How to Cite:

Murthy, R. K., Dhanraj, S., Manjunath, T. N., Prasad, A. N., Pareek, P. K., & Kumar, H. N. (2022). A human activity recognition using CNN and long term short term memory. International Journal of Health Sciences, 6(S6), 10797-10809. https://doi.org/10.53730/ijhs.v6nS6.12919

A human activity recognition using CNN and long term short term memory

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Abstract---Human activity recognition aims to work out the activities performed by someone in a picture or video. Examples of actions are running, sitting, sleeping, and standing. Complex movement patterns and harmful occurrences like falling may be a part of these activities.

Manuscript submitted: 9 May 2022, Manuscript revised: 18 July 2022, Accepted for publication: 27 August 2022

International Journal of Health Sciences ISSN 2550-6978 E-ISSN 2550-696X © 2022.

The suggested ConvLSTM network can be created by successively combining fully connected layers, long immediate memory (LSTM) networks, and convolutional neural networks (CNN). The acquisition system will pre calculate skeleton coordinates using human detection and pose estimation from the image/video sequence. The ConvLSTM model builds new controlled features from the raw skeleton coordinates and their distinctive geometric and kinematic properties. Raw skeleton coordinates are utilized to generate geometric and kinematic properties supported by relative joint position values, joint differences, and their angular velocities. By utilizing a multi-player trained CNN-LSTM combination, novel spatiotemporal directed features can be obtained. The classification head with completely connected layers is then utilized. The suggested model was tested using the KinectHAR dataset, which consists of 130,000 samples with 81 attribute variables and was compiled using the Kinect (v2) sensor Experimental data is used to compare the performance of independent CNN and LSTM networks.

Keywords---human activity recognition, convolutional neural network, deep learning, long-term short-term memory, machine learning, skeleton.

Introduction

The identification and recognition of events in a video sequence recorded from a surveillance stream is particularly difficult, making video-based action identification a fresh study area. Human-computer interaction, content-based video retrieval, private and activity recognition are a few examples of applications for video action recognition. To detect and recognize human actions and activities in the modern world, where digital content is expanding exponentially on a daily basis, effective artificial intelligence-based Internet of Things (IoT) solutions are required. In order to support interactive programmes and applications built on the Internet of Things, action recognition seeks to recognize and identify individuals, their behavior, and suspicious actions in films. Action recognition continues to pose a variety of difficulties for preserving resident safety and surveillance, security. including industrial violence detection. person identification, virtual reality, and cloud environments. This is despite significant advancements in camera movement, complex backgrounds, and lighting variations. For recognizing various human actions in videos, an understanding of location and time is necessary. The majority of techniques used to characterize the corresponding action in films during the last ten years have used handcrafted structural features to designate the spatial aspects of dynamic motion. Due of the motion style and intricate background clutter, the handmade feature technique for action detection is largely database-oriented and occasionally fails. In order to gather correct data, traditional techniques and representative motion elements gradually transition from 2D to 3D. For the purpose of simultaneously capturing dynamic information in a series of photos, these strategies converted spatial data into 3D spatiotemporal features.

Deep learning is the most well-liked and frequently applied technique for gathering highly selective features and structural systems in video-based action and behaviour identification. Existing deep learning techniques for action recognition (HAR) employ trained models to extract traits from video pictures before using basic convolutional neural network (CNN) methods. Using these convolutional layers, a model is trained for classification by extracting and learning spatial features. Traditional CNN models, in contrast, perform worse than manually created features in sequence data. These models do a decent job of collecting spatial data, but they struggle to collect temporal data, which is essential for capturing motion data for HAR in a video series. For instance, Dai et al. coupled characteristics obtained from CNNs with spatiotemporal information to perform action recognition utilising long-short-term memory (LSTM). A twostream design approach is necessary to create discrete modules that incorporate algorithms to capture dynamic information in sequence data for high-level videobased HAR methods. While LSTM was developed primarily for long-term video sequences to learn and grasp temporal data for HAR in surveillance systems, recurrent neural networks (RNN) have lately been employed to address spatiotemporal difficulties. The majority of researchers have developed a twostream action recognition technique that takes into account both temporal and spatial input for joint feature training in order to address the aforementioned problems as well as the existing limitations of HAR.

These facts show that reliable action detection in real-world videos is still difficult due to the lack of motion, style, and backdrop clutter information Traditional techniques have not been able to handle these problems because of problems handling continuous actions, difficulties modelling crowded situations due to occlusion, and susceptibility to noise .Similar to how existing HAR approaches have addressed the issue of sequence learning utilizing RNN, Without highlighting the selected information in the sequences, which is essential to preserving the association between earlier and later frames, LSTM and gated recurrent units perform better than one another. Our approach learns spatiotemporal features and concentrates solely on discriminative inputs in long-term sequences to recognize activities in video frames. This device works best as a surveillance system. In this system, we utilize DCNN with residual blocks to enhance the learnt features and BiLSTM with attention weights to selectively focus on the useful features in the input frame sequence and recognize the action in the video as suitable. The suggested system uses CNN spatial information extracts for action detection and convolution operations, which are then processed by BiLSTM to provide material that more effectively promotes human activities, we find numerous firsts. High-level discriminative information is extracted from every eighth frame of the video and supplied into an attention mechanism to change the attention weights for the selective stimuli that are given sequentially. The results show that these characteristics make the suggested method more appropriate for HAR for video surveillance streams.

Literature Review

In the science of computer vision, action identification is a prominent area of study. To identify human actions in video streams, researchers have developed a variety of algorithms, utilizing neural networks, classical machine learning, and

artificial intelligence. Researchers have primarily employed conventional machine learning methods to create effective HAR systems via feature engineering over the past ten years. To extract sequential and spatial information from a series of frames for action classification, researchers now use deep learning algorithms. As a result, an efficient action recognition classification approach may be applied to IoT-based security systems for smart portable devices and cybercrime investigation. The next sections provide a survey of the literature on relevant existing techniques.

Traditional Machine Learning and Manual Feature-based Action Recognition

The three primary stages of conventional machine learning-based action identification systems are feature extraction using manually created feature descriptors, feature representation using an algorithm, and feature classification using an appropriate machine learning algorithm. The two primary categories of feature extraction methods in computer vision are local feature-based approaches and global feature-based approaches. Features are independent patches, locations of attention, and gesture data that correspond to ingrained stimuli for a certain task in local feature-based techniques. In contrast, a region of interest is used to represent global features and is used to define background subtraction and tracking. Using manually created features like VLAD and BOW, researchers have created effective action detection systems for traditional machine learning. The majority of manually created feature extractors are domain-specific and created for certain datasets. They cannot be used for general feature learning. To speed up their systems' processing, some researchers have adopted key framework techniques. For instance, Yasin et al.' creation of a vital key frame selection method for HAR and subsequent development of action recognition in video sequences. Similar to this, Zhao et al. reported HAR built on multi-feature fusion with key frames using a traditional machine learning approach. In the past ten years, traditional machine learning algorithms have had considerable success. They still struggle with issues such being arduous, time-consuming, and difficult to choose structural parts since they are constrained by human cognition. Researchers have switched to deep learning to develop effective and cutting-edge methodologies for sophisticated video-based HAR systems as a result of the shortcomings and difficulties in hand-crafted HAR.

Deep Learning based Action Recognition

In contrast to the three-stage traditional machine learning approach, deep learning offers a modern end-to-end learning architecture and simultaneously exposes and classes high-level discriminative visual information. End-to-end is widely utilized Convolutional procedures are often used in CNN architectures to select the best features and change parameters as needed. Commonly, CNNbased feature learning techniques that are used to represent visual information in 2D data are insufficient for 3D data representations. Instead of using 2D photos, some researchers have created methods to extract features from video images. Their models outperformed 2D CNNs and manually created feature-based techniques in video analytics (activity recognition, tracking of objects, and video retrieval). Similar to this, Simonyan et al. proposed CNN and a two-stream architecture to recognize activities in movies to address the problem of obtaining motion signals from repeated video frames .A spatial and motion-based approach to action recognition was proposed by Feichtenhofer et al. To highlight the value of temporal information, they examined the system at UCF 101. A multi-stream CNN model was employed by Tu et al.to train human-related regions that could identify several activities in a movie. The authors of extracted spatiotemporal data from video sequences using a two-stream fused network based on LSTM. For feature fusion-based action recognition, researchers have created hybrid learning algorithms. Using an optimal path forest classifier, Guimaraes et al. created an anomaly detection technique that uses an intelligent IoT-based system to monitor and identify anomalies. These deep learning techniques are provided for comprehending and recognizing temporal information that occurs immediately; nevertheless, they are insufficient for understanding and recognizing sequences that occur over a longer period of time. Due to RNN's popularity, LSTM, a better variation that encodes long-term dependencies, was developed. LSTM networks are currently mostly used to categorize long sequence data in a number of fields, such as speech recognition, action detection, and weather forecasting. Xu et al. developed a deep learning technique and also used reinforcement learning for resource allocation based on IoT content to reduce large data duplication. High data redundancy is an issue as a result.

Attention based Mechanism

A variety of difficult temporal tasks, such as captioning movies, action detection, and sequence learning, may benefit from the recently proposed attention mechanism. The arrangement of the frames is important at different points to transmit shifting attention to the viewer's first impression in motion video materials displaying individuals walking, running, jogging, and doing other actions. Attention techniques for captioning videos and images achieved a SOTA performance to inform and define the contents using benchmark datasets. A system for translating from English to French utilizing an attention-based model was developed by Bahdanau et al. and is superior to the SOTA phrasebased approach. By leveraging attention mechanisms, the authors of created a method for extracting instructive frames from an extremely movie to recognize motion. A single attention process for action recognition was put up by certain researchers. For learning spatial and temporal information, they created distinct models. The two-stream attention strategy is used frequently in modern television shows, unintentionally bringing attention to related content.

Methodology

In this part, the proposed architecture for action recognition and its essential components—the DCNN, residual blocks, deep BiLSTM, and center loss function—are discussed. To recognize a person's behaviours in video frames, we employ a dilated convolution network and improved feature learning blocks. As a result, the deep BiLSTM network is strengthened by an attention mechanism and the acquired traits. In the suggested approach, we first use a DCNN to extract the CNN features from the input file. We secondly employ the skip connections to combine the dilated qualities with the enlarged features. The entire convolution network is then applied to the context vector. The middle and therefore the Softmax losses are estimated in order to get a conclusion for the action

recognition, and an aggregated loss is obtained. Fig. 1 depicts the proposed system's design, and the following sections provide a detailed explanation of the majority of its components.



Fig. 1. The entire design of the suggested attention-based LSTM with dilated CNN features human action recognition system

The proposed ConvLSTM model. 3D skeleton coordinates are retrieved from the unprocessed input movies and used to compute geometric and kinematic components. For automatic spatial feature extraction, the extracted features are sent to the CNN together with the unprocessed skeletal joint coordinates. Then, in order to extract temporal information, these spatial features are sent to an LSTM. Finally, the activities are classified and the Softmax score is calculated using fully linked layers.

Dilated Convolutional Neural Networks

In place of conventional CNNs, we describe the DCNN technique and how it collects features in this subsection. Compared to traditional CNNs feature abstraction, DCNNs employ receptive fields that are more open. We employ DCNN for semantic segmentation and to preserve the implicit information of the mask in order to increase efficiency. The majority of computer vision architectures include numerous pooling layers to minimize image size and extend and resample image size. In conventional CNNs, the pooling operation frequently resizes the image, which could result in the loss of some information. To solve this issue, we created DCNN. In addition, we employed a padding technique of "valid" and a CNN with 3 3 kernels and a step setting of 1. We also used a 2.2 maximum pooling and a step setting. The Upgrading Feature Learning Block (UFLB), another element of DCNN, is intended to extract the most discriminative salient action features. As seen in Fig. 2, each block is made up of a DCNN, a batch normalization (BN), and a leaky relay layer. We employ three upgrade training blocks in the proposed CNN model to uncover more salient features. In order to achieve higher performance with a high training rate, the DCNN's BN layer serves to normalize the learned features. Additionally, it prevents vanishing gradient issues during training.

ConvLSTM Architecture

It was suggested in this instance to use a ConvLSTM network that combined CNN, LSTM, and dense layers. In order to create a more separable space, spatial feature extraction is performed using CNNs, sequence prediction is performed using LSTMs, and feature mapping is performed using dense layers (Fig. 2). Figure 2 displays a conventional activity recognition model where the ConvLSTM model was created by performing a parallel fusion of CNN and LSTM. This has been used in other works before. Although this method is far superior to employing only CNN or solely LSTM, it does not fully utilize either model's efficacy.



Fig. 2. Sequential ConvLSTM Mode

This uses a sequential fusion of CNN, LSTM, and dense layers, as seen in Fig. 2. The CNN's final hidden layer outputs are routed into LSTM layers for classification, which are subsequently followed by fully connected layers.

Results and Discussion

In this part, the usefulness of the suggested strategy was assessed using three widely-used datasets: UCF11 [52], UCF Sports [53], and J-HMDB [54], which produce superior outcomes to the SOTA techniques. The datasets and experimental setup are thoroughly discussed in the following subsections, which are followed by a presentation of the obtained results. We contrasted the implemented system with SOTA techniques in our final presentation.

Datasets

Due to changes in lighting, fuzzy backdrops, and camera motions, UCF11 is a difficult dataset for video-based action recognition. A total of 1600 movies in the UCF11 dataset are divided into eleven action subcategories, including shooting, leaping, riding, swimming, etc. 30 frames per second was used to record all videos (fps).150 720 480 video sequences from a variety of activities, including lifting, skateboarding, horseback riding, and golfing, are included in the UCF Sports dataset. The assortment of action sports videos originates from a number of sources, including the BBC and ESPN, which are frequently shown on TV channels. In a variety of scenarios, these movies show genuine and authentic activities from various angles. There are 21 different action categories in the J-HMDB dataset, including catch, clutch, Jump, clap, brush hair, swing a baseball, and take a shot. With 923 videos featuring various actions. It is a substantial

video action collection, which complicates the task of recognizing when compared to other datasets, J-HMDB has done badly because of these challenges and issues, and however SOTA approaches perform better in terms of recognition rate. Figure 3 displays a graphic representation of representative actions from each data set.



Fig. 3. Visualizations of representative action categories from the UCF11, UCF Sports, and J-HMDB datasets

We conducted an extensive investigation to gauge how well our suggested action recognition system predicted classes based on the actual and anticipated data. The results are displayed in Fig. 3. The y-axis displays the real UCF labels, while the x-axis displays the anticipated labels. Sports and J-HMBD datasets. The confused classes are identified in each class's consistent rows, and the confusion matrices display all actions' actual invocation values diagonally. We sampled the video sequence every eight frames for an effective HAR system to ensure the suggested model would perform well in real-time, and then we extracted highly discriminating features. We conducted a number of studies using various video frames. The method shifts to every eight frames when it fails to capture the middle frames, prediction performance is reported to be higher. When compared to the suggested HAR system, the other leaps exhibit poorer performances. The experimental findings of the suggested system demonstrated the model for action recognition's great generalizability.

Conclusion

This study describes a Kinect (v2) sensor-based, ConvLSTM-based activity recognition and fall detection system that protects user privacy. Deep learning networks receive raw skeleton coordinates from the proposed system together with geometric and kinematic information. Instead of using actual photographs of the user, the system merely uses derived features and unprocessed skeletal joint coordinates. We proposed a fast and effective method based on the sequential fusion of CNN and LSTM called ConvLSTM model. Three deep learning-based classification techniques, CNN, LSTM, and ConvLSTM, were evaluated on a fresh dataset with 130,000 samples and 81 attribute values. The suggested system can

distinguish between behaviors such as standing, bending, falling, fast walking, sitting, and lying down. The suggested system is discrete to the user and unaffected by factors such as clothes, camera position, etc. The system's efficacy in recognizing activity and detecting falls is sufficient for widespread system implementation. The dataset and source code will both be made available to the general public.

Acknowledgments

I extend my deep sense of sincere gratitude to Dr. Channakesavalu K, Principal, East West Institute of Technology, Bengaluru, for having permitted to carry out the implementation on "A Human Activity Recognition using CNN and Long Term Short Term Memory" successfully. I express my heartfelt sincere gratitude to Dr. Achyutha Prasad N, Professor and Head, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru for his valuable guidance, encouragement and suggestions. I would like to express my sincere thanks to my internal guide Dhanraj S, Assistant Professor, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru for his valuable guidance, encouragement and suggestions. I would like to express my deep sense of sincere gratitude to my internal co-guide Manjunath T N, Assistant Professor, Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru for his valuable guidance, encouragement and suggestions. I would like to thank all the Teaching, Technical faculty and supporting staff members of Department of Computer Science and Engineering, East West Institute of Technology, Bengaluru, for their valuable suggestions and support. Finally, I would like to thank my Parents for their support.

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