International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 08 Issue: 04 | April - 2024 SJIF Rating: 8.448 ISSN: 2582-3930

Implementation of Sports Classification and Person Recognition System

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ABSTRACT

The Implementation of Sports Classification and Persons Recognition System addresses the growing demand for automated and intelligent solutions in the sports industry. This project focuses on the development and deployment of a robust system that combines sports classification and person recognition to enhance the overall experience for both athletes and spectators. Automatically categorize and classify different sports activities. The system utilizes real time video feeds or recorded footage to identify and distinguish various sports such as soccer, basketball, tennis, and more. This involves implementing facial recognition, body posture analysis, and other features to accurately throughout the sporting activities, athlete performance analysis, enables better coaching strategies, and enhances security measures in sports venues.

Keywords: Sports Classification, Person Recognition

I. INTRODUCTION

Sports are a major section of media, accounting for a massive portion of TV broadcasting, and they have become a dominant focus in the field of entertainment, to the massive commercial sports programs. With this rapid increase and the explosive spread of sport data, the need for fast and accurate access to the right information has become a challenging task with considerable importance for multiple practical applications. athlete detection, movement analysis and tracking,

The primary objective of the study is to evaluate the effectiveness of various algorithms or models used to detect and classify the sports and person recognition, Using Convolution Neural Networks and classified using various algorithms such as deep Implementation of Sports Classification and Person Recognition Deep learning architectures like ResNet, VGG (Visual Geometry Group), YOLO (You Only Look Once), and Faster R-CNN.

II. RELATED WORK

M. Ramesh and K. Mahesh (2022) [1] put forward a CNN (Convolution Neutral Network) on UCF101 and Sports1-M Dataset. Sports video classification begins with preprocessing. It involves a process known as frame extraction, which entails converting the given sports video into frames. A single video frame, or image, is obtained by pausing the sequence at a particular frame. Data collection and preprocessing proceeded before the key frame extraction task. Noise reduction is a highly attractive process for better video quality. In this paper, a fuzzy adaptive window-based Mean Filter (FAWMF) is used for preprocessing the sports video after the frames are extracted.
Only the two benchmark datasets are used for training and testing the proposed system. The proposed framework produced better accuracy compared with the existing architecture with various optimizers.

Mohamad, Samah S. Baraheem and Tam V. Nguyen (2021)[2] used a Transfer Learning with Photo bombing Guided Data Augmentation Due to the lack of availability of a specific Olympic Games dataset, the novel OGED generated in this project is an essential step. This dataset is used for training and testing purposes. This dataset will be made public along with thepublication. Since our OGED dataset contains 1000 images of different Olympic Games events,data augmentation needs to be applied to overcome the over fitting problem. Transfer learning falls under two categories: transfer learning using feature extraction and transfer learning using fine-tuning methods. The second type of transfer learning is the method that we use in this work. The learned models are lacking in explain ability. In this it show that the highest accuracy is achieved in all architectures with photobombing guided data augmentation with 84%, 85%, and 90% for AlexNet, VGG-16,and ResNet-50 respectively

Na Feng, Zikaim Song, Junqingn Yu,Yi-Ping Phoebe Chen, Yizhu Zhao, Yunfeng He, Tao Guan(2020)[3] uses SSET datasets for shot segmentation, event detection, player tracking in soccer videos. Shot segmentation is the basic pre-processing step for video summarization, video retrieval, and other content-based video analysis. Event detection includes detecting videoclips that containing pre-defined events from untrimmed videos, including localization and recognition. The visual tracking of objects has been successfully tackled by two methods which includes correlation filter based trackers and deep learning based trackers. This dataset is quite different from the public dataset as it fully consider the unique structures of the soccer video and design three main data types that involve video segmentation, event detection and object tracking.

Yunjun Xu (2021)[4] uses deep learning for targeting low classification accuracy caused by the randomness of objective movement in sports training video. Camera Calibration technology is used to restore the position of the target in the real three-dimensional space. After the camera calibration in the video, the sports training video is preprocessed. Input video segment is divided into equal length segments to obtain the subvideo segment.)e motion vector field, brightness feature, color feature, and texture feature of the subvideo segment are extracted, and the extracted features are input into the AlexNet convolutional neural network. It has simple implementation, fast processing speed, high generalization ability, and adaptability.

Rabia A. Minhas, Ali Javed, Aun Irtaza, Muhammad Tariq Mahmood and Young Bok Joo (2019)[5] uses AlexNet Convolutional Neural Network .The sports video content analysis techniques considers the shot classification as a fundamental step to enhance the probability of achieving better accuracy for various important tasks, i.e., video summarization, key-events selection, and to suppress the misclassification rates. The performance of the resultant classifiers from the combination of weak classifiers such as random forest will be analyzed. Theeffectiveness of the framework in terms of shot classification of field sports videos is better. Manual processing of such content for selecting the important game segments is a laborious activity. Therefore, automatic video content analysis techniques plays a important role inhandling the huge sports video repositories.

Siyu Zhang [6] uses faster R-CNN and aiming at the problems existing in faster R-CNN, the feature pyramid network (FPN) is used to extract aerobics action image features. So, the low- level semantic information in the images can be extracted, and it can be converted into high- resolution deep-level semantic information. Finally, the target detector is constructed by the above-extracted anchor points so as to realize the detection of aerobics action. It is difficult to adapt to the detection needs of multiscale and small target application scenarios in the processof aerobics action target detection.The vertical and horizontal ratio of anchors scientifically optimizes the overall neural network and improves the detection effect of multiscale and multi- person aerobics movements.

Yan Wang, Yuchen Zhang , LinJun Shen, and ShuMingWang[7] proposed a Convolution Neural Network(CNN) and deep learning gradient descent algorithm as the main research method to classify and regress the image features of sports video output. It uses 2D Human Pose Estimation which is based on OpenPose Architecture. This architecture employs deep learning techniques, specifically a real-time multi-person keypoint detection neural network. It uses a part affinity field (PAF) to associate body parts and accurately estimate keypoint locations, making it a powerful tool for human pose estimation in various applications, including action recognition and augmented reality. This achieves 95.1% accuracy and achievesthe best in all indexes.

S. Uma Maheswaril and R. Ramakrishnan [8] used a Nearest Neighbour Classifier which is based on distance function, KNN classifier assigns the class of the unknown object into one of the known training object's class. It also usesNon Subsampled Shearlet Transform (NSST),in order to design an efficient sport categorization system, novel multi-scale geometric characteristics of NSST is employed as feature extraction technique due to its optimal representation of image edges and capturing the geometric features of multidimensional data. The proposed system achieves maximum average classification accuracy of 94.80% at 4 directions of 2-scale NSST features while using city block distance measure in KNN classifier.

III. COMPARISON AMONG MODELS

The Comparision of various models proposed by different authors is given by Table- 1 depictedbelow. Table-1: Comparision Among Models

Title	Reference	Research Focus	Remarks
Sports Video Classification Framework Using Enhanced Threshold Based Keyframe Selection Algorithm and Customized CNN on UCF101 and Sports1-M Dataset.	M. Ramesh and K. Mahesh (published 2022)	CNN (ConvolutionNeutral Network) [85%-89%]	Limited Datasets are Used.
Olympic Games Event Recognition viaTransfer Learning with Photobombing Guided Data .	Mohamad ,Samah S. Baraheem and Tam V.Nguyen (published 2021)	Transfer learning andphoto bombing guide data augmentation. [84%-90%]	Learned models lacking in explain abilities.
SSET:a dataset forshot segmentation, event detection, player tracking insoccer videos.	Na Feng,Zikai Song,Junqing Yu,Yi-Ping Phobebe Chen,Yizhu Zhao,YunfengHe,Tao Guan.	Unique datasets are used for soccer video and design.	Lack of Comprensive and available datasets for soccer event detection.
Sports Training Video Classification Model Based onDeep Learning.	Yunjun Xu (published 2021)	Camera Calibration Video PreprocessingFeature Extraction.	Accuracy is not high compared to similar projects.

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Shot Classificationof Field Sports Videos Using AlexNet Convolutional Neural Network.	Rabia A. Minhas , Ali Javed, Aun Irtaza, Muhammad Tariq Mahmood andYoung Bok Joo (published 2019)	AlexNet CNN. Convolutional neural networks. Deep learning. Rectified linear unitlayer Shot classification.	Performance of the resultant classifiers from the combinaton of weak classifiers such as random forest will not be analysed.
Detection of Aerobics ActionBased on Convolutional Neural Network.	Siyu Zhang (published 2022)	FPN MultiscaleFeatures. The Multiscale Multiplayer Aerobics Action Target Detection Algorithm of CNN. ROIs Extracted from Multiscale RPN. Multiscale Aerobics Action Target Detector.	Difficult to adapt to the detection needs of multiscale and small target applications in aerobics.
Analysis and Research on HumanMovementin SportsScene	Yan Wang, Yuchen Zhang, Lin Jun (published 2021)	Deep Learning Method.2D Human Pose. Estimation Based on Open Pose. [95.1%]	Not sufficient for high efficient from large number of exercise data.
Sports Video Classification using Multi Scale Framework and Nearest Neighbour Classifier.	S. Uma Maheswaril and R. Ramakrishnan	K-Nearest Neighbour Classifier and Non Subsampled Shearlet Transform (NSST) [94.80%]	While increasing the NSST decomposition from 2 to 3,the performance of the proposed sports video is degraded.

IV CONCLUSION

Analysis of the processed video data is one of the hot topics in imaging and video field where segmentation plays a vital role. Here the tasks was further more complicated because along with the images the video should also be segmented as image and then analyzed.

By referred many techniques for implementation of our project and at last founded that we can use the CNN(Computer Neural Network), the project employs deep learning architectures like ResNet, VGG, YOLO (You Only Look Once), and Faster R- CNN for tasks such as image and video analysis, object detection, and facial recognition. GPU acceleration ensures efficient processing of computationally intensive tasks, enabling real-time or near-real-time performance. Additionally, ethical considerations are addressed through privacy-preserving techniques, ethical AI guidelines, and adherence to privacy regulations.

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