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High Jump, Long Jump, Triple Jump Pole Vault Classification

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***Abstract*— This paper discusses computer vision-based human activity recognition. The major issue is being able to identify human behavior. The main issue for video categorization systems is common human actions in videos. For instance, a running motion will be included in a long jump or running sports film. Due to its multiple applications in areas like person monitoring, human-to-object interaction, and more, human action recognition is a crucial study subject in the science of computer vision.**

A pre-trained CNN model for feature extraction serves as the foundation for human action recognition. Deep learning methods include convolutional neural networks (CNN). The majority of convolutional neural networks (CNNs) used for recognition tasks are constructed using convolution and pooling layers, followed by a small number of fully connected layers, and identifying similar patterns in an interval to recognize the action with accuracy of 79–90% depending on the task.

The computer vision community finds the video classification problem to be very difficult. The main reason that the video categorization problem is so challenging is the shared activities that are seen in the video. A high jump sport film, for instance, combines two distinct actions—running and high jumping—that are also shown in other videos, like running or hurdling sports videos.

With just one frame that captures the specific action of the event, the human brain can quickly identify the correct occurrence in a film. By removing a few significant frames from the video and using those frames to conduct the classification procedure, the same premise may also be used to video classification systems.

***Index Terms*— Object Detection, Video Classification, open-CV, Human Activity Recognition, Human Behavior Analysis, CNN.**

I. INTRODUCTION

A method of predicting a person's activities based on a predetermined sequence of that person's actions and external factors is known as human activity detection. The challenge of activity recognition affects a number of social applications, including smart surveillance, smart robots, and other tracking systems. The method of analysing human motion using computer and machine vision technology is known as human activity recognition (HAR). Sensors can record activities, gestures, or behaviours that are interpreted as human motion. The action commands are then transformed from the movement data into human activity recognition code that computers can interpret and execute.

In order to correctly classify the action that is being performed, Human Activity Recognition is a particular kind of time series classification challenge. From the straightforward structure from motion paradigm to the identification of actions as events, image processing has advanced. The vast area of research known as "human activity recognition," or simply "HAR," focuses on pinpointing a person's precise movement or action using sensor data. Movements include common indoor activities like walking, talking, sitting, and standing.

Object detection, environmental change, agriculture, land use/land planning, urban planning, surveillance, geographic mapping, and disaster management are just a few of the applications for which image classification is crucial in remote sensing images. It is also a hot research topic in the remote sensing community. The technique of classifying and labelling groups of pixels or vectors within an image according to predetermined rules is known as image classification. Supervised and unsupervised classification are two techniques.

The method of classifying a specific object in an image is known as image classification. The main objective of this technique is to precisely detect visual features. The two types of image categorization methods are supervised and unsupervised. This method gives the results for supervised classification based on the decision boundary produced, which primarily depends on the input and output provided during training the model. Unsupervised classification, however, relies on study of the input dataset to provide results; features are not directly fed into the models.

Choosing an acceptable classification system, feature extraction, selecting quality training samples, choosing an ideal classification method, post-classification processing, and ultimately evaluating overall accuracy are the primary phases in image classification systems. The most prominent neural network model that we can use to solve the picture classification problem is convolutional neural networks (CNNs).

The location of items in a picture, also known as object localization, and the categories to which they belong, or their categorization, are determined through object detection. Simply put, object detection is a form of image classification

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technique that locates instances of objects in natural photos from a wide number of specified categories.

The next-generation image and video processing systems have successfully adopted this technology, which may be used to look for a certain class of objects like automobiles, people, animals, etc. Only with the introduction of deep learning approaches have the most recent improvements in this methodology been made available. Therefore, for high jump, long jump, and pole vault classification, we will use video.

II. LITERATURE SURVEY

The fundamental challenge in this paper's discussion of human behavior recognition is bridging the semantic divide between analogue observations of the physical world and the symbolic realm of human interpretation. In the communities of computer vision and video processing, human motion analysis is a significant subject of interest.A new architecture for online human action recognition in athletics sports videos is suggested in the article. Because the TBM framework is used rather than the conventional probability theory, the proposed approach is new. Belief functions, which are more versatile than probabilities, constitute the foundation of the TBM [1].It primarily concentrates on modelling the human body, high-level recognition algorithms with domain expertise, and the amount of detail required to comprehend human activities. Knowing what is happening in the situation is the ultimate goal of learning human motion. High-level scene and context knowledge is part of the objective [2]. Computer analysis of human behavior is becoming a subject of increasing interest. The act of capturing the motion, also known as human motion capture, is a crucial component of this endeavor. Applications where one or more subjects are tracked over time and maybe watched for specific actions fall under the surveillance category. The surveillance of a parking lot is a well-known example, where a system monitors individuals to determine whether they may be going to conduct a crime, such as car theft [3]. Video human action recognition is a difficult topic with many potential solutions. In this study, a straightforward representation is suggested that is intended to reflect such motion interactions. To describe motion information and make the final representation resistant to camera movement, we use both global and local reference points.In computer vision, there is currently considerable study on the problem of human activity recognition in videos. Recent years have seen significant advancements, particularly with the development of the bag-of-features architecture and local invariant features. We have outlined a method for motion-based action modelling in this study [4].This study presents a method for video recognition that involves extracting the key frames from a video, classifying those frames with a CNN classifier, and averaging the predictions for all of the extracted frames. The concept behind the system was drawn from how people categories events in videos, where the most significant or captivating frames have a greater influence on the choice of event category than other, less consequential frames [5].Applications for human motion analysis can be found in a wide range of fields, including sports analysis, surveillance, and content-based image storage and retrieval. Detecting, locating, and identifying humans as well as recognizing human activity are the key scientific difficulties in human motion analysis. In this study, they covered topics such as pole identification, motion analysis of human shape, and human shape.The Transferable Belief Model (TBM)-based framework for human motion analysis has shown to perform well in identifying athletes' motions and activities. The TBM enables the representation of uncertainty and conflict that is not possible in conventional probability theory. Both the Temporal Credal Filter, which smooths belief on actions, and the Belief State Scheduler, which identified activities as a sequence of intelligible actions, fully exploit these principles in this study [6].Finding groupings of athletic disciplines that have an impact on men's decathlon performance is the issue. The clustering techniques for categorizing groupings of sports disciplines in the decathlon structure were employed in this paper. Using hierarchical models, groups of athletic disciplines that influence sports performance can be identified [7].In this paper, we provide a tool termed the temporal credal filter with conflict-based model modification for online smoothing of belief functions in the transferable belief model (TBM) framework. In order to combine beliefs, the TCF-CMC explicitly models conflict information in TBM and considers temporal characteristics of belief functions [8].

This study demonstrates the value of using temporal structures to distinguish between simple and sophisticated human actions. Other sorts of contextual data as well as richer video representations are other future directions [9].The detection of the launch frame in long jump videos is the issue. Matlab is the programme utilised, and the OpenPose method is what builds the project[10].The issue is centred on the use of computer vision in sports analysis, ball tracking, and player monitoring. For this project, no hardware is used at all. The benefit is that it expands the scope of applications for resumes[11].Convolutional and recurrent neural networks are used to categorise 15 different sports, which is the issue. The programme is called Vs-code. CNN, RNN, GRU, and VGG-16 are the algorithms that are employed[12].Object detection and identification is the issue. The vs-code programme is also utilised here [13].Long Jump Mathematical Analysis is the issue. No software is utilised here [14].Using computer vision to detect and track things is problematic. Single Shot Detector (SSD) and MobileNets algorithms are the ones that are utilised. The benefit is an average real-time detection level for all items above 99% [15].The issue is Python-based face detection, eye detection, and Haar-features. The Cascade Classification algorithm is employed [16].Finding objects in videos to extract is the key issue. Background separation and

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Haar Cascade methods are employed in the algorithm. Long Range Detection offers an advantage [17].

III. METHODOLOGY

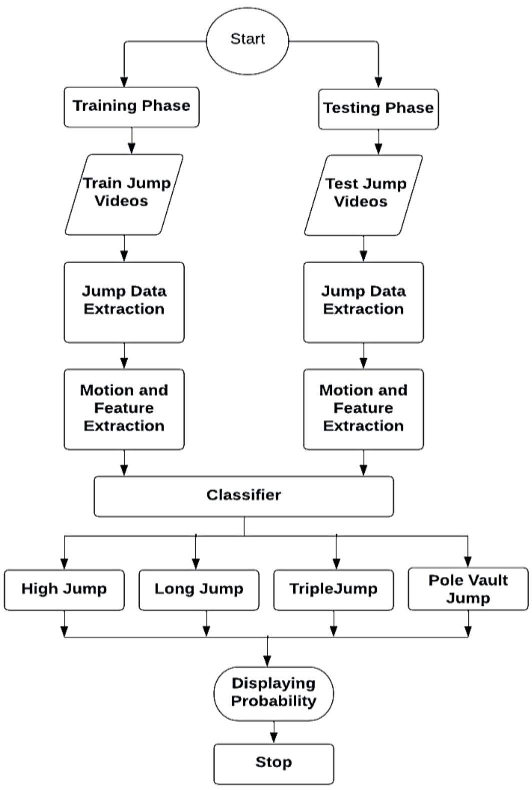

Fig 3.1. Flowchart of proposed system.

This paper intends to classify the four different types of jumps, High jump, long jump, Pole Vault jump and Triple Jump. Various python modules have been used to train the model or create the dataset, extract features from the video for creating the model. Sample videos are installed in the train dataset which are referred to or compared with the test videos given to the system. Since jumping is an action then comparison between different videos shall be done. Image comparison becomes easy as it has two single frames. In this paper, when it comes to video comparison the videos are accessed with python function videocapture so multiple frames or images are captured of the video and since each image may give a different output then a collective output is obtained using the concept of CNN. Also, there can be different number of frames in different videos so it becomes difficult to compare frames. Here the concept of padding is used. (Padding is the concept where null or empty frames are added in the video for the purpose of making the number of frames in both the videos equal.) Comparison is done on the basis of features of the image. The features of each frame are different and are extracted using the keras function of the tensorflow module. Comparison of these images is done on basis these features.

Fig 3.2: High Jump

Fig 3.3: Long Jump

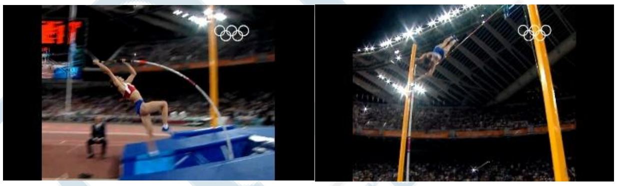

Fig 3.4: Pole Vault Jump

Fig 3.5: Triple Jump

Since these jumps are quite similar sometimes error May appear because the body positions and postures of the jumps are quite similar. If long jump(Fig 3.3) and triple jump (Fig 3.5) is considered then the most common similarity in the frame is sand. If the frames are not divided properly during the time of hop then results appear will not be well and good..

Same happens with vault and high jump since the body postures are similar. If the pole Is properly detected then the results will be accurate. If else the results might be confusing between high and vault jump.

IV. RESULTS AND DISCUSSION

Table I. Comparison Between Different Types Of Jumps

Type of jumps	Dataset size	Accuracy	Prediction
High Jump and Long Jump.	169	92.84%	HIGH JUMP: 60.24% LONG JUMP: 39.76%
High Jump, Long jump and Triple Jump.	298	80.56%	HIGH JUMP: 42.68 LONG JUMP: 29.94 TRIPLE JUMP: 27.38
High Jump, Long jump, Triple Jump and Pole vault Jump.	482	75.0%	High Jump: 20.10% Long Jump: 20.07% Pole Vault: 19.94% Triple Jump: 19.94% [UNK]: 19.94%

In the above table, the results have been discussed of this paper. As one sees that when two sports have been selected the accuracy is seen to be 92.84%. Whereas when the category of the jumps is increased to three. That is when high jump, long jump, and triple jump are included the accuracy is dropped by almost 11 percent. Again in the final row when the jump categories are made 4 then the accuracy is dropped to 75 percentage. What concludes here is that when the jump categories are increased and the number of samples of a particular jump are increased then the accuracy is dropped accordingly. The reason behind this is that when the number of samples are increased then the computation part increases. Also, when the number of jump categories are increased the same happens.

In the first case in high jump and long jump, the body posture of the athlete trying to perform the jump is completely different and the major difference in them is that the landing destination of both the jumps is completely different. The landing destination of long jump is sand pit whereas the landing destination of high jump is soft cushioning material, which helps in distinguishing the type of jump that is performed.

In the second case where the triple jump is included along with high jump and long jump, the major resemblance is between long and triple jump. The common factors are the posture of the body and the landing destination that is the sand pit. The only factor helpful to distinguish between these two is that the triple jump itself includes three hops and long jump contains only one. Due to so much resemblance, the accuracy drops by such margin.

In the final case, all the jumps have been included. Long and triple resemble like discussed above. Here the high jump and pole vault jump are almost similar because the way the athlete jumps, his/her body posture in most of the cases are equal. In distinguishing these two, the difference is the pole that is used in the pole vault jump. Finally concluding, one can observe that due to the similarity between the jumps it becomes difficult to differ, but it is distinguishable. But, as the categories are increased, the accuracy drops.

V. CONCLUSION

We can conclude that the model can give results with an accuracy of around 80 percent. It is able to differentiate between the high jump, long jump, triple jump and pole vault jump. Video classification and feature extraction with good accuracy is possible by using the CNN algorithm. As the dataset increases the accuracy of the model may vary according to the quality of the videos that are included in the dataset. The duration of the video on a small scale won't matter, much as the minimum number of frames in the videos are the same.

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