



TECHNISCHE UNIVERSITÄT
CHEMNITZ

TU Chemnitz

Faculty of Natural Sciences
Institute of Physics

Bachelor Thesis

In the course of degree in computational science (B.Sc.)

To obtain the academic degree Bachelor of Science

Topic:	Investigation of strategies for image classification on small training data sets
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Version from:	March 3, 2020
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Abstract

Artificial neural networks have achieved an error rate of less than 5 percent in the ImageNet software competitions in recent years and are well suited to find patterns in data. Therefore, these networks have to be trained with known data sets and adapted accordingly. Data sets are usually very expensive to obtain and should therefore be used with care and good quality. The training of the models takes place under the influence of many hyperparameters, which have to be determined beforehand. It is important to use the best possible model with its best possible parameters. In this thesis the creation of models for image classification by machine learning (ML) is discussed and the model accuracies are compared. The main goal of the thesis is to find optimal hyperparameters (HPs) and techniques for classification, which also allows to create an optimal model from a small training data set.

Keywords

Image Classification, Small Data Set, Hyperparameter, Data Augmentation, Convolutional Neural Network (CNN), Machine Learning, Deep Learning

Kurzfassung

Künstliche neuronale Netze haben es in den letzten Jahren bei den ImageNet Software-Wettbewerben auf unter 5 Prozent Fehlerrate geschafft und eignen sich gut darin Muster in Daten zu finden. Hierzu müssen diese Netze vorher mit bekannten Datensätzen trainiert und entsprechend angepasst werden. Datensätze sind meist sehr teuer in der Beschaffung und sollten deshalb mit Bedacht und guter Qualität eingesetzt werden. Das Training der Modelle findet unter dem Einfluss vieler Hyperparameter statt, welche es vorher zu bestimmen gilt. Dabei ist darauf zu achten das bestmögliche Modell mit seinen bestmöglichen Parametern zu verwenden. In dieser Arbeit wird auf das Erstellen von Modellen für die Bildklassifikation mittels maschinellem Lernen eingegangen und es werden die Modellgenauigkeiten miteinander verglichen. Das Hauptziel der Arbeit ist es, optimale Hyperparameter und Techniken für die Klassifikation zu finden, die es auch ermöglichen, mit einem kleinen Trainingsdatensatz ein optimales Modell zu erstellen.

Schlüsselwörter

Bildklassifizierung, Kleiner Datensatz, Hyperparameter, Data Augmentation, Convolutional Neural Network (CNN), Machine Learning, Deep Learning

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1 Introduction

This thesis deals with the creation of models for image classification using machine learning (ML). Many variable parameters (hyperparameters) will have a decisive influence on the accuracy of the model when creating the models and are compared here in detail. In addition to the accuracy of the models, the computing time required to create the models also plays a role and should be included in the evaluation. I assume that a small learning rate combined with many learning epochs and correspondingly more computing time required will achieve better results than a few learning epochs combined with a high learning rate (slow adaptation vs. fast adaptation). I also assume that a high quality and a larger amount of data will have a significantly positive influence on the result. New and more complex CNNs are more successful in model accuracy than older and smaller models.

1.1 Insufficient amount of data

If one gives a person a doughnut and explain to him that it is a doughnut, then after some repetition he is able to recognize any kind of doughnut in the future. With ML this problem is a bit more complex. As with most ML methods, a large amount of data is required. How much is not properly documented. Especially when one is dealing with many classes to be predicted, experience shows that the amount of data increases. In a paper from 2012, a procedure was described for winning first place in the annual ImageNet competition. This was done using 1000 images per class with a class count of 1000 and a top-5 error rate of 15.3%.¹ Other articles dealing with this topic confirm this number of images per class.^{2,3}

Depending on the number of classes to be trained, one will quickly arrive at the required data set, which consists of several gigabytes of data. With transfer learning (TL) it is possible to reduce this number a little bit, but the problem of the large amount of data remains. A paper from Microsoft in 2001⁴ showed at that time that simple algorithms with enough data gave similar results as complex algorithms based on less data. The researchers referred to data which should classify language constructs:

"We have shown that for a prototypical natural language classification task, the performance of learners can benefit significantly from much larger training sets."

Another article only a few years later also addresses this issue. This referred to data that learn from texts and that usually only small or medium sized data sets are available. To improve efficiency also in this case, it is a good idea to improve the algorithms or approach to use data efficiently:⁵

"Choose a representation that can use unsupervised learning on unlabeled data, which is so much more plentiful than labeled data."

¹Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. "Imagenet classification with deep convolutional neural networks". In: *Advances in neural information processing systems*. 2012, pp. 1097–1105. URL: <https://papers.nips.cc/paper/4824-imagenet-classification-with-deep-convolutional-neural-networks.pdf>.

²Abhinav Sagar. *Deep Learning for Image Classification with Less Data*. en. Library Catalog: [towardsdatascience.com](https://towardsdatascience.com/deep-learning-for-image-classification-with-less-data-90e5df0a7b8e). Nov. 2019. URL: <https://towardsdatascience.com/deep-learning-for-image-classification-with-less-data-90e5df0a7b8e> (visited on 02/25/2020).

³Pete Warden. *How many images do you need to train a neural network?* en. Library Catalog: [petewarden.com](https://petewarden.com/2017/12/14/how-many-images-do-you-need-to-train-a-neural-network/). Dec. 2017. URL: <https://petewarden.com/2017/12/14/how-many-images-do-you-need-to-train-a-neural-network/> (visited on 02/25/2020).

⁴Michele Banko and Eric Brill. "Scaling to very very large corpora for natural language disambiguation". In: *Proceedings of the 39th annual meeting on association for computational linguistics*. Association for Computational Linguistics. 2001, pp. 26–33. URL: <https://www.aclweb.org/anthology/P01-1005.pdf>.

⁵Alon Halevy, Peter Norvig, and Fernando Pereira. "The unreasonable effectiveness of data". In: *IEEE Intelligent Systems* 24.2 (2009), pp. 8–12. URL: <https://static.googleusercontent.com/media/research.google.com/de//pubs/archive/35179.pdf>.

2 Background

2.1 Image classification

Classifications are a process of identifying to which class an unobserved object belongs. Several predefined classes can be specified and, based on their properties, an attempt can be made to classify unknown and previously unobserved objects. The procedure for image classification is similar. The previously mentioned objects are now simply images (as shown in Figure 1).



Figure 1: Cat and dog comparison

For a long time, the automatic recognition of objects, people and scenes in images by computers was considered impossible. The complexity seemed too great to be programmatically taught to an algorithm. Until a few decades ago, attempts were made to achieve image classification by manually developed algorithms. Automated classification based on given and pre-classified data sets and the automated creation of models was a new step into a new approach. The ever increasing amount of available computing time plays as much a decisive role in the success as parallel computations on several graphics processing units (GPUs), the development of more efficient algorithms and methods such as data augmentation and the establishment of online databases with large amounts of labeled data (ImageNet).⁶ Meanwhile, image recognition has become a widespread application area of ML. So-called "CNNs"⁷ or "ConvNets" are often used for images.

The image classification algorithm accepts an image as input and classifies it into one of the possible output categories. The approach to learn knowledge from existing data is called machine learning (ML).⁸ In combination with artificial neural networks (ANNs) it is more precisely called deep learning (DL).⁹ Various convolutional neural networks (CNNs), such as ResNet, DenseNet, Inception, etc. have been developed as high-precision networks for image classification. At the same time, image data sets were created to capture tagged image data. These are now primarily used to train existing networks and to organize annual challenges that compete with the model accuracies already known and developed. ImageNet is such a large data set with more than 11 million images and over 11,000 categories.¹⁰ Once a network has been trained with ImageNet data, it can be generalized with other data sets by simple re-compilation or optimization. In this transfer learning approach, a network is initialized with weights that come from a previously trained network. This previously initialized network is now simply adapted for a new image classification task.

The underlying thesis here is mainly concerned with supervised learning, in which a mathematical model is trained based on existing known data sets. The goal of the trained model is to make the best possible predictions even for unknown images. These known data sets are usually created

⁶George Seif. *Deep Learning for Image Recognition: why it's challenging, where we've been, and what's next*. en. Library Catalog: towardsdatascience.com. May 2019. URL: <https://towardsdatascience.com/deep-learning-for-image-classification-why-its-challenging-where-we-ve-been-and-what-s-next-93b56948fcef> (visited on 02/28/2020).

⁷Convolutional neural network. en. Page Version ID: 942501792. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Convolutional_neural_network&oldid=942501792 (visited on 02/25/2020).

⁸Machine learning. en. Page Version ID: 942989288. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Machine_learning&oldid=942989288 (visited on 02/28/2020).

⁹Deep learning. en. Page Version ID: 942561541. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Deep_learning&oldid=942561541 (visited on 02/28/2020).

¹⁰ImageNet. en. Page Version ID: 929993952. Dec. 2019. URL: <https://en.wikipedia.org/w/index.php?title=ImageNet&oldid=929993952> (visited on 02/28/2020).

manually, automatically determined based on known facts, or determined in a semi-automatic process.

2.1.1 Deductive approach

Since the late 1960s, attempts have been made to classify images with *self-written* algorithms. This part of computer vision deals with techniques such as image creation, image processing and image segmentation. In the field of image processing, well-known techniques such as edge detection, feature detectors, edge linking, contrast enhancement, etc. are used.¹¹ Common to all techniques is the use of the deductive approach. With the deductive approach, one creates rules (feature detectors) which are supposed to predict the desired result. These rules are given and described and thus allow later classification of unknown objects. Since the model and its algorithm are sufficiently well known, this procedure is called a white-box procedure (Figure 2).

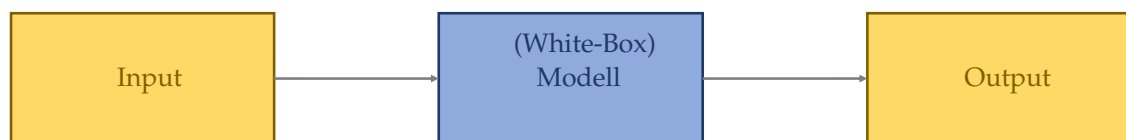


Figure 2: Deductive approach

2.1.2 Inductive approach

The inductive approach, on the other hand, takes a different approach to classifying images. The goal is not to specify a rule, but to learn a rule (model) automatically from already known individual objects. A model is usually a complex function and a mathematical representation of a space, in which individual objects with their properties can be mapped and separated. This measure of the capacity that can be learned by this complex function is called Vapnik–Chervonenkis dimension (VCD).¹² The model is adapted piece by piece to the known objects in such a way that the input value corresponds to the output value or corresponds to a large extent (backpropagation). The goal is to create a function with this model, which can classify unknown objects in the best possible way. Because the space of this model is mostly far away from the imagination and the possibility of explanation, this procedure is also called a black-box procedure (Figure 3). The procedure described here is mostly used for any kind of supervised learning (see chapter “Supervised learning”) and is a part of ML (see chapter “Machine learning”).

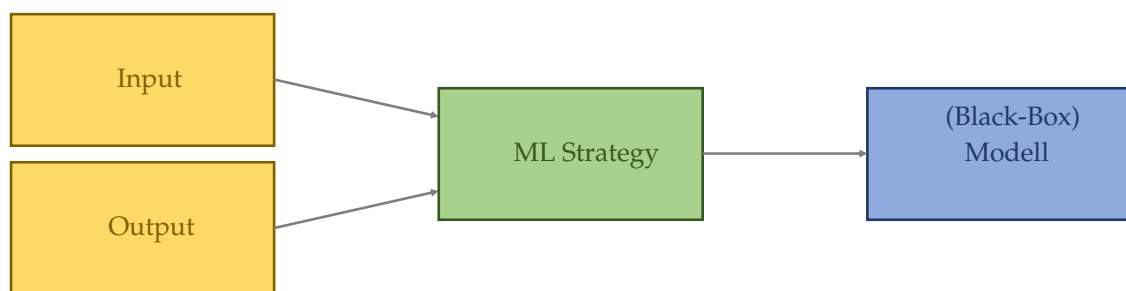


Figure 3: Inductive approach

¹¹Richard Szeliski. “Computer Vision: Algorithms and Applications”. en. In: (), p. 979.

¹²Vapnik–Chervonenkis dimension. en. Page Version ID: 942482212. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Vapnik%E2%80%93Chervonenkis_dimension&oldid=942482212 (visited on 02/25/2020).

2.1.3 Balanced training data set

Neural networks have made *enormous* progress in the field of pattern recognition in recent years. A decisive factor is that the data for learning must be of high quality and easy for the network to process. Wrongly classified or irrelevant data could cause the network to learn something wrong. This also applies to non-existent or unsuitable pre-processing.¹³

With the beginning of a classification project, the question arises what exactly one wants to classify and how extensive the classification should be. Assuming one wants to identify different classes of food, this could be classified as burgers (as shown in Figure 4a), doughnuts (Figure 4b) or pizza (Figure 4c), etc. For these classes, one now needs a large number of images. Ideally, this data should reflect reality as well as possible. A large variation is advantageous (balanced data set): different viewing angles, size, position, colour brightness, variations, number, etc. Images of e.g. only one colour brightness or only one viewing angle should be avoided. If the data are not balanced, they must be corrected accordingly: e.g. by adding further data, image processing or by removing data that causes an imbalance. Furthermore, the selected classes should be clearly optically separable from each other. If two classes are visually very similar and not really distinguishable even by a human, consideration should be given to combining them (e.g. "burger" and "veggie burger").

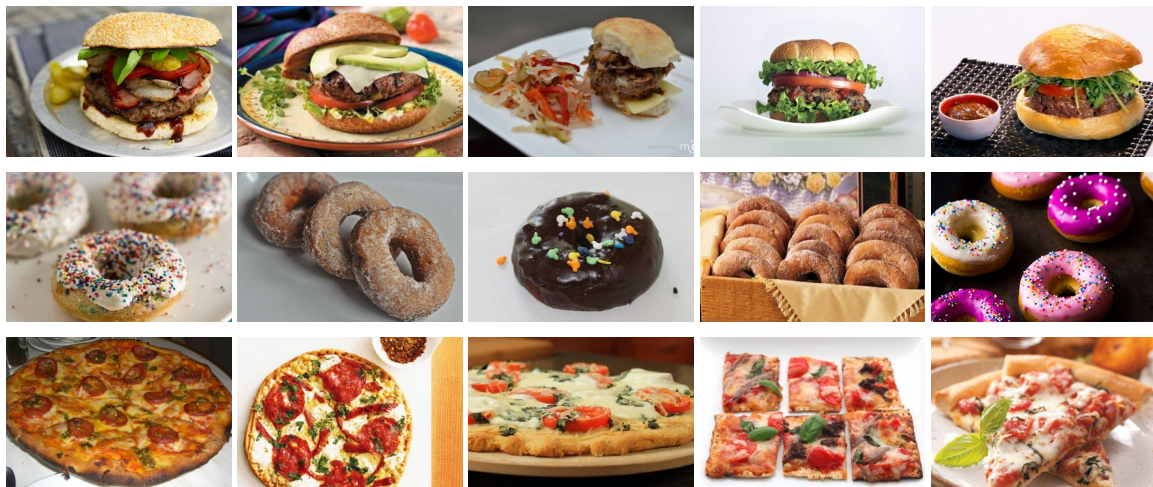


Figure 4: (a) Example of pictures of a burger class (top), (b) Example pictures of a doughnut class (middle), (c) Example of pictures of a burger class (bottom)

Accessing data is often not that easy. Every data source has its own special features. One way to access data would be an automatic crawling of image databases (Flickr¹⁴), search engines (Google,¹⁵ Bing¹⁶) or reviews (TripAdvisor), in which images appear and can be associated with the text ("This here is the best doughnut I've ever eaten."). A creative approach is an advantage here.

Probably the most expensive way to obtain data is to search and classify them manually, e.g. by an ontologist. The ontologist evaluates and searches for different images and manually classifies them in the appropriate classes. A combined variant is also possible and probably preferable: automatic crawling and manual sorting out of incorrect, unfavorable or irrelevant images.

2.1.4 Training, validation and test data set

Before starting the training of balanced images, they must be divided into a training, a test and possibly a validation data set. This is necessary because neural networks (NNs) will not generalize to

¹³Douwe Osinga. *Deep Learning Kochbuch: Praxisrezepte für einen schnellen Einstieg*. O'Reilly Verlag, 2019, pp. 19–26. ISBN: 9783960090977.

¹⁴Flickr images - Donut. de-de. Library Catalog: [www.flickr.com. URL: https://www.flickr.com/search/?text=donut](https://www.flickr.com/search/?text=donut) (visited on 03/01/2020).

¹⁵Google images - Donut. URL: <https://www.google.de/search?q=donut&tbm=isch> (visited on 03/01/2020).

¹⁶Bing images - Donut. URL: <https://www.bing.com/images/search?q=donut> (visited on 03/01/2020).

some extent, but will learn by heart (overfitting¹⁷). The idea is to train with a training data set, while the validation data set is used to monitor the general validity of the network and its parameters. Based on the results, adjustments are made at runtime. Since the adjustment of the parameters is carried out using the test data, there is also an independent test data set, which carries out a renewed check of the model for previously uninvolved data. This ensures that hyperparameters are not inadvertently optimized for the validation data set only.¹⁸ The use of the test data set is optional and simulates the model under real conditions. If the number of data is limited, this data record can also be added to the training data record, for example. In this thesis, the test data set is not used and all evaluations refer to the validation data set.

An optimal division of the training and validation data set depends on the existing classification problem and the amount of data available. In this thesis a ratio of 80 percent training data and 20 percent validation data is used according to the Pareto principle, unless otherwise stated.

2.2 Classification metrics and confusion matrix

Choosing the right metric is crucial in evaluating ML models. Metrics are used to monitor and measure the performance of a model during training and testing. Some important metrics are explained below.

2.2.1 Confusion matrix

The confusion matrix is a special quadratic matrix in the field of ML that allows the visualization of the performance of a predictive model (Figure 5). Each row of the matrix represents the actual class, while each column indicates the number or a numerical value as a percentage of the predicted class (or vice versa). A special class $class_1$ is considered: True positive (TP) corresponds to the value of the correctly determined predictions of the class currently under consideration. False negative (FN) indicates how often other classes are detected as the class currently under consideration. False positive (FP) indicates how often classes other than the currently viewed class were determined. True negative (TN) in turn indicates that classes other than the current class were correctly predicted as the other classes.¹⁹

		predicted			
		$class_1$	$class_2$...	$class_n$
actual	$class_1$	TP	FN		
	$class_2$	FP	TN		
	...				
	$class_n$				

Figure 5: Confusion matrix

Finally, the confusion matrix has the following structure, where the number of elements in the class P_i was predicted (P - predicted) although (\cong) it should have been class A_j (A - actual). All values on the diagonal were correctly predicted ($\hat{=}$, i and j are equal).

$$\mathbf{M}_{confusion} = \begin{bmatrix} \#(P_1 \hat{=} A_1) & \dots & \#(P_n \cong A_1) \\ \vdots & \ddots & \vdots \\ \#(P_1 \cong A_n) & \dots & \#(P_n \hat{=} A_n) \end{bmatrix} = (m_{mn}) \quad (1)$$

¹⁷Overfitting. en. Page Version ID: 942053730. Feb. 2020. URL: <https://en.wikipedia.org/w/index.php?title=Overfitting&oldid=942053730> (visited on 02/25/2020).

¹⁸Osinga, Deep Learning Kochbuch: Praxisrezepte für einen schnellen Einstieg.

¹⁹Confusion matrix. en. Page Version ID: 940280604. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Confusion_matrix&oldid=940280604 (visited on 02/28/2020).

If all elements next to the main diagonal are 0, then all classes were correctly predicted.

$$\mathbf{M}_{confusion} = \begin{bmatrix} \#(P_1 \hat{=} A_1) & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \#(P_n \hat{=} A_n) \end{bmatrix} = (m_{nn}) \quad (2)$$

2.2.2 Accuracy

Top-1 accuracy is probably the most important accuracy. It tells one the percentage of the model's best prediction of the data in the validation set that matches the expected class.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} = \frac{\sum_{i,j=1}^n a_{ij}}{\sum_{i=1}^n \sum_{j=1}^n a_{ij}} = \frac{Correct_{all}}{CorrectPossible_{all}} \quad (3)$$

The **Top 5 Accuracy** is another accuracy specification. However, not only the best hit is included here, but also the next four. As soon as the correct class can be found within the first five predicted classes, this prediction is also true:

$$Accuracy_{top-5} = \frac{CorrectWithinTheBest5Classes_{all}}{CorrectPossible_{all}} \quad (4)$$

The accuracy of the entire model is a good indication of the performance of the model. However, a problem occurs in extreme cases where assumptions can no longer be made reliably. For example, if one is working with an unbalanced dataset.²⁰ Example: Suppose one has a model that always predicts the class *class*₁. The class *class*₁ consists of 9990 elements and from the other classes *class*₂ to *class*_n one has exactly 10. Then the confusion matrix looks like in the following figure (Figure 6).

		predicted			
		<i>class</i> ₁	<i>class</i> ₂	...	<i>class</i> _n
actual	<i>class</i> ₁	TP = 9990	FN = 0		
	<i>class</i> ₂	FP = 10	TN = 0		
	...				
	<i>class</i> _n				

Figure 6: Confusion matrix example

The model accuracy in this case is 99.9%, although it is a bad model:

$$Accuracy = 99,9\% \quad (5)$$

Therefore there are additional performance metrics like Precision, Recall and F-Measure.

2.2.3 Precision

Precision²¹ expresses how reliable the statement of a prediction of a class is:

$$Precision = \frac{Correct}{Actual} = \frac{TP}{TP + FP} \quad (6)$$

²⁰Aurélien Géron. "Praxiseinstieg Machine Learning mit Scikit-Learn und TensorFlow: Konzepte, Tools und Techniken für intelligente Systeme". In: O'Reilly Verlag, 2017. Chap. Konfusionsmatrix, pp. 86–88. ISBN: 9783960090618.

²¹Precision and recall. en. Page Version ID: 943009117. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Precision_and_recall&oldid=943009117 (visited on 02/28/2020).

Or more precisely for class c :

$$Precision_{@c} = \frac{a_{cc}}{\sum_{i=1}^n a_{ic}} \quad (7)$$

2.2.4 Recall

Recall²² is the accuracy of a class. This means how well the class could be predicted:

$$Recall = \frac{Correct}{CorrectPossible} = \frac{TP}{TP + FN} \quad (8)$$

Or more precisely for class c :

$$Recall_{@c} = \frac{a_{cc}}{\sum_{i=1}^n a_{ci}} \quad (9)$$

2.2.5 F-Measure

F-Measure²³ combines precision and recall, with the parameter β representing the weighting:

$$F_{\beta} = (1 + \beta^2) \cdot \frac{Precision \cdot Recall}{\beta^2 \cdot Precision + Recall} = \frac{(1 + \beta^2) \cdot TP}{(1 + \beta^2) \cdot TP + \beta^2 \cdot FN + FP} \quad (10)$$

The higher β the more importance is placed on precision instead of recall. This is important if one puts more importance on the quality of the prediction than on the accuracy of prediction. For example, when predicting diseases: assigning class “ill” to healthy people is just as fatal as assigning class “healthy” to sick people. A value of $\beta = 0.5$ one gets an equal distribution of both values and is called F1 score:

$$F_1 = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall} = \frac{2 \cdot TP}{2 \cdot TP + FN + FP} \quad (11)$$

2.2.6 Loss function

Since this is a classification problem and not a regression problem, the prediction is based on softmax regression. After each prediction, a vector λ of the size n is returned, where n corresponds to the number of classes to be distinguished.²⁴ Each individual \hat{p} value corresponds to the probability that it is class $class_n$:

$$\lambda = \begin{pmatrix} \hat{p}_1 \\ \hat{p}_2 \\ \hat{p}_3 \\ \vdots \\ \hat{p}_n \end{pmatrix} \quad \left| \quad \sum_{i=1}^n \hat{p}_i = 1 \right. \quad (12)$$

The expected value of the parameter function and thus of the current class is returned as a one hot vector. The value 1 corresponds to the expected class. All other classes return 0. This is also

²²Precision and recall.

²³F1 score. en. Page Version ID: 938382811. Jan. 2020. URL: https://en.wikipedia.org/w/index.php?title=F1_score&oldid=938382811 (visited on 02/28/2020).

²⁴Aurélien Géron. “Praxiseinstieg Machine Learning mit Scikit-Learn und TensorFlow: Konzepte, Tools und Techniken für intelligente Systeme”. In: O’Reilly Verlag, 2017. Chap. Entscheidungsgrenzen, pp. 138–140. ISBN: 9783960090618.

called one hot encoding (using the example of class 2):

$$g(\vartheta_2) = \begin{pmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \quad (13)$$

The loss function²⁵ assigns a loss to each prediction, which results from the comparison with the true value or parameter. For this purpose, the distance between the predicted class and the true class is calculated (if they are equal, the distance is 0). If the adaptation of the model (learning process) improves the prediction of all predicted classes to their true classes, the value of the loss function is also reduced. A typical loss function is e.g. for an r -dimensional space:

$$L_r(\vartheta, \lambda) := \|\lambda - g(\vartheta)\|^r \quad (14)$$

λ represents the estimated value and $g(\vartheta)$ the parameter function which returns the actual value for ϑ . The average loss on the entire data set with n elements is thus:

$$\hat{L} = \frac{1}{k} \sum_{i=1}^k L_r(\vartheta_i, \lambda_i) \quad (15)$$

2.3 Machine learning

Machine learning is a generic term for the artificial generation of knowledge from experience. It follows the approach of inductive learning (see also chapter Inductive approach).

2.3.1 Short definitions

2.3.1.1 Learning epoch

A learning epoch is understood to be the one time training run with all training data sets. Usually one training run is not sufficient, which is why further learning epochs follow. As soon as the performance of the network does not increase anymore with further epochs, the training is terminated.

2.3.1.2 Learning rate

The learning rate is a tuning parameter in an optimization algorithm. It expresses how large the step size is for each iteration with which the parameters move closer to the minimum of a loss function. It should not be too high (minimum is not found) and not too small (very slow learning). The learning rate is often indicated by the character η or α .

2.3.1.3 Batch size

The batch size defines the number of images that are simultaneously passed forward and backward through the NN before the parameters in the network are adjusted (gradient update). Normally it is intended to train all training data per epoch with one process. Especially in the field of image classification this is usually not possible due to the limited memory, which is why an epoch is divided into many small batches (mini-batches). The advantage is that one only has to keep the data in memory that is necessary for the current batch and an overfitting can be regulated. The

²⁵Verlustfunktion (Statistik). de. Page Version ID: 177095272. May 2018. URL: [https://de.wikipedia.org/w/index.php?title=Verlustfunktion_\(Statistik\)&oldid=177095272](https://de.wikipedia.org/w/index.php?title=Verlustfunktion_(Statistik)&oldid=177095272) (visited on 02/26/2020).

disadvantage is an increased variance (noise in the accuracy of the model), since it is unlikely that a small batch is a good representation of the entire data set. The computing time increases as well, since the backpropagation increases according to the number of mini-batches. There is no magic rule for choosing the right batch size. This is a hyperparameter that must be determined before the training begins.²⁶

2.3.1.4 Data augmentation

Data augmentation is the artificial augmentation of a data set. This technique is primarily used when only little data is available or the data set is not sufficiently balanced (unbalanced data set). Existing images are rotated, mirrored, color adjusted, cropped, etc. Data Augmentation can improve model accuracy during training.²⁷

2.3.2 Methods of machine learning

Different ML systems can be classified according to the type and procedure of monitoring the training. A distinction is made as to which type of data is available or has to be determined by the user.

2.3.2.1 Supervised learning

Supervised learning refers to ML with known training data sets (see also chapter “Inductive approach”). The learning process in turn refers to the ability of an artificial intelligence (AI) to reproduce regularities and patterns. The results are known by laws of nature or expert knowledge and are used to teach the system by creating a training set containing the desired solutions. This is also called labelled data. The learning algorithm now tries to find a hypothesis epoch by epoch, which allows the most accurate predictions on unknown data. A hypothesis in this case is an image that assigns the assumed output value (the predicted class) to each input value (the image itself). This thesis makes extensive use of supervised learning.

In supervised learning, an input vector is fed to a classification function (usually an artificial neural network). The input vector generates an output vector using the classification function, which produces this neural network in its current state²⁸. This value is compared with the value that it should actually output. The comparison of the nominal and actual state provides information on how and in what form changes must be made to the network in order to further approximate the actual state and minimize the error. For ANN without a hidden layer (single-layer perceptron²⁹), the delta rule³⁰ for correction can be applied. For networks with one or more hidden layers backpropagation³¹ is used to minimize the error. Backpropagation is a generalization of the delta rule.

The neural network is only one algorithm from the category of supervised learning algorithms. Other possible algorithms are:

- k-nearest neighbors³²

²⁶*Epochs, Batch Size, & Iterations*. Library Catalog: docs.paperspace.com. URL: <https://docs.paperspace.com/machine-learning/wiki/epoch> (visited on 02/29/2020).

²⁷Luis Perez and Jason Wang. “The effectiveness of data augmentation in image classification using deep learning”. In: *arXiv preprint arXiv:1712.04621* (2017). URL: <https://arxiv.org/pdf/1712.04621.pdf>.

²⁸The neural network consists of many (usually millions) parameters, which can be adjusted during the learning process to minimize the error.

²⁹*Perceptron*. en. Page Version ID: 942271496. Feb. 2020. URL: <https://en.wikipedia.org/w/index.php?title=Perceptron&oldid=942271496> (visited on 02/25/2020).

³⁰*Least mean squares filter*. en. Page Version ID: 941899198. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Least_mean_squares_filter&oldid=941899198 (visited on 02/25/2020).

³¹*Backpropagation*. en. Page Version ID: 939314095. Feb. 2020. URL: <https://en.wikipedia.org/w/index.php?title=Backpropagation&oldid=939314095> (visited on 02/25/2020).

³²*k-nearest neighbors algorithm*. en. Page Version ID: 942113305. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=K-nearest_neighbors_algorithm&oldid=942113305 (visited on 02/28/2020).

- Linear regression³³
- Logistic regression³⁴
- Support-vector machine³⁵
- Random forest³⁶
- etc.

2.3.2.2 Unsupervised learning

In unsupervised learning, one tries to gain knowledge of patterns even without labelled data. Suppose one has several pictures of burgers, pizza and doughnuts, which are unsorted in a data set. Unsupervised learning now tries to find similarities in order to cluster these images. In the best case one gets three unnamed groups *A*, *B* and *C* at the end. Analysts will take a closer look at these groups afterwards and draw a conclusion if possible: Group *A* is then called Burger, Group *B* Pizzas, etc.

The following unsupervised learning algorithms can be used for clustering:

- k-means³⁷
- Hierarchical clustering³⁸
- Expectation–maximization³⁹
- etc.

One technique, hierarchical clustering (see chapter “Hierarchical classification”), is used later to facilitate the introduction of hierarchies. For the general analysis, the finding of optimal parameters for learning models, this kind of learning is not used in this thesis.

2.3.2.3 Reinforcement learning

Reinforcement learning⁴⁰ is a type of ML in which an agent independently learns the best possible strategy for achieving a goal. To achieve the goal, actions are necessary which produce rewards at certain points in time. These rewards can also be negative (punishment). Based on these rewards, the aim is to achieve the best possible reward value. This type of learning is not relevant for the classification of images, which is why it will not be discussed further here.

2.3.3 Artificial neural network

Artificial neural networks provide functions that are able to separate highly complex data in multidimensional space. For large and highly complex tasks, such as the classification of billions of images, speech and text recognition, neural networks usually perform better than other ML methods. The significant increase in computational capacity since the 1990s allows the training of large neural

³³Linear regression. en. Page Version ID: 935782381. Jan. 2020. URL: https://en.wikipedia.org/w/index.php?title=Linear_regression&oldid=935782381 (visited on 02/28/2020).

³⁴Logistic regression. en. Page Version ID: 941157282. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Logistic_regression&oldid=941157282 (visited on 02/28/2020).

³⁵Support-vector machine. en. Page Version ID: 942477636. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Support-vector_machine&oldid=942477636 (visited on 02/28/2020).

³⁶Random forest. en. Page Version ID: 938369502. Jan. 2020. URL: https://en.wikipedia.org/w/index.php?title=Random_forest&oldid=938369502 (visited on 02/28/2020).

³⁷k-means clustering. en. Page Version ID: 942500957. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=K-means_clustering&oldid=942500957 (visited on 02/28/2020).

³⁸Hierarchical clustering. en. Page Version ID: 934548831. Jan. 2020. URL: https://en.wikipedia.org/w/index.php?title=Hierarchical_clustering&oldid=934548831 (visited on 02/28/2020).

³⁹Expectation–maximization algorithm. en. Page Version ID: 936223068. Jan. 2020. URL: https://en.wikipedia.org/w/index.php?title=Expectation%E2%80%93maximization_algorithm&oldid=936223068 (visited on 02/28/2020).

⁴⁰Reinforcement learning. en. Page Version ID: 939437819. Feb. 2020. URL: https://en.wikipedia.org/w/index.php?title=Reinforcement_learning&oldid=939437819 (visited on 02/28/2020).

networks within a reasonable period of time. Artificial neural networks are the core component of deep learning, which denotes a method of ML.

Neural networks process an input vector \bar{x} and convert it into a new output vector $\hat{\bar{x}}$. They are networks of many artificial neurons connected in series and parallel. An artificial neuron in turn converts a vector into a scalar by scaling and summing the inputs \bar{x} with the changeable parameters $\bar{\omega}$ and correcting them with a bias b (the bias is also a changeable variable). The activation function ensures that the first degree polynomial (linear regression model) becomes a nonlinear function⁴¹ (Figure 7).

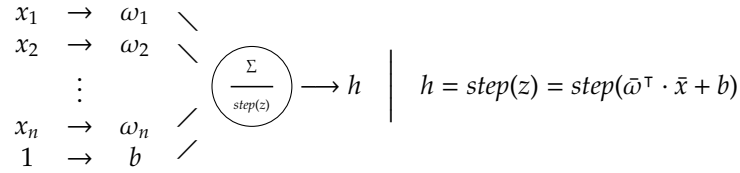


Figure 7: The construction of an artificial neuron

The artificial neural network is composed of many layers connected in series, which again contain neurons connected in parallel (Figure 8).

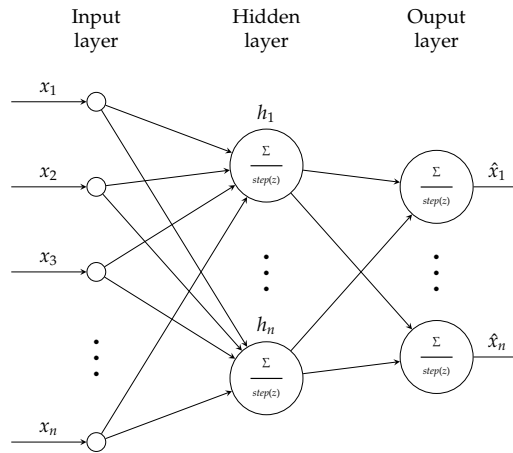


Figure 8: The construction of a simple neural network

A neural network is able to classify complex inputs. But how exactly does that work? The following classification function is able to separate simple class problems, where \bar{x} represent the coordinates of the corresponding class points and $\bar{\omega}$ and b are learnable parameters:

$$f(\bar{x}, \bar{\omega}, b) = \text{sgn}(\bar{\omega}^T \cdot \bar{x} + b) \quad (16)$$

With this linear function, the classification problem of the first representation of Figure 9 (i) can be easily classified. The function corresponds to a neural network without a hidden layer and contains only one input and one output layer with one artificial neuron without activation function. The dimension that this function can separate is two and is called VC dimension⁴². In other words, this function can separate exactly two classes linearly. But what about nonlinear problems?

⁴¹Aktivierungsfunktionen, ihre Arten und Verwendungsmöglichkeiten. de-DE. Library Catalog: www.ai-united.de Section: Mathematik. Jan. 2019. URL: <https://www.ai-united.de/aktivierungsfunktionen-ihre-arten-und-verwendungsmoeglichkeiten/> (visited on 02/28/2020).

⁴²Vapnik–Chervonenkis dimension: https://en.wikipedia.org/wiki/Convolutional_neural_network

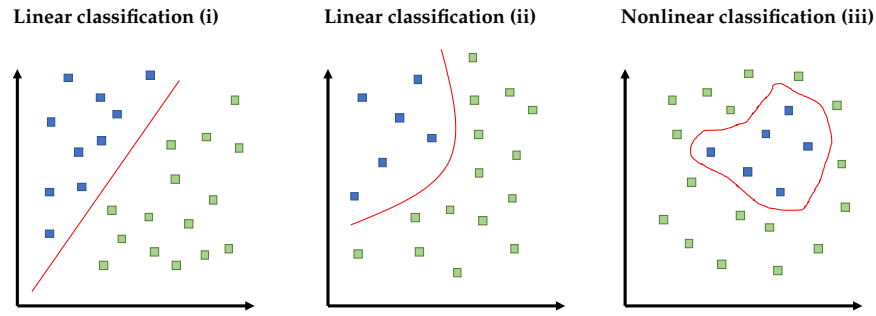


Figure 9: Linear vs. nonlinear classification

For the second classification problem one can still adjust the function (Figure 9, ii). For the third nonlinear problem (Figure 9, iii) the classification space is no longer sufficient and requires a different algorithm. And this is where the neural networks come into play. A tool to visualize the separation of data and to test the functionality of the individual layers is <https://playground.tensorflow.org>⁴³. In the simplest case, a nonlinear problem can be solved by adding a hidden layer with three additional neurons (Figure 10).

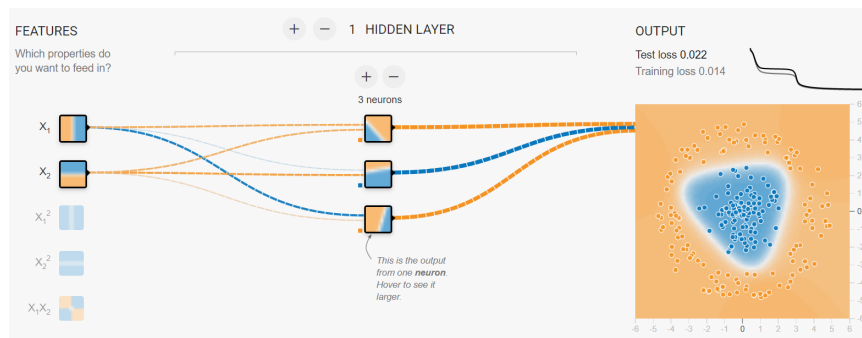


Figure 10: Simple neural network with one hidden layer⁴⁴

2.3.4 Convolutional neural network

An artificial neural network processes a vector and returns a new vector. The problem with input data such as images is that at first view they cannot be successfully described as vectors to be trained with a normal neural network. One needs an algorithm that can handle matrix-like inputs and that is able to recognize patterns. In the past the principle of the convolutional layer was developed. A convolutional layer receives a matrix input, transforms it and returns an output value (in this case another matrix). This output value is then passed on to the next layer. A convolutional layer contains a set n of square matrices (usually 3×3 or 5×5 matrices). These matrices are called filters. Each filter⁴⁵ is now calculated from top left to bottom right over the pixels of the image using a scalar product, which creates a new image (Figure 11, i). The so-called Feature Map. With a number of n filters, n feature maps are created at the end and highlight the features defined in the filters in the newly calculated image. This process is also called convolution.⁴⁶

⁴³Neural Network Right Here in Your Browser: <https://playground.tensorflow.org>

⁴⁴Source: <http://playground.tensorflow.org/>

⁴⁵Filters, which can recognize edges, corners, squares, etc. and in deeper layers things like eyes, ears, hair, etc.

⁴⁶deeplizard. *Convolutional Neural Networks (CNNs) explained*. Youtube. 2017. URL: https://www.youtube.com/watch?v=YRhxdVkf_sIs.

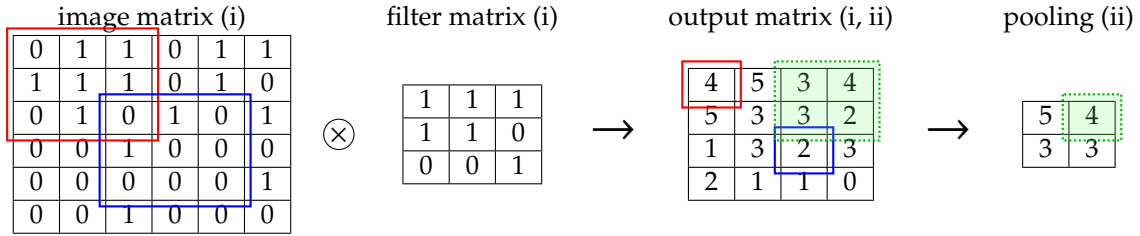


Figure 11: Simple convolution and simple pooling

Neural networks that make use of convolutional layers are called convolutional neural networks (CNNs) and have made a decisive contribution to the progress of image classification and also in other areas like speech recognition. In addition to the convolutional layers, a CNN has other special layers that differ from normal neural networks: For example the Pooling Layer. In a pooling layer, unnecessary information is discarded and feature maps are reduced in size (Figure 11, ii). This process reduces memory requirements and increases calculation speed. The convolutional layer and the pooling layer usually alternate until a large vector is created at the end instead of a $n \times n$ matrix of the input image, which can be further processed by a normal neural network and finally ends in the already described one hot vector (Figure 12).

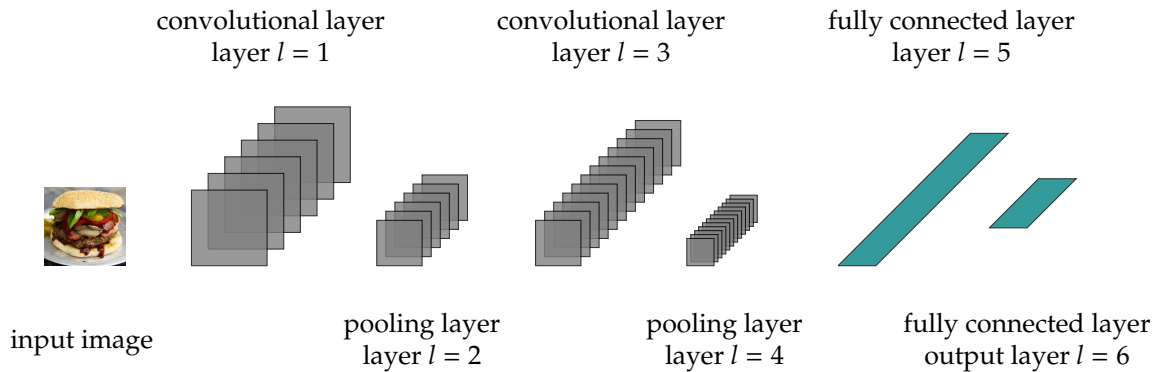


Figure 12: Architecture of a traditional convolutional neural network

A big advantage of convolutional neural networks should not remain unmentioned: They require relatively little preprocessing compared to other image classification algorithms. This means that the network independently learns the filters that are normally developed by hand in conventional algorithms, if trained with adequate training. This property of these networks is a great advantage because they can be automated and change independently when the input data changes and do not require human intervention.

2.3.5 Transfer learning

CNNs are great and have made a significant contribution to the classification of images. With the foundation of the research database ImageNet in 2006, annual competitions are organized to compare developed neural networks. ImageNet is an image database with more than 14 million images. A CNN called AlexNet in 2012 got a top-5 error of 15.3% and is currently increasing steadily every year. But the architecture of a CNN has a problem. All convolutional layers are randomly initialized from the beginning and do not yet contain any patterns. For it to work reliably, it needs to be trained with many images. If one would develop and use a CNN from scratch, all convolutional layers have to be trained in advance.

The convolutional layers extract features such as edges, squares, circles, etc. These are present in almost every image and the question arises whether one can reuse them to reduce the training effort. The idea of transfer learning is to use an already pre-trained CNN and just adapt the neural network at the end of the convolutional neural network to the own problem (Figure 13).



Figure 13: The green area (see Figure 12) was replaced by a new neural network (red) adapted to the new problem.

The advantage of a pre-trained network can be seen in the chapter "Use of the transfer learning (TL) approach" of this thesis.

2.3.6 Overview of current and known convolutional neural networks

Last but not least, here are a few current and well-known convolutional neural networks (Figure 14). They differ mainly in the following metrics, whereby in combination each network has its advantages and disadvantages:

- the top-1 accuracy (based on the ImageNet image dataset)
- the computing operations which are required for a single forward pass (G-Ops)
- the model size (for comparison: the model size of InceptionV3 is about 180 MB)

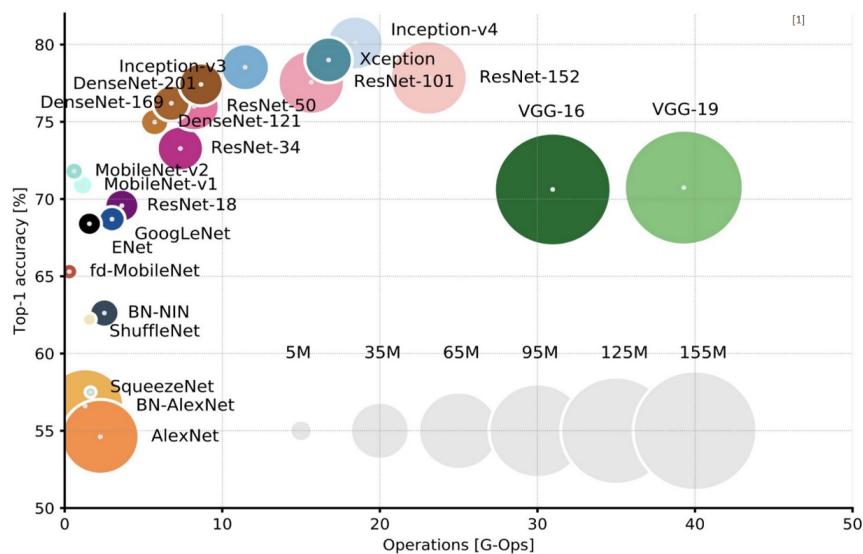


Figure 14: Overview of current and known convolutional neural networks⁴⁷

⁴⁷Source: <https://towardsdatascience.com/neural-network-architectures-156e5bad51ba>

3 Related work

There are a number of studies on image classification on very large datasets.^{48,49,50} Most of the time this huge number of classification classes and datasets is not desired. Furthermore, there are many investigations on small data sets.^{51,52} What these investigations usually lack is an overview and comparison of the common hyperparameters with respect to model accuracy in a single thesis. This thesis will deal with this. Data is expensive to obtain and usually not easy to get (see chapter “Balanced training data set”). And in contrast, image classifications are appearing in more and more areas of our life and are also being used directly in more and more companies that have not made use of them so far and are now considering introducing their own implementations. There are e.g. companies which try to classify products based on different data. Is it a good idea to implement your own implementation or is the step to the software tools of company giants like Microsoft, Google and Co. unavoidable? A person sees a product X and classifies it: From the text, the description or an image. Sometimes only an image remains, because e.g. texts have not been maintained properly or only return cryptic values. And even then, this classification is often not a challenge for humans: Because in this case, they recognize the product X based on the still existing image.

⁴⁸Jia Deng et al. “What does classifying more than 10,000 image categories tell us?” In: *European conference on computer vision*. Springer. 2010, pp. 71–84. URL: http://vision.stanford.edu/pdf/DengBergLiFei-Fei_{_}ECCV2010.pdf.

⁴⁹Yi Sun, Xiaogang Wang, and Xiaoou Tang. “Deep learning face representation from predicting 10,000 classes”. In: *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2014, pp. 1891–1898. URL: https://www.cv-foundation.org/openaccess/content/{_}cvpr/{_}2014/papers/Sun_{_}Deep_{_}Learning_{_}Face_{_}2014_{_}{CVPR_{_}paper.pdf.

⁵⁰Krizhevsky, Sutskever, and Hinton, “Imagenet classification with deep convolutional neural networks”.

⁵¹Francois Chollet. “Building powerful image classification models using very little data”. In: *Keras Blog* (2016). URL: <http://deeplearning.lipinyang.org/wp-content/uploads/2016/12/Building-powerful-image-classification-models-using-very-little-data.pdf>.

⁵²Sagar, *Deep Learning for Image Classification with Less Data*.

4 Considerations and implementation

4.1 Research questions and hypothesis section

This thesis deals with the image classification part. For example in the application for companies or environments with limited resources. The following questions arise: With which tools, techniques and ideas is it possible to create a successful image classification model even with few resources? Do the conditions mentioned in subsection 1.1: Insufficient amount of data have to be fulfilled or are successful classifications already possible with less? Is it possible to get the most out of model creation by adjusting certain tuning parameters? For example, is a cluster analysis and the associated categorical breakdown of the classification a successful approach? These and other questions are to be clarified with this thesis. And I dare to say at this point that it is possible to reach a good goal even with fewer requirements.

4.2 Working environment and model creation

All source code for the environment and the framework to train models and which has been used for this thesis is available in a GitHub repository.⁵³ This framework allows to set all the hyperparameters mentioned in this thesis.⁵⁴ Below is an example of a command line call with the default values from the chapter “Default setup” (Listing 1). The created model is located in the specified directory with the name `model.h5`:

```
1 user$ ml train \  
2     --use-train-val \  
3     --data-path=./data/raw/food-50 \  
4     --model-file=./data/processed/experiment1/type-of-experiment/model.h5
```

Listing 1: Example command line call to train the given data path

4.3 Performance

If one intends to implement and optimize deep neural networks (DNNs), the calculations must take place on the GPU. It is also possible to run calculations on the central processing unit (CPU). Also, the installation of Keras for CPU driven computations is much easier, because the installation of the GPU drivers is not necessary. The disadvantage of this, however, is that it takes much longer to train larger models. Good models for the classification of e.g. pictures are only achieved after several training units. Training units require a lot of computing power in the form of many matrix operations. A GPU is predestined for matrix operations.⁵⁵

Table 1 shows a tabular comparison of performance based on the Kaggle flower data set training.⁵⁶ This image set consists of 5 classes with about 4242 training images (10 epochs, InceptionV3)⁵⁷ and was trained with the default values from chapter “Default setup”.

While the type of computing device (CPU or GPU) makes no difference in terms of preparation and postprocessing, it does make a significant difference in training time. The slowest CPU takes more than 80 times as many time as the fastest graphics card unit. The choice of the computing device for all further tests clearly falls on the GPU.

⁵³Björn Hempel. *Keras Machine Learning Framework*. original-date: 2019-09-12T21:51:11Z. Feb. 2020. URL: <https://github.com/bjoern-hempel/keras-machine-learning-framework> (visited on 02/29/2020).

⁵⁴Björn Hempel. *Keras Machine Learning Framework - Arguments of the training process*. en. Library Catalog: github.com. URL: <https://github.com/bjoern-hempel/keras-machine-learning-framework> (visited on 02/29/2020).

⁵⁵Kayvon Fatahalian, Jeremy Sugerman, and Pat Hanrahan. “Understanding the efficiency of GPU algorithms for matrix-matrix multiplication”. In: *Proceedings of the ACM SIGGRAPH/EUROGRAPHICS conference on Graphics hardware*. 2004, pp. 133–137. URL: <https://graphics.stanford.edu/papers/gpumatrixmult/gpumatrixmult.pdf>.

⁵⁶*Flowers Recognition*. en. Library Catalog: www.kaggle.com. URL: <https://kaggle.com/alxmamaev/flowers-recognition> (visited on 02/29/2020).

⁵⁷Björn Hempel. *Keras Machine Learning Framework - GPU vs CPU*. en. Library Catalog: github.com. URL: <https://github.com/bjoern-hempel/keras-machine-learning-framework> (visited on 02/29/2020).

Device	Preparation	Train	Train (Factor)	Save model
NVIDIA GeForce GTX 1060 6GB (Desktop) - Windows 10	17.5s	303.5s 00:05:03.5	1.00x	33.8s
NVIDIA GeForce GT 750M 2GB (Notebook) - Windows 10	18.4s	2415.0s 00:40:15.0	7.96x	29.8s
Intel(R) Core(TM) i7-6700HQ CPU @ 2.60GHz (Single Core) - MacOS	19.1s	6393.7s 01:46:33.7	21.07x	41.4s
Intel(R) Core(TM) i7-4712HQ CPU @ 2.30GHz (Single Core) - Windows	16.9s	9016.8s 02:30:16.8	29.71x	28.7s
Intel(R) Core(TM) i7-3770 CPU @ 3.40GHz (Single Core) - Windows	16.3s	25183.4s 06:59:43.4	82.97x	28.3s

Table 1: Performance comparison

4.4 Experiment Setup

4.4.1 Software specifics

Python v3.6.9

Python has become one of the most important programming languages in the field of machine learning and data sciences in recent years.⁵⁸ The language was chosen as programming language because it has a large number of ML libraries to choose from. The fact that the TensorFlow application programming interface (API) is mainly designed for use with Python and thus allows stable development is also a contributing factor to the choice.

TensorFlow GPU v1.14.0 and Keras-GPU v2.2.4

TensorFlow GPU was chosen in conjunction with Keras GPU v2.2.4 to perform the calculations on the GPU and not on the CPU. This has significantly reduced the time of model creation (see chapter "Performance").

Keras v2.2.4

In the following experiments TensorFlow is used as backend. Keras translates the function calls into the corresponding functions of TensorFlow. Keras as the parent library simplifies the use of TensorFlow, makes the code easier to read and minimizes errors.

Deeplearning4j v1.0.0-beta3

Deeplearning4j is a deep learning programming library written for Java and a computer framework with wide support for deep learning algorithms.⁵⁹ It is not explicitly used for model creation in this thesis, but it should be mentioned that this programming library allows to read in and use Keras models.⁶⁰

⁵⁸The Most Popular Language For Machine Learning Is ... (IT Best Kept Secret Is Optimization). en. CT904. Library Catalog: www.ibm.com. Aug. 2015. URL: www.ibm.com/developerworks/community/blogs/jfp/entry/what_language_is_best_for_machine_learning_and_data_science (visited on 02/25/2020).

⁵⁹Deeplearning4j. en. Page Version ID: 927846637. Nov. 2019. URL: <https://en.wikipedia.org/w/index.php?title=Deeplearning4j&oldid=927846637> (visited on 02/29/2020).

⁶⁰Björn Hempel. Keras Machine Learning Framework (Java Sources). original-date: 2019-09-27T22:14:28Z. Oct. 2019. URL: <https://github.com/bjoern-hempel/keras-machine-learning-framework-java-sources> (visited on 02/29/2020).

4.4.2 Used data set

The used data set is a food data set consisting of 50 classes, 14,866 image files and has a size of 765 MB (food-50). This data set was created and labelled manually. The files are unevenly distributed between the classes (unbalanced). Before you can start the training process, the used data set must be split into a training and a validation data set. As a ratio 80% training and 20% validation data was chosen (11,913 images versus 2,953 images). The class with the smallest image set is `french_fries` and contains 36 training images and 8 validation images. The class with the largest image set is `grilled_cheese_sandwich` and contains over 390 images in the training data set and over 97 images in the validation data set. On average, all classes contain about 240 training data and 60 test data (see Figure A.1 for details). A test data set is not used in this thesis.

4.4.3 Default setup

With the exception of the CNN model tests, all tests were based on the following parameters (whereby one value of the parameters varied depending on the chapter):

- **model:** InceptionV3
- **learning rate:** 0,001 (decreases every 7 epochs to 50% of the previous value)
- **epochs:** 21 (the learning rate η from epoch 15 to 21 is 0,00025)
- **image size:** 299x299 pixels⁶¹
- **batch size:** 16
- **drop out:** 50%
- **CNN weights:** ImageNet
- **activation function:** ReLU
- **optimizer:** SGD with Nesterov
- **momentum:** 0.9 (with decay 0.0)
- the entire training and validation set (14866 images - unless otherwise specified)

Different models were tried out in chapter “Comparison of different CNN models” with the same parameters as above: DenseNet121, DenseNet201, InceptionResNetV2, InceptionV3, NASNetLarge, ResNet50, VGG19 and Xception

⁶¹The original image is reduced to 299 pixels. If it is not a square image, the larger side is scaled down to 299 pixels.

5 Results

In this part of the thesis the investigations and the corresponding evaluations will be presented. For each chapter models with the given parameters and techniques have been created with which image classifications can be performed. The model has to be trained, whereby a decision has to be made on many variable parameters like the learning rate η , the optimizers, but also things such as the CNN model. The basis is a standard setup, which was explained in chapter “Default setup”. Starting from this standard setup, the variable parameters are changed and discussed in the corresponding chapters. The goal is to find the parameters with which the recognition accuracy of the models is particularly high: high accuracy and small loss function.

5.1 Model validation

5.1.1 Influence of number of trained images on accuracy

The first question that comes up: What influence does the amount of data to be trained have on the accuracy of the model? For this purpose, the standard setup from the chapter “Default setup” is used and the model is trained with a different number of training data. While the validation data set always stays the same, the total number of data to be trained is increased from 500 data sets to the total number of 11913. Since this is an unbalanced data set, the number remains the same in each class in percentage terms. Only the total number is changed to the corresponding values: 500, 1000, 2000, etc. (Figure 15).

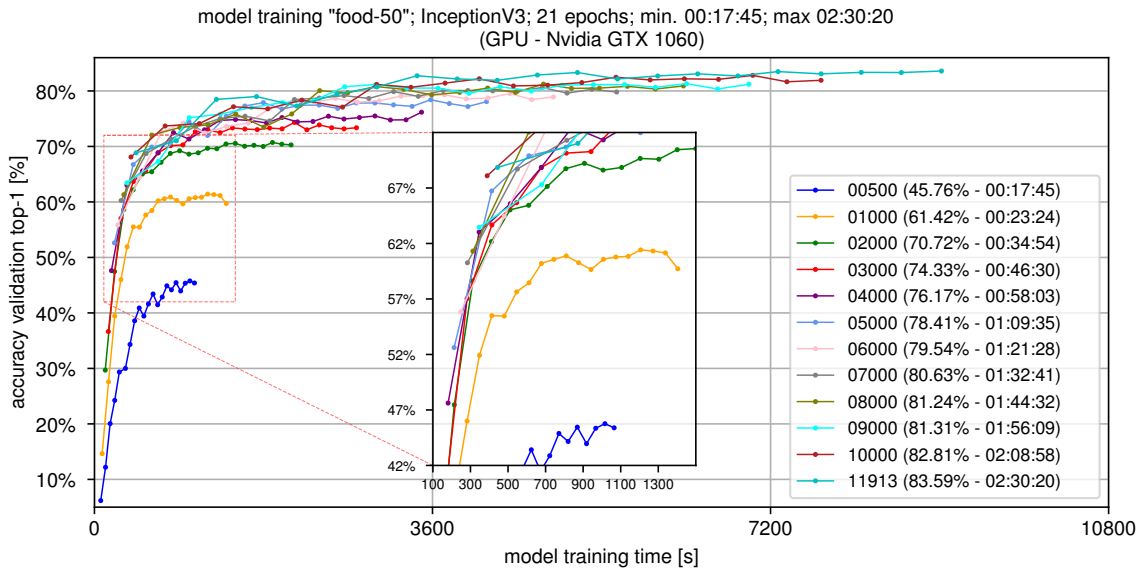


Figure 15: Overview of influence of number of trained images on accuracy

As expected, the number of images to be trained has a significant influence on the model accuracy. While with 500 images an accuracy of 45.76% can be achieved, with almost 12000 images it is already 83.59% after 21 epochs. With every increase in the number of images, an improvement in accuracy can be observed. The improvement in accuracy is not linear with an increase in training data sets. Although the accuracy in the upper range (>8000 images) still seems to increase, the jumps are not very big anymore and seem to be moving to a limit. For further research, it would be a good idea to find out from which number of training data sets no further significant increases in accuracy are possible. Since no further data was available in this data set, this project will not be pursued further here.

Another interesting point is the fact that increasing the training data theoretically saves computing time up to a certain point. If the data sets are significantly too small, one will never reach an accuracy during training, which models with much more data reach and exceed already with the first epoch. Clearly to see: With 1000 images (orange trace) one gets a maximum accuracy of

61.42% after 18 epochs and about 20 minutes of computing time. If one uses 10 times the amount of images (10000 images - brown trace), one reaches an accuracy of 68.1% already in the first epoch after six and a half minutes.

5.1.2 Comparison of different CNN models

There are currently many CNN models and each year with the annual ImageNet competition new models with better accuracy are released. These models are trained with the ImageNet dataset and the results are compared using this set of data. What is the result with smaller sets of data? The training result according to the standard setup and with different CNN models of eight models is as follows (Figure 16).

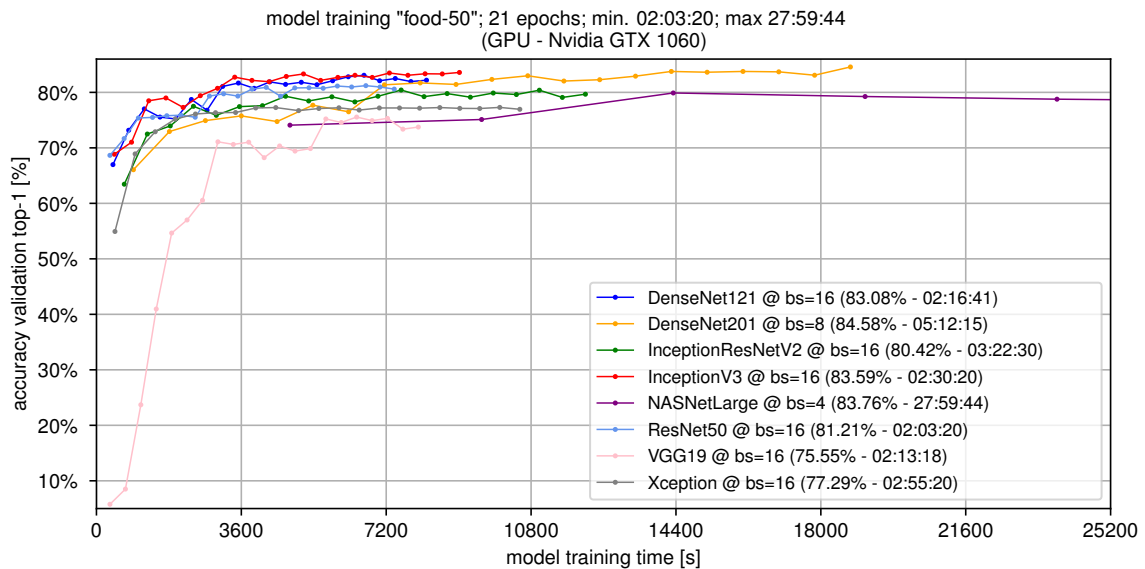


Figure 16: Overview of known CNN models

All models except DenseNet201 and NASNetLarge were trained with a batch size of 16 ($bs = 16$). Due to the limited 6GB memory of the Nvidia GTX 1060⁶², DenseNet201 was trained with a batch size of 8 and NASNetLarge with a batch size of 4. A real comparison of these two exceptions isn't really possible, but shouldn't be omitted at this point. A larger batch value is associated with increased computing time and slower increase in accuracy (see chapter "Different batch sizes"). A comparison with Figure 14 ("Overview of current and known convolutional neural networks") shows similar accuracies and required computing time: The best model was achieved with DenseNet201 with an accuracy of 88.58%. The model with the lowest accuracy is the somewhat older VGG19 model with 77.29%. If one compares the computing time and the accuracies to be achieved, one notices the InceptionV3 model (red trace). It is the second best model and reaches the result in a medium range of about two and a half hours. The best model DenseNet201 needs more than twice as much time for its result. The choice for all further experiments is therefore the CNN model InceptionV3, because it achieves a good result within a comparatively short period of time.

5.1.3 Use of the transfer learning (TL) approach

What influence does the use of transfer learning have on accuracy? As described in the chapter "Transfer learning", the TL approach immediately improves accuracy because the model already has recognition features that an unlearned network has yet to learn. The approach is applied to the data set food-50. Furthermore, it is examined what happens if the data set without TL approach is trained with 49 epochs instead of the 21 epochs used so far. A dropout of $dropout = 0.5$ from the

⁶²GeForce 10 series, Wikipedia contributors, February 22, 2020, https://en.wikipedia.org/wiki/GeForce_10_series

default setup and a dropout of $dropout = 0.0$ is used to force overfitting and focus on learning the recognition features (Figure 17).

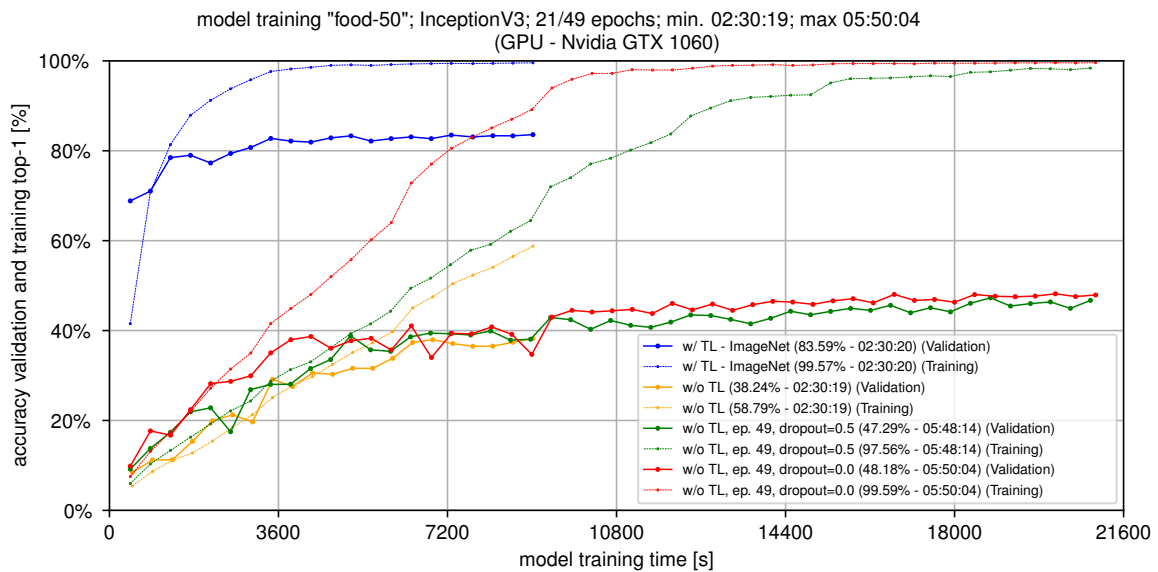


Figure 17: Overview of use of the TL approach

As expected, the model with the TL approach achieves a better result in the same computing time (blue trace versus orange trace). In the first epoch the model without transfer learning approach reaches an accuracy value of 8.5% and increases to 38.2% in 21 learning epochs. The training accuracy of 58.8% is still far below the values achieved with TL after a few epochs. This means that learning of features can be continued with the existing data set. If one starts with a pre-trained network, a better accuracy value of 68.9% is achieved in the first epoch and can be further increased to 83.6% in the 21st epoch. The red and green trace follow the approach to increase the accuracy even without TL. Especially with a dropout of $dropout = 0.0$ an accuracy of 48.2% could be achieved (still below the value with TL approach), whereas the training accuracy has already reached 99.59%. Thus, further generalization is theoretically no longer possible. In order to make further progress and to achieve better accuracies on previously unseen images, more images are needed to learn features. Conclusion: For the training of approaches without TL the currently available image set is no longer sufficient to achieve better or the same values as with TL approaches. Using transfer learning is a good idea especially when using small data sets.

5.1.4 Influence of the number of trained layers on the accuracy

A pre-trained network has a decisive influence on the accuracy that can be achieved in a certain computing time. With increasing depth of the layers of a CNN model, the associated filters have learned more and more complex recognition features⁶³: In the first layers, the filters learn basic shapes to recognize features such as edges and corners. The middle layers learn to recognize parts of objects. The last layers learn complete objects in different shapes and positions. The question that immediately comes up: Is it necessary to relearn the lower layers or is it possible to omit them to save computing time? This will be tested in the following experiment (Figure 18).

⁶³ Advanced Topics in Deep Convolutional Neural Networks, <https://towardsdatascience.com>, February 22, 2020, <https://towardsdatascience.com/advanced-topics-in-deep-convolutional-neural-networks-71ef1190522d>

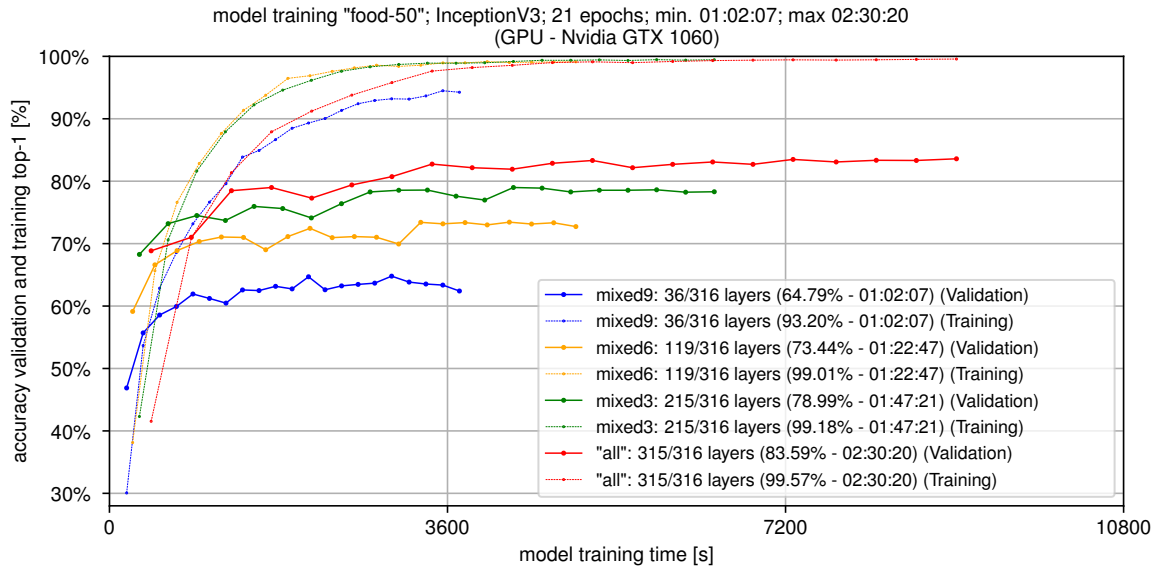


Figure 18: Overview of influence of the number of trained layers

The idea of not training the lowest layers is unfortunately not a good idea. One can save a lot of computing time if one only trains the last 36 levels (about one hour of computing time compared to two and a half hours if one trains all levels), but the accuracy of the model increases steadily with the training of additional layers. The model accuracy could be improved from 64.8% to 83.6% when training all levels. It is a good idea to invest in computing time to get good models.

5.1.5 Influence of different error optimizers

The optimizer in the training process is used to reduce the value of the loss function to reflect the value of the predictions as correctly as possible. The value of the loss function is the difference between the expected value and the estimated value of the function. Optimizers determine the value and adjust the error to minimize the loss function. The simplest approach is the gradient descent algorithm⁶⁴, which has been improved over time and further optimization algorithms have been developed, which sometimes work better and sometimes not so well according to their tasks and goals. The learning rate η determines the value of the weighting with which the error is corrected (see also chapter "Loss function"):

$$x_{n+1} = x_n - \eta \cdot \nabla F(x_n) = x_n - \eta \cdot L_r(\vartheta, \lambda), n \geq 0 \quad (17)$$

This area deals with the topic of optimizers and their parameters (especially the learning rate η) and what decisive influence they have on the accuracy of the model.

5.1.5.1 Comparison optimizer

In addition to the gradient descent algorithm, there are a lot of other methods which are intended to improve the descent to the optimum. For example, techniques are used which, together with the learning rate, prevent or limit jumping between the optimum and thus optimize convergence⁶⁵. Below is a comparison of current optimization methods (Figure 19).

⁶⁴Gradient descent, Wikipedia contributors, February 22, 2020, https://en.wikipedia.org/wiki/Gradient_descent

⁶⁵A Look at Gradient Descent and RMSprop Optimizers, <https://towardsdatascience.com>, February 22, 2020, <https://towardsdatascience.com/a-look-at-gradient-descent-and-rmsprop-optimizers-f77d483ef08b>

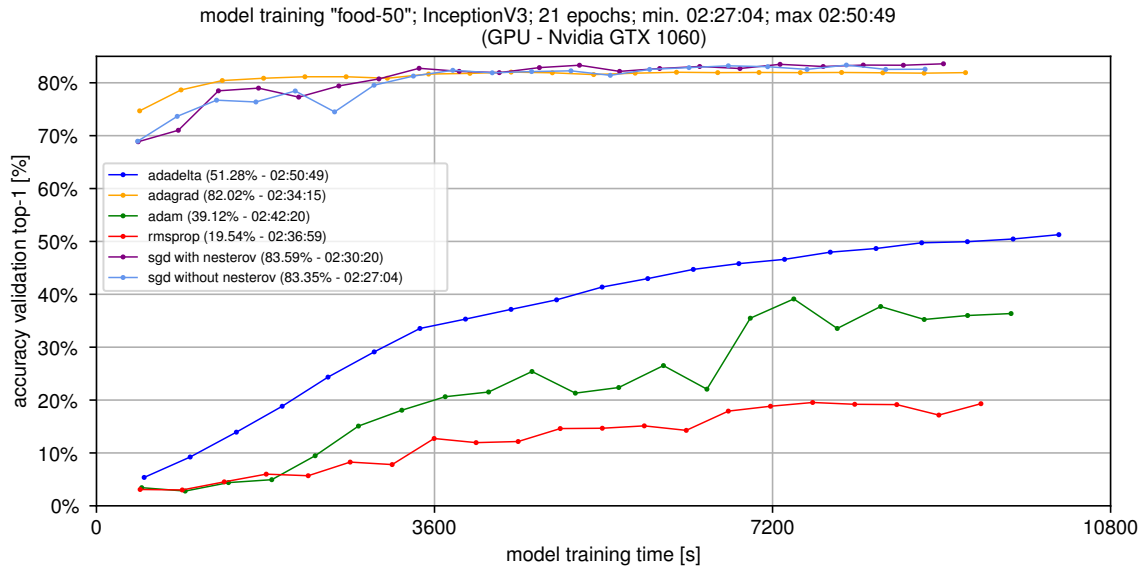


Figure 19: Overview of best optimizer

As one can see, the results are very different. While the gradient descent method with and without Nesterov and the Adagrad method provide good values (82.0% to 83.6% accuracy), the other methods do not look very useful at first sight. They converge very slowly: Adadelta, Adam and RMSprop. All procedures were performed with the recommended settings according to the Keras documentation⁶⁶. A learning rate of $\eta = 0.001$ was chosen for all procedures.

5.1.5.2 Influence of the momentum and the Nesterov momentum

The two best methods from the previous chapter "Comparison optimizer" SGD with Nesterov and SGD without Nesterov will be examined here in more detail. The learning parameter η plays a decisive role. It is varied from 0.5 to the critical range of 0.98 (Figure 20). The learning rate decreases by 50% after every seven epochs. The results will then be compared and discussed.

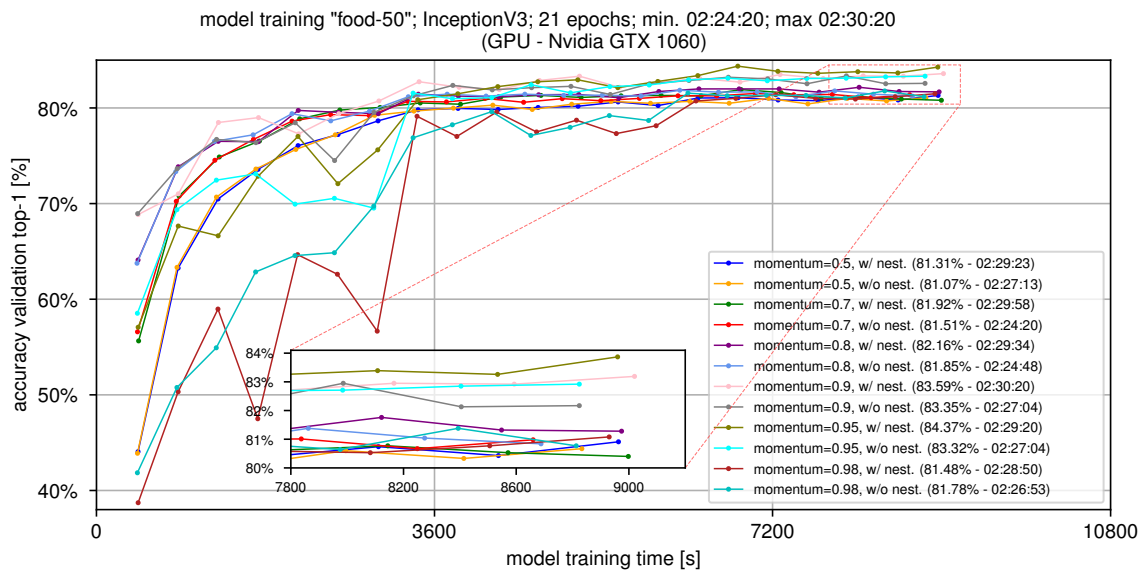


Figure 20: Overview momentum vs Nesterov momentum

⁶⁶Usage of optimizers, <https://keras.io>, February 22, 2020, <https://keras.io/optimizers/>

The accuracy of both models with (w/ nest.) and without Nesterov (w/o nest.) increases steadily with increasing learning rate η until they reach their zenith at 83.35% and 84.37% with $\eta = 0,9$ (w/o nest.) and $\eta = 0,95$ (w/ nest.) respectively. It is noticeable that the smaller the learning rate η , the accuracy increases more evenly, but the “maximum” at 21 epochs is not reached. With increasing learning rate, e.g. at the maximum of $\eta = 0,98$ for the Nesterov model (brown trace), the model accuracies jump and can sometimes run completely in the negative direction with another epoch. With the best model (olive trace, w/ nest.) exactly the same happens, but in the end the best results are achieved.

5.1.5.3 Influence of a dynamic learning rate on accuracy (scheduling)

The learning rate η indicates how much of the error is returned to the model (step size). After a certain number of learning epochs, the model accuracy does not increase any more but jumps around a value (see green trace in the following figure), because the optimum cannot be achieved due to a too large step size in error correction. It is therefore a good idea to adjust and reduce the step size step by step over the epochs. For this purpose the learning rate η is adjusted after a certain number of epochs \mathcal{E} with the momentum β . The value for η_1 corresponds to the initial value for the learning rate:

$$\eta_{m \rightarrow next} = \beta \cdot \eta_m, m \in [1 + 0 \cdot \mathcal{E}, 1 + 1 \cdot \mathcal{E}, 1 + 2 \cdot \mathcal{E}, \dots] \quad (18)$$

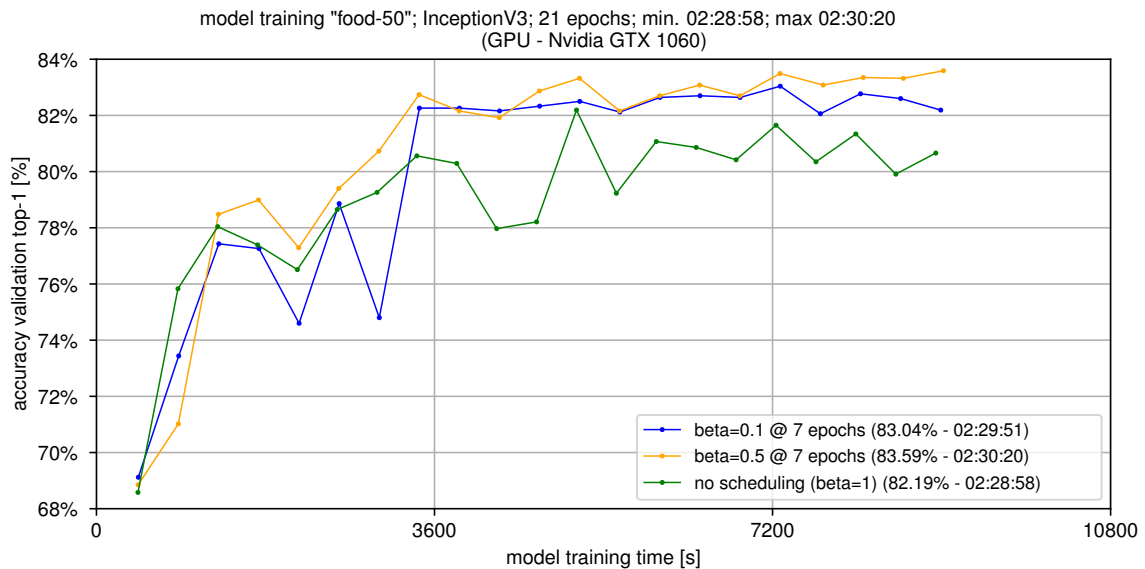


Figure 21: Overview of a dynamic learning rate on accuracy

As suspected, a reduction of the learning rate over time improves the possible model accuracy (Figure 21). However, it must not be reduced too much, as this would limit the further learning possibilities too much. While a momentum of $\beta = 0.5$ still provides a model accuracy of 83.6%, this decreases to 83.0% at $\beta = 0.1$. A static learning rate does not improve the learning ability from about the 8th epoch onwards. It then jumps around the value of 81% and even seems to worsen a little. Momentum belongs to the group of hyperparameters⁶⁷ and must be determined experimentally. An empirical value can be used as a starting value.

⁶⁷Hyperparameter optimization, Wikipedia contributors, February 22, 2020, https://en.wikipedia.org/wiki/Hyperparameter_optimization

5.1.6 Different batch sizes

The batch size is one of the regularization parameters, since it can counteract overfitting. As described in the chapter “Batch Size” it is not always a good idea to train the complete data set at once and to divide the epoch into several smaller mini-batches. The question in this evaluation is how different sizes of batch size affect the accuracy of the model. In a paper by Pavlo M. Radiuk from 2017, the highest possible batch size of 1024 provided the best accuracy and helped to avoid a high degree of variance. However, Pavlo M. Radiuk also found that the improvements in accuracy in high ranges were only very small.⁶⁸ It should also be mentioned that his dataset consisted of 60,000 images distributed in 10 classes (compared to 50 classes with about 250 images per class in this thesis) and he used very small images (32x32 pixels) to allow a high value of batch size. The different batch size sizes are also applied to the food-50 dataset (Figure 22). A batch size higher than 32 could not be used due to technical reasons.

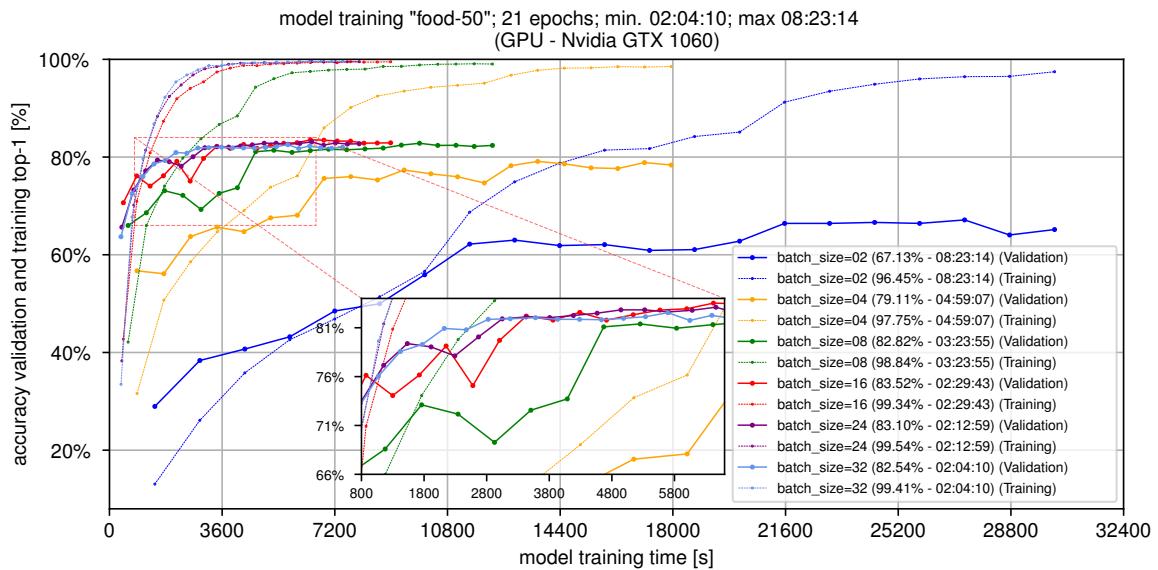


Figure 22: Overview of the influence of a different batch size

A higher batch size value obviously leads to a faster and more predictable (more even) increase in validation accuracy in the first epochs (light blue trace with $batch_size = 32$), compared to a batch size of 16 (red trace), for example, where the accuracy “jumps” from epoch two to seven. However, it does not give the best result at the end of the 21 epochs. While a value of 16 for the batch size achieves an accuracy of 83.52%, it only achieves 82.54% with a value of 32. Up to a batch size of 16, however, it can be said that as the batch size increases, a better result is always achieved. Increasing the batch size reduces the required computing time as expected. In this case, it has been improved from eight hours to two hours. Overfitting is achieved very slowly with a batch size of 2, but this model is also the worst one with a detection accuracy of 67.13%. Investigations with a slightly more balanced data set and an even higher batch size should be aimed at to further study the influence of the batch size.

5.1.7 Different activation functions

The activation function ensures that the linear classification function becomes a non-linear function (see chapter “Artificial neural network”) and with its help it is possible to create the classification space for image classifications..⁶⁹ There are a lot of different activation functions, which differ a

⁶⁸Pavlo M Radiuk. “Impact of training set batch size on the performance of convolutional neural networks for diverse datasets”. In: *Information Technology and Management Science* 20.1 (2017), pp. 20–24. URL: <https://www.degruyter.com/downloadpdf/j/itms.2017.20.issue-1/itms-2017-0003/itms-2017-0003.pdf>.

⁶⁹Aktivierungsfunktionen, ihre Arten und Verwendungsmöglichkeiten.

little bit in their manner. The influence on the model accuracy to be achieved by these different activation functions is shown in Figure 23.

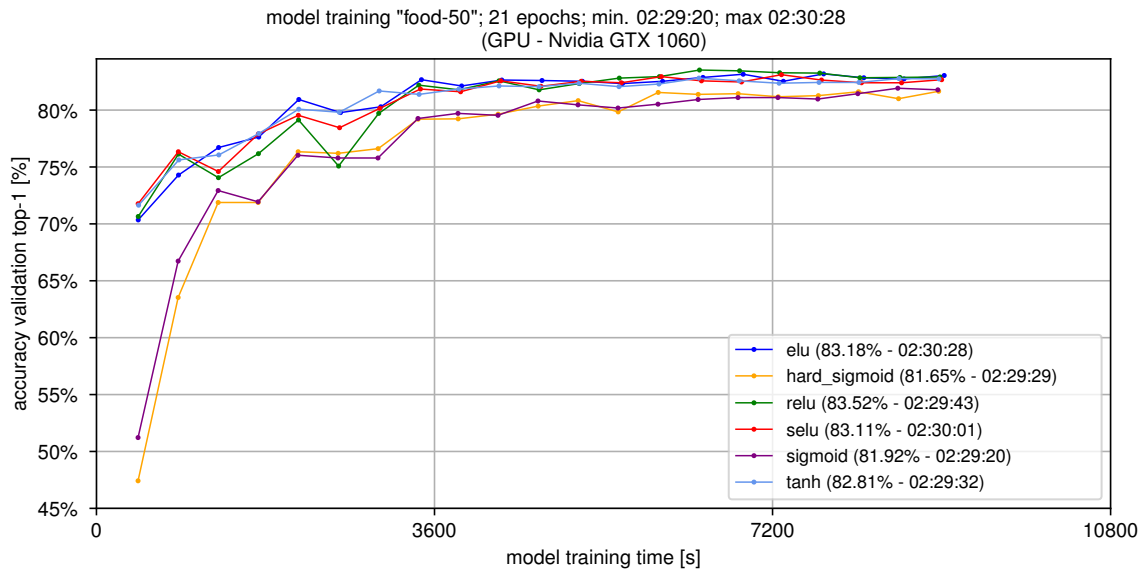


Figure 23: Overview of the influence of difference activation functions

The model accuracies to be achieved are very similar in the result. Nevertheless, there are small differences. The sigmoid function, as well as the activation function "Hard sigmoid" converge more slowly to the maximum possible model accuracy. The other four activation functions converge faster and are further ahead with about 20% more model accuracy in the first epoch. They do not differ very much in their results. The best result is achieved by the activation function "ReLU" with 83.52%.

5.1.8 Different number of learned epochs

All experiments performed here so far have been carried out with 21 learning epochs, whereby the learning rate dropped from 0.001 to 0.0025. The validation accuracies at the end of the training processes were mostly over 99% (see for example Figure 22, *batch_size* = 16) which indicates overfitting and theoretically no further improvements are possible. It will now be examined what happens if one trains over the 21 learning epochs with further decreasing learning rates η . SGD with Nesterov is used as optimizer. Once with 0.9 and once with the best value 0.95 from chapter "Influence of the momentum and the Nesterov momentum" (Figure 24).

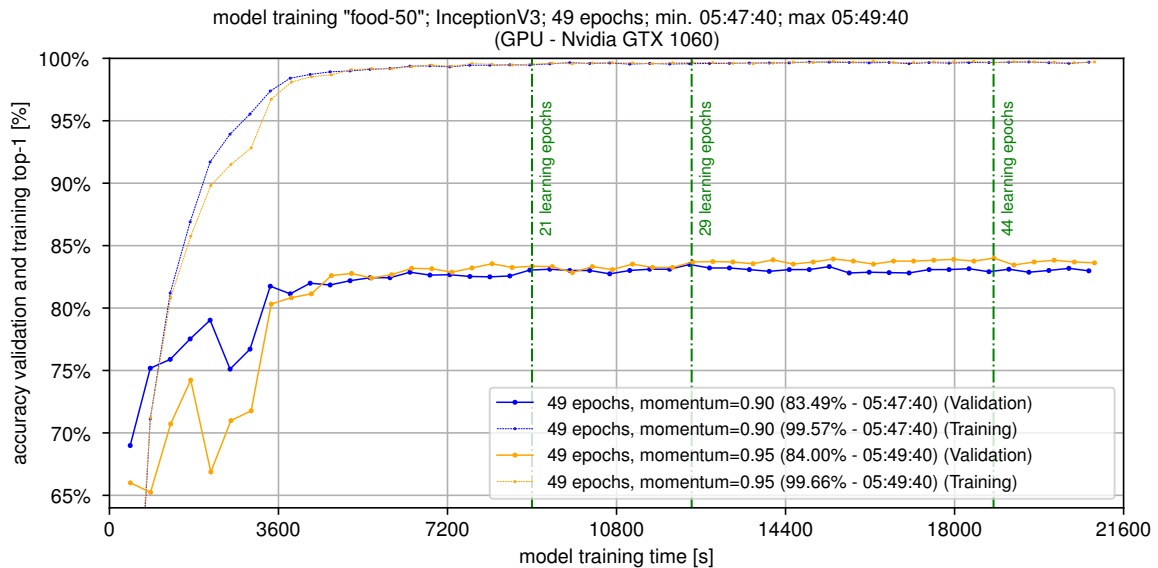


Figure 24: Overview of the influence of a longer training period with more epochs

As suspected, there is no significant improvement after 21 learning periods. The best result until the 21st learning epoch was achieved after the 21st epoch (*momentum* = 0.9, 83.04%) and after the 19th epoch (*momentum* = 0.95, 83.55%). This could then be improved in the 29th epoch to 83.49% (*momentum* = 0.9) and in the 44th epoch to 84.00% (*momentum* = 0.95). Conclusion: Increases are still possible, but an improvement of about 0.5% requires a doubling of the computing time.

5.1.9 Influence of dropout

The dropout parameter also belongs to the regularization parameter group. It also helps to avoid overfitting, in which individual neurons in the NN are randomly deactivated and do not contribute to training without affecting the rest of the model. This forces that not always all features are learned at once, but only a part of them. In the Figure 25 the results of different dropout values are compared. The dropout layer is used after the CNN within the connected neural network (Listing 2).

```

1  # definition of some parameters
2  num_classes = 50
3  dim=299
4  dropout=0.5
5
6  # get the transfer learning model, add dropout and and build the final
7  # model
8  base_model = InceptionV3(input_shape=(dim, dim, 3), weights='imagenet',
9                          include_top=False)
10 x = base_model.output
11 x = GlobalAveragePooling2D()(x)
12 x = Dropout(dropout)(x)
13 predictions = Dense(num_classes, activation='softmax')(x)
14 model = Model(inputs = base_model.input, outputs = predictions)

```

Listing 2: Example of a dropout layer after the CNN model

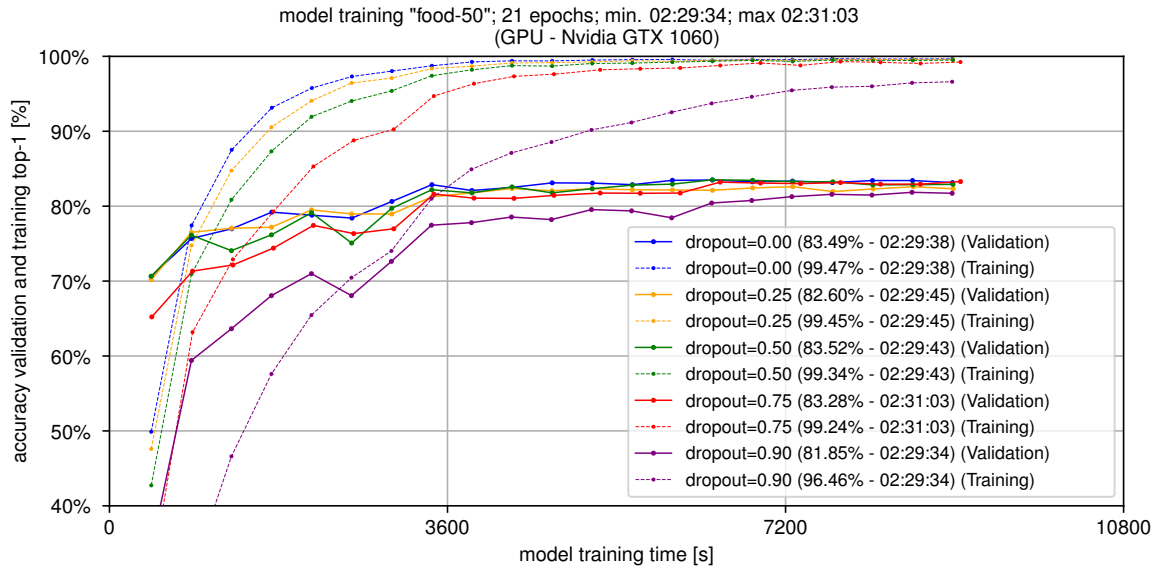


Figure 25: Overview of the dropout parameter

As one can see the dropout technique helps to avoid overfitting. The higher the dropout value, the slower the training accuracy value increases. The best result with the same computing time of all experiments is obtained with a dropout value of 0.5 which reaches a model accuracy of 83.52%. Beyond that and below the model accuracy decreases again slightly with one exception: In the experiment without dropout ($dropout = 0.0$) a model accuracy of 83.49% is achieved in the 15th epoch. Compared to the best result, this result differs only minimally (by 0.03%). This result is interesting and should be investigated further. The assumption is that higher dropout values require longer training times and that the experiment quickly reached a maximum without dropout. Especially with a dropout value of 0.9 it is probable that with more training epochs an even better value can be determined. Conclusion: With current CNNs it is obviously not necessary to use the regularization technique dropout with equal computing time. Even without dropout you get the highest model accuracy. However, the experiment should be repeated with further training data sets.

5.2 Optimization process

In addition to hyperparameters (or tuning parameters), there are a number of other techniques that influence model accuracy. It should be mentioned, for example, the problem in chapter "Influence of number of trained images on accuracy", where the model accuracy could not be further investigated with more than the existing 12000 images due to missing data, although the accuracy seemed to increase even more. Or the problem with the unbalanced data set. Wouldn't it be an idea to have the same amount of data in all classes without having to discard data or get additional data? What about other classification ideas? Currently, one model is used for all classes. Do hierarchies make sense? All these things will be examined in the following chapters.

As in chapter "Model validation", the same settings are used as the default setup, unless otherwise specified. InceptionV3 is used as CNN. The data set and also the division into training and validation data set corresponds to the procedure of the previous chapters.

5.2.1 Data augmentation

As described in chapter "Data augmentation" the main task of data augmentation is to generate new training data from the existing data. The training data set is artificially augmented in this way.

The model accuracy increases from 83.6% to 85.6%. An overall increase of 2%. Note: The validation data set is still the same! However, this also means an increase in the required computing time. While the calculation of the data set without data augmentation takes only two and a half hours, the new data set takes four times as long. Conclusion: Data Augmentation is associated with improved accuracy, but also requires more computing time in the same breath. If computing time is not important, this is one way to improve the accuracy a little.

5.2.2 Hierarchical classification

By using a single model for all classes, previous classifiers have been trained to minimize the loss of the class output vector. Each class used so far has the same rank in both training and classification. The prediction of "Pizza" costs the same as the prediction of "Martini".

The human ability to classify objects does not only work on one level. Categories will naturally overlap and have a hierarchical structure. For example, a human will classify a picture under "pizza", "tuna pizza" or even "fast food", which is correct from this point of view. Depending on the classification, there will only be a "loss of information". However, a person will not mistake a "pizza" as a "Martini", which is more likely to be classified as a "drink" or "cocktail".⁷¹

In order to find out whether a pre-classification improves the result, the classes are divided into groups. The idea is that no longer one model predicts all classes, but rather the images are pre-sorted into a group. The corresponding group then carries out the actual classification. For this purpose, a principal component analysis is performed to analyze the similarity of the classes from the food-50 training data set. The result will then be used to create groups. In preparation, a model will again be trained for all classes: InceptionV3, 21 epochs, batch size 16, learning rate $\eta = 0.001$ decreasing by factor 0.5 every seven epochs. Using this model, a prediction is made of all training and validation data and the probability vector is determined (One Hot Encoding):

$$\lambda_{class_m} = \begin{pmatrix} \hat{p}_1 \\ \hat{p}_2 \\ \vdots \\ \hat{p}_{50} \end{pmatrix} \quad \left| \quad \sum_{i=1}^{50} \hat{p}_i = 1 \right. \quad (19)$$

From these probability vectors, an average vector of all n elements is determined for each class, which really belong to the respective class. Thus, for this 50 class model, one obtains 50 class vectors with the dimension 50:

$$\forall 50 \text{ classes}, m = 1 \dots 50 : \bar{\lambda}_{class_m} = \frac{\sum_{i=1}^n \lambda_{class_m}}{n} \quad (20)$$

Principal component analysis is used to transform these multidimensional vectors into a two-dimensional space in order to display them visually (Figure 28).

⁷¹Eleanor Rosch et al. "Basic objects in natural categories". In: *Cognitive psychology: Key readings* 448 (2004).

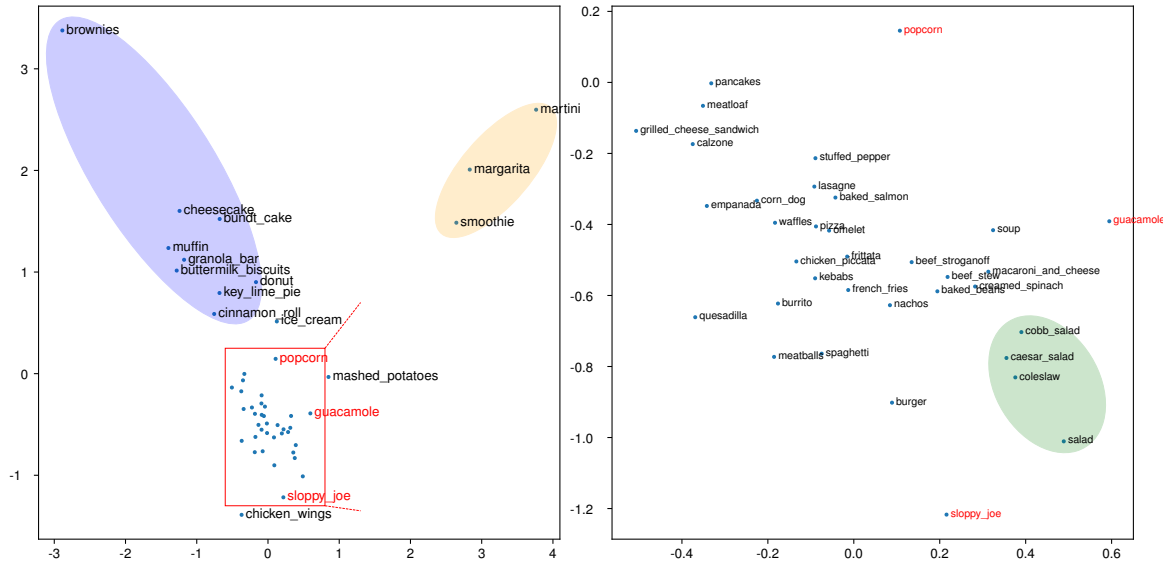


Figure 28: Principal component analysis of the food-50 model. The x and y axis have no significance. They only stand for the room and the similarity between the classes.

As expected, one can now immediately recognize similar classes: drinks (orange), cakes (blue) and salads (green). In the following two chapters, the model accuracies for the pre-classification as well as the subclasses are determined as usual. In order to determine the overall accuracy of the models, this would have to be done manually one at a time, since classification using subgroups is not intended. Instead, the overall accuracy is determined statistically:

$$\widehat{acc}_{group} = acc_{preclassification} \cdot acc_{group} \quad (21)$$

$$acc_{top-1} = \sum_{group=0}^7 ratio_{files_{val}, group} \cdot \widehat{acc}_{group} \quad (22)$$

5.2.2.1 *k*-means clustering

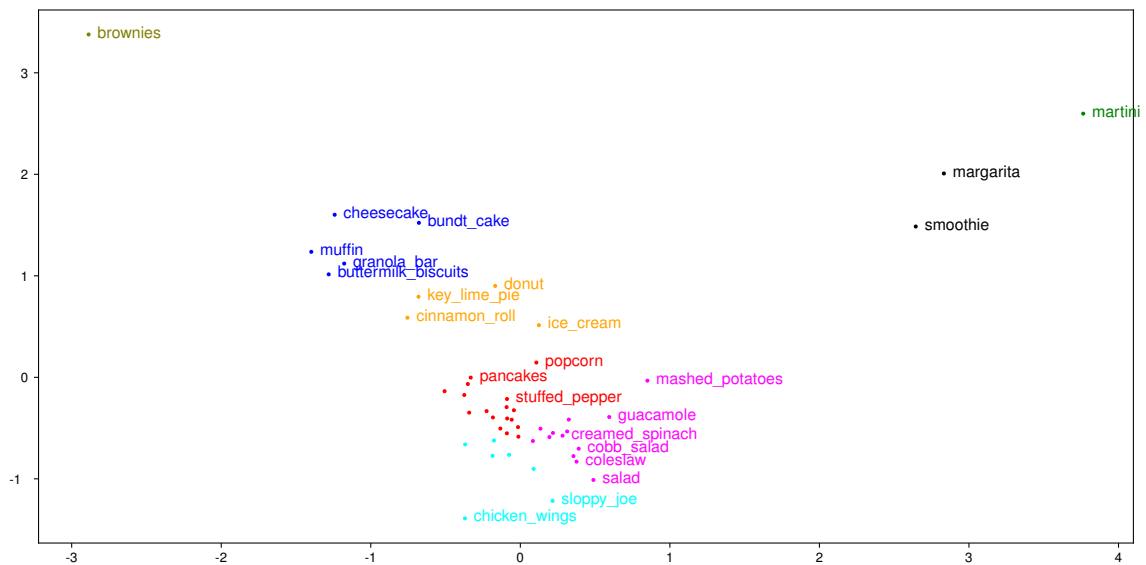


Figure 29: Grouped classes with k-means

Group	# _{classes}	# _{files_{val}}	ratio _{files_{val}}	acc [*]	\widehat{acc}^*	Classes
preclassification	8	2,953	100.0%	90.02% @ ep. 15		group ₀ , group ₁ , group ₂ , group ₃ , group ₄ , group ₅ , group ₆ , group ₇
group ₀	18	919	31.1%	83.94% @ ep. 11	75.56%	baked_salmon, calzone, chicken_piccata, corn_dog, empanada, french_fries, frittata, grilled_cheese_sandwich, kebabs, lasagne, meatloaf, omelet, pancakes, pizza, popcorn, stuffed_pepper, waffles
group ₁	2	158	5.4%	99.30% @ ep. 10	89.39%	margarita, smoothie
group ₂	5	296	10.0%	93.93% @ ep. 16	84.56%	bundt_cake, buttermilk_biscuits, cheesecake, granola_bar, muffin
group ₃	1	83	2,8%	100.0%	90.02%	brownies
group ₄	1	63	2,1%	100.0%	90.02%	martini
group ₅	4	221	7.5%	92.68% @ ep. 17	83.43%	cinnamon_roll, donut, ice_cream, key_lime_pie
group ₆	12	723	24.5%	81.90% @ ep. 10	73.73%	baked_beans, beef_stew, beef_stroganoff, caesar_salad, cobb_salad, coleslaw, creamed_spinach, guacamole, macaroni_and_cheese, mashed_potatoes, nachos, salad, soup
group ₇	7	490	16.6%	91.77% @ ep. 14	82.61%	burger, burrito, chicken_wings, meatballs, quesadilla, sloppy_joe, spaghetti
Overall	50	2,953	100,0%			$acc_{top-1} = 79.23\%$

Table 2: Grouped classes with k-means. *=All accuracies *acc* are top-1 accuracies.

5.2.2.2 Agglomerative hierarchical clustering

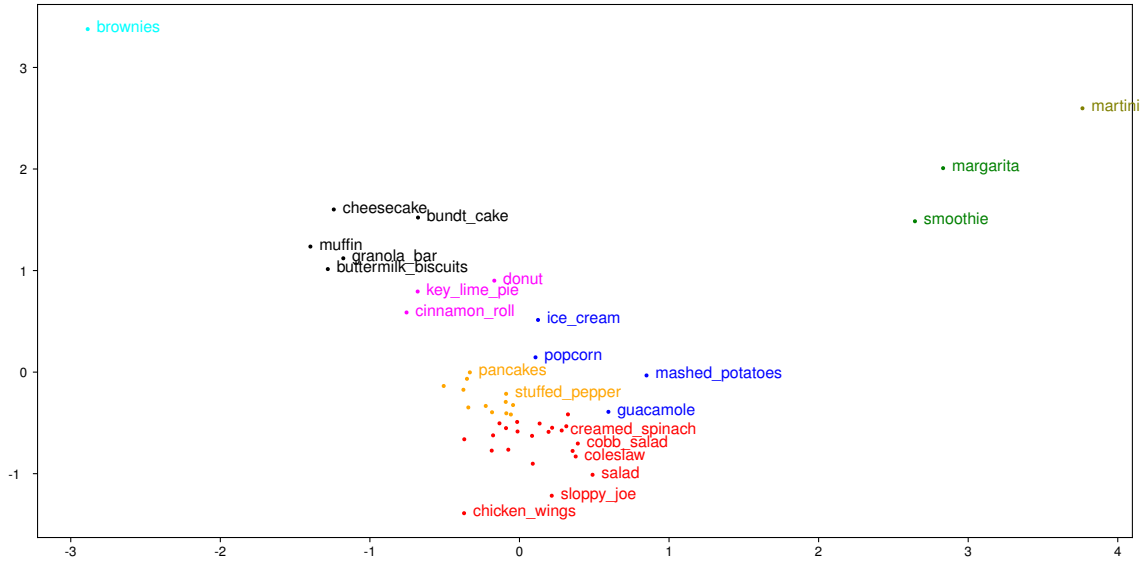


Figure 30: Grouped classes with agglomerative hierarchical clustering

5.2.3 Binary classifiers

...

Group	# _{classes}	# _{files_{val}}	ratio _{files_{val}}	acc [*]	\widehat{acc}^*	Classes
preclassification	8	2,953	100.0%	88.93% @ ep. 14		group ₀ , group ₁ , group ₂ , group ₃ , group ₄ , group ₅ , group ₆ , group ₇
group ₀	22	1,267	42.91%	84.17% @ ep. 18	74.85%	baked_beans, beef_stew, beef_stroganoff, burger, burrito, caesar_salad, chicken_piccata, chicken_wings, cobb_salad, coleslaw, creamed_spinach, french_fries, frittata, kebabs, macaroni_and_cheese, meatballs, nachos, quesadilla, salad, sloppy_joe, soup, spaghetti
group ₁	5	296	10.02%	93.21% @ ep. 16	82.89%	bundt_cake, buttermilk_biscuits, cheesecake, granola_bar, muffin
group ₂	4	249	8.43%	94.85% @ ep. 11	84.35%	guacamole, ice_cream, mashed_potatoes, popcorn
group ₃	1	63	2.13%	100.0%	88.93%	martini
group ₄	2	158	5.35%	99.30% @ ep. 10	88.31%	margarita, smoothie
group ₅	12	677	22.93%	85.63% @ ep. 11	76.15%	baked_salmon, calzone, corn_dog, empanada, grilled_cheese_sandwich, lasagne, meatloaf, omelet, pancakes, pizza, stuffed_pepper, waffles
group ₆	3	160	5.42%	93.13% @ ep. 5	82.82%	cinnamon_roll, donut, key_lime_pie
group ₇	1	83	2.81%	100.0%	88.93%	brownies
Overall	50	2,953	100,0%	$acc_{top-1} = 78.60\%$		

Table 3: Grouped classes with agglomerative hierarchical clustering. ^{*}=All accuracies *acc* are top-1 accuracies.

6 Summary and outlook

What's the outcome? What else is possible? How can this work be continued? In here!

- What are the best parameters?
- What is the best approach?
- What else should be investigated?
 - More precise analysis of incorrectly classified data: Is there any room for improvement here?
- What else is missing in this thesis?
- Questions asked in this thesis:
 - Is it a good idea to implement your own implementation or is the step to the software tools of company giants like Microsoft, Google and Co. unavoidable?
- More ideas
 - Don't Decay the Learning Rate, Increase the Batch Size: <https://arxiv.org/abs/1711.00489>
 - Enrichment of the data set from other data sources

List of acronyms

AI	artificial intelligence
API	application programming interface
ANN	artificial neural network
CNN	convolutional neural network
CPU	central processing unit
DA	data augmentation
DL	deep learning
DNN	deep neural network
DS	data set
FN	false negative
FP	false positive
GPU	graphics processing unit
HP	hyperparameter
ML	machine learning
NN	neural network
RL	reinforcement learning
SGD	stochastic gradient descent
TD	training data
TN	true negative
TP	true positive
TL	transfer learning
VC	Vapnik–Chervonenkis
VCD	Vapnik–Chervonenkis dimension
VD	validation data

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A Appendix

Number of training and validation files

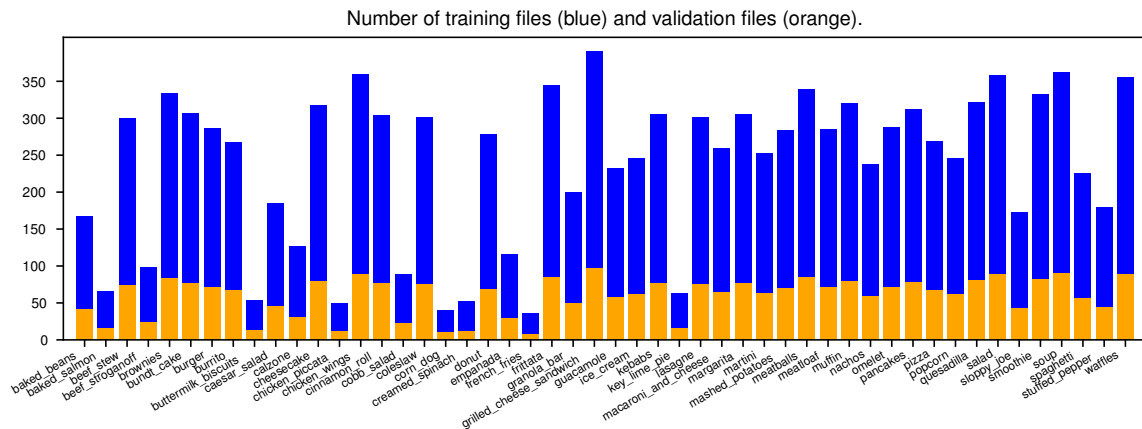


Figure A.1: Number of training and validation files.

Acknowledgement

The hardest part for me is this acknowledgment. Because it doesn't make any difference to me who comes first or last. Each person has done his or her part and is equally important for this thesis and me. Nevertheless I try: At this point I would like to thank all the people who have helped me to make this work a success. First and foremost: Prof. Dr. Karl Heinz Hoffmann, who encouraged me to resume my studies after I had broken off my studies more than 15 years ago and to catch up on my degree. In second place David Urbansky from the semknox company, a great expert in the field of sentiment analysis and classifications of all kinds of things. He was the one who accompanied me skin to skin the whole time and supported me with helpful tips and ideas. In third place Prof. Dr. Angela Thränhardt Professor for "Theoretical Physics - Simulation of New Materials" at the Chemnitz University of Technology, which enabled me to tackle a somewhat unrelated area in this work. In fourth place was my family, who was permanently at my side and supported me with this topic. And last but not least... **TODO**

Declaration

I hereby declare that the work presented in this thesis is solely my work and that to the best of my knowledge this work is original, except where indicated by references to other authors. No part of this work has been submitted for any other degree or diploma.

Signature :

Place, Date :