Predicting a vehicles velocity using dashcam footage

A deep learning approach

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Machine Learning using ~~Matlab~~ Python
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The "comma ai speed challenge" [1]

Motivation

- autonomous driving is currently one of the most prominent problems in machine learning
- but quite hard to set up on a desktop pc
- predicting a vehicles velocity from video footage is a related but also much more simplified task

Initial Dataset:

- training video with 20400 frames (20 fps)
- data file with velocity of the car at each frame
- test video with 10798 frames (20 fps)

Evaluation:

- the mean squared error (MSE) is used to measure performance

$$\mathcal{L} = \sum_i (p(x_i) - y_i)^2$$

[1] https://github.com/commaai/speedchallenge

Analysis of the dataset

Video data:

- frame size of $(640, 480, 3)$ pixels
- cut off last 60 pixels, to remove black frame inside the car
- sample down the frame to half its size, to reduce computation time

Original frame

Cut off the last 60 pixels, downsampled

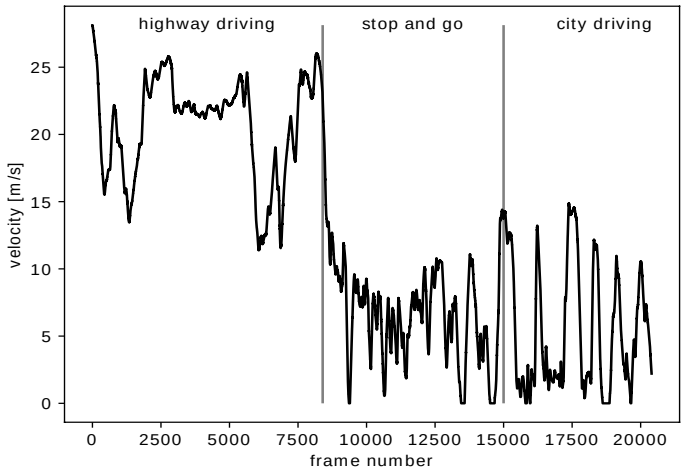
Analysis of the dataset

Situation data:

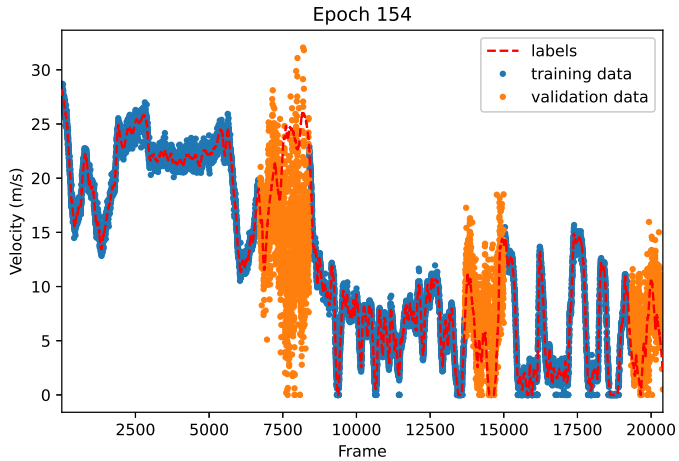
- test set with three different driving scenarios
- splitting with respect to them
  - divide dataset into different situations
  - splitting with 80% test and 20% validation data on each

Evaluation:

- variance $\sqrt{\mathcal{L}} \gtrsim 16$: no fitting
- $10 \lesssim \sqrt{\mathcal{L}} \lesssim 16$: average velocity fitted
- $5 \lesssim \sqrt{\mathcal{L}} \lesssim 10$: qualitative detection
- $1 \lesssim \sqrt{\mathcal{L}} \lesssim 5$: quantitative detection
- $\sqrt{\mathcal{L}} \lesssim 1$: perfect detection



driving situations in v-t-plot



example performance on training set

training: $\sqrt{\mathcal{L}} = 0.4$, test: $\sqrt{\mathcal{L}} = 6.3$

Optical flow using "Farneback pyramid method" [**Farneback2003**]

- Global method to solve the optical flow equation

$$\partial_x f \cdot V_x + \partial_y f \cdot V_y + \partial_t f = 0$$

  for an image sequence $(f_t)_t$ with $f_t : \Omega \to \mathbb{R}^3$, for all t, and the (dense) flow field $V : \Omega \to \mathbb{R}^2, \omega \mapsto (V_x(\omega), V_y(\omega))$.
- Uses a downsampling pyramid, to solve the equation for different resolutions of the image
- Parameters for the Farneback method

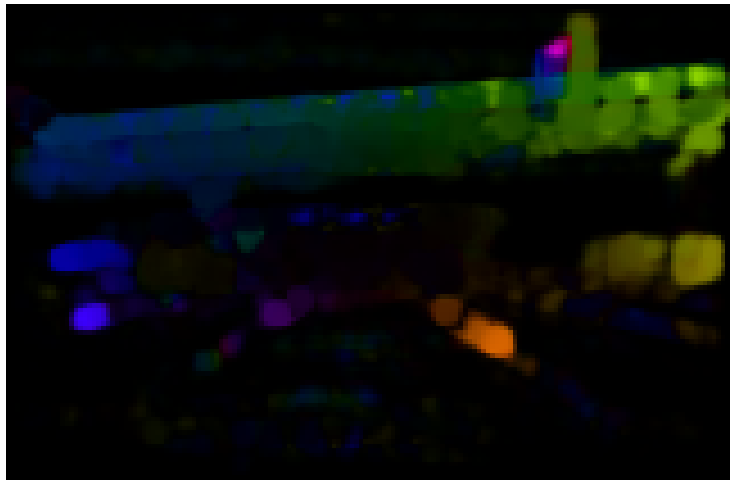
$$\begin{aligned} \text{pyramid levels} &:= 3 \\ \text{pyramid scaling} &:= 0.5 \\ \text{window size} &:= 6 \\ \text{pixel neighborhood size} &:= 5 \\ \text{SD of the gaussian filter} &:= 1.1 \end{aligned}$$

- Result: **Flow field with** $(160, 105, 3)$ **pixels**

Visualization of the flow field

- Flow field is a two-dimensional vector field
- RGB representation via
  - Transform flow field into polar coordinates $(V_x, V_y) \overset{\sim}{\mapsto} (r, \varphi)$
  - Normalize magnitudes r for the third channel
  - Values of the second channel are all set to 255
  - Multiply angle φ by factor $\frac{180}{2\pi}$ for the first channel
- Sample down the resolution again, to speed up the training

Input frame



Corresponding flow field

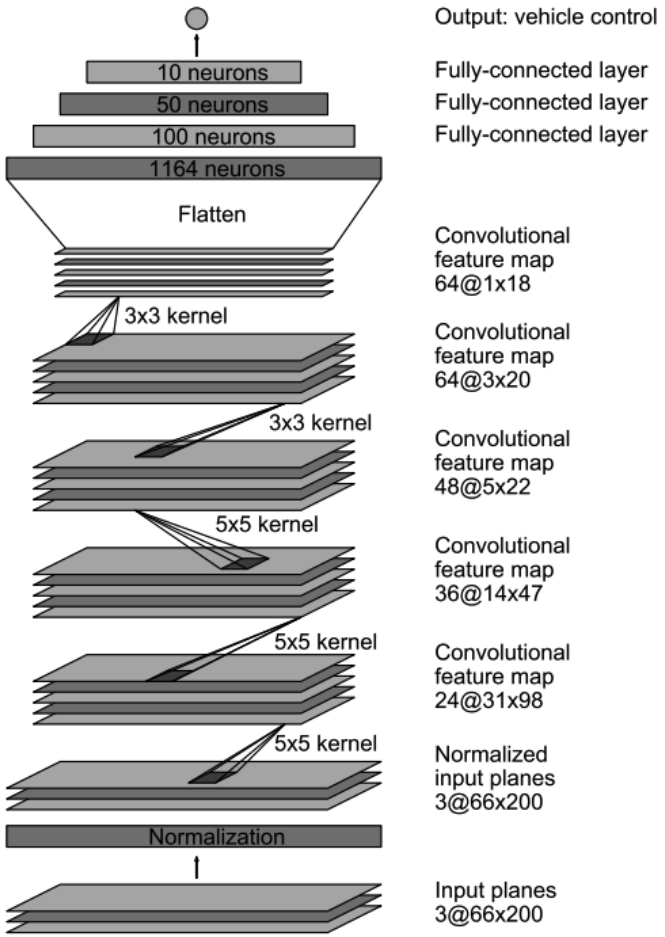
Choosing an initial architecture

Method selection

- speed prediction is a non-linear regression task ⇒ neural network
- task involves feature extraction ⇒ convolutional neural network (CNN)

Initial architecture

- using paper of *NVIDIA* work group [**NVIDIA2016**] of a CNN for self-driving cars adapted on our initial data
- enough complexity and layers to handle the task and lots of possibilities to fine-tune it
- Initial results with the raw model: $\mathcal{L} < 3$ on the training set and about $\mathcal{L} \approx 19$ (using an old splitting) on the test set



Original architecture of the *NVIDIA* paper [**NVIDIA2016**]

Our approaches to optimize the results

1. **change components of the initial architecture**
   - adding different pooling layers
   - use other activation functions
2. **change the architecture**
   - expand structure to Siamese network
   - use different setups
3. **change the input data**
   - use brightness augmentation
   - acquire more data

Batch Normalization, Dropout layers, activation function and pooling

- Batch normalization to speed up the training [**BatchNorm2015**]
- Initial activation function: $\mathrm{ReLu} : \mathbb{R} \to \mathbb{R}_0^+, x \mapsto \max\{0, x\}$, still MSE of over 15 on the testing set, less then 2 on the training set
  $\Rightarrow$ Overfitting problems
- Dropout layers [**Dropout2014**] to make the model more robust and reduce overfitting
- Solve problems of dead neurons using

$$\mathrm{leakyReLU} : \mathbb{R} \to \mathbb{R}, x \mapsto \begin{cases} x, x \geq 0 \\ c \cdot x, x < 0 \end{cases}$$

with $c = 0.01$, MSE of around 11 on the testing set and less than 3 on the training set

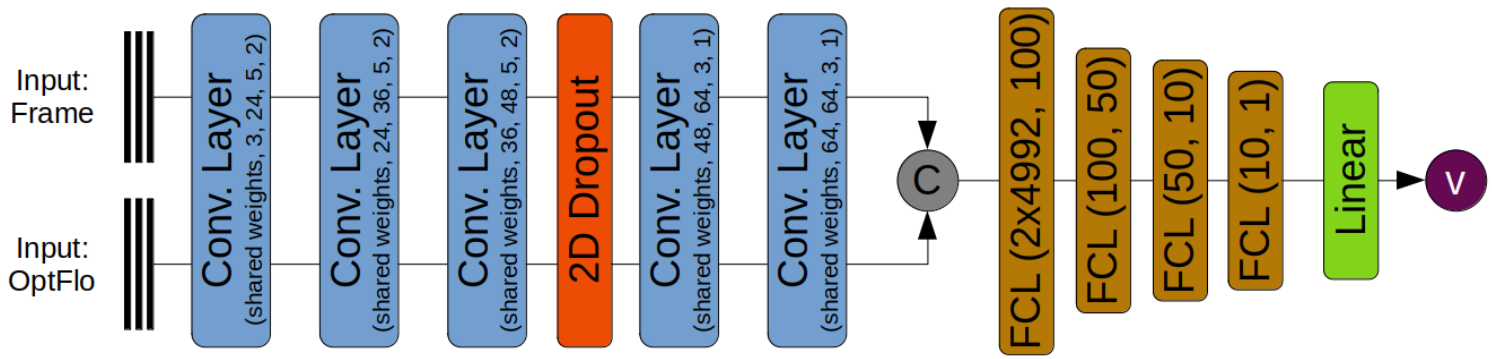
Pooling layers (initial splitting)

Initial splitting, 8 epochs	ReLU		leakyReLU	
	Train	Test	Train	Test
No pooling	2.85	12.08	2.45	10.75
Max pooling	5.62	11.82	5.52	10.29
Max pooling (15 epochs)	-	-	**3.22**	**9.63**
Average pooling	7.70	11.40	6.08	13.09

Table: MSE results of the network using different pooling strategies, one dropout layer, two different activation functions and the initial splitting. We trained each of the models for eight epochs.

Siamese Architecture: Setup

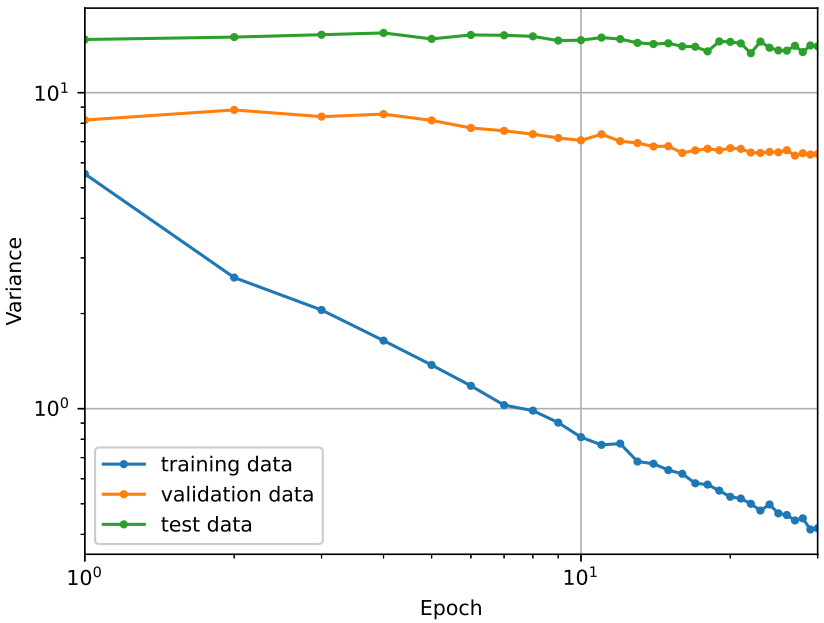
- based on the initial architecture
- using the same convolutional layers on frames and optical flow
- results are added with weights and feed into the fully connected layers

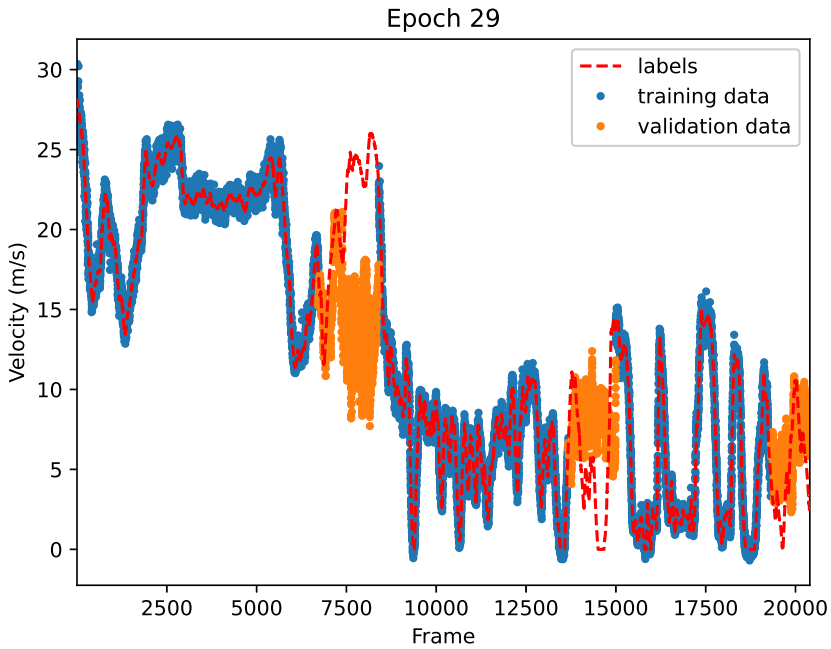


- using same model with both frames to predict the velocity between those
- advantage: no previous calculation of optical flow needed

Siamese Architecture: Performance

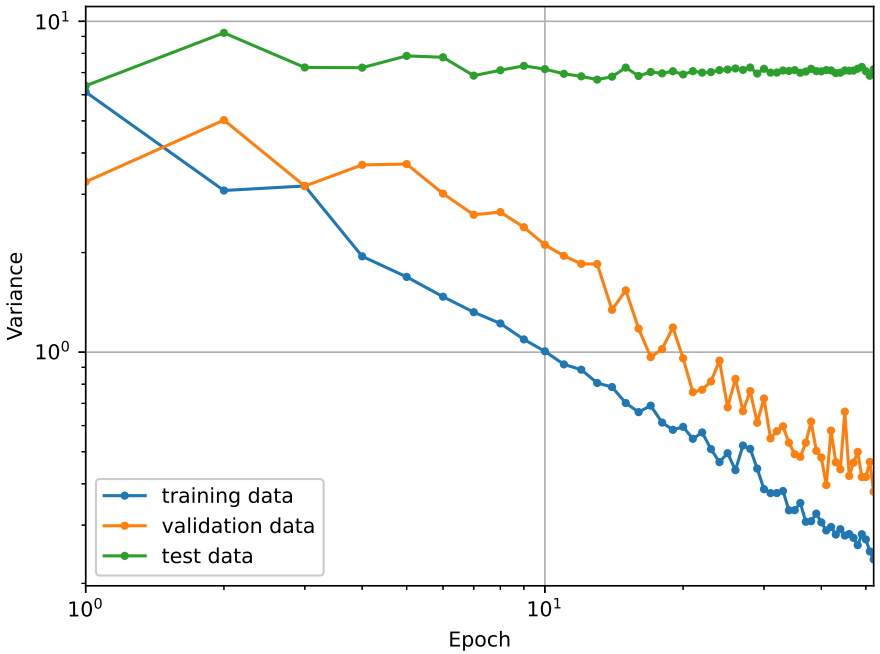
Performance (Siamese network frame with optical flow):

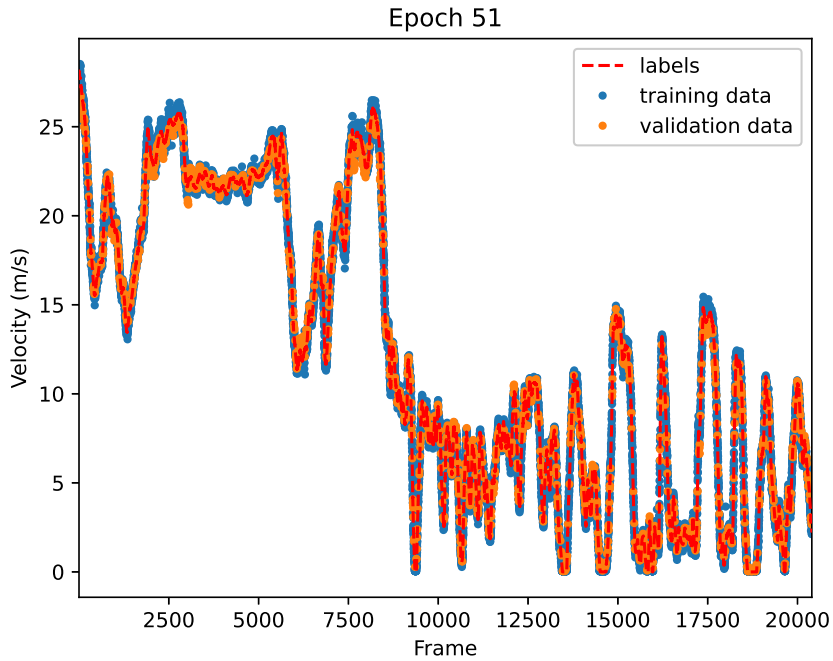




Siamese Architecture: Performance

Performance (Siamese network with two frames):

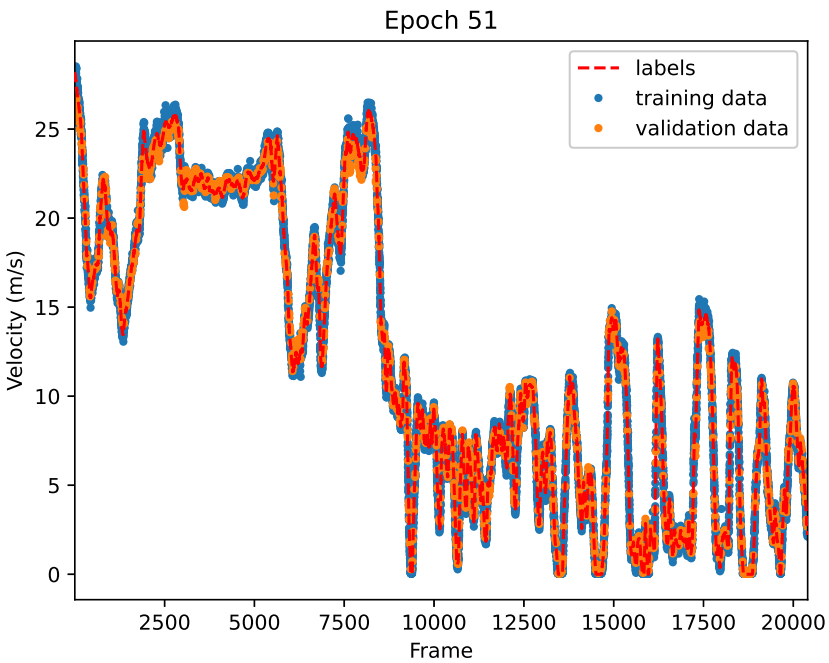




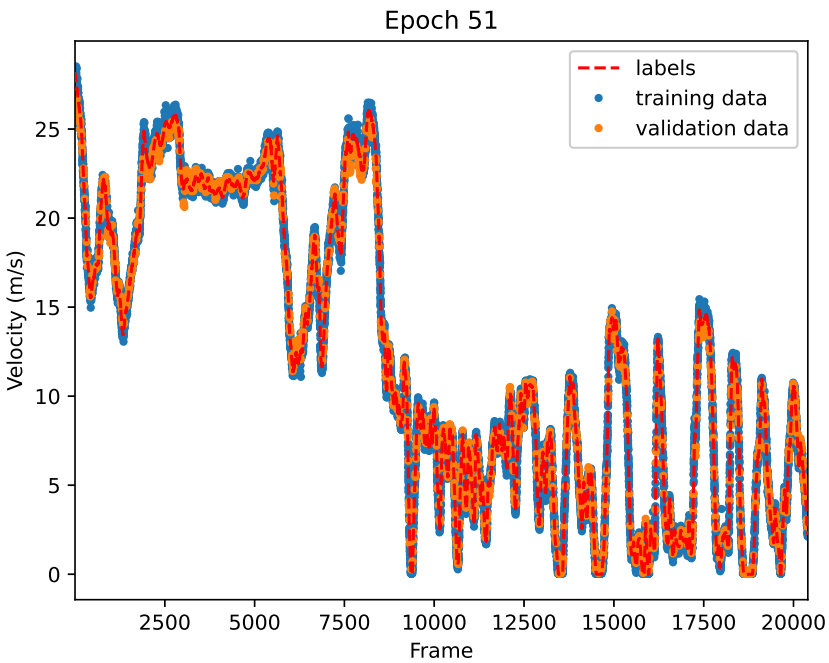
Problems

We identified three problems with our approaches

1. big overfit when validation data is not randomly distributed in the data but a continuing block
2. predictions are very susceptible for brightnesses/illumination changes in the frames, therefore unstable calculations of the optical flow



random shuffled validation data



block validation data

Problems

- predictions are limited to data very similar to the training data
- predictions do not generalize well

most likely explanations:

- very limited dataset for a complex model
- network is not prepared for unseen situations
- changes in brightness and illumination

Possible solutions

Process of detecting speed from a video

- extracting features from each frame
- check how the features have moved between two frames
- evaluate if the movement comes from own speed or other sources

$\Rightarrow$ for good generalization a complex model is necessary

Solutions:

- acquire more data for various driving situations
- use a technique to normalize different brightnesses
- add randomly noise to the data to negate wrong features
- use a much less complex model

Contrast and brightness augmentation

- Additional noise to frames **before** calculating the flow field.
- Change the brightness and contrast of an image via

$$\text{frame}_{\text{augmented}}(i,j) = \alpha(i,j) \cdot \text{frame}(i,j) + \beta(i,j)$$

with functions α (contrast: > 1 increase, < 1 decrease) and β (brightness). To get some noise into the frames, we used

$$\alpha \sim \mathcal{U}(0,1) + 0.35$$
$$\beta \sim \mathcal{U}(-5,35),$$

where $\mathcal{U}(a,b)$ is the uniform distribution in an interval $[a,b]$ for $a < b$.

Acquire more Data

- use mobile to create a video and track the velocity via GPS
- test run already worked
- data does not compare to the rest due to completely different brightness and angle
- but it would allow to create a greater data set with more training and labeld test data

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Usage in real application

- if we have good model we have written method that reads video and predicts velocity
- we reach 30 fps which is faster than the 20 fps of the video so life prediction would be possible

Evaluation with the test video

- rough check how model performs on unseen video with the same parameters
- no labels available so we can only compare key situations (stops, highway, ...)
- some models achieve at least a qualitative accordance with the video (hier noch ein Bild)
- best networks: altered original network and

References