Introduction to Deep Learning

Temporal Human Action Recognition

Group 4 - DSAI K65 - HUST

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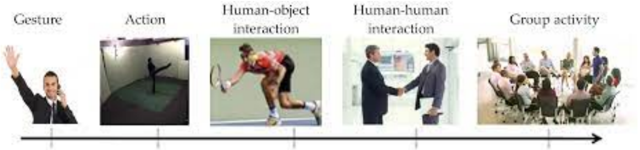
Introduction



- Temporal human action recognition is one of the most important applications in computer vision
- Our goal is to recognise the action in the short input video
- Using several deep-learning models and training them on two datasets UCF101 and HMDB51
- Challenges: large storage requirements, spatial and temporal combination

Datasets: Overview

Two benchmark datasets: HMDB51 and UCF101

HMDB51 - released in 2011

- Containing 6766 videos, divided into 51 distinct categories of action.
- Each class contains at least 101 videos
- Each video has the fixed width of 240 pixels and the frame rate of 30 frames per second.

UCF101 - released in 2012

- There are 13320 videos, categorized into 101 classes.
- Each type of action contains at least 100 videos
- 25 frames per second, with the identical resolution of 320×240.

Datasets: Examples

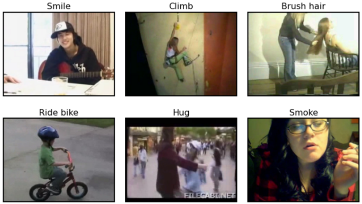


Figure 1: 6 video frames of HMDB51

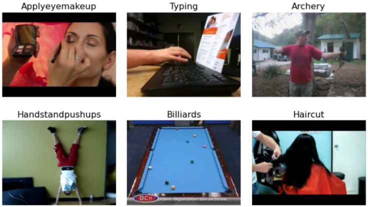


Figure 2: 6 video frames of UCF101

Figure 3: Pull Up video - UCF101

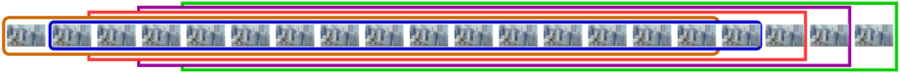
Datasets: Extracting Frames

Raw video

Uniform 5-frame

One 16-frame clip

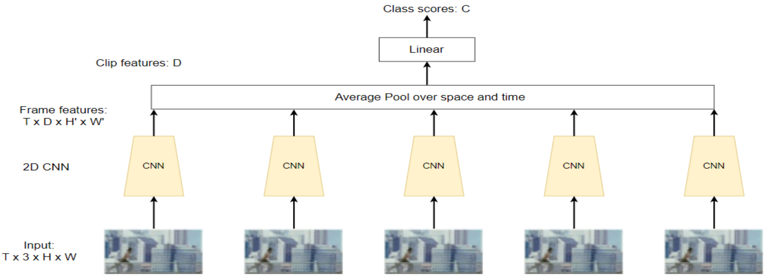
Five 16-frame clips



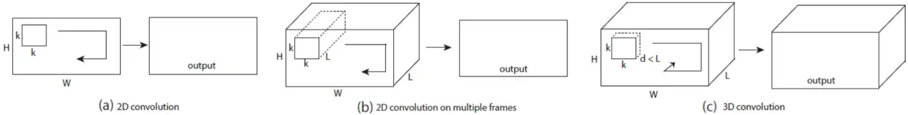
Modeling: Late Fusion

The Baseline Model

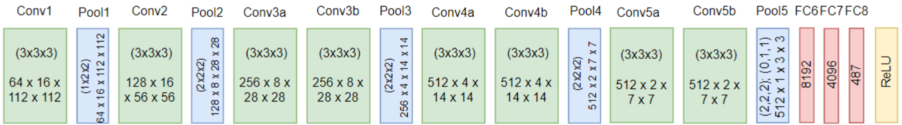
- Backbone 2D CNN architecture: Resnet-152
- The model does not consider temporal relations between frames
- Training time is fast.



3D Convolution Operation



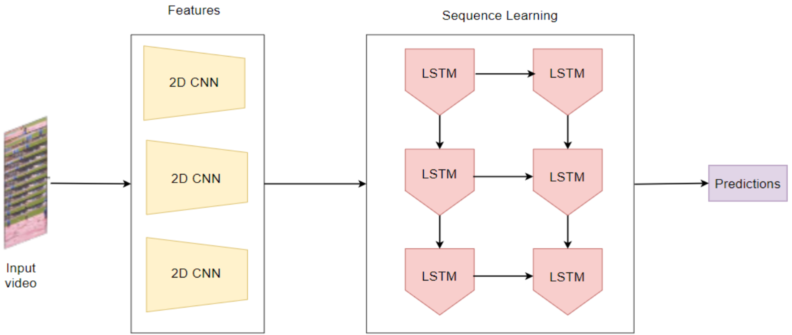
C3D: A 3D version of VGG16



Modeling: LRCN

Long-term Recurrent Convolutional Network

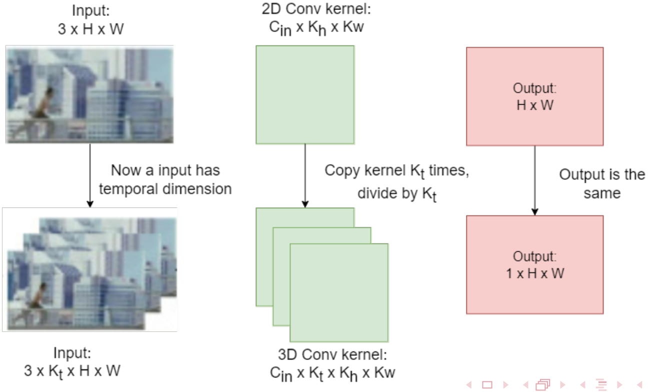
- Backbone 2D CNN architecture: Resnet-152
- Use RNN(s) to handle the temporal relations between frames
- But RNN layers make the training duration longer



Modeling: I3D

Inflated 3D Network: From 2D CNN to 3D CNN

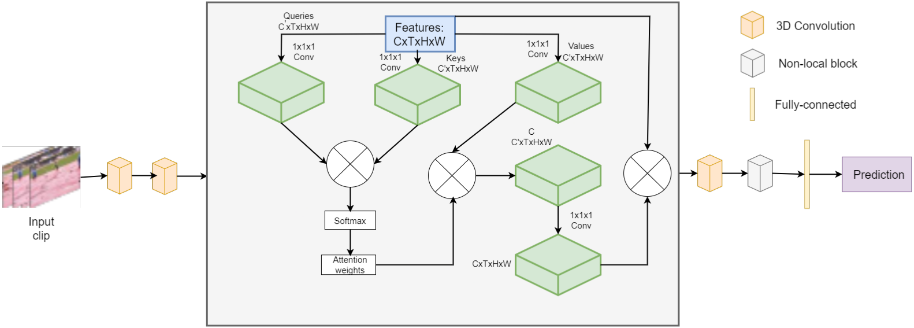
- Reuse the 2D CNN architecture and its pre-train weights
- Change in receptive fields



Modeling: Non-local Neural Networks

Non-local Neural Networks

- Implement self-attention to make Non-local blocks
- Use Non-local blocks inside existing 3D CNN architecture



Experiments: Training Strategies

Data Preparation, Augmentation

- Traning/Validation set: 80% and 20% based on class distribution
- Extracted frames based on models. For examples, sample 5 frames uniform for 2D-based model, 1-clip 16 frames for 3D-based model
- After trials and errors, augmentation technique: only use Resize and Normalization for all models

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Loss Function, Optimizer, Evaluation Metrics

- Loss Function: Cross Entropy Loss
- Evaluation Metrics: Accuracy, Confusion Matrix
- Optimizer and scheduler: Adam optimizers and Exponential Learning Rate scheduler: decrease the learning rate after one epoch

Experiments: Training Strategies

Models and hyperparameters settings

- Tools: Pytorch and Weight & Bias (Wandb)
- All models are pretrained.
- Hyperparameters such as learning rate, chosen through trails and errors

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Training two dataset simultaneously

- Make use of all two datasets
- Feed the training model two different batches of data of two dataset and changing the last fully connected layer correspondingly

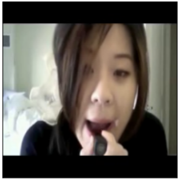
Experiments: Quantitative results

Models	Data Processing	Backbone / Pretrained	UCF101 Val_acc(%)	UCF101 Test_acc(%)	HMDB51 Val_acc(%)	HMDB51 Test_acc(%)
Training on dataset itself						
Late Fusion	5 frames	Resnet-152	95.44	74.19	61.33	41.62
C3D	16 frames clip	Sport-1M[3]	89.99	60.55	47.68	15.98
LRCN	5 frames	Resnet-152	96.61	74.50	65.94	43.87
I3D	16 frames clip	Resnet-50	93.27	66.73	59.59	36.47
Non-local	16 frames clip	Kinetics 400	**95.48**	**83.01**	**67.74**	**53.35**
Training on two datasets						
Late Fusion	5 frames	Resnet-152	92.49	72.85	63.78	37.63
C3D	16 frames clip	Sport-1M	89.18	60.50	56.03	32.34
Non-local	16 frames clip	Kinetics 400	**95.01**	**84.11**	**68.80**	**50.92**

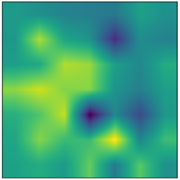
The results for each model for each dataset with two training strategies, on the dataset itself and two datasets

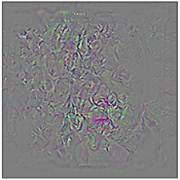
Experiments: Qualitative results

What I3D have learned through three techniques: Activation Map, Grad-Cam, and Guided Backpropagation

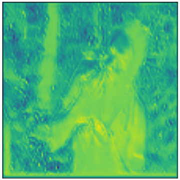

(a) Original image

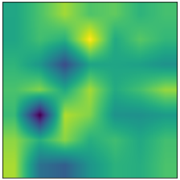

(b) Activation map

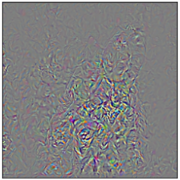

(c) Grad-CAM


(d) Guided Backpropagation


(a) Original image


(b) Activation map


(c) Grad-CAM


(d) Guided Backpropagation

Conclusion

Summary

- By using various methods and tools, we have trained five different models on two dataset benchmark for video recognition problem
- The best model among five ones is Non-local Neural Networks training on two datasets
- Besides quantitative results, we also analyse on qualtitative results based on visual explanation techniques

Possible extensions

- Research and implement new models like ViViT and new data preprocessing methods such as RandAugment
- Try to apply self-supervised and semi-supervised learning for this problem