An Information-rich Sampling Technique over Spatio-Temporal CNN for Classification of Human Actions in Videos

S H Shabbeer Basha, Viswanath Pulabaigari, Snehasis Mukherjee
Indian Institute of Information Technology Sri City, India

Abstract—We propose a novel scheme for human action recognition in videos, using a 3-dimensional Convolutional Neural Network (3D CNN) based classifier. Traditionally in deep learning based human activity recognition approaches, either a few random frames or every \(k\)th frame of the video is considered for training the 3D CNN, where \(k\) is a small positive integer, like 4, 5, or 6. This kind of sampling reduces the volume of the input data, which speeds-up training of the network and also avoids over-fitting to some extent, thus enhancing the performance of the 3D CNN model. In the proposed video sampling technique, consecutive \(k\) frames of a video are aggregated into a single frame by computing a Gaussian-weighted summation of the \(k\) frames. The resulting frame (aggregated frame) preserves the information in a better way than the conventional approaches and experimentally shown to perform better. In this paper, a 3D CNN architecture is proposed to extract the spatio-temporal features and follows Long Short-Term Memory (LSTM) to recognize the human actions. The proposed 3D CNN architecture is capable of handling the videos where the camera is placed at a distance from the performer. Experiments are performed with KTH and WEIZMANN human actions datasets, whereby it is shown to produce comparable results with the state-of-the-art techniques.

I. INTRODUCTION AND RELATED WORKS

Human action recognition in videos has been an active area of research, gaining the attention of Computer Vision and Machine Learning researchers during the last decade due to its potential applications in various domains, including intelligent video surveillance systems, \textit{viz.}, Human-Computer Interaction (HCI), robotics, elderly and child monitoring systems and several other real-world applications. However, recognizing human actions in the real world remains a challenging task due to several challenges involved in real-life videos, including cluttered backgrounds, viewpoint variations, occlusions, varying lighting conditions and many more. This paper proposes a technique for human activity recognition in videos, where the videos are captured by a camera placed at a distance from the performer.

The approaches for recognizing human actions from videos, found in the literature, can be broadly classified into two categories [1]. The first, make use of motion-related features (low, mid, and high level) for human action recognition [2], [3]. The other set of approaches experiment to learn a proper representation of the spatio-temporal features the during action using deep neural networks [4], [5], [6], [7].

Handcrafted features played a key role in various approaches for activity recognition [8]. Semantic features ease to identify similar activities that vary visually but have common semantics. Semantic features during an action contain human body parts (posture and poselet), background, motion and other features incorporating human perceptual knowledge about the activities. A study by Ziaeeafard et al. [1] examined human action recognition approaches using semantic features. Malgireddy et al. [9] proposed a hierarchical Bayesian model which interconnects low-level features in videos with postures, motion patterns, and categories of activities. Very recently, Nazir et al. [8] proposed a Bag of Expression (BOE) framework for activity recognition.

The most common handcrafted feature, used for action recognition, is optical flow [10], [11], [12], [13]. Chaudhry et al. [10] introduced the concept of Histogram of Oriented Optical Flow (HOOF) for action recognition, where the optical flow direction is divided into octants. Mukherjee et al. [12] proposed Gradient-Weighted Optical Flow (GWOF) to limit the effect of camera shaking, where the optical flow of every frame is multiplied by the image gradient. Wang et al. [13] introduced another approach to reduce the camera shaking effect, called Warped Optical Flow (WOF), where gradient is computed on the optical flow matrix. In [11], the effect of background clutter is reduced by multiplying Weighted Optical Flow (WOF) features with the image gradients. Optical flow based approaches help in dissecting the motion, but gives too much unnecessary information such as, motion information at all the background pixels, which reduces the efficacy of the action recognition system in many cases.

Spatio Temporal Interest Points (STIP) introduced by [14], identifies spatio-temporal interest points based on the extension of Harris Corner Detection approach [15] towards the temporal domain. Several researchers have shown interest to recognize human actions with the help of some other variants of spatio-temporal features like Motion- Scale Invariant Feature Transform (MoSIFT) [16] and sparse features [3]. A study on STIP based human activity recognition methods is published by Dawn et al. [17]. However, such spatio-temporal features are unable to handle the videos taken in real-world which suffers from background clutter and camera shake. Buddubariki et al. [18] combined the benefits of GWOF and STIP features by calculating GWOF on the STIP points. In [19], combination of 3-dimensional SIFT and HOOF features are used along with support vector machine (SVM) for classifying human actions.
Recently, deep learning based models are gaining the interest of researchers for recognizing human actions [5], [7], [20], [21], [22], [23]. Taylor et al. [21] proposed a multi-stage network, where in a Convolutional Restricted Boltzmann Machine (ConvRBM) retrieves motion-related information from each pair of successive frames at the initial layer. In [5], a two-stream convolutional network is proposed that comprises spatial-stream ConvNet and temporal-stream ConvNet. Ji et al. [20] introduced a 3-dimensional CNN architecture for action recognition, where a 3 dimensional convolutions are used to extract the spatio-temporal features. Tran et al. [22] enhanced 3D CNN model by applying Fisher vector encoding scheme on the learned features. Karpathy et al. [23] proposed a deep neural network for spatio-temporal resolutions: high and low resolutions, then merged them to train the CNN. Kar et al. [24] proposed a technique for temporal frame pooling in a video for human activity recognition. A survey by Herath et al. [25] discusses both engineered and deep learning based human action recognition techniques.

In the literature of human action recognition, researchers have used either the fully observed video or a portion of the video to train the deep neural networks. Training the models using a portion of the video will take less amount of training time compared to training the model using entire video. However, considering a portion of the video (considering 9 frames from the entire video as in [7] and 7 frames as in [20]) results in information loss. Srivastava et al. [26] used multi layer LSTM network to learn the representations of video sequences. Recently, Bilen et al. [27] introduced dynamic image, a very compact representation of video used for analyzing the video with CNNs. However, dynamic images eventually dilute the importance of spatial information during action. The proposed sampling technique for video frames preserves both spatial and temporal information together.

Baccouche et al. [7] proposed a completely automated deep learning architecture for KTH dataset [28], which figures out how to characterize human activities with no earlier information. This 3D CNN architecture learns spatio-temporal features automatically, then LSTM network [29] is used to classify the learned features. Motivated by the method introduced in [7], we propose a 3D CNN to learn spatio-temporal features and then apply LSTM to classify human actions. The proposed method uses small sized filters throughout the 3D CNN architecture, which helps to learn minute information present in the videos, which can help in recognizing the action of performers appearing very small in the video, due to the distance of the camera.

Our contributions in this paper are two-folds. First, a novel sampling technique is introduced to aggregate the entire video into a fewer number of frames. Second, a 3D CNN architecture is proposed for better classification of human actions in videos where the performer looks significantly small. The choice of smaller filter size enables the proposed model work well in such scenarios where the performer looks small due to distance from the camera. We experiment with the proposed deep learning model with transfer learning technique, by transferring the knowledge learned from KTH dataset to fine-tune over WEIZMANN dataset and vice versa.

The proposed pre-processing method is presented in Section II. Section III illustrates the proposed 3D CNN architecture. The experiments and results are described in Section IV. Finally, Section V concludes and provides scope for future research.

II. PRE-PROCESSING USING AN INFORMATION SAMPLING APPROACH

The primary objective of this pre-processing step is to reduce the amount of training time and at the same time motion information should be given utmost importance. We propose a novel sampling technique to aggregate a large number of frames into a fewer set of frames using Gaussian Weighing Function (GWF), which minimizes the information loss. The proposed video pre-processing scheme is shown in Figure 1.

Gaussian Weighing Function (GWF) is used to aggregate the entire video into a fewer number of frames. Let us consider \( \{I_n\}_{n \in N} \), an exhaustive non-overlapping sequence (collection of all frames of a video), which is given by

\[
\{I_n\} = \{I_1, I_2, \ldots, I_k, \ldots\},
\]

where \( \{I_k\} \) is the \( k^{th} \) sub-sequence of \( \{I_n\} \) and \( k < n \). Mathematically, Gaussian Weighing Function \( G \), for a sub-sequence \( \{I_k\} \), is given as follows:

\[
G(I_k, W) = \sum_{j=1}^{5} I_{kj} \times \frac{W_j}{\sum_{j=1}^{5} W_j}.
\]

The function \( G \) takes a sub-sequence \( \{I_k\} \), and Gaussian weight vector \( W \) as input, and aggregates the information into a single frame. Here \( W_j \) represents the \( j^{th} \) element of Gaussian weight vector \( W \). For example, if the size of the Gaussian weight vector (i.e., \( W \)) is 5 and the sub-sequence is \( \{I_k\} \), which has five frames of the video. The vector \( W \) is given by \( W = [0.13, 0.6, 1, 0.6, 0.13] \). A single frame is obtained by performing weighted summation of the five frames belonging to the sub-sequence \( \{I_k\} \) as shown in equation (2). In other words, five frames are aggregated into a single frame using Gaussian weighing function. Similarly, the same process is repeated for subsequent five frames belonging to the next sub-sequence and so on. This sampling approach reduces the volume of data for training the deep learning model and also preserves the information in better way which helps to obtain better results in human activity recognition.

III. SPATIO-TEMPORAL FEATURES EXTRACTION USING DEEP LEARNING MODELS

In this section, initially we describe 2-D CNNs, and then we present a detailed discussion about the proposed 3-D CNN architecture, which learns the spatio-temporal features.
A. Convolutional Neural Networks

There are two major problems with Artificial Neural Networks (ANN) while dealing with real world data like images, videos, and any other high-dimensional data.

- ANNs do not maintain the local relationship among the neighboring pixels in a frame.
- Since full connectivity is maintained throughout the network, the number of parameters are proportional to the input size.

To address these problems, Lecun et al. [30] introduced Convolutional Neural Networks (CNN), which are also called ConvNets. Extensive amount of research is being carried out in computer vision and machine learning. However, their application in video stream classification is comparatively a less explored area of research. In this paper, we performed 3D convolutions in the convolutional layers of proposed 3D CNN architecture to extract the spatial and temporal features.

B. Proposed 3D CNN Model: Extracting Spatio-Temporal Features

In 2-D CNNs, features are computed by applying the convolutions spatially over images. Whereas in case of videos, we have to consider the temporal information along with spatial features. So, it is required to extract the motion information encoded in contiguous frames using 3D convolutions. The proposed 3-dimensional CNN architecture, shown in Fig. 2 uses 3D convolutions.

Initially, the Gaussian Weighing function is used to aggregate the entire video into 20 frames (considered 100 frames from each video throughout our experiments). To reduce the memory overhead, person centered bounding boxes are retrieved as in [31], [20], which results in frames of spatial dimension $34 \times 54$ and $64 \times 48$ in case of KTH [28] and WEIZMANN [32] datasets, respectively.

In this paper, a 3D CNN model is proposed to extract spatio-temporal features, which is shown in Fig. 2. The proposed model considers the input of dimension $34 \times 54 \times 20$, corresponding to 20 frames (encoded using GWF) of $34 \times 54$ pixels each. The proposed 3D CNN architecture has 5 learnable layers, viz., $Conv1$, $Conv2$, $Conv3$, $Conv4$, and $FC1$. Pool1 and Pool2 max pooling layers are applied after $Conv1$ and $Conv2$ to reduce the spatial dimension of the feature maps by half. The $Conv1$ layer generates 16 feature maps of size $32 \times 52 \times 18$ by convolving 16 3-D kernels of size $3 \times 3 \times 3$. Pool1 layer down samples the feature maps by half, after applying sub-sampling operation with a receptive field of $2 \times 2 \times 1$, which results in a $16 \times 26 \times 18$ dimensional feature vector. The $Conv2$ layer results in a $12 \times 22 \times 16$ dimensional feature map by convolving 16 filters of size $5 \times 5 \times 3 \times 16$. The Pool2 layer produces a $6 \times 11 \times 16$ dimensional feature vector, by applying sub-sampling operation with a receptive field of $2 \times 2 \times 1$. The $3^{rd}$ convolution layer ($Conv3$) produces 32 feature maps of dimension $4 \times 9 \times 14$, which is obtained by convolving 32 kernels of dimension $3 \times 3 \times 3 \times 16$. The $Conv4$ layer generates 32 feature maps of dimension $2 \times 7 \times 12$, which is obtained by convolving 32 filters of dimension $3 \times 3 \times 3 \times 32$. The feature maps produced by $Conv4$ layer are flattened into a single feature vector of dimension $5376 \times 1$, which is given as input to the $1^{st}$ fully connected layer ($FC1$). Finally, the $FC1$ layer produces 256 dimensional feature vector. The 3D CNN architecture proposed for spatio-temporal feature extraction, consists a total of 1,437,712 trainable parameters.

For WEIZMANN dataset, we used same architecture with necessary modifications. However, throughout the architecture same hyper-parameters (number of filters, filter size) are maintained as in the case of KTH dataset. The 3D CNN model proposed for WEIZMANN dataset takes input of dimension $64 \times 48 \times 20$. This model has four Conv layers ($Conv1$, $Conv2$, $Conv3$, and $Conv4$) and two max-Pooling layers ($Pool1$, $Pool2$) layers, and towards the end one fully connected layer ($FC1$). The $Conv1$ layer results
in 16 feature maps of dimension $62 \times 46 \times 18$, which is obtained by convolving 16 kernels of size $3 \times 3 \times 3$. The Pool1 layer generates reduce the spatial dimension by half, after applying sub-sampling with a receptive field of $2 \times 2 \times 1$, which generates $31 \times 23 \times 18$ dimensional feature vector. The Conv2 layer generates 16 feature maps of dimension $27 \times 19 \times 16$, this is obtained by applying 16 filters of size $5 \times 5 \times 3 \times 16$. The Pool2 layer generates a $13 \times 9 \times 16$ dimensional feature vector by sub-sampling with a receptive field of $2 \times 2 \times 1$. The Pool2 layer does not consider the right and bottom border feature values to avoid the dimension mismatch between input and filter size. The Conv3 layer results in a $11 \times 7 \times 14$ dimensional feature vector, which is obtained by convolving 32 filters of size $3 \times 3 \times 3 \times 16$. The Conv4 layer results in 32 feature maps of dimension $9 \times 5 \times 12$, which is obtained by convolving 32 filters of dimension $3 \times 3 \times 3 \times 32$. The output of Conv4 layer is rolled into a single column vector of dimension $17280 \times 1$. At the end of the architecture, FC1 layer has 256 neurons, which results in a 256 dimensional feature vector. The proposed 3D CNN architecture for WEIZMANN human action dataset consists of 4,485,136 number of learnable parameters. The learned spatio-temporal features are given as input to LSTM model to learn the label of the entire sequence.

C. Classification using Long Short-Term Memory (LSTM)

Once the 3D-CNN architecture is trained, it learns the spatio-temporal features automatically. The learned features are provided as input to an LSTM architecture (a Recurrent Neural Networks (RNN)) for classification. RNNs are widely used deep learning models to accumulate the individual decisions related to small temporal neighborhood of the video. RNNs make use of recurrent connections to analyze the temporal data. However, RNNs able to learn the information which are about short duration. To learn the class label of the entire sequence, Long Short-Term Memory (LSTM) [29] is employed, which accumulates the individual decisions corresponds to each small temporal neighborhood. To obtain a sequence, we have considered every 4 frames as a temporal neighborhood. To classify human actions, we employ an RNN model having a hidden layer of LSTM cells. Figure 3 shows the overview of the proposed two-steps learning process. The input to this RNN architecture is 256 FC1 features per time step. These 256 dimensional input features are fully connected with LSTM cells. The number of LSTM cells considered are 50 as in [7]. The training details of the proposed 3D CNN architecture is presented in section IV-C.

IV. EXPERIMENTS, RESULTS AND DISCUSSIONS

As the proposed method aims to classify human actions in a video, where the videos are captured at a distance from the performer, we trained and evaluated the proposed 3D CNN model on KTH and WEIZMANN datasets. Also we experimented with transfer learning techniques, where proposed method is trained with KTH and then tested on WEIZMANN dataset, and vice versa.

A. KTH dataset

KTH dataset [28] is one among the popular datasets in human action recognition. This dataset consists of six actions, viz., walking, jogging, running, boxing, hand-waving, and hand-clapping which were carried out by 25 persons and the videos were recorded in four different scenarios (outdoor, variations in scale, variations in cloths, and indoor). The spatial dimension of each frame is $160 \times 120$ pixels and the rate of frames per second (fps) is 25. This dataset has 600 videos. All the videos were captured from a distance from the performer. As a result, the area covered by the person is less than 10% of the whole frame.

B. WEIZMANN dataset

The WEIZMANN human activity recognition dataset [32] consists of 84 videos that correspond to ten actions, which were performed by nine different people. The ten actions are gallop sideways (Side), jumping-back (jack), bending, one-hand-waving (Wave1), two-hands-waving (Wave2), walking, skipping, jumping in place (Pjump), jumping-forward (jump), and running. The spatial dimension of each frame is

Fig. 2. Proposed 3-dimensional CNN for spatio-temporal feature construction (KTH dataset). The first two convolution layers Conv1 and Conv2, both have 16 feature maps of dimension $32 \times 52 \times 18$ and $12 \times 22 \times 16$, respectively. The Pool1 and Pool2 layers are followed by Conv3 and Conv4, to reduce the spatial dimension by half. Conv3 and Conv4 layers have 32 feature maps of dimension $4 \times 9 \times 14$ and $2 \times 7 \times 12$. Finally, a fully connected layer FC1 has 256 neurons.
**C. Experimental Results**

To validate the performance of the proposed 3-D CNN model, throughout our experiments, we have considered videos up to 4 seconds length (100 frames) and aggregated them into 20 frames using Gaussian Weighing Function as discussed in Section II. To reduce the memory consumption, we have used the person-centered bounding boxes as in [31], [20]. Apart from these simple preprocessing steps we have not performed any other complex preprocessing like optical flow, gradients, etc.

1) Training Setup: To train the proposed 3-D CNN architectures, ReLU [33] is used as the activation function after every Conv and FC layers (except output FC layer). Initially learning rate is considered as $1 \times 10^{-4}$. The value of the learning rate reduced with a factor of $\sqrt{0.1}$ after every 100 epochs. The developed models are trained for 300 epochs using Adam optimizer [34] with $\beta_1 = 0.9$, $\beta_2 = 0.99$, and decay $= 1 \times 10^{-6}$. The 80% of entire data is used to train the 3D CNN model and remaining data is utilized to test the performance of the model. After employing Gaussian Weighting function, we obtained 20 frames corresponding to an entire video. To reduce the amount of over-fitting, we generated 1800 and 270 videos (of length 20 frames) for KTH and WEIZMANN datasets, respectively, using data-augmentation techniques like vertical flip, horizontal flip, rotation by $30^\circ$. We also employed dropout [35] (after each Conv, FC layers except final FC layer with a rate of 0.4, after ReLU is applied) along with data augmentation to reduce the amount of over-fitting.

2) Results and Discussions: The obtained results are compared with the state-of-the-art methods as shown in Tables I and II on WEIZMANN and KTH datasets, respectively. [7] reported 94.39% accuracy over KTH dataset using a 3D CNN architecture having five trainable layers. However, they have not evaluated their model on WEIZMANN dataset, we obtained 94.58% accuracy through our experiment (input dimension is $64\times48\times9$) using the same architecture (same w.r.t number of features, filter size, number of neurons in FC layers) as in [7]. After employing the proposed scheme of generating aggregated video to the 3D CNN model proposed in [7], we observed that the model outperforming the original model. However, the Dynamic Image Network introduced by Bilen et al. [27] results in high amount of over-fitting due to which it produces only 85.2%, 86.8% accuracies for KTH, WEIZMANN datasets. The proposed 3D CNN model produces 95.27% and 95.78% accuracies on KTH and WEIZMANN datasets, respectively, when the size of Gaussian weight vector is 5. From Table I and Table II we can observe that the proposed 3D CNN model outperforming other deep learning based models on both the datasets.

When compared with human action recognition methods involving hand-crafted features, our method produces comparable results with state-of-the-art on both KTH and WEIZMANN datasets. We also experimented the performance of our model by varying the size of Gaussian weight vector $W$ in the range from 3 to 8. The performance variation of proposed model is shown in Figure 4 by varying the size of Gaussian weight vector $W'$. We observe that the proposed 3D CNN architecture is showing the best accuracy, when the size of Gaussian weight vector $W = 5$. Based on the results depicted in Table I and Table II we can conclude that, our 3D CNN architecture outperforms the state-of-the-art deep learning architectures. However, due to the small size of the available dataset of such kind, the proposed deep learning based method could not outperform the hand-crafted feature based methods (although showing a comparable result).

---

**Fig. 3.** The proposed two-steps deep neural network approach. Encoded frames are given as input to the 3D CNN model to extract spatio-temporal features as discussed in Section II. The proposed 3D CNN model generates $256 \times 1$ dimensional feature vector, which is given as input the LSTM model to classify human actions. The LSTM has one hidden layer with 50 cells, that accumulates the individual decisions corresponding to small temporal neighborhood (4 frames) of the video.

---

**Fig. 4.** A performance comparison of proposed 3D CNN model by varying the size of Gaussian weight vector. The size of the Gaussian weight vector is considered as 3, 4, 5, 6, 7, and 8 in our experiments.

Basha et al. [40] shown the necessity of the fully connected layers based on the depth of the CNN. Motivated by their work, experiments are conducted by varying the number of trainable layers in the proposed 3D CNN architecture. The
TABLE I
A PERFORMANCE COMPARISON OF STATE-OF-THE-ART METHODS ON WEIZMANN DATASET WITH PROPOSED 3D CNN MODEL USING 5-FOLDS CROSS VALIDATION TEST.

| S.No. | Method                        | Features                                      | Classification Accuracy |
|-------|-------------------------------|-----------------------------------------------|-------------------------|
| 1     | Baccouche et al. [7]          | 3D CNN features                               | 94.58                   |
| 2     | Gorelick et al. [32]          | Space-time saliency, Action dynamics          | 97.83                   |
| 3     | Falci et al. [36]             | Mid-level motion features                     | 100                     |
| 4     | Bilen et al. [27]             | 2D CNN features                               | 85.2                    |
| 5     | Proposed method               | 3D CNN features                               | 95.78 ± 0.58            |
| 6     | Proposed method applying Transfer Learning | 3D CNN features | 96.53 ± 0.07 |

* Fine-tuning the last two FC layers of pre-trained model, which is trained on KTH dataset.

TABLE II
COMPARING THE STATE-OF-THE-ART HUMAN ACTION RECOGNITION APPROACHES ON KTH DATASET WITH THE PROPOSED 3D CNN MODEL USING 5-FOLDS CROSS VALIDATION TEST.

| S.No. | Method                        | Features                                      | Classification Accuracy |
|-------|-------------------------------|-----------------------------------------------|-------------------------|
| 1     | Nazir et al. [8]              | Bag of Expressions (BoE)                      | 99.51                   |
| 2     | Baccouche et al. [7]          | 3D CNN features                               | 94.39                   |
| 3     | Abdalmunem et al. [19]        | Bag of Visual Words                           | 97.20                   |
| 4     | Ji et al. [20]                | 3D CNN features                               | 90.20                   |
| 5     | Wang et al. [13]              | Dense Trajectories and motion boundary descriptor | 95.00                   |
| 6     | Gilbert et al. [37]           | Mined Hierarchical compound features          | 94.30                   |
| 7     | Yang et al. [38]              | Multi-scale oriented neighborhood features    | 96.50                   |
| 8     | Kovashka et al. [39]          | Hierarchical Space time neighborhood features | 94.53                   |
| 9     | Bilen et al. [27]             | 2D CNN features                               | 86.8                    |
| 10    | Baccouche et al. [7][5]       | 3D CNN features                               | 94.78 ± 0.11            |
| 11    | Proposed Method               | 3D CNN features                               | 95.27 ± 0.45            |
| 12    | Proposed Method applying Transfer learning [5] | 3D CNN features | 95.86 ± 0.3 |

* Encoded frames are given as input to the 3D CNN model proposed in [7]. (the size of Gaussian vector is 5).

Fine-tuning the last two FC layers of pre-trained model, which is trained on WEIZMANN dataset.

amount of over-fitting increases in the context of both the datasets after inclusion of more FC layers. The performance of the proposed 3D CNN architecture with varying number of trainable layers is depicted in Figure 5.

![Figure 5](image)

Fig. 5. Comparing the Training and Testing accuracies of both the datasets by varying the number of trainable layers (5, 6, 7, and 8) in the proposed 3D CNN architecture.

A common practice in deep learning community (especially to deal with small datasets) is that, using the pre-trained models to reduce the training time and obtaining competitive results by training the models for a fewer number of epochs. Generally, these pre-trained models work as feature extractors. With this motivation, we utilized the pre-trained model of KTH dataset to fine-tune over WEIZMANN dataset and vice-versa. The last two layers (Conv4, FC1) of the proposed 3D CNN model are fine-tuned in both the cases. Results of the above experiments are reported in the last rows of the Table I and Table II respectively. We can observe a little increase in the classification accuracy for both the datasets, after applying the above scheme.

V. CONCLUSION

We introduced an information-rich sampling technique using Gaussian weighing function as a pre-processing step before giving it as input to any deep learning model, for better classification of human actions from videos. The proposed scheme aggregates consecutive k frames into a single frame by applying a Gaussian weighted summation of the k frames. We further proposed a 3D CNN model that learns and extracts spatio-temporal features by performing 3D convolutions. The classification of the human actions are performed using LSTM. Experimental results on both KTH and WEIZMANN datasets show that proposed model produces comparable results, among the state-of-the-art. Whereas, the proposed 3D CNN model outperforms the state-of-the-art deep CNN models. Learning the weights for frame aggregation may be a potential future research direction.

ACKNOWLEDGMENTS

We acknowledge the support of NVIDIA with the donation of the GeForce Titan XP GPU used for this research.

REFERENCES

[1] M. ZiaeeFard and R. Bergevin, “Semantic human activity recognition: A literature review,” Pattern Recognition, vol. 48, no. 8, pp. 2329–2345, 2015.
[2] I. Laptev and P. Perez, “Retrieving actions in movies,” in Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on. IEEE, 2007, pp. 1–8.

[3] P. Dollár, V. Rabaud, G. Cottrell, and S. Belongie, “Behavior recognition via sparse spatio-temporal features,” in Visual Surveillance and Performance Evaluation of Tracking and Surveillance, 2005. 2nd Joint IEEE International Workshop on. IEEE, 2005, pp. 65–72.

[4] L. Sun, K. Jia, K. Chen, D.-Y. Yeung, B. E. Shi, and S. Savarese, “Lattice long short-term memory for human action recognition,” in The IEEE International Conference on Computer Vision (ICCV), Oct 2017.

[5] K. Simonyan and A. Zisserman, “Two-stream convolutional networks for action recognition in videos,” in Advances in neural information processing systems, 2014, pp. 568–576.

[6] L. Wang, Y. Xiong, Z. Wang, Y. Qiao, D. Lin, X. Tang, and L. Van Gool, “Temporal segment networks: Towards good practices for deep action recognition,” in European Conference on Computer Vision. Springer, 2016, pp. 20–36.

[7] M. Baccouche, F. Mamalet, C. Wolf, C. Garcia, and A. Baskurt, “Sequential deep learning for human action recognition,” in International Workshop on Human Behavior Understanding. Springer, 2011, pp. 29–39.

[8] S. Nazir, M. H. Yousaf, J.-C. Nebel, and S. A. Velastin, “A bag of expressions framework for improved human action recognition,” Pattern Recognition Letters, 2018.

[9] M. R. Malgireddy, I. Nwogu, and V. Govindaraju, “Language-motivated approaches to action recognition,” The Journal of Machine Learning Research, vol. 14, no. 1, pp. 2189–2221, 2013.

[10] R. Chaudhry, A. Ravichandran, G. Hager, and R. Vidal, “Histograms of oriented optical flow and binet-cauchy kernels on nonlinear dynamical systems for the recognition of human actions,” in 2009 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, 2009, pp. 1932–1939.

[11] S. Mukherjee, “Human action recognition using dominant pose duplet,” in International Conference on Computer Vision Systems. Springer, 2015, pp. 488–497.

[12] S. Mukherjee, S. K. Biswas, and D. P. Mukherjee, “Recognizing interactions between human performers by dominating pose doublet,” Machine Vision and Applications, vol. 25, no. 4, pp. 1033–1052, 2014.

[13] H. Wang, A. Kläser, C. Schmid, and C.-L. Liu, “Dense trajectories and motion boundary descriptors for action recognition,” International journal of computer vision, vol. 103, no. 1, pp. 60–79, 2013.

[14] I. Laptev, “On space-time interest points,” International journal of computer vision, vol. 64, no. 2-3, pp. 107–123, 2005.

[15] C. G. Harris, M. Stephens et al., “A combined corner and edge detector,” in Alvey vision conference, vol. 15, no. 50. Citeseer, 1988, pp. 10–524.

[16] M.-y. Chen and A. Hauptmann, “Mosif: Recognizing human actions in surveillance videos,” 2009.

[17] D. D. Dawn and S. H. Shaikh, “A comprehensive survey of human action recognition with spatio-temporal interest point (stip) detector.” The Visual Computer, vol. 32, no. 3, pp. 289–306, 2016.

[18] V. Buddhikot, S. S. Tulluri, and S. Mukherjee, “Event recognition in egocentric videos using a novel trajectory based feature,” in Proceedings of the Tenth Indian Conference on Computer Vision, Graphics and Image Processing. ACM, 2016, p. 76.

[19] A. Abdulmunem, Y.-K. Lai, and X. Sun, “Saliency guided local and global descriptors for effective action recognition,” Computational Visual Media, vol. 2, no. 1, pp. 97–106, 2016.

[20] S. Ji, W. Xu, M. Yang, and K. Yu, “3d convolutional neural networks for human action recognition,” IEEE transactions on pattern analysis and machine intelligence, vol. 35, no. 1, pp. 221–231, 2013.

[21] G. W. Taylor, R. Fergus, Y. LeCun, and C. Bregler, “Convolutional learning of spatio-temporal features,” in European conference on computer vision. Springer, 2010, pp. 140–153.

[22] D. Tran, L. Bourdev, R. Fergus, L. Torresani, and M. Paluri, “Learning spatiotemporal features with 3d convolutional networks,” in Computer Vision (ICCV), 2015 IEEE International Conference on. IEEE, 2015, pp. 4489–4497.

[23] A. Karpachy, G. Toderici, S. Shetty, T. Leung, R. Sukthankar, and L. Fei-Fei, “Large-scale video classification with convolutional neural networks,” in Proceedings of the IEEE conference on Computer Vision and Pattern Recognition, 2014, pp. 1725–1732.

[24] A. Kar, N. Rai, K. Sikka, and G. Sharma, “Adascan: Adaptive scan pooling in deep convolutional neural networks for human action recognition in videos,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017, pp. 3376–3385.

[25] S. Herath, M. Harandi, and F. Porikli, “Going deeper into action recognition: A survey,” Image and vision computing, vol. 60, pp. 4–21, 2017.

[26] N. Srivastava, E. Mansimov, and R. Salakhudinov, “Unsupervised learning of video representations using lstms,” in International conference on machine learning, 2015, pp. 843–852.

[27] H. Bilen, B. Fernando, E. Gavves, A. Vedaldi, and S. Gould, “Dynamic image networks for action recognition,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2016, pp. 3034–3042.

[28] C. Schuldt, I. Laptev, and B. Caputo, “Recognizing human actions: a local svm approach,” in Pattern Recognition, 2004. ICPR 2004. Proceedings of the 17th International Conference on, vol. 3. IEEE, 2004, pp. 32–36.

[29] F. A. Gers, N. N. Schraudolph, and J. Schmidhuber, “Learning precise timing with lstm recurrent networks,” Journal of machine learning research, vol. 3, no. Aug, pp. 115–143, 2002.

[30] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, “Gradient-based learning applied to document recognition,” Proceedings of the IEEE, vol. 86, no. 11, pp. 2278–2324, 1998.

[31] H. Jhuang, T. Serre, L. Wolf, and T. Poggio, “A biologically inspired system for action recognition,” in Computer Vision, 2007. ICCV 2007. IEEE 11th International Conference on. Ieee, 2007, pp. 1–8.

[32] L. Gorelick, M. Blank, E. Shechtman, M. Irani, and R. Basri, “Actions as space-time shapes,” IEEE transactions on pattern analysis and machine intelligence, vol. 29, no. 12, pp. 2247–2253, 2007.

[33] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in neural information processing systems, 2012, pp. 1097–1105.

[34] D. P. Kingma and J. Ba, “Adam: A method for stochastic optimization,” arXiv preprint arXiv:1412.6980, 2014.

[35] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever, and R. Salakhutdinov, “Dropout: A simple way to prevent neural networks from overfitting,” The Journal of Machine Learning Research, vol. 15, no. 1, pp. 1929–1958, 2014.

[36] A. Fathi and G. Mori, “Action recognition by learning mid-level motion features,” in Computer Vision and Pattern Recognition, 2008. CVPR 2008. IEEE Conference on. IEEE, 2008, pp. 1–8.

[37] A. Gilbert, J. Illingworth, and R. Bowden, “Action recognition using mined hierarchical compound features,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 33, no. 5, pp. 883–897, 2011.

[38] J. Yang, Z. Ma, and M. Xie, “Action recognition based on multi-scale oriented neighborhood features,” International Journal of Signal Processing, Image Processing and Pattern Recognition, vol. 8, no. 1, pp. 241–254, 2015.

[39] A. Kovashka and K. Grauman, “Learning a hierarchy of discriminative space-time neighborhood features for human action recognition,” in Computer Vision and Pattern Recognition (CVPR), 2010 IEEE Conference on. IEEE, 2010, pp. 2046–2053.

[40] S. S. Basha, S. R. Dubey, V. Pulabigari, and S. Mukherjee, “Impact of fully connected layers on performance of convolutional neural networks for image classification,” Neurocomputing, vol. 378, pp. 112–119, 2020.