptor is implemented.

Many different types of datasets are compiled together into 3 different datasets namely facial behavior, mouse behavior and human activity. As the differences between behaviors can be very minute or indistinct therefore the optical flow calculation can sometimes be faulty or imperfect. To overcome such defects the datasets are highly trained in recognition of activities having different characteristics and occurrences. The repetition of some activities are also stored as subsets in a dataset.

Action Recognition with Improved Trajectories: (Heng Wang, Cordelia Schmid) In this paper improvisation of dense trajectories is done by explicitly estimating the camera motion. It is shown that performance can be improvised by removing the background trajectories by estimating approximation in camera motion.

In this model four datasets are used – Hollywood2, HDMB51, Olympic Sports and UCF50. These datasets are implemented for effective categorization of activity detection. In the experimental setup of this model the presentation of

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implementation details of the features of trajectories is done. Firstly a brief description of dense trajectories is given which are used as baseline in the experiment. The features are
encoded using bag of features and Fisher vector.

III. METHODOLOGY

1. **Video Processing:** By identifying the actions of the video input, a specific video play is analyzed. The entire video is framed independently at a certain frame rate. Actions on video are framed by frame and appropriately labeled based on a pre-trained data set used for this project. Video processing is a form of signal processing, especially image processing, in which input and output signals are video or video streams. We can also process video processing with the help of image processing if we are able to increase the speed or rate at which the frames in the video are processed. If we process images in batches, the same processing power can be used and we can speed up the process.
2. **Image Processing:** Image processing is a method of performing specific tasks or analyzing an image. In this process, we get an improved image or extract some useful information from a particular image. Image processing is a type of signal processing where we provide input such as an image and output that we receive can be an image or features associated with that image. Two types of image processing methods are analogue and digital image processing. Analogue image processing is often used for hard copies such as printing and photography. Digital image processing techniques create the illusion of digital images with the help of computers. Other common categories that all types of data are required to use while using the digital process are pre-processing, development, display and retrieval of information.

2.1. OpenCV: OpenCV (Open Source Computer Vision Library) is a library of program functions that focuses on real computer vision. OpenCV-Python is a library of Python bonds designed to 9 solve computer vision problems. OpenCV-Python uses Numpy, a highly optimized library of numerical performance with the MATLAB syntax. All properties of the same OpenCV members are converted and removed from the same Numpy members. This also makes it much easier to integrate with other Numpy libraries such as SciPy and Matplotlib.

3. **Artificial Neural Networks**: A neural network consists of artificial neurons or layered nodes, which take a specific input vector and convert it to output. In this process, each neuron picks up input and activates a function that is usually a nonlinear activity and transmits the result to the next layer.

4. **Python:** Python is a goal-oriented programming language developed by Guido van Rossum that is becoming increasingly popular, especially because of its easy-to-read and code-readability. It enables the program editor to display ideas in a few lines of code without reducing readability. Python is a very simple and easy to use language compared to other languages such as Java, C, etc. The functionality in python is also useful compared to working in MATLAB. Also, one of the disadvantages of MATLAB is that it is not an open source and license is very expensive. Since python is an open source, in the event of an error, we can search it directly online and fix it. Some benefits of python are Easy to read, learn and write, Portability, Free and Open-Source, etc.

5. **Extreme Learning Machines (ELM):** Extreme Learning Machines (ELM) is a feedforward neural network used for division, retrieval, integration, feature reading and compression by a single layer or multiple layers of hidden modes. ELM has advantages such as countless functions, pattern matching, automatic code formatting, good error correction and overcoming slow learning speed. ELM makes managing the flow of data between objects much easier as it offers new design code editing. With the use of ELM, we do not need to compare between the various components of the system so we can focus on problem solving.

6. **Tools Used:** Anaconda is a distribution of Python and R computer programming languages for computer science including data science, machine learning applications, big data processing, forecasting statistics, etc. It aims to simplify package management and shipping. This distribution includes data science packages suitable for Windows, Linux, and MacOS. Anaconda distribution has more than 250 automated packages, and more than 7,500 open-source packages can be downloaded from PyPI as well as a conda package with a visual environment manager. Anaconda is an industry standard for growing, testing and training on a single machine.

7. **Flowchart:** At first the input image is taken, this input image is taken after converting to frame-by-frame from video input. The image will be checked through neural network, for this purpose the unlabelled data is used. The image that matches with the dataset is used. Feature extraction is used to recognise action and after recognising the action the movement is recognised in feature extraction. Classifier is used to select the particular class from the multiple classes to give the data. The data with which the input image matches the most is chosen. Finally, the image tag is displayed which gives the information about the action being performed in the video sequence.

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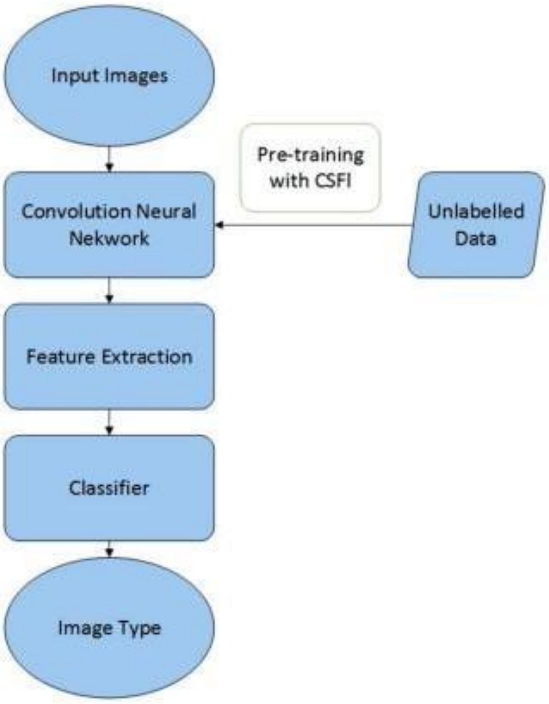

8. CNN classifier for human action recognition: In this section, we describe the underlying principles in the computation of action bank features for a video. We will later explain some of the characteristics and advantages of action bank features that motivated us in their use as input features. Finally, the design of the convolutional neural network classifier for human action recognition from action bank features is explained in detail.

8.1. Input features: Introduced by Sadanand et al. in [8], the action bank representation of videos is a high level representation used for activity recognition. An action bank is a collection of multiple action detectors covering a broad semantic and viewpoint space. An action detector is a template video of an action. To generate action bank features for a video, the correlation video volume of each action detector is transformed into a 73- dimensional response vector by volumetric-max-pooling. Thus, if an action bank of size m is used for computing action bank features of a video, the generated action bank features will be of size m _ 73. Since, an action detector may have similar response vector for multiple instance of the same action, their action bank representation may also have similar local patterns. The action bank representation of boxing and running videos from KTH dataset is shown in Fig. 3. It can be observed that videos of same action will have similar local patterns corresponding to some action detectors, depending on their nature and extent of similarity. Therefore, it is possible to discriminate actions by using a pattern recognition approach that can learn local patterns associated with each action. In this work, a convolutional neural network classifier capable of recognizing local patterns with some degree of noise is used to recognize human actions from action bank features.

8.2. Configuration of CNN classifier: A convolutional neural network (CNN) classifier comprises of a convolutional neural network for feature extraction and a classifier in the last step for classification. The architecture of CNN classifier used for human action recognition from action bank features is shown in Fig. 4. To avoid padding during computation, the first 72 elements of action bank features are considered, resulting in an input of size m 72. Here, m represents the size of action bank used for generating action bank features. During training, the convolution masks are learned to recognize the necessary discriminative local patterns for classification. As the local patterns in action bank features are horizontal and independent of its vertical neighbors, only linear (horizontal) convolution masks are used in the CNN classifier. A single convolution mask is considered in the first convolution layer due to the simplicity of the pattern being recognized (a white line) and to minimize the computational complexity. We doubled the number of masks in the respective succeeding layers and used two convolution masks in the second convolution layer. In addition, to use the same mask size in both convolution layers, we chose a mask size of 1_21. The subsampling masks of size 1_2 are used to minimize the loss of data during sub-sampling. The deep convolutional features extracted by CNN are given as input to a fully connected, single layer neural network for classification. The action labels are determined from the binary decoded outputs of the classifier. As the convolution masks in CNN classifier act as feature detectors, optimal initialization of these kernels is crucial for the design of an effective CNN classifier.

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Parameters	Results from Proposed Method	"Robust Human Action Recognition System via Image Processing" Anitha Umanath, R. Narmadha, D. Raja Sumanth, D. Naveen Kumar.	"Human Action Recognition using Image Processing and Artificial Neural Network" Chaitra B H, Anupama H S, Cauvery N K.
Accuracy	94 %	---	---
Kinetics data set	400	350	300
Prediction time	2 sec	3 sec	5 sec
Video duration	16 sec	18 sec	22 sec
Software Used	Anaconda	MATLAB	2D- DCT
Image processing method	CNN	KNN Classifier	Self Organizing Map (SOM) Neural Network

Table 1. Comparison with different methods

IV. APPLICATIONS

The major applications of human body action tracking and recognition using ELM algorithm are: to track suspicious actions from CCTV footage's, violence detection on the road and public places, to track the most wanted human's action and walking pattern so police can recognize them on a fake face, in sports for recognizing player's action while playing, in tracking motion patterns of humans that could be used to help identify people experiencing dangerous conditions such as a seizure, heart attack or serious fall, in the exercise and fitness field, in gaming and animations.

V. FUTURE SCOPE

In future, system can be made more precise, for example, it will make clear distinction between almost similar types of activities like Stair Case Down-and-Walking and Jogging-and-Running. We can also make advancements in our system so that it can carry out different kinds of human physical analysis like heartbeat, pressure, specific disease like asthma and other medical issues. Constant monitoring and implementation for better analysis can be done by improving the system further. Implementation of wireless client-server architecture can be developed. Moreover, Innovations such as implementation of complete automated on-chip system for data collection and analysis can be made and accounting other prospective of data classification, application of digital filters with variable filter size.

VI. CONCLUSION

In this paper we have presented the technique by which we can identify the human actions being performed in the video input. The literature survey on human action recognition shows that there has been plenty of research in the area of video analysis and human action recognition. After the emergence of neural networks, there has been a lot of research related to this topic in past 5-6 years. The Frame-by-Frame application of CNNs helped in improving the accuracies as compared to the manual feature extraction techniques. After that, 3D-CNNs has further improved the accuracies of CNNs by processing multiple frames at a time. More recent architectures have started focusing on Extreme Learning Machine (ELM) in order to factor in the temporal component of the videos. The most recent architectures have started developing attention mechanisms to focus on the important parts of the videos. Human action recognition is still an active research area, and new approaches are being presented to solve the issues with the current approaches. Some of the existing issues with human action recognition are background clutter or fast irregular motion in videos, view point changes, high computational complexity and responsiveness to illumination changes.

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