Università degli Studi di Milano – Bicocca
Master's Degree in Data Science - Foundations of Deep Learning
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VIDEO CLASSIFICATION: HUMAN ACTION RECOGNITION ON HMDB51 DATASET

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Task: Human action recognition in videos

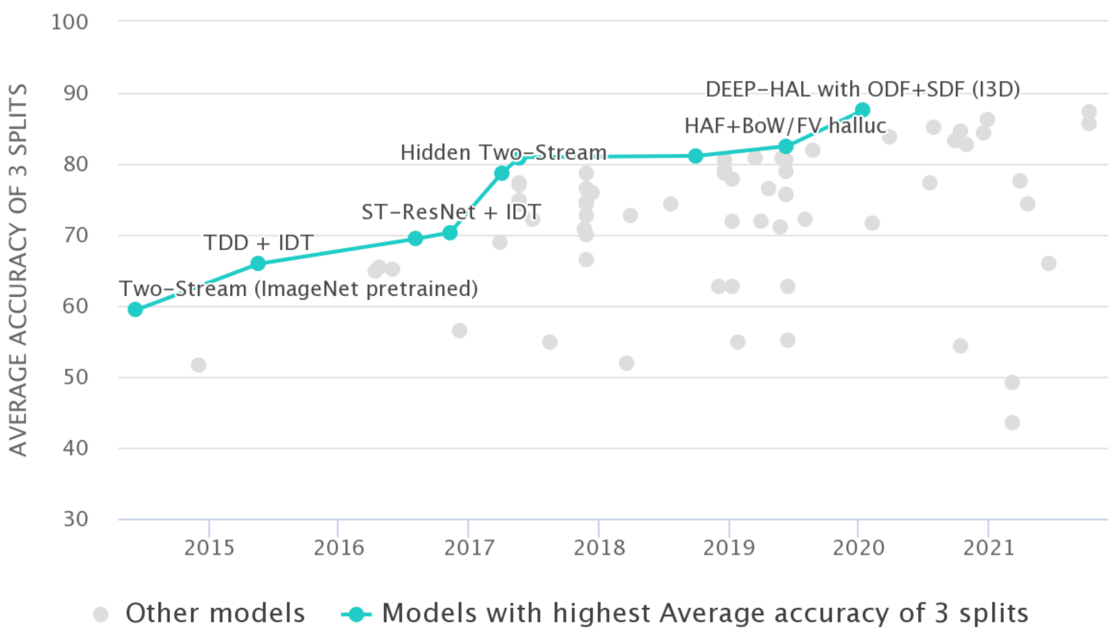
- **Human Action Recognition** (**HAR**): **time series classification** problem that involves classifying an action performed by someone
- **Vision-based** Human Action Recognition (**V-HAR**): classification of actions performed in **video clips**
- **Video** classification vs **image** classification:
  - Higher **computational cost**
  - **Spatial** and **temporal** information
  - Capturing **long spatiotemporal context**
- **Simple Action Recognition**: model that classifies singular global actions in short video clips

Action: waving

Simple Action Recognition: Video Classification Methods

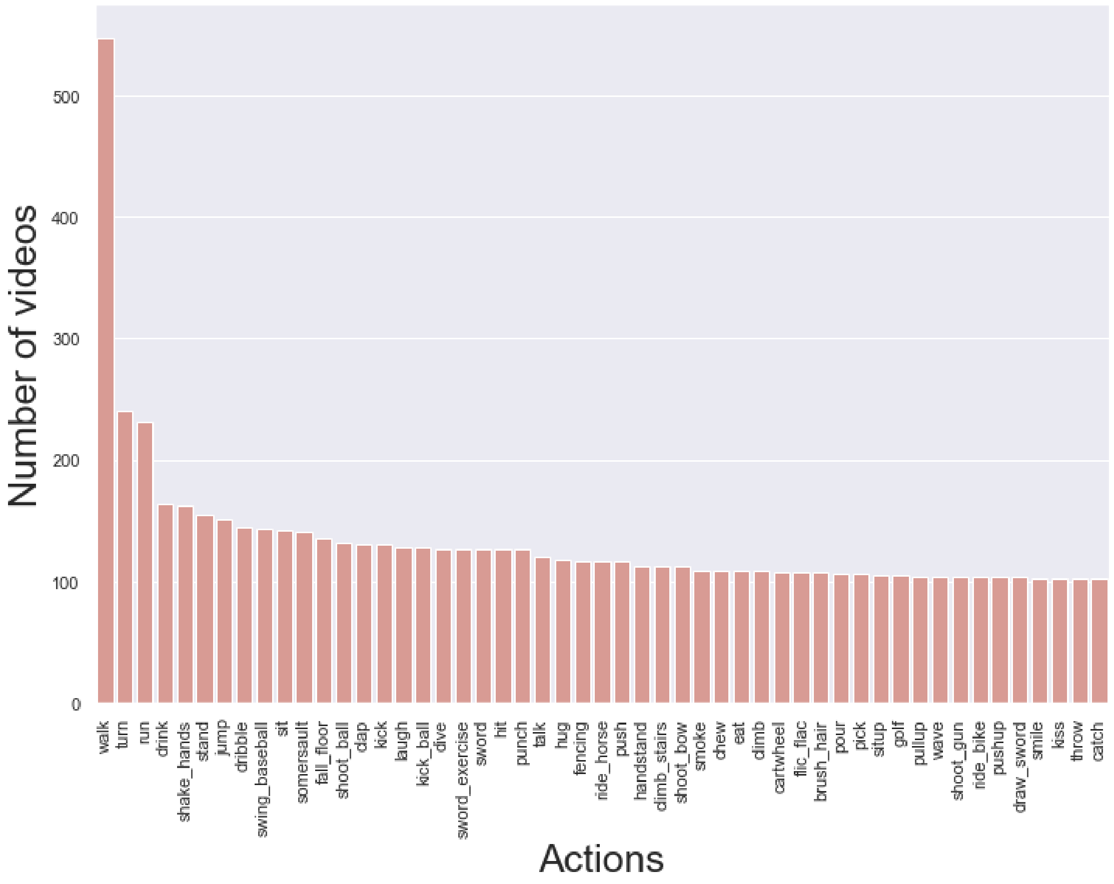
- ❑ **Hand-crafted Features**
- ❑ **Single Stream Networks**
  - Single-Frame CNN (2D CNN's)
  - Late Fusion / Early Fusion / Slow Fusion (2D CNN's)
  - 3D ConvNet (C3D)
  - CNN with LSTM's
  - Pose Detection and LSTM
- ❑ **Two Stream Networks**
  - Optical Flow and CNN's
  - SlowFast Networks

- ❑ Action Recognition on **HMDB-51: State-of-the-Art:**
  - DEEP-HAL with ODF+SDF (I3D) 2020 -> **87.56%**



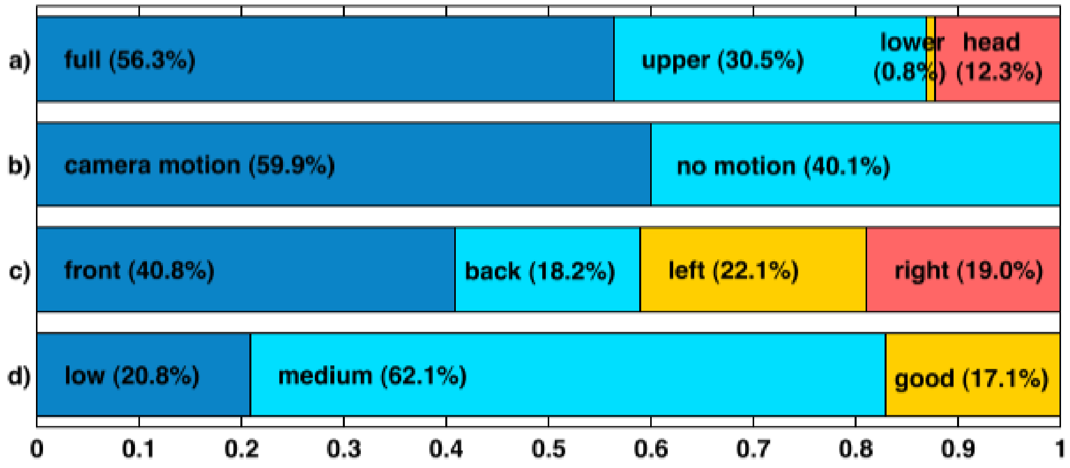
HMDB51: A Large Video Database for Human Motion Recognition

- **6766** annotated clips
- Different **sources**: Youtube, Google videos, movies.
- **51 categories** with a minimum of 101 clips per action
- **Categories** grouped in **five types:**
  - General **facial actions**
  - **Facial actions** with **object manipulation**
  - General **body movements**
  - **Body movements with object** interaction
  - **Body movements for human interaction**



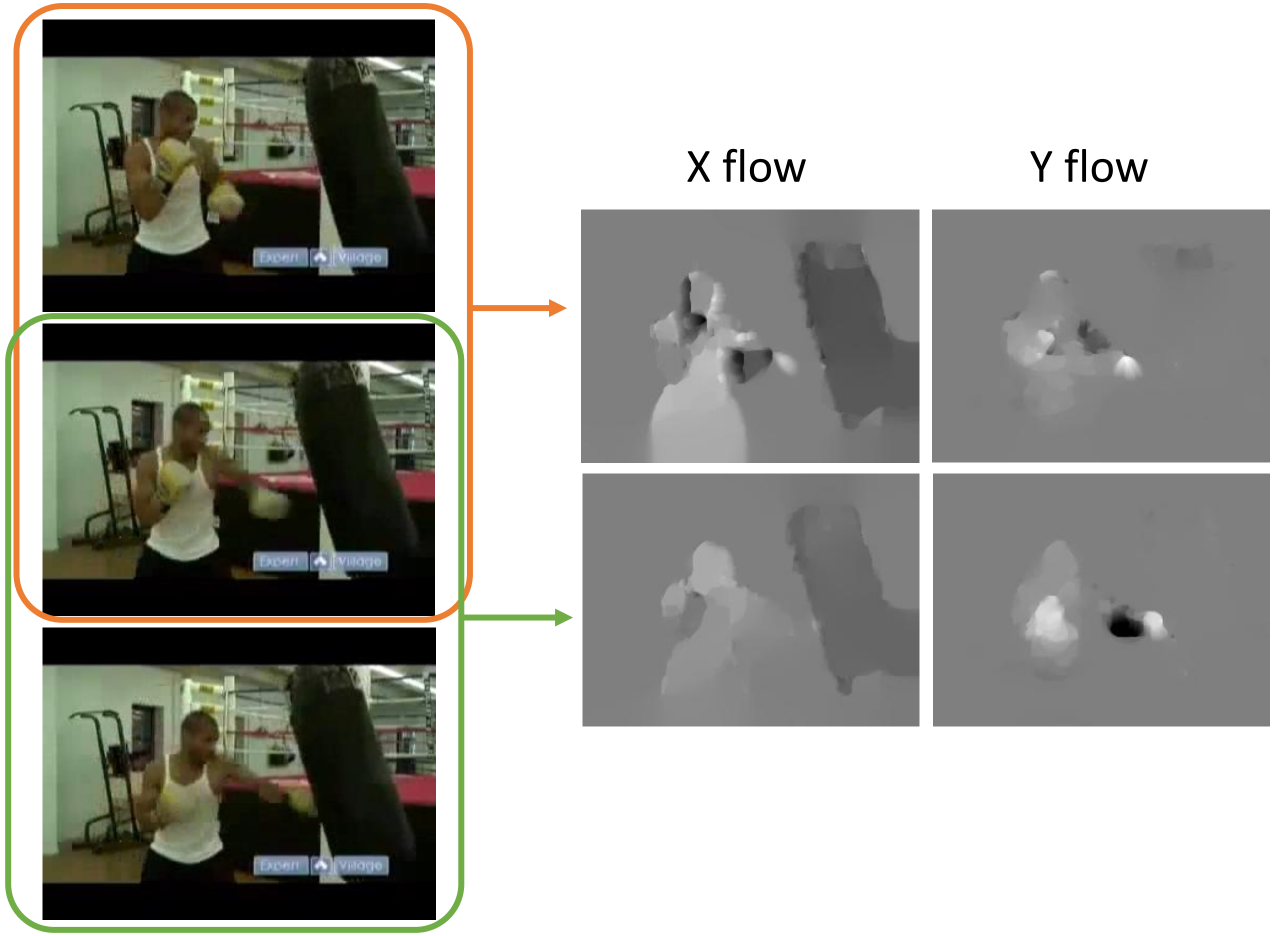
HMDB51: Data Exploration

- ❑ Additional **meta information**:
  - a) **Visible body parts / occlusions**: full, upper, lower, head
  - b) **Camera motion:** motion or static
  - c) **Camera viewpoint:** front, back, left, right
  - d) **Video quality:** good, medium or bad
  - ▪ **Number of people** involved
- ❑ Video **normalization:**
  - ▪ **Height** of all the frames is scaled to **240** pixels
  - ▪ **Width** is scaled to maintain aspect ratio
  - ▪ Frame rate of **30 fps**



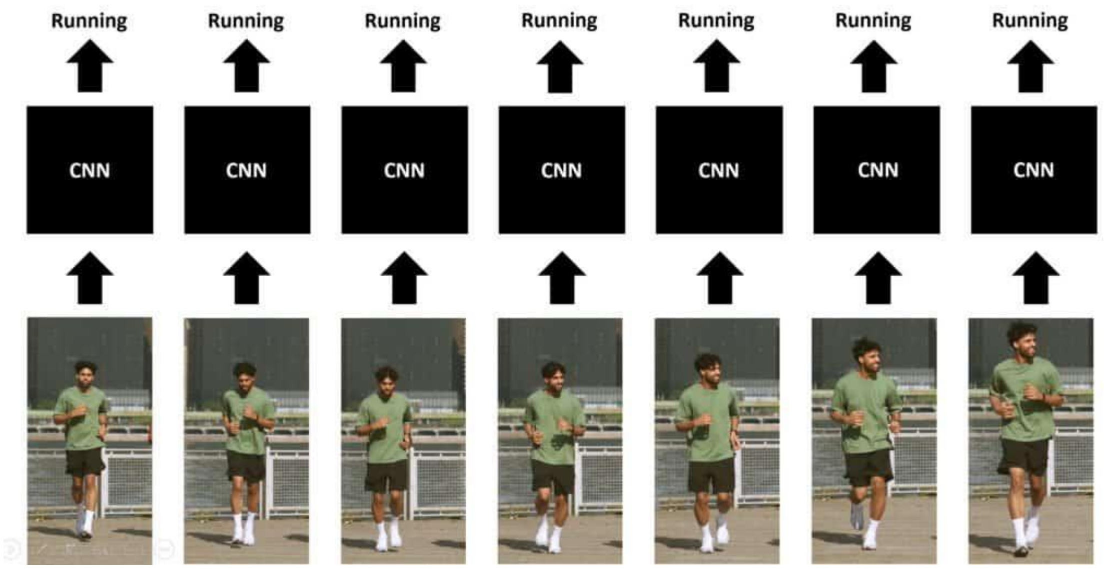
Data Preparation

1. **Training** (70 clip/class) and **test** (30 clip/class) split
2. **Frame extraction** (625775 total frames)
3. **Dense Optical Flow extraction**
   - 2 consecutive frames
   - Dual TV-L1 Optical Flow
4. **Sampling**
5. **Data augmentation** on frames & optical flows:
   - Random **Horizontal flip** (50% probability)
   - Random **Crop** (224x224)
   - Random **Rotation** (0.15)
6. **Centering**, **scaling** and **Resizing** (224x224)

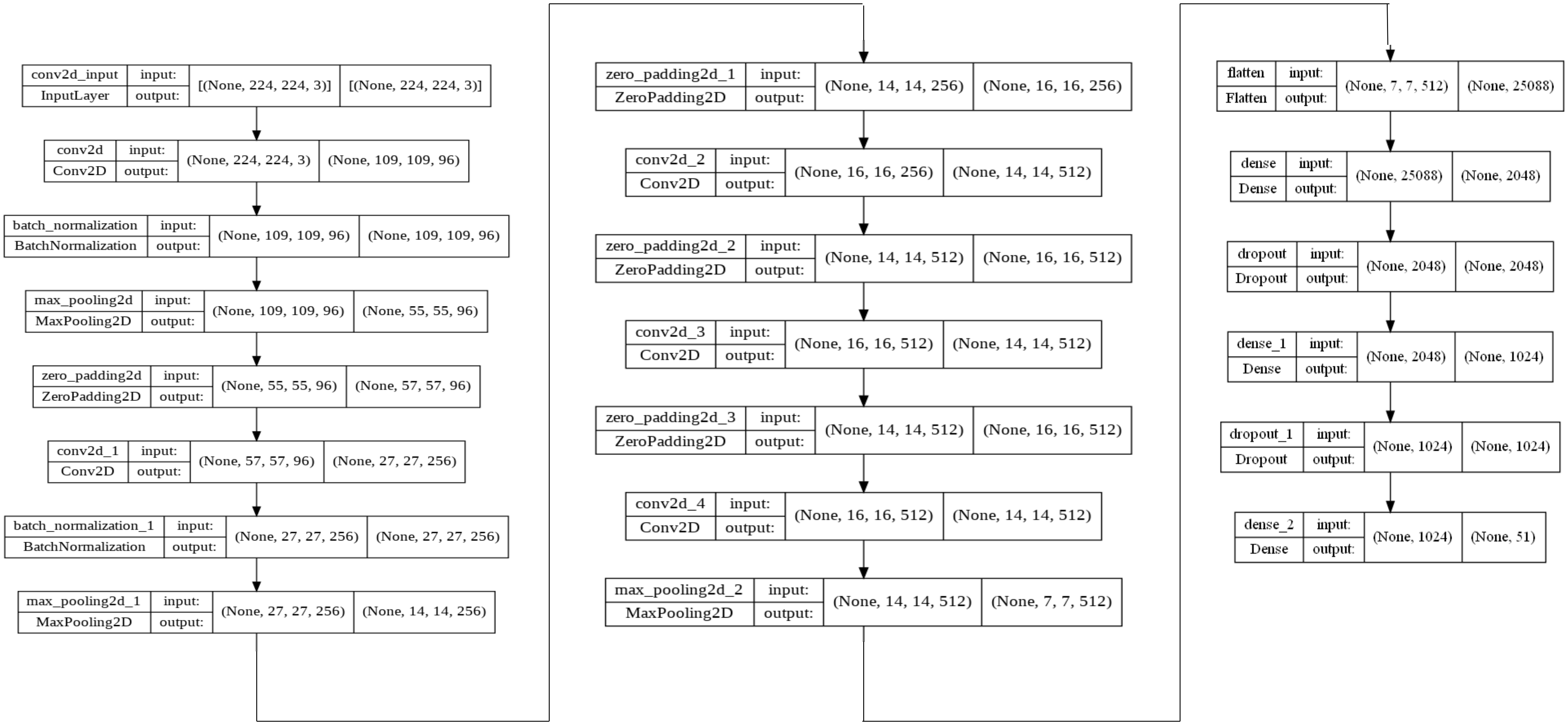


First approach: CNN single frame classification

- **Architecture**
  - Convolutional Neural Network
  - 17 frames per video
- **Layers:**
  - Preprocessing (224 x 224 x 3)
  - Convolutional2D (activation: Relu)
  - Zero padding
  - Batch normalization
  - MaxPooling (pool size: 3x3, stride: 2)
  - Dense (dropout: 0.5, activation: ReLu, Softmax)

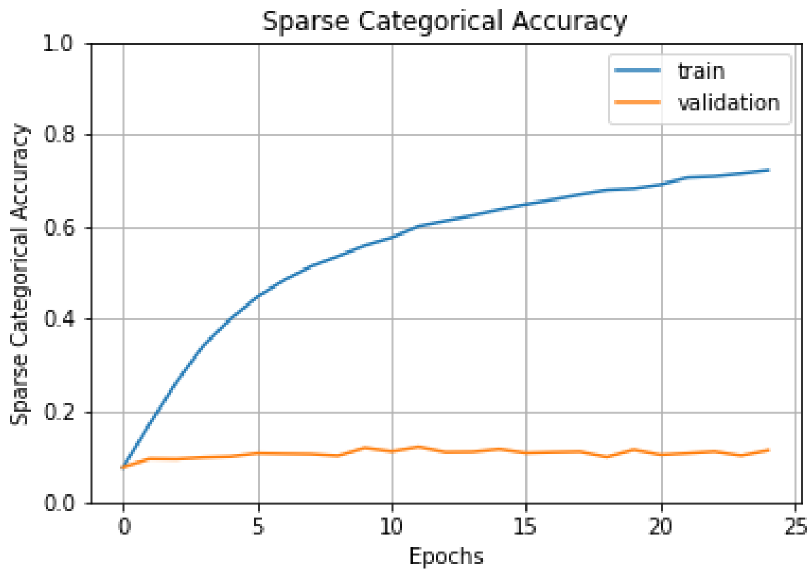


First approach: CNN single frame classification



First approach: CNN single frame classification

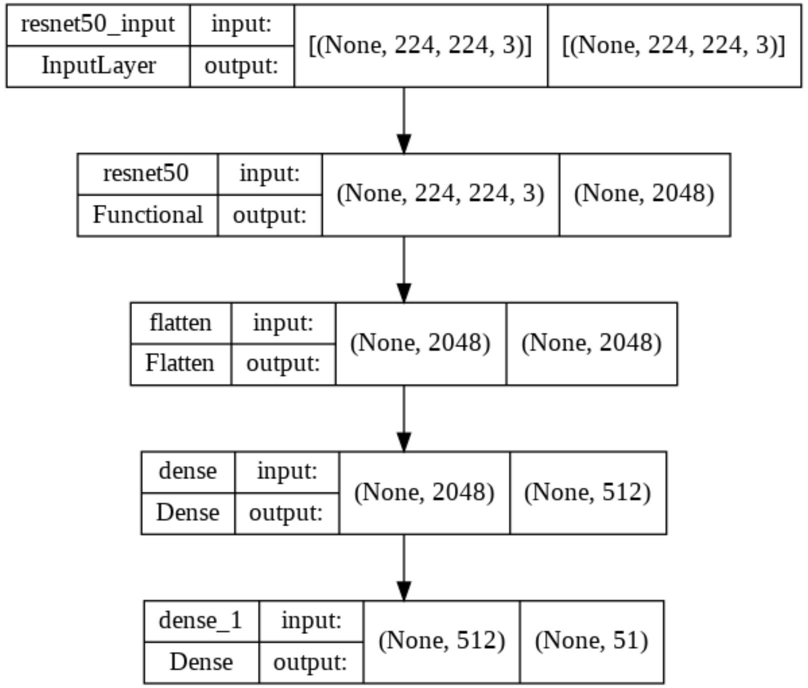
- First train:
  - Validation loss: **13.73**
  - Top 1 accuracy: **6.6%**
- Best train:
  - Validation loss: **4.74**
  - Top 1 accuracy: **12.1%**
  - Top 5 accuracy: **34.4%**



	Optimizer	Epochs	L.R.	Batch	Train. P.	Data Aug.	Norm.
First	Adam	100	0.001	64	117,789,043	Resize	[0, 255]
Best	Adam	25	0.001	128	60,142,035	Flip, Rot, Crop	[−1, 1]

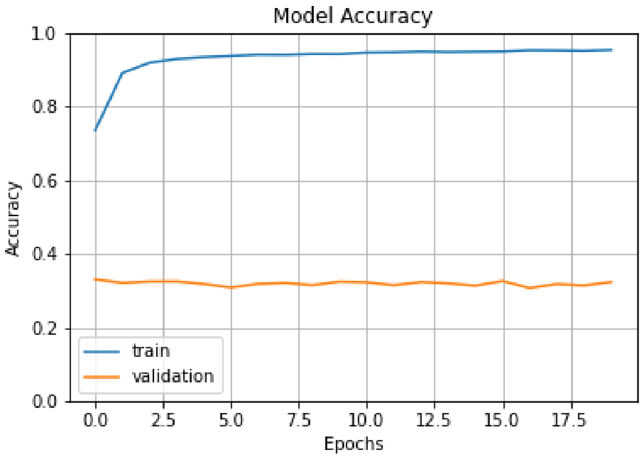
Second approach: Transfer Learning

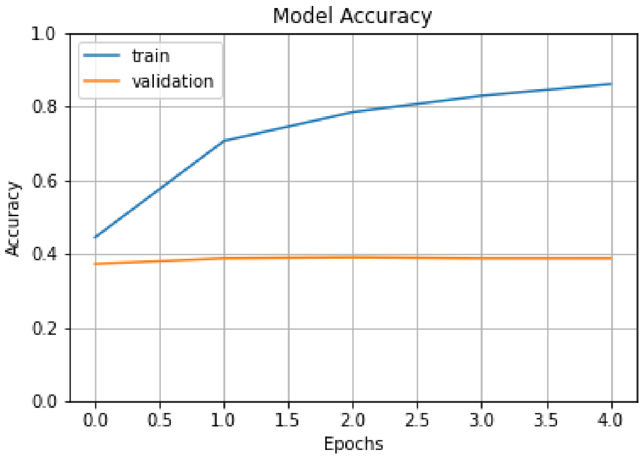
- **Architecture**
  - Finetuned CNN based of ResNet50
  - 17 frames per video
- **Layers:**
  - ResNet50 (not trainable, weights from ImageNet)
  - Flatten
  - Dense (activation: ReLu, SoftMax)



Second approach: Transfer Learning

- First train:
  - Validation loss: **2.91**
  - Top 1 accuracy: **31.9%**
  - Top 5 accuracy: **59.1%**
- Best train:
  - Validation loss: **2.30**
  - Top 1 accuracy: **39.0% -> 45.0%** (integral video)
  - Top 5 accuracy: **71.6% -> 78.5%** (integral video)

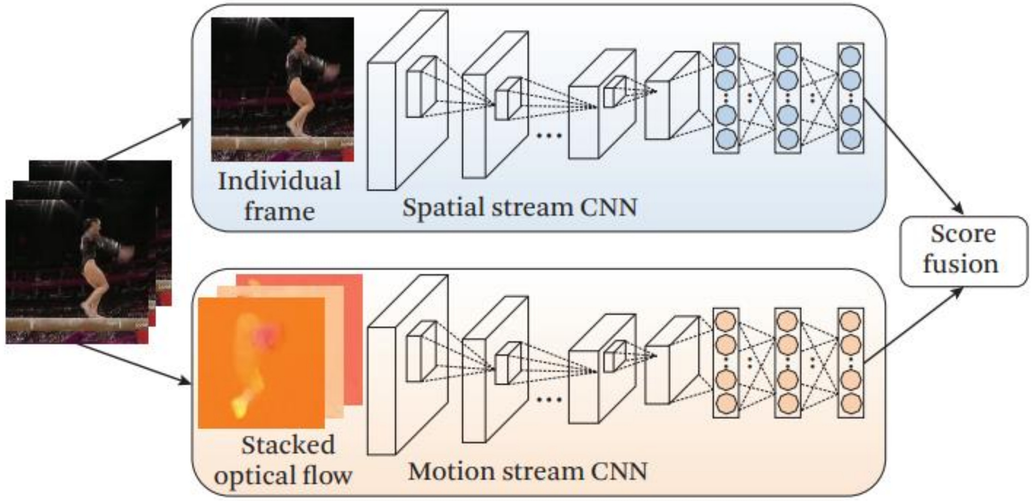




	Optimizer	Epochs	L.R.	Batch	Train. P.	Data Aug.	Norm
First	Adam	20	0.001	64	1,075,251	Resize, Flip	[0,255]
Best	Adam	5	0.0001	64	1,075,251	Resize, Flip	Centered

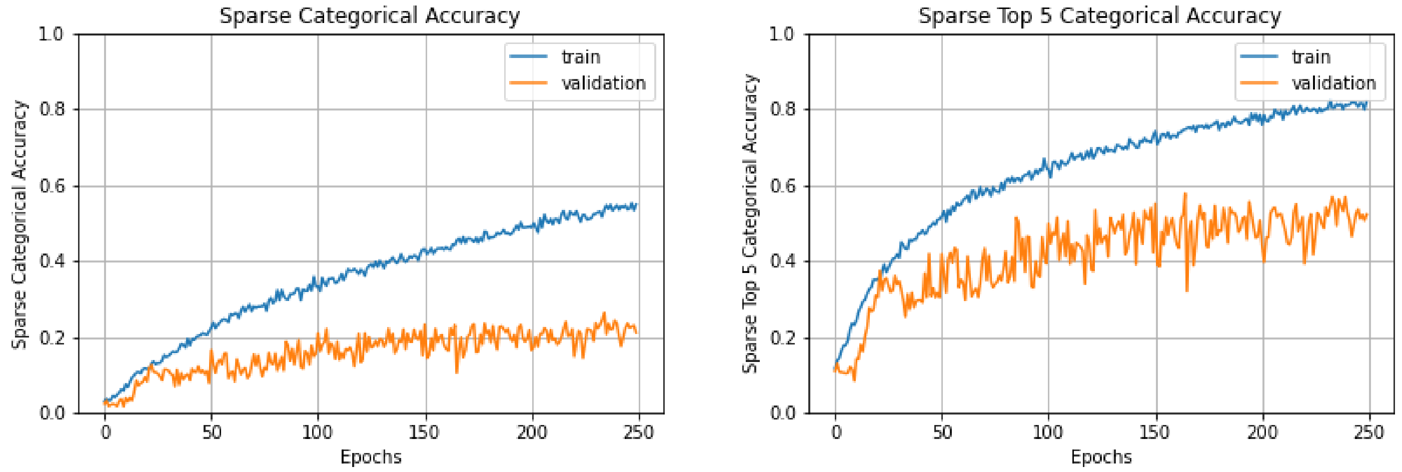
Third approach: two-stream CNN

- **Architecture:**
  - Spatial CNN + Temporal CNN
  - Averaging SoftMax results
- **Spatial stream:**
  - Finetuned ResNet
- **Motion stream:**
  - Same architecture as “first approach CNN” with input size (224, 224, 20)
  - Semi-randomly selected batch of N stacked optical flow from N randomly selected videos
  - Each flow stack is composed of 10 x-channels and 10 y-channels consecutive optical flows



Third approach: two-stream CNN (motion stream)

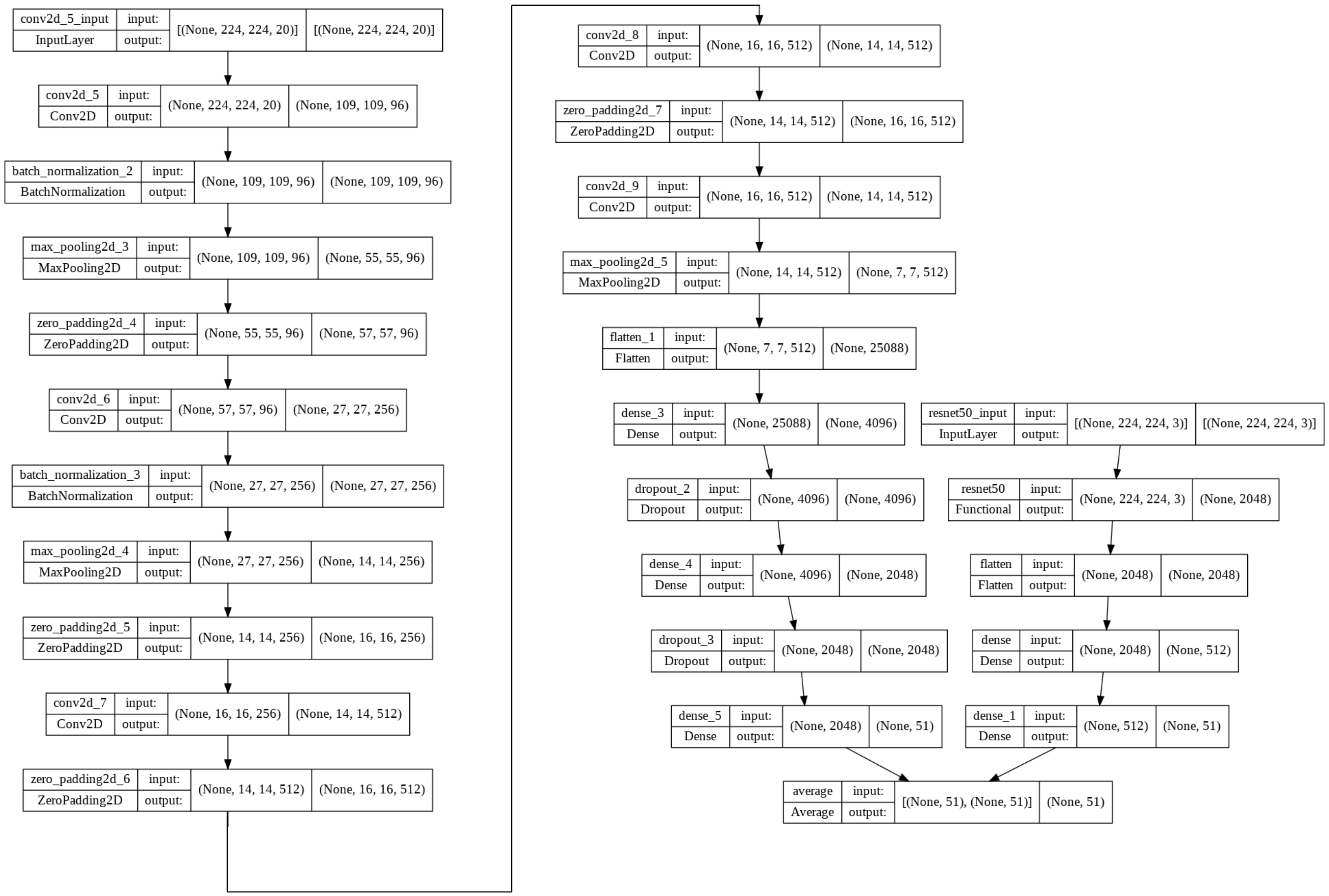
- **First train:**
  - Validation loss: **3.46**
  - Top 1 accuracy: **15.0%**
  - Top 5 accuracy: **42.4%**
- **Best train:**
  - Validation loss: **3.27**
  - Top 1 accuracy: **25.8%**
  - Top 5 accuracy: **54.3%**



	Optimizer	Epochs	L.R.	Batch	Train. P.	Data Aug.	Norm
First	SGD (mom. 0.9)	100	0.01	64	117,789,043	Resize	[0, 255]
Best	SGD (mom. 0.9)	250	0.01	128	60,142,035	Flip, Crop, Resize	Cent + Scal

Third approach: two-stream CNN

- **Two-stream CNN:**
  - Validation loss: **2,33**
  - Top 1 accuracy: **38%**
  - Top 5 accuracy: **70%**



Models prediction on integral video (example)

- **Spatial net:**
  - golf: 98,38 %
  - shoot_bow: 0,81%
  - catch: 0,40 %
  - kick_ball: 0,25 %
  - handstand: 0,03 %

- **Temporal net:**
  - golf: 66,3 %
  - climb: 6,1 %
  - handstand: 5,0 %
  - walk: 2,0 %
  - pick: 2,0 %

- **Spatial net:**
  - ride_bike: 75,6 %
  - push: 17,1 %
  - draw_sword: 1,1 %
  - ride_horse: 0,9 %
  - dive: 0,7 %

- **Temporal net:**
  - catch: 19,2 %
  - cartwheel: 6,8 %
  - sommersault: 6,6 %
  - dide_horse: 5,3 %
  - climb: 5,3 %

Final evaluation

- ❑ **Best method**:
  - ▪ ResNet (accuracy: **45,0%** , top 5 accuracy: **78,5%**)
  - ▪ Possibly the two-stream CNN in case of steady or stabilized videos
- ❑ Possible causes of **low accuracy:**
  - ▪ **Dataset:**
    - Nuisances (camera motion, scenes cuts, low quality videos)
    - Limited number of individual videos (6849 clips extracted from 1407 videos)
    - Short action duration compared to video length (can be missed during the sampling phase)
  - ▪ **Models:**
    - Not optimal training parameters
    - Too many weights compared to data (first model)

Bibliography

- Kuehne, Hildegard, et al. "HMDB: a large video database for human motion recognition." 2011 International conference on computer vision. IEEE, 2011.
- Wang, Lei, and Piotr Koniusz. "Self-supervising action recognition by statistical moment and subspace descriptors." Proceedings of the 29th ACM International Conference on Multimedia (2021.)
- Simonyan, Karen, and Andrew Zisserman. "Two-stream convolutional networks for action recognition in videos." Advances in neural information processing systems 27 (2014).
- Wang, Limin, et al. "Temporal segment networks: Towards good practices for deep action recognition." European conference on computer vision. Springer, Cham, (2016).
- Sargano, Allah Bux, Plamen Angelov, and Zulfiqar Habib. "A comprehensive review on handcrafted and learning-based action representation approaches for human activity recognition." applied sciences 7.1 (2017).
- Laptev, Ivan, et al. "Learning realistic human actions from movies." 2008 IEEE Conference on Computer Vision and Pattern Recognition. IEEE, (2008).

Bibliography

- Zach, Christopher, Thomas Pock, and Horst Bischof. "A duality based approach for realtime tv-l 1 optical flow." Joint pattern recognition symposium. Springer, Berlin, Heidelberg, (2007).
- Karpathy, Andrej, et al. "Large-scale video classification with convolutional neural networks." Proceedings of the IEEE conference on Computer Vision and Pattern Recognition. (2014).

Sitography

- *Serre Lab.* URL: https://serre-lab.clps.brown.edu/resource/hmdb-a-large-human-motion-database/
- Introduction to Video Classification and Human Activity Recognition URL: https://learnopencv.com/introduction-to-video-classification-and-human-activity-recognition/
- Deep Learning for Videos: A 2018 Guide to Action Recognition: https://blog.qure.ai/notes/deep-learning-for-videos-action-recognition-review
- HMDB-51 Benchmark (Action Recognition) https://paperswithcode.com/sota/action-recognition-in-videos-on-hmdb-51