Radboud University Nijmegen

Faculty of Science

Convolutional Neural Networks applied to Keyword Spotting using Transfer Learning

Thesis in Automatic Speech Recognition
(LET-REMA-LCEX10)

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August 14, 2019

Contents

1 Introduction

The task of keyword spotting (KWS) is interesting to different domains where a hands-free interaction experience is required or desired like Google's feature of interacting with mobile devices (include "OK Google" reference).

Different approaches to keyword spotting like:

- Deep Neural Networks (DNNs)
- Convolutional Neural Networks (CNNs)
- (Keyword/Filler) Hiddem Markov Models (HMMs)

1. Problem
2. Background (literature overview)
3. Research Question, Hypotheses, intro to experiment

1.1 Literature review

This section contains the most prominent approaches to the KWS task which have been successfully applied in the past and serve as baseline models or inspirations for the proposed model in this thesis.

1.1.1 Raw waveform-based audio classification using sample-level CNN architectures

- Raw waveform-based audio classification using sample-level CNN architectures [11]

1.1.2 Transferable deep features for keyword spotting

- Transferable deep features for keyword spotting [13]

1.1.3 Imagenet: A large-scale hierarchical image database

- Imagenet: A large-scale hierarchical image database [6]

1.1.4 Imagenet classification with deep convolutional neural networks

- Imagenet classification with deep convolutional neural networks [9]

1.1.5 Speech Recognition: Keyword Spotting Through Image Recognition.

The authors of the paper "Speech Recognition: Keyword Spotting Through Image Recognition" [8] transformed the KWS task which incoporates audio data into the domain of image classification. They used the Speech Commands Dataset [18] which contains spoken words of the length of one second in order to train and evalutate their model. According to [18], the Speech Commands Dataset V2 [2] comprises one-second audio clips which were sampled at 16KHz and containing ten words, namely "Yes", "No", "Up", "Down", "Left", "Right", "On", "Off", "Stop", and "Go", and have one additional special label for "Unknown Word", and another for "Silence" (no speech detected). A vector representation of these one-second audio clips would therefore be of the form $\mathbb{R}^{16000}$.

The authors used three different models, namely:

- A Low Latency Convolutional Neural Network which is designed to reduce its memory footprint by limiting the number of model parameters. This model is similar to the model called ”cnn-one-fstride4” which is used in [14] but differs in terms of filter size, stride, channels, dense and params. The model has been trained using Stochastic Gradient Descent and Xavier Initialization has been used in order to initialize the model weights.

- The MNIST TensorFlow CNN / Basic CNN where some tweaks have been performed to the first layer in order to fix dimension mismatches. A baseline architecture is described in [14] (3 module setup?).

  - `https://github.com/tensorflow/docs/blob/master/site/en/tutorials/estimators/cnn.ipynb`
  - `https://github.com/tensorflow/tensorflow/tree/master/tensorflow/examples/tutorials/mnist`

- Adversarially trained CNN which is inspired by MCDNN [5] and AlexNet [9]. One shallow CNN which has been used for prototyping and hyperparameter tuning. Dropout was counter-productive and therefore Virtual Adversarial Training was used, inspired by [7].

Evaluated parameters in this paper:

- Adversarial Training Results and Comparison with Vanilla CNN

- increase in training and validation accuracy over the first ten epochs for the low-latency convolution and VAT models: a zoomed-in version of Figure 12

- decrease of costs over 500 epochs for the lowlatency convolution and VAT models: a zoomed-out version of Figure 13

- increase of training and validation accuracy over 500 epochs for the low-latency convolution and VAT models: a zoomed-out version of Figure 10

- reduction of cost over the first ten epochs for the low-latency convolution and VAT models: a zoomed-in version of Figure 11

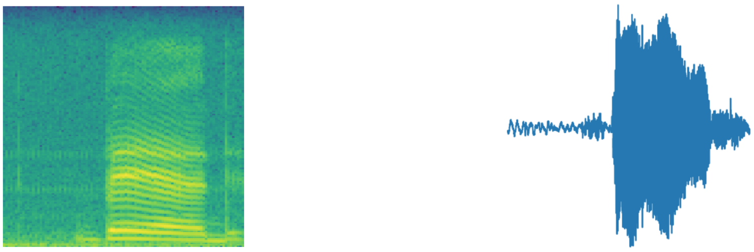
- the evolution of training cross-entropy loss (blue and green) and validation accuracy (red and orange) compared between Xavier and truncated normal initialization; Xavier converges much faster and may attain better results

- the evolution of training cross-entropy loss (blue and green) and validation accuracy (red and orange) compared between Adam and SGD optimization; Adam converges faster than SGD but reaches the same results

- effect of the number of frequency-counting buckets on the accuracy of the low-latency convolution model. The model did not benefit from the increase in available data caused by increasing the number of buckets.

- effect of the spectrogram window size on the accuracy of the low-latency convolution model. There is a local optimum, as there was for stride in Figure 18.

- effect of added background noise on the final accuracy of the low-latency convolution model. The horizontal axis is signal-noise ratio in linear units.



(a)

(b)

Figure 1: A comparison of the spectrogram (a) and the amplitude-vs.-time plot (b) for the same audio recording of a person saying the word “bed”.

- effect of the spectrogram window stride on the accuracy of the low-latency convolution model. For low values of stride, there is too much redundancy, while larger values result in lost information.

Conlusion

In this project we tackled the speech recognition problem by applying different CNN models on image data formed using log spectrograms of the audio clips. We also successfully implemented a regularization method ”Virtual Adversarial Training” that achieved a maximum of 92% validation accuracy on 20% random sample of the input data.
The significant work done in this project was the demonstration of how to convert a problem in audio recognition into the better-studied domain of image classification, where the powerful techniques of convolutional neural networks are fully developed. We also saw, particularly in the case of the low-latency convolution model, how crucial good hyperparameter tuning is to the accuracy of the model. A great number of hyperparameters must be tuned, including the many choices that go into network architecture, and any of the hyperparameters, poorly chosen, can make or break the overall performance of the model. Another contribution was the use of adversarial training to provide a regularization effect in audio recognition; this technique improved results relative even to well-established techniques such as dropout, and therefore has promising applications in the future.

Include summary about the approach of converting the long, one dimensional vector of audio data into a spectrograms and therefore making it a image classification problem.

1.1.6 Convolutional neural networks for small-footprint keyword spotting

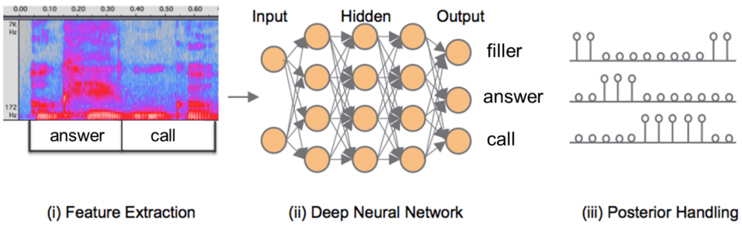


Figure 2: Framework of Deep KWS system, components from left to right: (i) Feature Extraction (ii) Deep Neural Network (iii) Posterior Handling

This framework originally comes from [4]. The only difference is the exchange of the DNN for a CNN.

- Convolutional neural networks for small-footprint keyword spotting [14]

Include summary about the different CNNs approaches which have been put into the 3 module framework of the below framework where the DNN has been exchanged for a CNN. How do the authors handle the long, one dimensional vector?

1.1.7 Small-footprint keyword spotting using deep neural networks

- Small-footprint keyword spotting using deep neural networks [4]

Include summary about the comparison between DNNs and HMMs and the general 3 module approach here: 1. Feature extraction. 2. Deep Neural Network 3. Posterior Handling. DNNs do not need a decoding algorithm like HMMs with Viterbi which makes it low latency.

1.1.8 Speech Commands: A Dataset for Limited-Vocabulary Speech Recognition

- Speech Commands: A Dataset for Limited-Vocabulary Speech Recognition [18]

Include summary and say why the Speech Commands Dataset is a good fit for this thesis. You probably do not need a Voice-activity detection (VAD) system here.

Properties

> The final dataset consisted of 105,829 utterances of 35 words[...].
> Each utterance is stored as a one-second (or less) WAVE format file, with the sample data encoded as linear 16-bit single-channel PCM values, at a 16 KHz rate. There are 2,618 speaker recorded, each with a unique eight-digit hexadecimal identifier assigned as described above. The uncompressed files take up approximately 3.8 GB on disk, and can be stored as a 2.7 GB gzip-compressed tar archive.

Top-One Error

> The standard chosen for the TensorFlow speech commands example code is to look for the ten words "Yes", "No", "Up", "Down", "Left", "Right", "On", "Off", "Stop", and "Go", and have one additional special label for "Unknown Word", and another for "Silence" (no speech detected). The testing is then done by providing equal numbers of examples for each of the twelve categories, which means each class accounts for approximately 8.3% of the total. The "Unknown Word" category contains words randomly samples from classes that are part of the target set. The "Silence" category has one-second clips extracted randomly from the background noise audio files.

Applications

> The TensorFlow tutorial gives a variety of baseline models, but one of the goals of the dataset is to enable the creation and comparison of a wide range of models on a lot of different platforms, and version one of has enabled some interesting applications. CMSISNN [21] covers a new optimized implementation of neural network operations for ARM microcontrollers, and uses Soeech Commands to train and evaluate the results. Listening to the World [22] demonstrates how combining the dataset and UrbanSounds [23] can improve the noise tolerance of recognition models. Did you Hear That [24] uses the dataset to test adversarial attacks on voice interfaces. Deep Residual Learning for Small Footprint Keyword Spotting [16] shows how approaches learned from ResNet can produce more efficient and accurate models. Raw Waveformbased Audio Classification [11] investigates alternatives to traditional feature extraction for speech and music models. Keyword Spotting

Data	V1 Training	V2 Training
V1 Test	85.4%	89.7%
V2 Test	82.7%	88.2%

Table 1: Top-One accuracy evaluations using different training data

through Image Recognition [8] looks at the effect of virtual adversarial training on the keyword task.

Evaluation

One of this dataset's primary goals is to enable meaningful comparisons between different models' results, so it's important to suggest some precise testing protocols. As a starting point, it's useful to specify exactly which utterances can be used for training, and which must be reserved for testing, to avoid overfitting. The dataset download includes a text file called `validation_list.txt`, which contains a list of files that are expected to be used for validating results during training, and so can be used frequently to help adjust hyperparameters and make other model changes. The `testing_list.txt` file contains the names of audio clips that should only be used for measuring the results of trained models, not for training or validation. The set that a file belongs to is chosen using a hash function on its name. This is to ensure that files remain in the same set across releases, even as the total number in the same set across releases, even as the total number changes, so avoid set corss-contaimination when trying old models on the more recent test data. The Python implementation of the set assignment algorithm is given in the TensorFlow tutorial code [12] that is a companion to the dataset.

Historical Evaluations

Version 1 of the dataset [1] was released August 3rd 2017, and contained 64,727 utterances from 1,881 speakers. Training the default convolution model from the TensorFlow tutorial (based on Convolutional Neural Networks for Small-footprint Keyword Spotting [14]) using the V1 training data gave a Top-One score of 85.4%, when evaluated against the test set from V1. Training the same model against version 2 of the data set [2], documented in this paper, produces a model that scores 88.2% Top-One on the training set extracted from the V2 data. A model trained on V2 data, but evaluated against the V1 test set gives 89.7% Top-One, which indicates that the V2 training data is responsible for a substantial improvement in accuracy over V1. The full set of results are shown in Table 8

- Convolutional recurrent neural networks for small-footprint keyword spotting [3]
- Honk: A PyTorch reimplementation of convolutional neural networks for keyword spotting [15]
- An experimental analysis of the power consumption of convolutional neural networks for keyword spotting [17]
- Transfer learning for speech recognition on a budget [10]
- Learning and transferring mid-level image representations using convolutional neural networks [12]
- Deep residual learning for small-footprint keyword spotting [16]

2 Method

1. methodology, types of analyses, selection of the method

3 Set-up

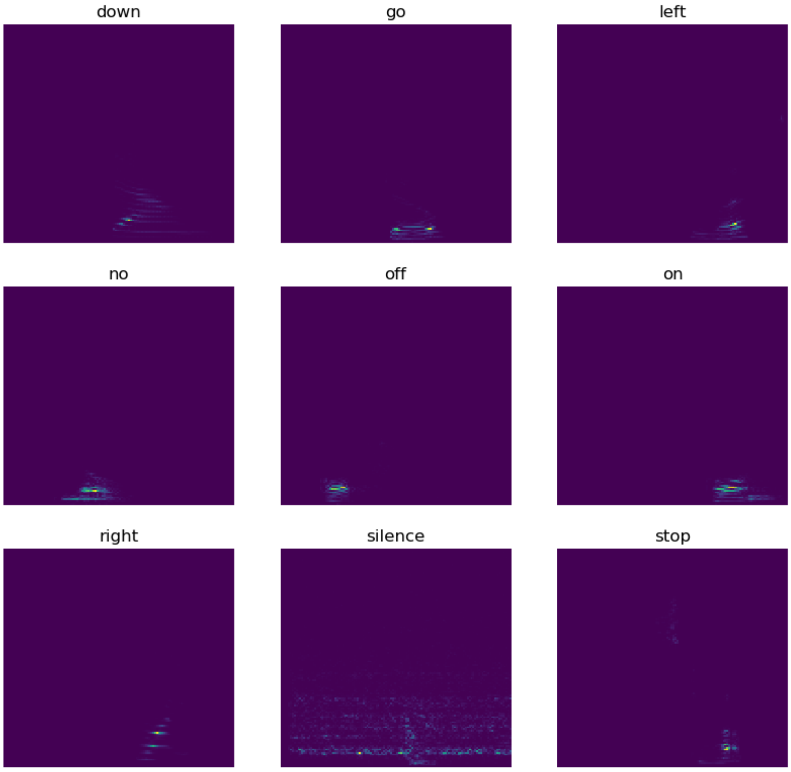


Figure 3: Samples of nine different spectrograms

1. selection of the speech data, description of the data, tuning/adaptation model parameters
2. types of experiments (generalizations to which unseen conditions, etc.)

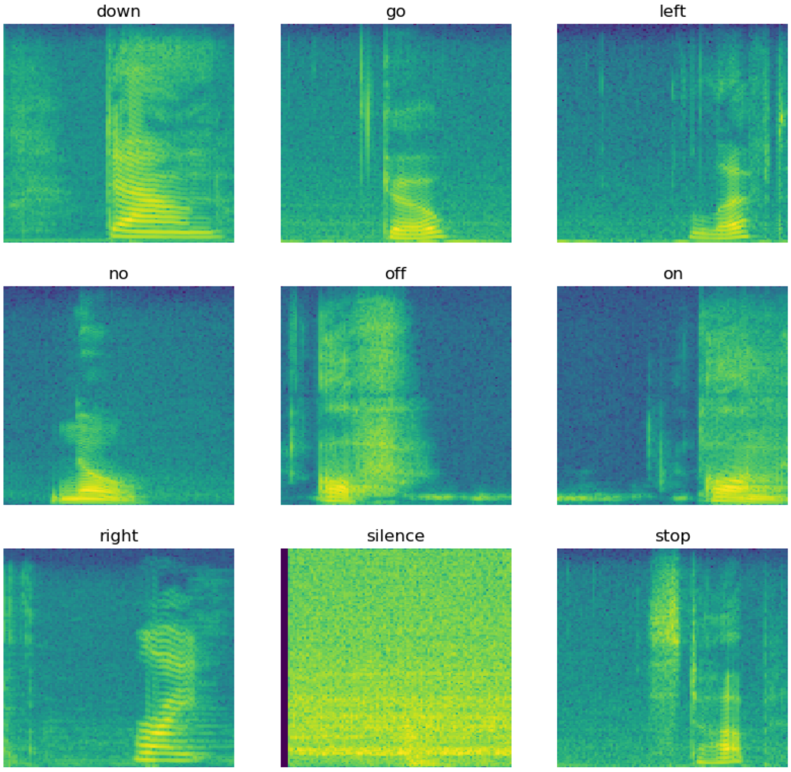
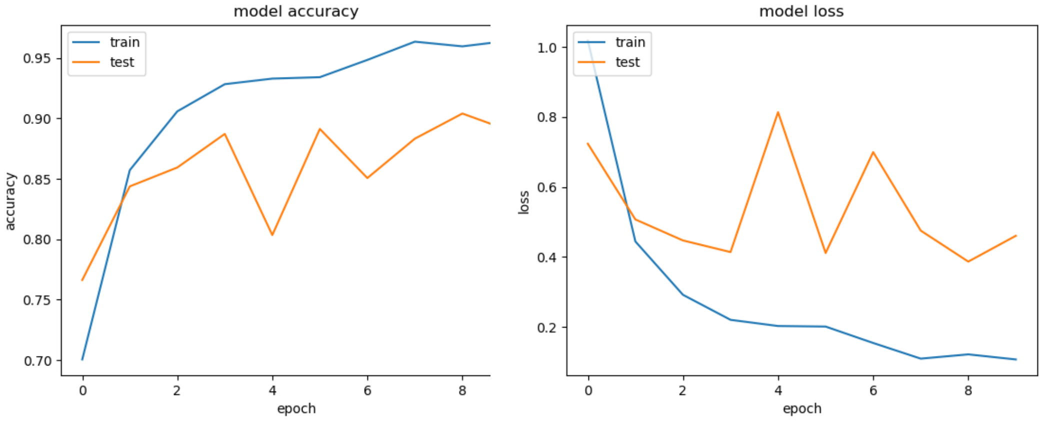


Figure 4: Samples of nine different log spectrograms

Model	Total params	Trainable params	Non-trainable params
Leightweight CNN	723,968	723,454	514
VGG16	23,676,748	23,659,340	17,408
Inception V3	29,185,836	29,137,068	48,768
MNIST	55,038,988	54,929,868	109,120
ResNet50	75,182,988	75,029,516	153,472

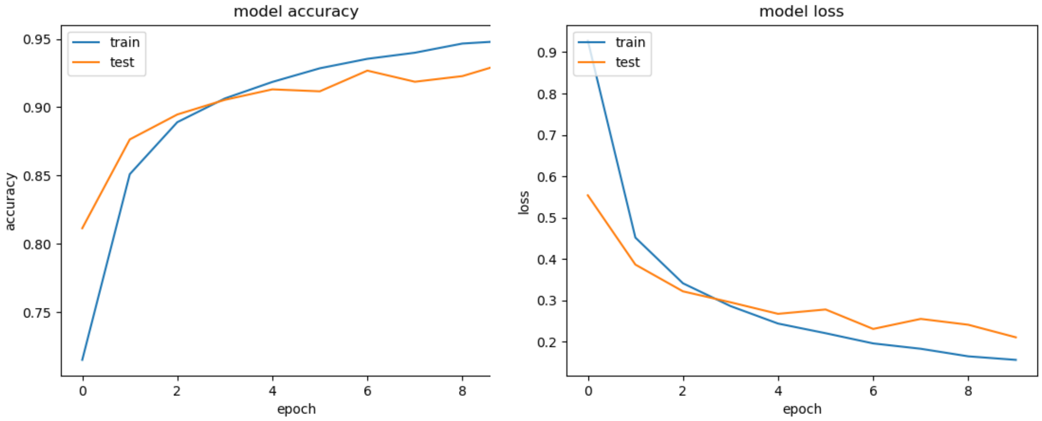
Table 2: Model complexity ordered by amount of parameters



(a) Accuracy

(b) Loss

Figure 5: Accuracy and loss after 10 epochs for the MNIST model with Xavier Glorot initialization



(a) Accuracy

(b) Loss

Figure 6: Accuracy and loss after 10 epochs for the Lightweight CNN model with Xavier Glorot initialization

Model	**Train Acc**	**Train Loss**	**Val Acc**	**Val Loss**	**Time (sec)**
MNIST	0.9595	0.1213	0.9039	0.3866	1064.72
Leightweight CNN	0.9487	0.1564	0.9332	0.2109	532.73

Table 3: Final baseline results with Xavier Glorot initialization

Model	**Train Acc**	**Train Loss**	**Val Acc**	**Val Loss**
MNIST	0.7005	1.0187	0.7662	0.7237
Leight CNN	0.7150	0.9276	0.8114	0.5540

Table 4: Baseline results after one epoch with Xavier Glorot initialization

4 Experiments

4.1 Baseline

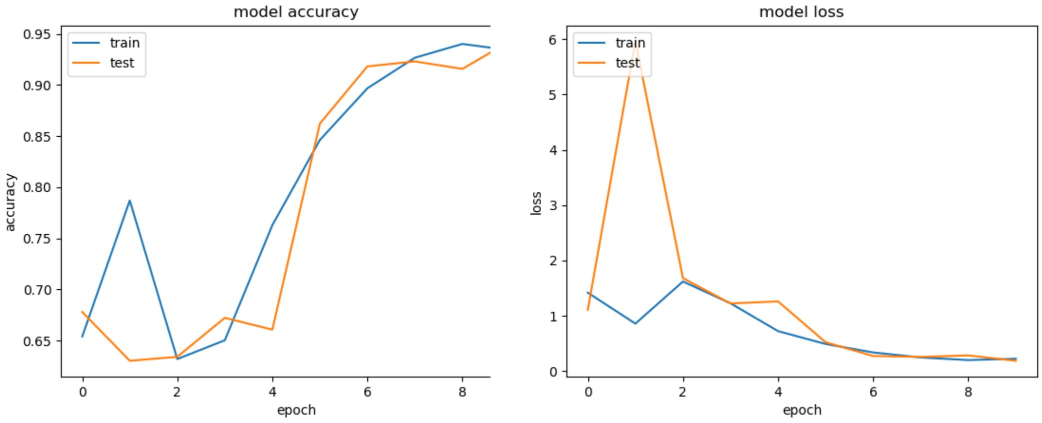
4.2 CNNs

5 Analysis and Results

5.1 Baseline

5.2 CNNs

5.2.1 Xavier initialization



(a) Accuracy

(b) Loss

Figure 7: Accuracy and loss after 10 epochs for the Inception V3 model with Xavier Glorot initialization

Model	Train Acc	Train Loss	Val Acc	Val Loss	Time (sec)
Inception V3	0.9338	0.2238	0.9427	0.1868	2332.23
VGG16	0.9723	0.0900	0.9583	0.2011	2530.47
ResNet50	0.9548	0.1421	0.9445	0.1873	3807.93

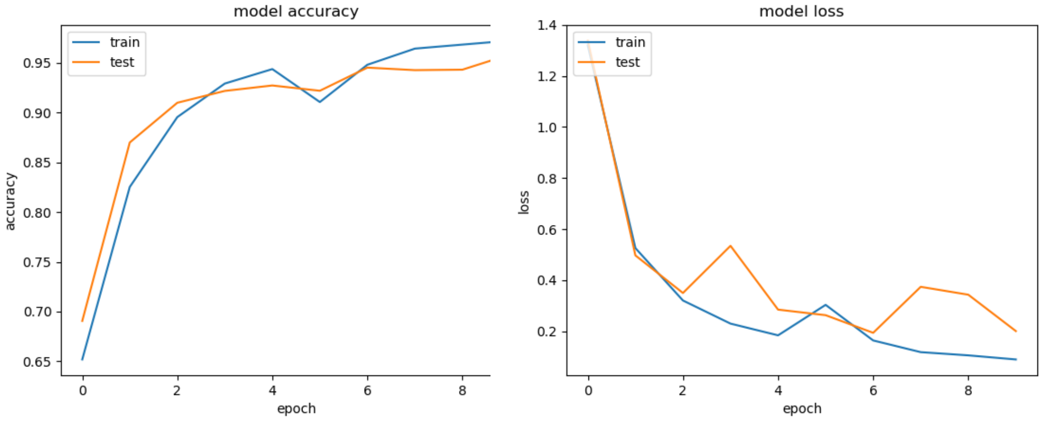
Table 5: Final CNN results with with Xavier Glorot initialization

Model	Train Acc	Train Loss	Val Acc	Val Loss
Inception V3	0.6539	1.4176	0.6778	1.1090
VGG16	0.6519	1.3202	0.6906	1.3379
ResNet50	0.6916	1.2478	0.6351	5.7467

Table 6: CNN results after one epoch with Xavier Glorot initialization

5.2.2 Imagenet weight initialization

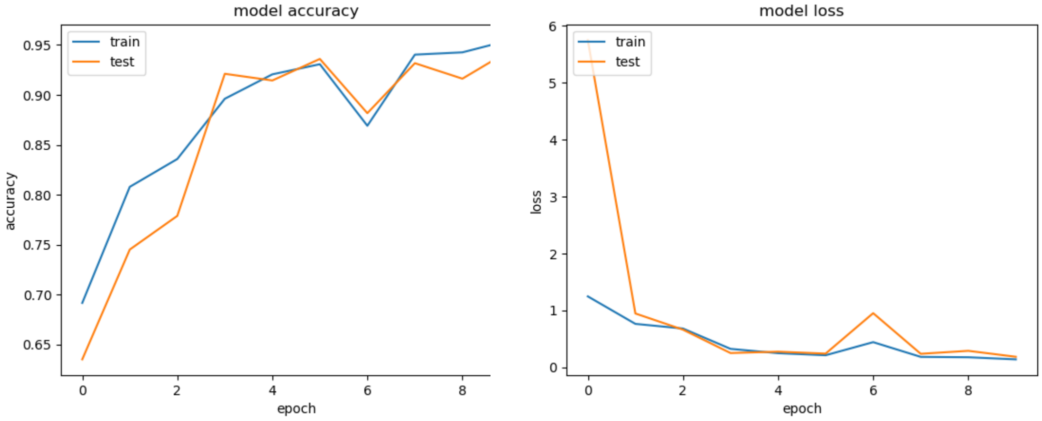
Test



(a) Accuracy

(b) Loss

Figure 8: Accuracy and loss after 10 epochs for the VGG16 model with Xavier Glorot initialization



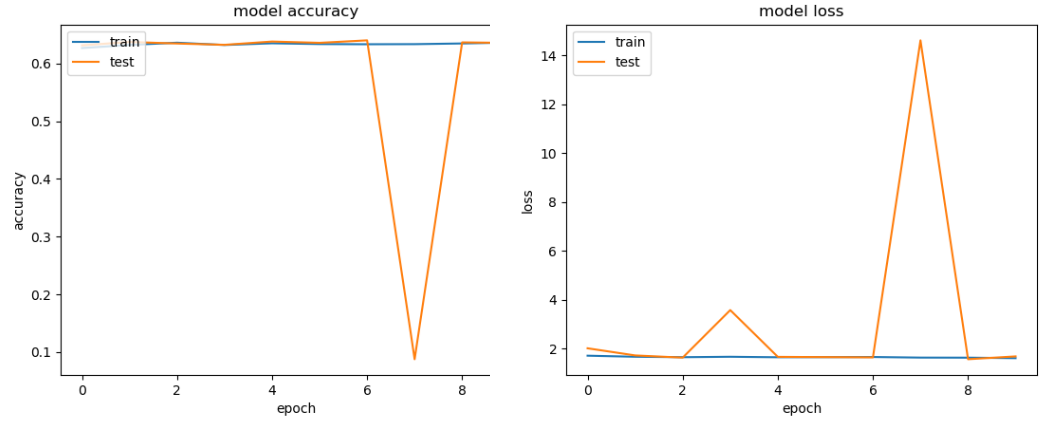
(a) Accuracy

(b) Loss

Figure 9: Accuracy and loss after 10 epochs for the ResNet50 model with Xavier Glorot initialization

Model	**Train Acc**	**Train Loss**	**Val Acc**	**Val Loss**	**Time (sec)**
Inception V3	0.6334	1.6597	0.6401	1.6433	2184.54
VGG16	0.9745	0.0912	0.9611	0.1730	2541.83
ResNet50	0.9134	0.2991	0.9252	0.3055	3653.67

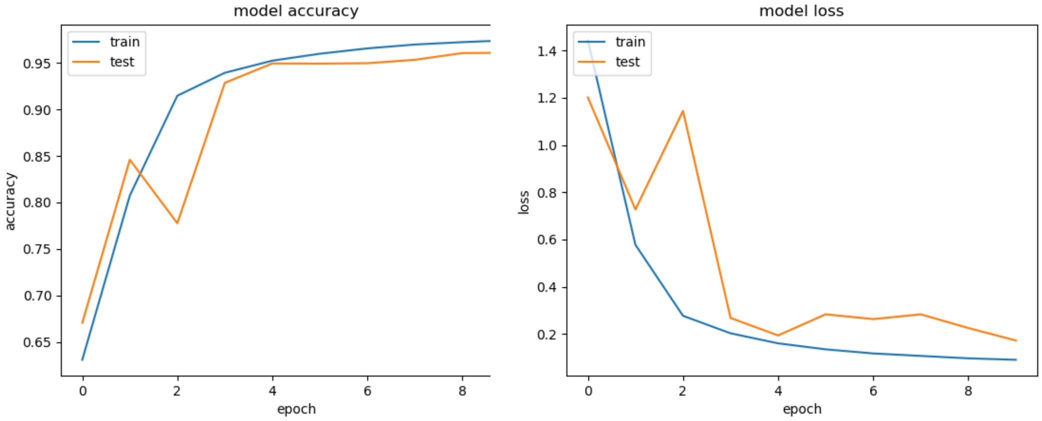
Table 7: Final CNN results with Imagenet initialization



(a) Accuracy

(b) Loss

Figure 10: Accuracy and loss after 10 epochs for the Inception V3 model with Imagenet initialization



(a) Accuracy

(b) Loss

Figure 11: Accuracy and loss after 10 epochs for the VGG16 model with Imagenet initialization

Model	**Train Acc**	**Train Loss**	**Val Acc**	**Val Loss**
Inception V3	0.6268	1.7132	0.6315	2.0153
VGG16	0.6307	1.4430	0.6706	1.2011
ResNet50	0.6389	1.4214	0.5931	5.1381

Table 8: CNN results after one epoch with Imagenet initialization

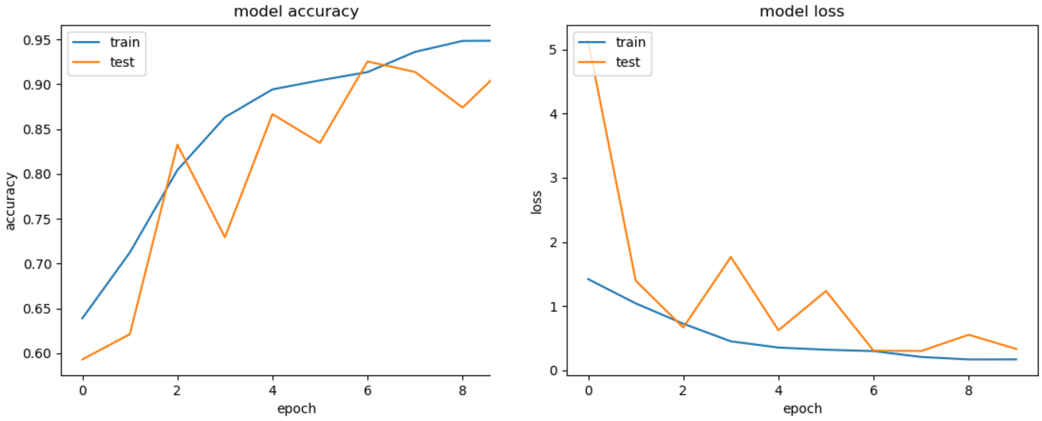
6 Discussion

7 Conclusion

8 References

9 Appendix

- the experiment(s) may be carried out in collaboration with others. In that case: specify in the "author's statement" everybody's contribution



(a) Accuracy

(b) Loss

Figure 12: Accuracy and loss after 10 epochs for the ResNet50 model with Imagenet initialization

- the thesis itself is written individually and assessed individually
- the ASR performance itself is not relevant for the assessment of the thesis
- the RQ, the literature embedding of the RQ, the description of the method, the justification and set-up of the experiment are relevant for the assessment
- the general university guidelines apply (e.g., with respect to plagiarism)
- there is no minimum number of pages for the thesis

10 Complex stuff

10.1 Domains

Let's start with the following definition:

Definition 10.1. A set $U \subseteq \mathbb{C}$ is a *domain* if:

- U is open in $\mathbb{C}$, and
- U is connected.

10.2 Yumyumyumyum

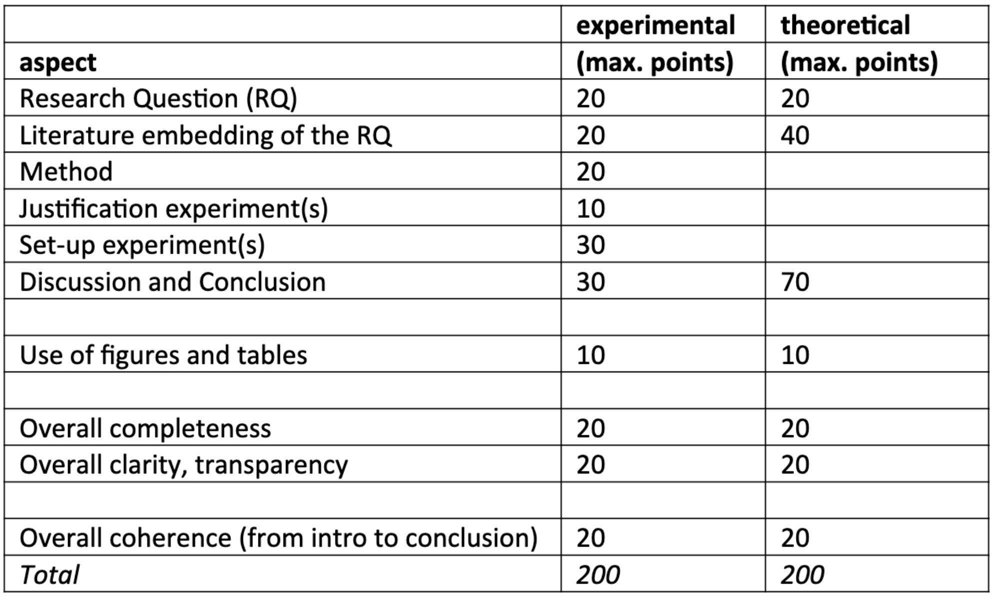
TO WRITE: an introduction and some examples

Theorem 10.2. *Suppose $n \in \mathbb{Z}$, then the following are equivalent:*

i. $n > 5$.

ii. $5 > 5$.

This doesn't seem right...



	experimental	theoretical
aspect	**(max. points)**	**(max. points)**
Research Question (RQ)	20	20
Literature embedding of the RQ	20	40
Method	20	
Justification experiment(s)	10	
Set-up experiment(s)	30	
Discussion and Conclusion	30	70
Use of figures and tables	10	10
Overall completeness	20	20
Overall clarity, transparency	20	20
Overall coherence (from intro to conclusion)	20	20
Total	*200*	*200*

Figure 13: Weighted grading

iii. For each $n \in n$, we have:

$$n > n + 1 > n + 1^2 > \cdots > n + 7. \tag{1}$$

where 7 is an arbitrary element of

$$\oint_a^b \operatorname{supersin} \alpha + i \operatorname{supercos} \beta db(a).$$

Remark. Interesting!

Proof. See [**?**]. □

Figure 14: Motivational illustration. Similar to [**?**, **?**].

Corollary 10.2.1. *Suppose $U \subseteq \mathbb{C}$ is a domain (see Definition 10.1), and $f : \overline{U} \to \mathbb{C}$ is continuous on $\overline{U}$ and holomorphic on U. If $z \mapsto |f(z)|$ is constant on ∂U, then f has a zero in U.*

Proof. If not, consider $\frac{1}{f}$. □

The proof of this theorem is illustrated in Figure 14.

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