Using Curriculum learning to improve the performance of Deep Learning Models used for Classification Purposes

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1 Abstract

Keywords: *Curriculum learning, Age of Aquisition, Deep Learning, Convolutional Network, ResNet50, ImageNet*

The current growth of neural networks means that the importance of the speed and accuracy of these neural networks, especially during training, is becoming more and more important. Although the construction of Convolutional Neural Networks has grown a lot, with pruning nodes, removing completely linked layers, and cutting down on filters, the training processes of these neural networks leaves a lot to be desired. This paper focuses on increasing the training performance and speed of neural networks using a technique called curriculum learning. This method was formulated to represent the manner in which humans learn, starting with easier concepts and following it up with harder ones. To use this strategy, a curriculum must be made based on a metric. In this research, this metric was chosen to be the Age of Acquisition for words, ranking concepts on at what age humans learn words. Both easy and hard AoA classes were tested on accuracy and training performance, together with multiple test as a baseline. The results show a significant improvement, but further research must be done to confirm it and to explore this idea further.

Contents

2 Introduction

2.1 Deep Learning

Deep learning, Artificial Intelligence and Neural Networks are more and more prevalent in the ever changing digital industry. Deep learning constitutes a modern technique for image processing and data analysis, with a large potential. An important advantage of using Deep Learning in image processing is the reduced need of feature engineering [1, 20], because the important features are located automatically by the algorithm through training, instead of manually implemented. Without a doubt, the amount of applications possible for deep learning are boundless, however, the learning process requires large training sets and considerable resources in computation, energy consumption and time.

Because of the wide range of applicable scenarios of Deep Learning, the use of and interest in this technique is increasing rapidly [2], therefore increasing the performance of these networks is an important challenge. Hence, this paper will focus on providing an overview of research done on the improvements of the performance of Deep Learning models, especially convolutional neural networks, with regards to the difference in training methods available. Focusing on how curriculum learning, e.g. first learning basic concepts before learning more difficult objectives, can affect this process. The literary review will provide an understanding of curriculum learning and to give an overview of different methods of training a Neural Network with curriculum learning. The first part will serve as an explanation of curriculum learning. Following this, this review will focus on the effect curriculum learning can have on a convolutional neural network. From there, an experiment using curriculum learning based on a concept called Age of Acquisition will be conducted.

2.2 Curriculum Learning

Curriculum learning is a tool that is being used more and more in the field of Deep Learning and Neural Networks. Bengio et al.[7] describes curriculum learning as a "starting small" strategy. This strategy is reflected in schools all around the world as teachers start with typical 'easy' examples first, and later go on to explain more ambiguous examples [16]. In order to execute this task, teachers often create a curriculum. The process of Curriculum Learning thus, means learning through a meaningful order of concepts or examples, instead of randomly picking one concept and learning those before moving on. We as humans have shown to greatly improve our learning speed this way.

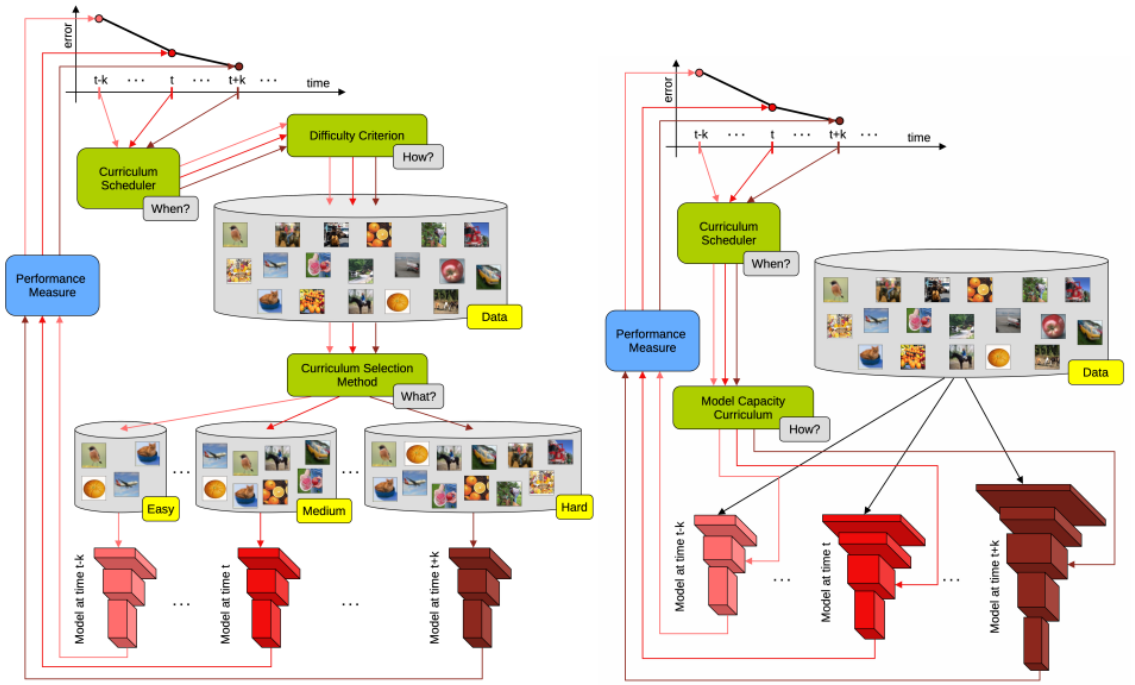
3 Background

3.1 History

The idea to use this strategy as a tool for training machine learning algorithms in the same way can at least be resolved back to Elman in 1993 [17]. They concluded that starting with an architecture which was restrained in its complexity, and gradually increasing that complexity, could lead to more successful results. Related ideas have been explored a lot in the years since then. The first to formally establish this gradual increase in difficulty into Deep Learning was Bengio et al [7]. They evaluated two experiments, one on geometric shapes, the other on language modelling. The geometric shape networks was asked to classify 3 different classes of shapes: rectangles, ellipses, and triangles. The curriculum was implemented by dividing the data set in two, a *BasicShapes* set containing only squares, circles and equilateral triangles, and a *GeomShapes* set containing rectangles, ellipses and all kinds of triangles. Furthermore, the second set showed not only more variety in shape, but also differences in position, size, orientation and were blended more into the background. Then, by first giving the network the set of *Basicshapes* and afterwards inputting the *GeomShapes* set gave significantly better results than presenting the algorithm with a mixture of the two sets at once, right from the beginning. The second experiment involved predicting the best word which could follow a given context of word. Here the curriculum was implemented by slowly increasing the data set of words to give a score to, based on how well they would fit. Meaning the curriculum version steadily grew the vocabulary by 5.000 words after each pass on the context. In this experiment, they also observed an improvement in accuracy with this curriculum trained model. Since this paper, curriculum learning has been used in more than 150 academic scenarios involving machine learning, from object detection, neural machine translation and speech recognition.

3.2 Curriculum Learning Methods

While there has always been a clear consensus of the definition of curriculum learning in the context of Neural Networks, the approach to implementing this learning strategy varies. Soviany et al [8] describes the four main components of any deep learning algorithm as: *'the data, the model, the task and the performance measure'*. They also stated that curriculum learning can be applied to each of these components. Avramova (2015), Hacohen et al (2019), Zhang et al (2018) and Wang (2019) [4-6,12] all think of curriculum learning as a tool to structure the data, or more specifically the order of the data. This approach is known as the 'natural approach' to curriculum learning [8], which applies curriculum learning on the data level, and involves steadily giving the neural network more difficult concepts during the training process (Figure 1.a). Another method proposed by Karras et al. [13] is to grow the capacity of the model by adding or activating more neural units during the training process to accelerate the models ability to interpret data (Figure 1.b), which is applying curriculum learning to the model level.



a General framework for data-level curriculum learning.

b General framework for model-level curriculum.

Figure 1: Two different approaches to curriculum learning, one on the data-level, and the other (b) on the model-level [8]

However, each method does have it's positives and negatives. An issue with the model-level approach to curriculum learning that the natural approach does not suffer from, is that the increase in the capacity of the model is not dependent on the difficulty of the training data, but only on the size, which means it is an easier general approach, but for optimal performance, the natural approach can be more suited. A crucial part of finding a suitable approach is creating the right curriculum, so either creating an accurate classification teacher model, or to accurately classifying the data from easy to difficult. This aspect is essential for improvements in performance [6]. The natural approach, for instance, suffers from the fact that the curriculum selection has to be implemented, either externally, or through an internal process. The problem with having to implement this curriculum externally is that external qualification is not always possible. But this disadvantage of the natural approach can also be solved in a number of ways. The problem of qualification of difficulty is a big topic related to, and involved in, curriculum learning, and multiple means have been implemented to help this aspect of curriculum learning. Currently there have been five most used 'categories' of Curriculum Learning in literature:

3.2.1 Vanilla Curriculum Learning

Vanilla Curriculum Learning is mostly used when a data set has clearly defined labels of difficulty beforehand. This strategy only has an influence on the data level of the model, structuring it in an ascending manner, based on this label of difficulty. An example of this is Bengio et al. [7], where

they used this approach in their geometric shapes qualifier to split the data into two sets, one containing easier and clearer images of 'perfect' shapes, and the other containing more convoluted shapes and sizes. And using the easy dataset to gain an advantage on the accuracy of the model when tested on the second set.

3.2.2 Self-Paced Learning

Self-paced learning is a more dynamic and advanced method for implementing Curriculum Learning in Neural Networks. This strategy is dynamic in the sense that during training, the difficulty is measured and with this measure, the order of the training samples is altered to further improve the training process. This difficulty can be measured in a number of ways, with one of the more common values being the loss function of samples. For instance, Avramova [4] looked into using Self Paced Learning strategies to determine difficulty of a sample using the sample's loss function calculated based on the goal of the network. They found that all different versions of SPL performed within 1 per cent of each other. But most importantly that inverse SPL networks performed slightly better, and had '*marginally higher accuracy results*'

3.2.3 Self-Paced Curriculum Learning

Self-Paced Curriculum is a combination of the first two, combining both initial labels to define the order of samples, but also dynamically changing this order using difficulty measures during training. This combination was first implemented by Jaing et al. [21] where they found that Self-Paced Learning strategy missed 'a way to incorporate prior guidance in learning'[21].

3.2.4 Progressive Curriculum Learning

Progressive Curriculum Learning differs from the previous methods in the way that those all changed the order of the data during training, and individually calculated this difficulty per sample. Progressive Curriculum Learning is a strategy where this individual difficulty is not used as a measure for the network, but rather, it uses the collective difficulty of the task setting to gradually increase or decrease settings in the algorithm, either in the model or in the task to create an improvement in training efficiency. Karras et al. [13] uses this more progressive form of CL to it's advantage in gradually growing the scope of a GAN (Generative Adversarial Network) to obtain higher quality results.

3.2.5 Teacher-Student Curriculum Learning

Both Hacohen et al. [5] and Kim et al. [14] use a type of curriculum learning which is usually classified as teacher-student CL, which divides the training process of the model into two separate tasks. One of those will still focus on the primary task (student) while the teacher subsection will focus on defining the optimal hyperparameters and training process for the student. The first to propose this strategy was Kim et al. [14], where they use a second 'ScreenerNet' to assist a main network, integrating this second network in the loss function of the primary.

3.3 Results of Curriculum Learning

The implementation of Curriculum Learning has actually shown to have positive results on the training of a network. Bengio et al. [7] hypothesized that curriculum learning has an effect on the speed of convergence. In this case convergence is meant as the state of the neural network where the training has progressed enough to accurately respond to the training data provided with some defined margin of error. In certain cases, they discovered that easier sets of data could be more instructional than more difficult sets in earlier stages of the algorithms. They concluded that in their specific case they achieved better accuracy when working with curriculum learning, and finding a better local minima. Kerras et al. [13] uses a more implicit form of curriculum learning using a model approach, which progressively increases the amount of layers and in that way increases the networks capacity. Using the earlier resources to determine the structure of the samples before focusing it's resources for recognising details later. Hacohen et al. [5] evaluated multiple approaches, calculating the difference in confidence between a teacher-student network in a conventional way. They established that the teacher-student network had a faster training speed and allowed them to create new images of 'unprecedented quality'. They came to the conclusion that 'as long as the curriculum is positively correlated with the optimal utility, it can improve the learning'. Kim and Choi [14] take a different approach, using the student-teacher method to figure out the optimal weights for it's student network. It combines this with a self-paced strategy, using the loss of the student for optimal prediction of the weights of the network. Avramova [4] uses multiple variants of Self Paced Learning (SPL) and did find an increase in accuracy, because of the usage of a Curriculum Learning strategy.

Table 1. Results of Curriculum learning

Results of Curriculum Learning				
Paper	**Task**	**Method**	**Improvement**	**Dataset**
Bengio et al. [7]	Shape recognition	CL	*significantly better*	Geometric Shapes
Avramova [4]	Computer Vision	SPL/SPDL	~1%*	CIFAR-10
Kim et al.[14]	Computer Vision	Teacher-student	2%/ 0.15%	CIFAR-10/MNIST
Gong et al.[22]	Computer Vision	Teacher-student/CL (MMCL)	2-5%	Multiple (CIFAR100)
Jaing et al.[21]	Video Event Recognition	SPCL	*outperformance*	MED13/14Test
Tang et al.[23]	Computer Vision	SPDL	0.9% over ScSPM[26]	Caltech-101
Weinshall et al.[10]	Computer Vision	CL	~0.03%	CIFAR-100
Castells et al. [24]	Computer Vision	Dynamic-CL	0.45%	CIFAR-10/100
Qin et al.[25]	Computer Visions	Teacher-student (BLCL)	0.8-3.6%	CIFAR-10/100
Hacohen et al.[5]	Computer Vision	Teacher-student	0.5-1%	CIFAR-10/100
Li et al.[3]	Computer Vision	MICL	7.7%	VOC07

3.4 Age of acquisition

The Age of Acquisition is a theory and concept in language processing and acquisition, reflecting on the age and order of words learned in children and young adults ranging from the age of 1 to 25[27]. Words with a lower Age of Acquisition rating are usually shorter and more frequently appear during the neurological development of children. Brysbaert et al. [27] improved on the existing set of AoA ratings, by taking into account ambiguity of words. They updated the a database created in 1981 by validating AoA estimates and adding different sets of AoA research into the current set. This new set will be used as the ratings to base a curriculum on.

4 Methodology

This paper's contribution will focus on the effect of a curriculum, based on AoA, on a convolutional neural network. A combination of a pre-trained model (ResNet with ImageNet weights) together with the ILSVRC2017_CLS-LOC Imagenet dataset will be used to set a baseline and execute the experiment. To establish a difference in performance of the artificial intelligence, a baseline top-1 accuracy per class will be set. To study the effect of a curriculum in this particular case, the base of ResNet will be used with additional layers on top. These layers on top will consist of two dense (https://keras.io/api/layers/core_layers/dense/) layers, the first taking the output of the resnet model, using ReLu activation and outputting a (None,2048) shape. The second layer will function as the output classification layer and will therefore take the input of the last layer, and with an softmax activation output a (None, 1000) shape (The amount of classes in ImageNet). The code used for training can be found in *Appendix B*. The main focus of this paper lies on the effect of an Age of Acquisition based Curriculum, therefore, two primary experiments will be conducted, together forming a more clear image on how the Age of Acquisition for children could affect the training process of Neural networks.

4.1 Hypothesis

The main question to be answered in this section of the paper is:

Does a curriculum based on Age of Acquisition ratings positively influence generalisation and accuracy in convolutional neural networks?

This question will be answered using a supervised vanilla curriculum learning strategy, where the labels of difficulty are pre-defined by the researcher. I currently hypothesise that the main factors which have an effect on generalisation speed and accuracy do not necessarily coincide with elements that make a concept easier for us humans to understand. Meaning that I think a curriculum based on Age of Acquisition ratings, either low or high ratings, will not make a significant difference in generalisation or accuracy. To give an example to this train of thought; when Bengio et al[7] conducted the Geometric shapes experiment, they chose to implement more difficult images later on in the experiment (difficult meaning more complex, with more clutter and variety). This gave them significant results, whereas the classes to be picked by the Age of Acquisition rating do not necessarily conform to this order of complexity. To confirm this idea, this research will also feature an experiment which will feature two test with a curriculum based on accuracy from a baseline test. These test should provide more significant results if my hypothesis is correct, because these classes should contain images which should contain factors that have an greater effect on accuracy, and maybe generalisation.

4.2 ImageNet

The Dataset that is going to be used in this paper is the ImageNet Large Scale Visual Recognition Challenge database of 2017 [28], this is a dataset with the primary focus on being a benchmark in object category classification and detection. It contains 1000 classes of objects, with 1.3 million training images along with 100.000 test and 50.000 validation images. For the interest of this paper, only the object detection, not localisation, will be tested. This dataset was chosen for this paper as it has a great amount of classes, and variety between those classes. One of the earlier

datasets that was considered a possibility was COCo (https://cocodataset.org/home), but those 80 classes provided less freedom to accurately create an AoA-based curriculum. The ImageNet dataset provided ample freedom to map the AoA dataset onto the classes.

4.3 ResNet Baseline

The baseline will be created with a standard Resnet50 model, with weights trained on imagenet, and the dataset consisting of the validation set from the ILSVRC2017 dataset. Resnet50 is a variation of the ResNet model. It contains 48 convolutional layers together with 1 Max Pool and an Average Pool layer. The code for the validation of the created models is the same as the validation code in *Appendix E*, but with the model being:

```
model = tf.keras.applications.ResNet50(include_top=True, weights="imagenet",classes
    =1000, input_shape=None)
```

Each time a 'baseline' test or validation set is referenced, it will be a reference to this pre-trained resnet model and it's accuracy.

4.4 Age of Aquistition

The Age of Acquisition dataset that was chosen are the Test-based age-of-acquisition norms for 44 thousand English word meanings, created by Marc Brysbaert & Andrew Biemiller [27], based on a list from Dale and O'Rourke's Living Word Vocabulary. It contains 31.000 unique words and the corresponding AoA-Rating, for more information on this measure and information about how this rating came to be, I would recommend their paper. Of this set of 44 thousand words, 33.500 have an Age of Acquisition rating ranging from 1,6 (Mommy) to 25,0 (eisteddfod (being a musical contest)). Of these 33.500 words, 225 have a direct match with ImageNet Classes. For this research I decided against manually matching more of the ImageNet classes against the AoA set, the primary reason for this being the distinctness of some of the categories. To illustrate this; ImageNet has 5 classes which all feature a 'retriever' of some kind: *flat-coated retriever, curly-coated retriever, golden retriever, Labrador retriever, Chesapeake Bay retriever*. These could all be classified under 'retriever' with an AoA-rating of 8.7, but they could also be simplified down to 'dog' with an AoA-rating of 3.2, not even mentioning all the other types of dogs available. And the same is true for a multitude of animals. This pre-processing of the combination of the Age of Acquisition set and the ImageNet classes resulted in the total list which can be found in *Appendix B*, ranging from word like 'sock' (3.4) and 'cup' (3.4), to 'obelisk' (13.7) and 'bulbul' (17.2). From this table, the first and last 20 will be used as classes for training:

Table 2. Easiest AoA-rated ImageNet classes

ImageNet class	Class Name	AoA-rating
n04254777	sock	3,4
n02346627	cup	3,4
n02190166	fly	3,6
n07753592	banana	3,6
n02782093	balloon	3,7
n07747607	orange	3,8
n03938244	pillow	4
n02422106	bee	4
n07745940	strawberry	4,2
n03961711	plate	4,3
n02834397	bib	4,5
n09229709	bubble	4,5
n04371774	swing	4,5
n01608432	kite	4,6
n02799071	baseball	4,7
n03775071	mitten	4,7
n07697313	cheeseburger	4,8
n03814906	necklace	4,9
n01773549	barn	4,9
n01806143	peacock	4,9

Table 3. Hardest AoA-rated ImageNet classes

ImageNet class	Class Name	AoA-rating
n03680355	Loafer	11,9
n04147183	schooner	12,4
n02490219	marmoset	12,5
n01847000	drake	12,5
n04136333	sarong	12,9
n02091134	whippet	13,1
n03788195	mosque	13,2
n03297495	espresso	13,3
n04532670	viaduct	13,3
n03837869	obelisk	13,7
n04501370	turnstile	13,7
n02361337	marmot	13,9
n02389026	sorrel	14
n04141327	scabbard	14,1
n02011460	bittern	14,5
n02981792	catamaran	15,6
n02018795	bustard	15,8
n03146219	cuirass	15,9
n02006656	spoonbill	16
n01560419	bulbul	17,2

4.5 Approach

This research will feature 4 main tests. Two of them to visualise the difference in training between a curriculum of easy and hard classes based on the Age of Acquisition rating. The other two will function to get a closer look at the difference between classes with a higher and lower accuracy/-confidence (from the ResNet model). Next to these 4 training experiments, two 'validation' test will be conducted on randomly selected classes, these to verify the results from the earlier tests and provide a baseline for the difference in accuracy and loss during the training process. The chosen classes for high and low initial accuracy, and the randomly selected classes can be found in tables 4,5,6 and 7 respectively. All experiments will consist of training (*Appendix C*) with the specified classes, followed by using the generated model to determine the per class accuracy (*Appendix E*)

Table 4. Highest Accuracy classes (from ResNet)

ImageNet class	ImageNet Class Name	ResNet Accuracy
n02090622	borzoi	98
n02111129	Leonberg	98
n02342885	hamster	98
n01872401	echidna	98
n11939491	daisy	98
n12057211	yellow lady's slipper	98
n09288635	geyser	98
n01518878	ostrich	98
n01820546	lorikeet	98
n02006656	spoonbill	98
n02007558	flamingo	98
n06359193	web site	98
n13044778	earthstar	98
n02389026	sorrel	96
n02107683	Bernese mountain dog	96
n02489166	proboscis monkey	96
n02130308	cheetah	96
n03344393	fireboat	96
n12620546	hip	96
n11879895	rapeseed	96

Table 5. Lowest accuracy classes

ImageNet class	ImageNet Class Name	ResNet Accuracy
n03692522	loupe	26
n03476684	hair slide	26
n04286575	spotlight	26
n03045698	cloak	26
n01740131	night snake	24
n04008634	projectile	24
n04270147	spatula	24
n04264628	space bar	24
n03016953	chiffonier	20
n04356056	sunglasses	20
n03532672	hook	20
n04591157	Windsor tie	20
n03866082	overskirt	20
n03658185	letter opener	18
n02123159	tiger cat	16
n04152593	screen	16
n04355933	sunglass	16
n03710637	maillot	16
n04525038	velvet	14
n03832673	notebook	12

Table 6. Random ImageNet classes 1

ImageNet class	ImageNet Class Name	ResNet Accuracy
n01740131	night snake	24
n01742172	boa constrictor	76
n01744401	rock python	30
n07753592	banana	84
n04376876	syringe	56
n03761084	microwave	56
n03908618	pencil box	60
n02107908	Appenzeller	30
n02105855	Shetland sheepdog	60
n04033995	quilt	54
n07747607	orange	74
n04200800	shoe shop	68
n09288635	geyser	98
n04505470	typewriter keyboard	76
n02965783	car mirror	92
n09229709	bubble	78
n07831146	carbonara	74
n02102040	English springer	92
n02412080	ram	68
n04552348	warplane	76

Table 7. Random ImageNet classes 2

ImageNet class	ImageNet Class Name	ResNet Accuracy
n03838899	oboe	70
n04141076	sax	68
n03372029	flute	32
n11939491	daisy	98
n12057211	yellow lady's slipper	98
n09246464	cliff	62
n09468604	valley	82
n09193705	alp	50
n09472597	volcano	68
n09399592	promontory	44
n09421951	sandbar	58
n09256479	coral reef	82
n09332890	lakeside	54
n09428293	seashore	42
n09288635	geyser	98
n03498962	hatchet	50
n03393912	freight car	94
n03895866	passenger car	54
n02797295	barrow	74
n04204347	shopping cart	74

These six tables provide the basis for the experiments as the classes that will be used for training in each of the six examples. Each experiment will have two main outputs to be measured, the first is the training output, consisting of the training and validation loss, together with the training accuracy and validation accuracy for each epoch. The second output is the per class accuracy of the model created by each of the six training processes.

4.5.1 Limitations

Because of the size of the dataset (160Gb), it is not possible to upload the entirety or even a subset of it to a service like Google Collab (https://research.google.com/colaboratory/) which provides a lot more processing power for training these new layers. Therefore, the main limitation of this research was the specifications of the local machine on which the training was executed (Specs as found in DxDiag):

- **Motherboard:** MSI MPG X570 GAMING PLUS, AM4
- **Processor:** AMD Ryzen 7 3700X 8-Core (16 CPUs), 3.6GHz
- **Graphics Card:** NVIDIA GeForce RTX 2060
- **Memory:** 2x 8Gb - G.SKILL Trident Z RGB F4-3200C16D-16GTZR (16Gb - DDR4)
- **Operating System:** Windows 10 Pro 64-bit (10.0, Build 19042)
- **Storage:** Samsung SSD 970 EVO 1TB M.2 80mm

This system will run a WSL (Windows Subsystem for Linux) with Ubuntu 20.04 LTS from which python scripts will be ran.

These specifications, with the main constraint being the 16Gb of memory, means that there is a maximum to the amount of images that can be loaded and processed to be used for training. A heavy influence on this amount of images will be the batch size used in the training epochs. In general, smaller batch sizes could mean that the model can converge faster, but will train slower. With multiple experiments with the only variables being the total amount of images used for training and the batch size, a balance was struck on using 6000 images, with a batch size of 8. This however, bring with is another limitation. The ImageNet training dataset consists of 1.300 images per class. Using only 6000 images means that training on all classes with training weight assigned or oversampling would give results with an accuracy of less than 1.5% on all classes, with no significant difference in accuracy on oversampled or heavier weighed classes.

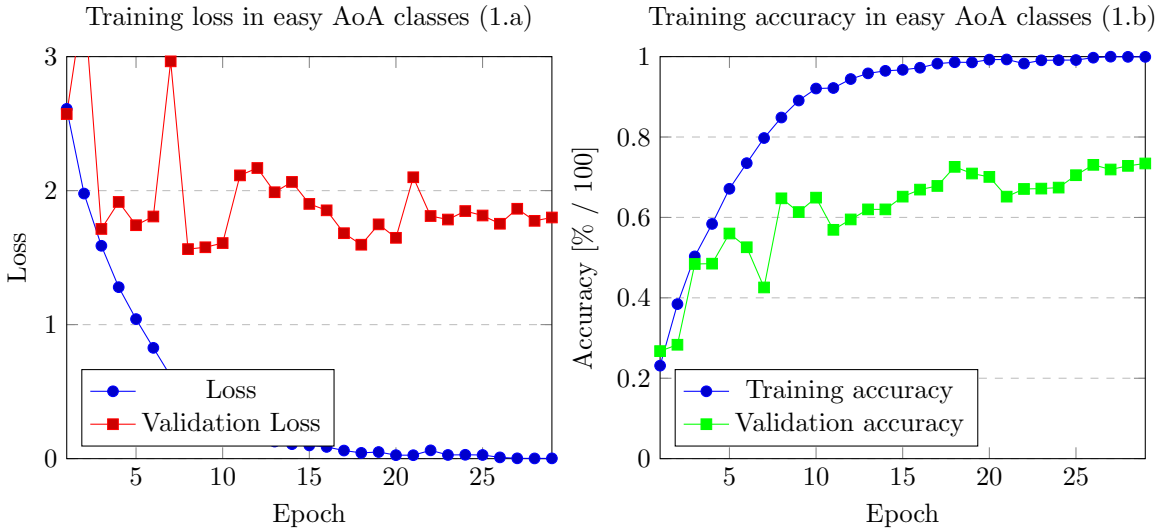
Hence the choice was made to solely train the top two added layers on the classes selected for that experiment. This will mean that this paper will not give the full answer to the question of how this version of curriculum learning affects the full training of a neural networks, but it will give more insight into the effect of training on different classes and their outcomes.

5 Results

5.1 Training process

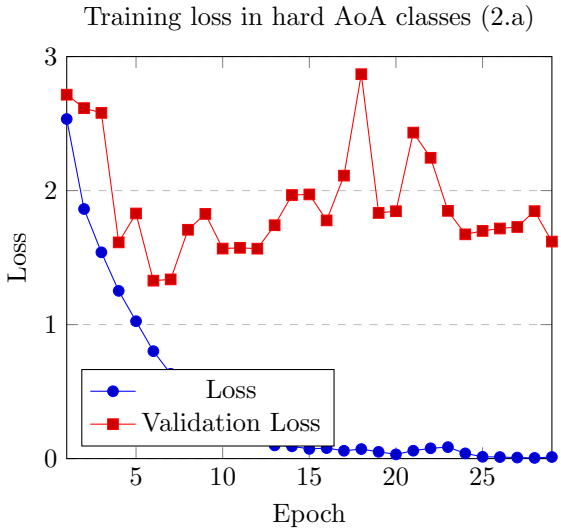
The training process consisted of using the code in *Appendix D* set to 29 epochs, which was chosen after multiple test showed no more than 2% increase on top of the values set in epoch 29 . Each epoch on average finished after 737 seconds (12m17s). Each experiment will feature two tables of output (*Appendix E*) split into three graphs. The first two graphs (a & b) will be featured in this subsection, and will feature the loss (a) and accuracy (b) during the training process. The last graph (c) will feature the validation accuracy on each individual class that was trained on, in comparison to the baseline ResNet model.

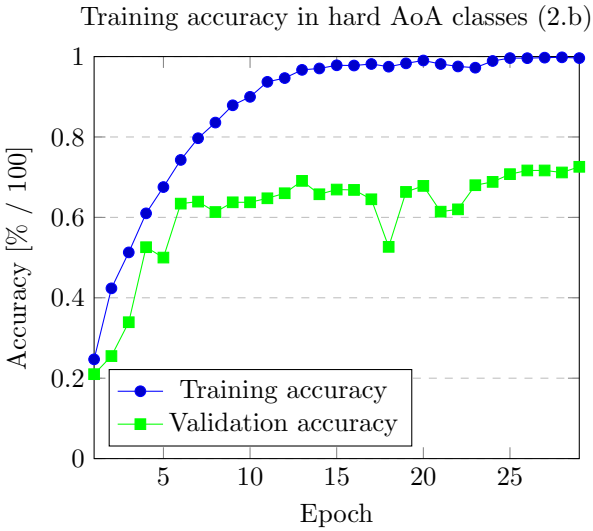
5.1.1 Easy AoA



The model based on the easiest classes in the Age of Acquisition set achieved the lowest training loss on epoch 28 with 0.0017. It's accuracy was the highest on epoch 27 with 0.9998. It's validation loss was the lowest on epoch 8 with 1.5636, and it achieved a maximum validation accuracy of 0.7342 on epoch 29.

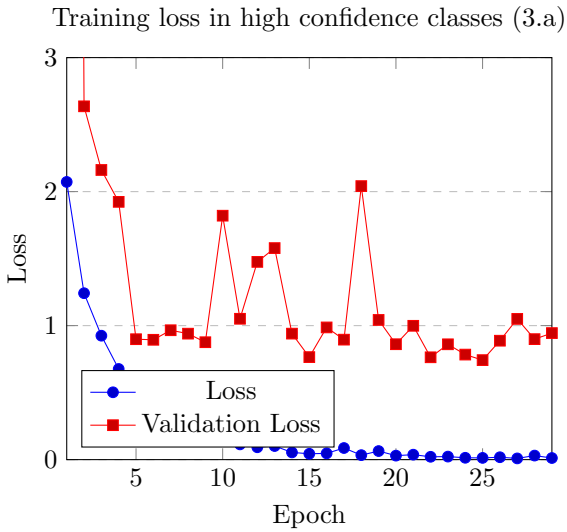
5.1.2 Hard AoA

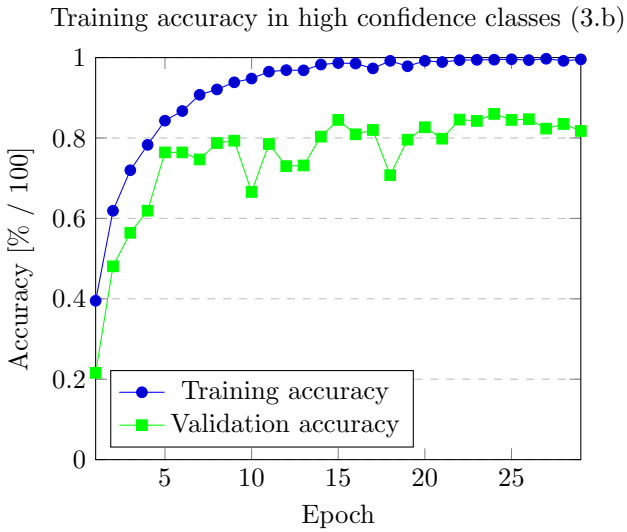




The model based on the hardest classes in the Age of Acquisition set achieved the lowest training loss on epoch 27 with 0.0077. It's accuracy was the highest on epoch 28 with 0.9981. It's validation loss was the lowest on epoch 7 with 1.3373, and it achieved a maximum validation accuracy of 0.7258 on epoch 29, which is 0.0084 lower than the Easy AoA model.

5.1.3 High confidence (High CI)

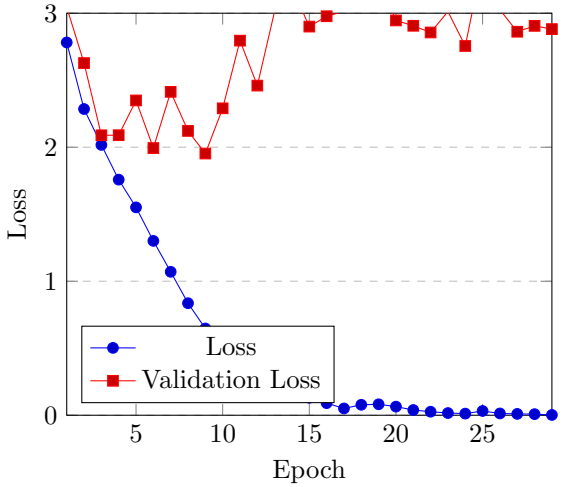




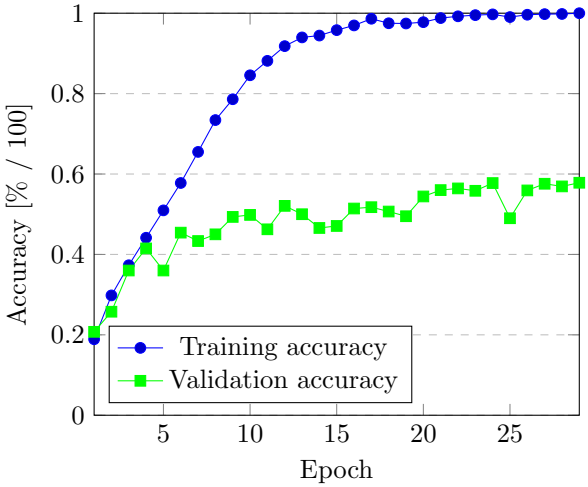
The model based on the highest confidence classes from the baseline achieved the lowest training loss on epoch 29 with 0.0012. It's accuracy was the highest on epoch 27 with 0.9971. It's validation loss was the lowest of all experiments on epoch 25 with 0.7425, and it achieved a maximum validation accuracy of all experiments of 0.86 on epoch 24.

5.1.4 Low confidence (Low CI)

Training loss in low confidence classes (4.a)



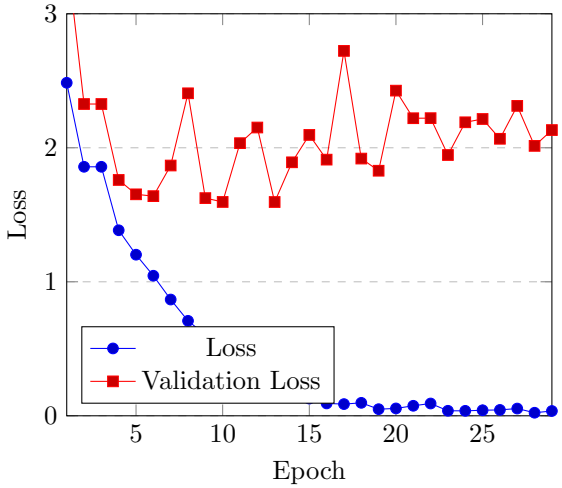
Training accuracy in low confidence classes (4.b)



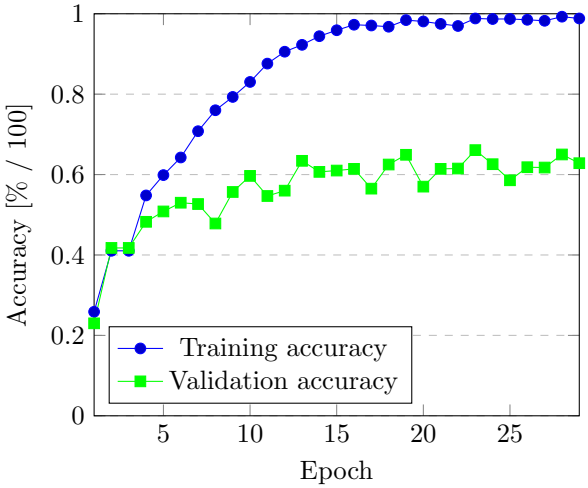
The model based on the lowest confidence classes from the baseline achieved the lowest training loss of all experiments on epoch 27 with 0.001. It's accuracy was the highest off all experiments on epoch 29 with 1. It's validation loss was the lowest on epoch 9 with 1.9529, and it achieved a maximum validation accuracy of 0.5783 on epoch 29.

5.1.5 Random Categories 1

Training loss in random classes (5.a)



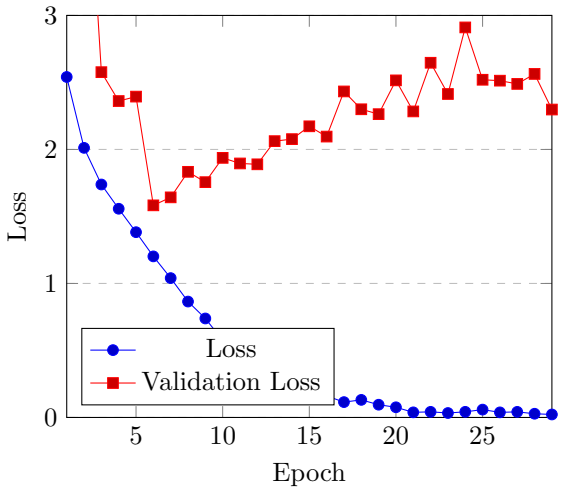
Training accuracy in random classes (5.b)



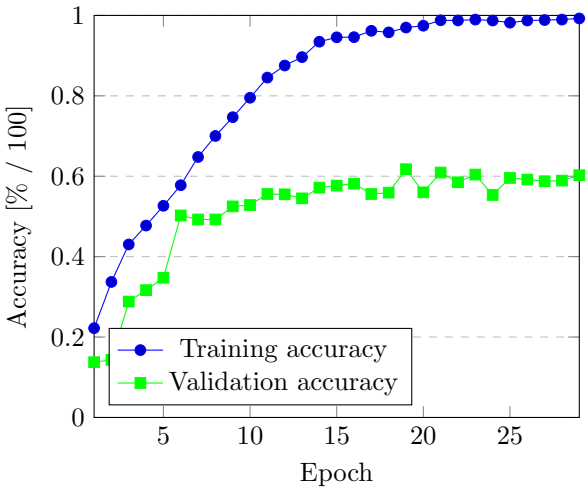
The first model trained on randomly selected classes achieved the lowest training loss on epoch 28 with 0.0228. It's accuracy was the highest on epoch 28 with 0.9927. It's validation loss was the lowest on epoch 13 with 1.5953, and it achieved a maximum validation accuracy of 0.6608 on epoch 23.

5.1.6 Random Categories 2

Training loss in random classes 2 (6.a)



Training accuracy in random classes 2 (6.b)



The second model trained on randomly selected classes achieved the lowest training loss on epoch 29 with 0.0223. It's accuracy was the highest on epoch 29 with 0.9925. It's validation loss was the lowest on epoch 6 with 1.5829, and it achieved a maximum validation accuracy of 0.6175 on epoch 19. Below are all the maximum scores the models achieved during training:

Table 8. Maximum scores from the training process of all models

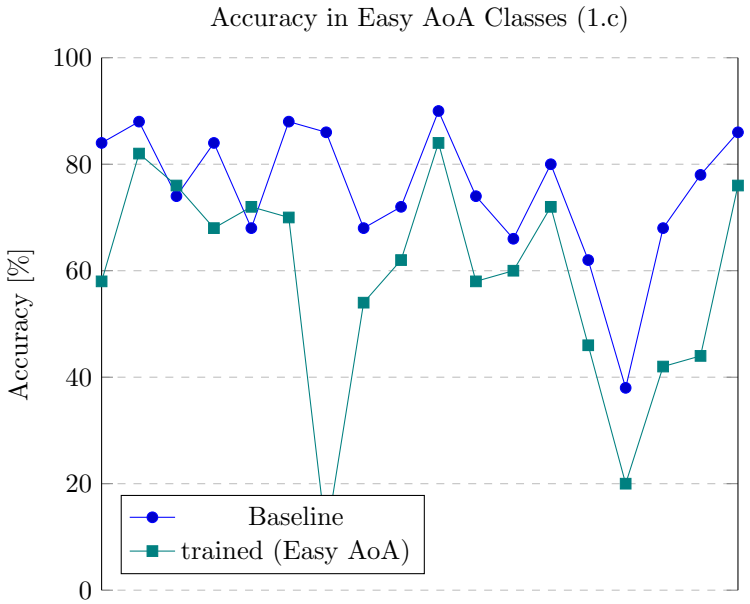
Max Scores	Loss		Accuracy		Val_loss		Val_accuracy	
	Epoch	Loss	Epoch	Accuracy	Epoch	Val_loss	Epoch	Val_accuracy
Easy AoA	28	0.0017	27	0.9998	8	1.5636	29	0.7342
Hard AoA	27	0.0077	28	0.9981	7	1.3373	29	0.7258
High CI	29	0.0012	27	0.9971	25	0.7425	24	0.86
Low CI	27	0.001	29	1	9	1.9529	29	0.5783
Random	28	0.0228	28	0.9927	13	1.5953	23	0.6608
Random2	29	0.0223	29	0.9925	6	1.5829	19	0.6175

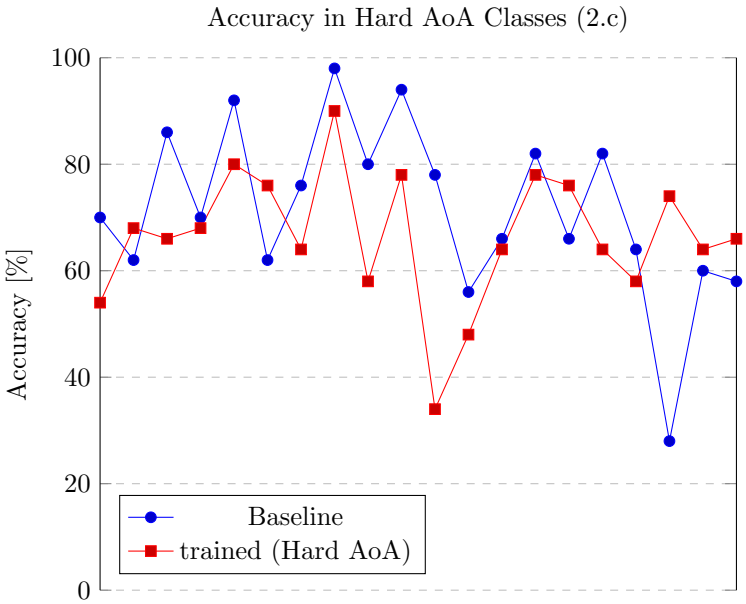
The most interesting/remarkable item in this table is the High CI Validation Loss, both because it is high in Epoch, but also because it is by far the lowest validation loss achieved by any model. Furthermore, the loss of both the Random trained models, as they are far higher than the curriculum trained models and almost equal. Next to that, it is noteworthy that 3/4 curriculum trained models outperform the random trained models, the only model not to achieve a higher validation accuracy is the model trained only on the 'hardest' classes in ImageNet (classes with the lowest

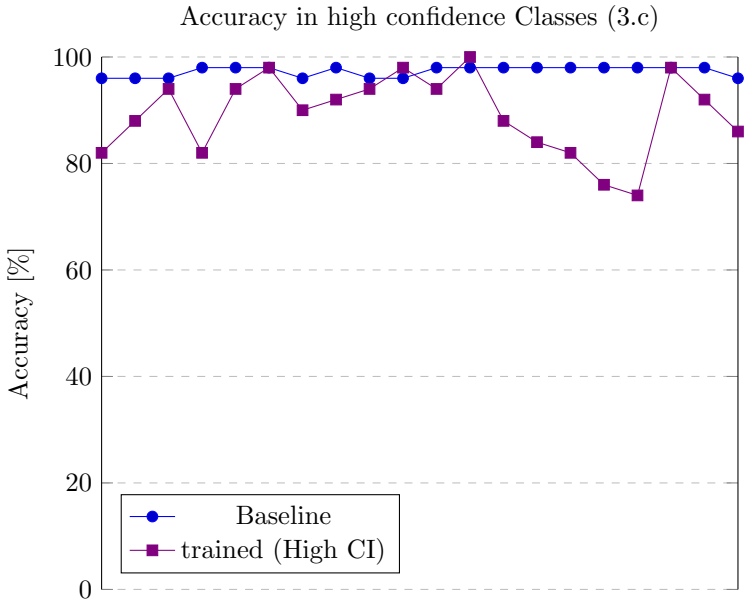
baseline accuracy) but which on the other hand showed the best increase in accuracy from the baseline.

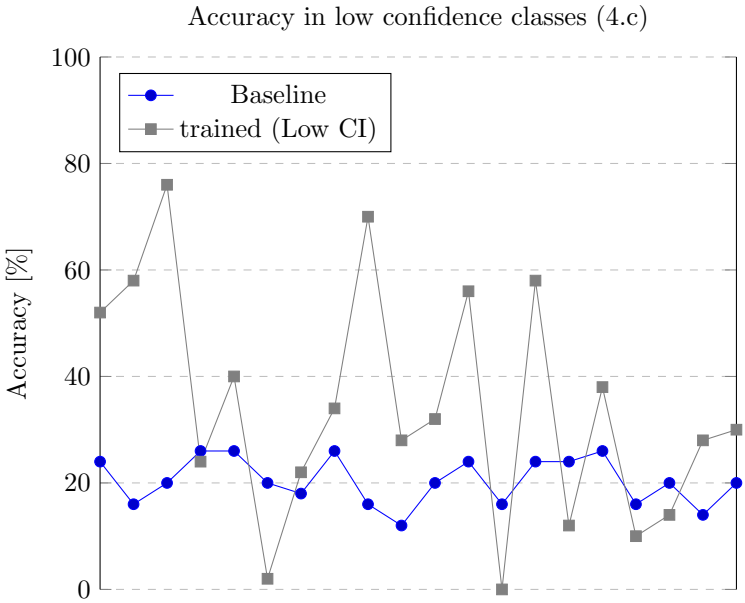
5.2 Accuracy

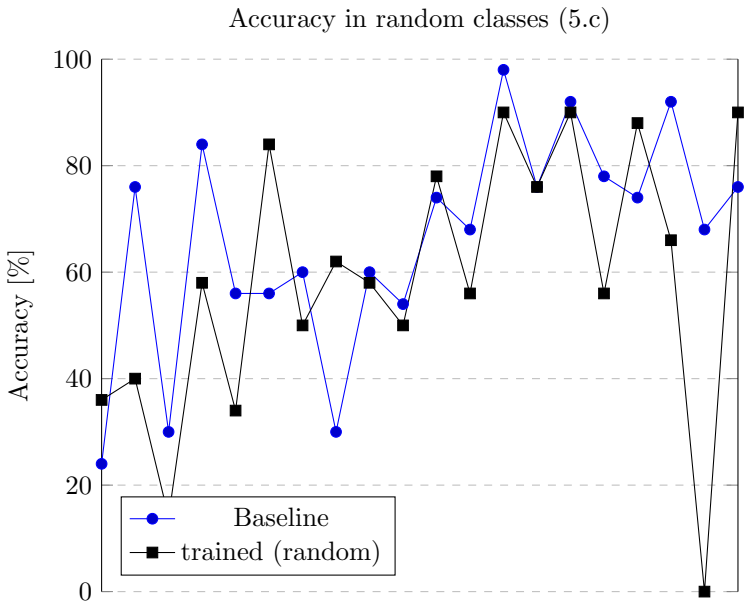
This section covers the accuracy of the baseline model in comparison to the trained models. The first graphs will provide an overview of the accuracy per class of each of the 20 classes used for training (1.c,2.c,3.c,4.c) for each curriculum, together with the accuracy of the random classes (5.c,6.c).











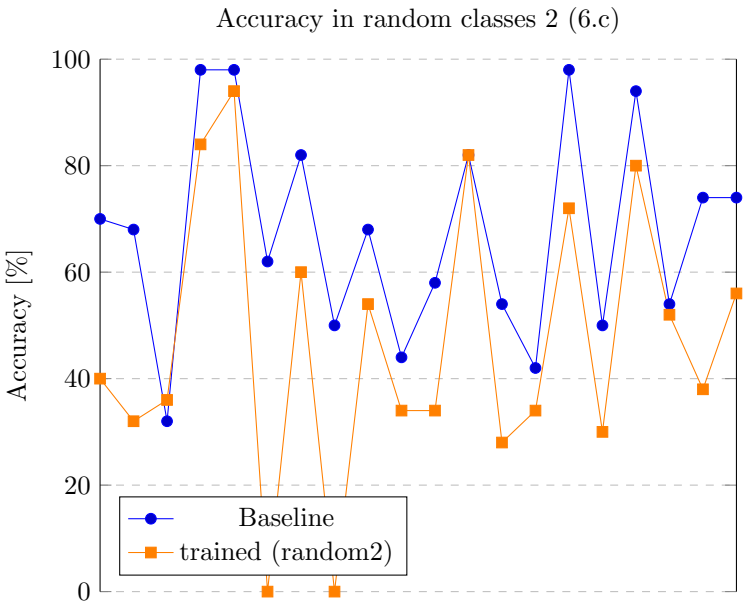


Table 9. Average accuracy of curriculum baseline and trained models

Curriculum	Baseline average accuracy	Trained average accuracy	Difference in accuracy
Easy AoA	75.22	58.55	-16.67
hard AoA	69.8	66.4	-3.4
high CI	97.3	85	-12.3
low CI	20.4	34.2	13.8
Random	66.3	58.8	-7.5
Random2	67.6	47	-20.6

The biggest outlier in this section of the experiment is the low confidence classes, the trained average is still much lower than those of the randomly chosen classes or even the AoA classes for that matter, but it is also the only curriculum where the average accuracy increased from the baseline to the trained model. Also notable is the big difference in trained average accuracy in the two random classes with repesct to the baseline average. While the baselines only differ 1.3%, the trained models have a difference of 11.8%. The difference between the baseline averages of the AoA classes comes down to (75.22 - 69.8 =) 5.42%, and the trained averages differ (58.55 - 66.4 =) -7.85%.

6 Discussion

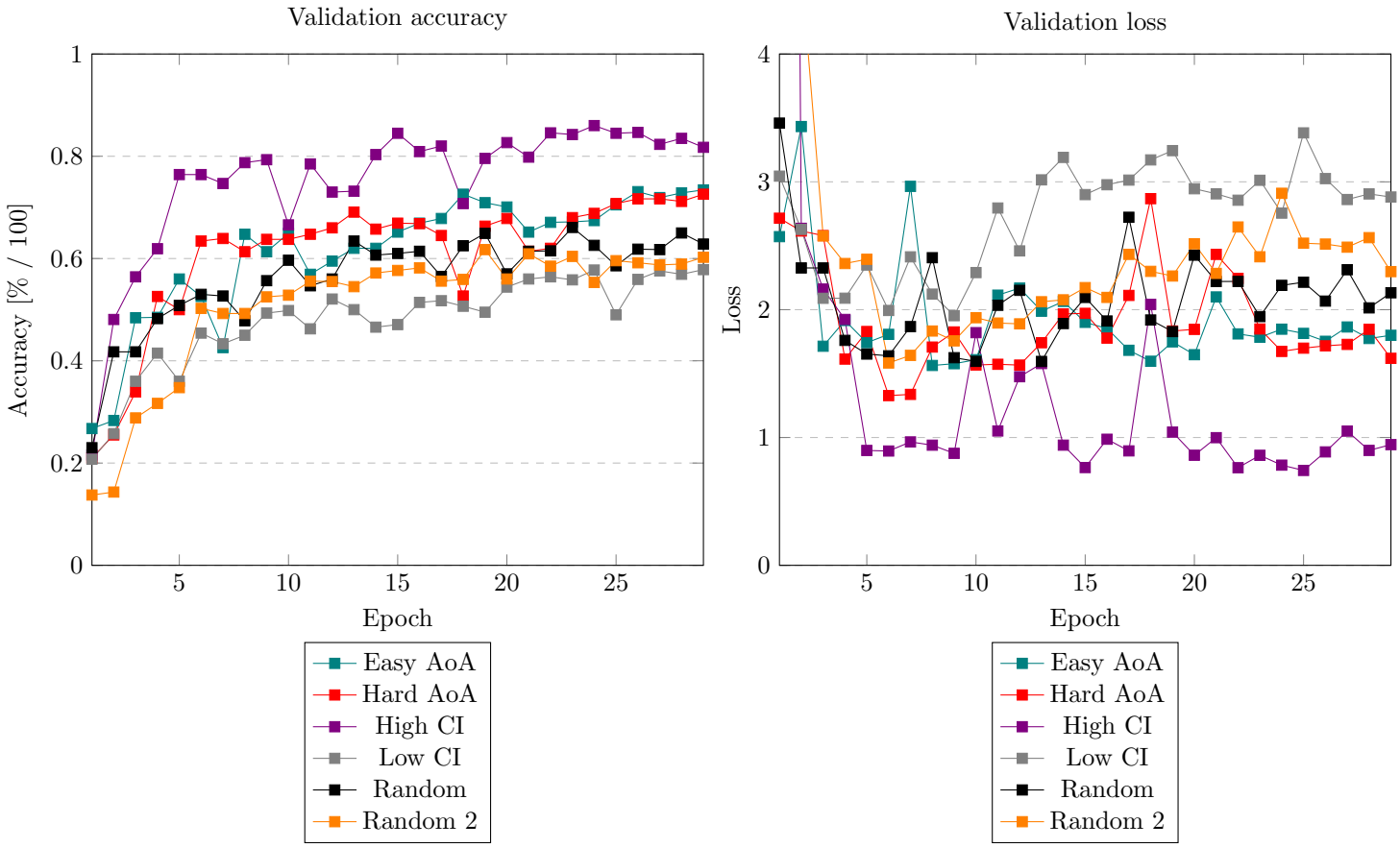
6.1 Results

The training process results as described in table 7 show the most promising results, in this data, there is a distinct difference in the validation accuracy of both the AoA-based curriculum models (0.73422 & 0.7258) and the randomly chosen models (0.6608 & 0.6175). However this difference does not seem to be reflected in the average accuracy of the trained models (58.55 & 66.4 for the AoA models and 58.8 & 47 for the random models. On the other hand, this could be explained by the low amount of images used in training; Because this quantity was limited to 6000, only 23.07% of the 26.000 available images (20 * 1.300), meaning only about 240 (1.300*23%*0.8) images per class were used for training (20 per cent of images were used as the validation split (60)). This could mean that some features found in the 1000 other not-used images would not be analysed during training meaning the validation accuracy of the 50 val images could differ drastically. Because of this limitation, I am hesitant to draw conclusions from the accuracy of the trained models, as multiple factors, not just the Age of Acquisition could have had an effect on the training process, especially because the differences in accuracy between the random classes and the AoA classes are also much higher than expected and seen in the validation accuracy during training. The validation accuracy during training however do show a significant difference, 0.7342 and 0.7258 for the AoA trained models, while the random trained models sit at 0.6608 and 0.6175. This disparity could mean that the AoA-classes do contain qualities which improve training validation accuracy. The training accuracy of these models also differ, with 0.9998 and 0.9981 to the randomly trained 0.9927 and 0.9925, but only with an average of about 0.64% (against the validation accuracy's 9.08%) The curriculum's based on the initial confidence of the ResNet model show that factors other than the Age of Acquisition seem to have a bigger effect on the training process. The high CI curriculum has by far the lowest validation loss and highest validation accuracy of all of the models, whereas the low CI curriculum had the highest validation loss and the lowest validation accuracy. This in my opinion could be the result of one of two factors.

1. The training images for the high confidence classes have a higher similarity to their validation counterparts than normal or randomly selected classes, and the low confidence's validation images are the most different from their training versions. Meaning the training process is more efficient for these classes.

2. The high confidence images are easier for the network to recognise features in, e.g. the clutter in these images is lower, or the shape distinctiveness is more prevalent, etc. And the opposite would be true for the lower confidence classes.

The high confidence training validation accuracy is the first to reach a value within 5% of it's final score (0.776625) on epoch 9, and the low confidence training is the last to achieve a value within 5% (Easy AoA: 18, Hard AoA: 13, High CI: 9, Low CI: 21, Random: 13, Random2: 15). This shows that the high confidence model seems to converge faster than any other model, whereas the low confidence model is the slowest to converge, and would therefore need the most amount of training time to get to a model which could generalise.



In both validation metrics, the High CI stands out as the main outlier, almost fully outperforming all other models on both cases. Both AoA cases also almost seem to conform to each other, both outperforming the randomly chosen categories.

6.2 Hypothesis

While the limitations of this research could influence the results, both AoA curriculum models do exceed the performance of the models without a curriculum, in validation accuracy during training and in validaiton loss during training. However, apart from the difference in validation accuracy of the trained model on the validation set, both AoA-based curriculum models perform almost equal. While I am hesitant to attribute the success of these AoA-based curriculum models to the selection of classes based on Age of Acquisition, the models in this particular scenario do perform better. However, the biggest point of uncertainty is that, as a result of the limitations, only the performance on the selected classes was measured. This raises the question whether the improvements found in the AoA-based curriculum models would also apply to an over-sampled or weighed training setup. Which is one of the main points of hesitation with these results in comparison to the hypothesis.

6.3 Further Work

To fortify these results, this experiment absolutely needs to be repeated on more datasets, and on a larger scale. The limitation of the researcher's hardware could have hurt this experiment more than can be researched at the moment. Repeating this experiment on different datasets could sketch a better understanding on the variation in classes which are both low in AoA-rating, but also perform better. To validate if these results also hold true when only a slight bias or oversampling is given to the chosen classes, a larger experiment is needed.

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A Full data

A.1 Easy AoA

Table 10.a Easy AoA training

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.61	0.2313	2.5714	0.2675
2	1.9781	0.3844	3.4327	0.2833
3	1.5884	0.5031	1.7141	0.4842
4	1.2796	0.5838	1.9155	0.485
5	1.0413	0.6712	1.7419	0.56
6	0.8267	0.735	1.8069	0.5258
7	0.6151	0.7975	2.9648	0.4258
8	0.4651	0.8485	1.5636	0.6475
9	0.331	0.8908	1.5773	0.6133
10	0.2415	0.9206	1.6087	0.6492
11	0.2449	0.9219	2.1137	0.5692
12	0.1742	0.9442	2.1688	0.595
13	0.1274	0.9583	1.988	0.62
14	0.108	0.9646	2.0649	0.62
15	0.0988	0.9671	1.9009	0.6517
16	0.0875	0.9723	1.853	0.6692
17	0.0604	0.9825	1.6823	0.6783
18	0.0431	0.986	1.5964	0.7258
19	0.0494	0.9856	1.7483	0.7092
20	0.0261	0.9925	1.6478	0.7008
21	0.0257	0.9929	2.0997	0.6517
22	0.062	0.9827	1.8105	0.6708
23	0.0275	0.9908	1.7843	0.6717
24	0.0288	0.9912	1.8475	0.6742
25	0.0273	0.9915	1.8144	0.705
26	0.0094	0.9973	1.7528	0.7308
27	0.0024	0.9998	1.8647	0.7192
28	0.0017	0.9994	1.7746	0.7283
29	0.0021	0.9994	1.7995	0.7342

Table 10.b Easy AoA accuracy

Class	Baseline	Trained
n07745940	84	58
n02782093	88	82
n07747607	74	76
n07753592	84	68
n01608432	68	72
n01806143	88	70
n01828970	86	10
n04371774	68	54
n02190166	72	62
n03814906	90	84
n02799071	74	58
n03775071	66	60
n03938244	80	72
n02834397	62	46
n02895154	38	20
n04254777	68	42
n09229709	78	44
n07697313	86	76

A.2 Hard AoA

Table 11.a Hard AoA training

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.5339	0.2469	2.7155	0.21
2	1.8625	0.4235	2.6153	0.255
3	1.5393	0.5129	2.5798	0.3392
4	1.2516	0.61	1.6135	0.5258
5	1.0252	0.6754	1.8292	0.5
6	0.8016	0.7429	1.3278	0.6342
7	0.6325	0.7969	1.3373	0.6392
8	0.4881	0.8358	1.7075	0.6133
9	0.3694	0.8788	1.8259	0.6375
10	0.2991	0.8998	1.5673	0.6375
11	0.2059	0.9371	1.5729	0.6475
12	0.164	0.9465	1.5664	0.66
13	0.0986	0.9669	1.7416	0.6908
14	0.0918	0.9704	1.9666	0.6575
15	0.0724	0.9783	1.9714	0.6692
16	0.0784	0.9777	1.7775	0.6683
17	0.0584	0.9815	2.1115	0.645
18	0.0711	0.9748	2.8685	0.5267
19	0.0505	0.9831	1.8333	0.6633
20	0.0315	0.9902	1.846	0.6783
21	0.0588	0.9815	2.4327	0.6142
22	0.0769	0.9754	2.2447	0.62
23	0.0858	0.9723	1.8488	0.68
24	0.039	0.989	1.6736	0.6883
25	0.0136	0.9962	1.699	0.7075
26	0.0115	0.996	1.7171	0.7167
27	0.0077	0.9973	1.7284	0.7167
28	0.0051	0.9981	1.8465	0.7117
29	0.0119	0.9962	1.6195	0.7258
30	0.0229	0.9929	1.9447	0.6983

Table 11.b Hard AoA accuracy

Class	Baseline	Trained
n02442845	70	54
n02113186	62	68
n02454379	86	66
n01883070	70	68
n03447447	92	80
n03868242	62	76
n02804610	76	64
n09288635	98	90
n01582220	80	58
n01592084	94	78
n01797886	78	34
n04376876	56	48
n01943899	66	64
n03781244	48	78
n02859443	66	76
n04277352	82	64
n03527444	64	58
n03782006	28	74
n02790996	60	64
n03443371	58	66

A.3 High CI

Table 12.a High CI training

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.0723	0.3952	26.1011	0.2158
2	1.2419	0.619	2.6365	0.4808
3	0.9248	0.7198	2.1614	0.5642
4	0.6765	0.7829	1.9236	0.6192
5	0.502	0.8431	0.8986	0.7642
6	0.4129	0.8671	0.8943	0.7642
7	0.2933	0.9075	0.9655	0.7467
8	0.249	0.9208	0.94	0.7875
9	0.1896	0.9385	0.8761	0.7933
10	0.1576	0.9479	1.8203	0.6658
11	0.1137	0.965	1.0511	0.785
12	0.0922	0.9688	1.4756	0.73
13	0.1014	0.9683	1.5785	0.7317
14	0.0538	0.9827	0.9402	0.8033
15	0.0437	0.9865	0.765	0.845
16	0.0467	0.9852	0.9866	0.8092
17	0.0866	0.9731	0.8953	0.82
18	0.0335	0.9919	2.0411	0.7075
19	0.0639	0.9785	1.0422	0.7958
20	0.0298	0.9919	0.8611	0.8267
21	0.0369	0.989	0.9987	0.7983
22	0.0212	0.9937	0.7637	0.8458
23	0.0226	0.9944	0.8607	0.8425
24	0.0138	0.9948	0.7838	0.86
25	0.0129	0.9958	0.7425	0.845
26	0.0179	0.9937	0.8874	0.8467
27	0.0091	0.9971	1.0501	0.8233
28	0.0302	0.9919	0.8991	0.835
29	0.012	0.9956	0.9443	0.8175

Table 12.b High CI accuracy

Class	Baseline	Trained
n02389026	96	82
n02107683	96	88
n02489166	96	94
n02090622	98	82
n02111129	98	94
n02342885	98	98
n02130308	96	90
n01872401	98	92
n03344393	96	94
n11879895	96	98
n11939491	98	94
n12057211	98	100
n09288635	98	88
n01518878	98	84
n01820546	98	82
n02006656	98	76
n02007558	98	74
n06359193	98	98
n13044778	98	92
n12620546	96	0

A.4 Low CI

Table 13.a Low CI training

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.7819	0.189	3.0447	0.2075
2	2.2851	0.2981	2.628	0.2575
3	2.0173	0.3731	2.0891	0.36
4	1.7581	0.4415	2.0898	0.415
5	1.5512	0.5096	2.3492	0.36
6	1.301	0.5777	1.9938	0.4542
7	1.0703	0.655	2.4133	0.4333
8	0.8361	0.7342	2.1217	0.45
9	0.6474	0.786	1.9529	0.4933
10	0.4507	0.8456	2.2903	0.4983
11	0.3486	0.8815	2.7954	0.4625
12	0.2343	0.9181	2.4598	0.5208
13	0.1856	0.9398	3.0156	0.5
14	0.1673	0.9444	3.1913	0.4658
15	0.1302	0.9579	2.9002	0.4708
16	0.0903	0.9696	2.9774	0.5142
17	0.0507	0.9862	3.0137	0.5175
18	0.078	0.975	3.1717	0.5067
19	0.0818	0.9744	3.2444	0.495
20	0.0643	0.9777	2.9461	0.5442
21	0.039	0.9879	2.9063	0.56
22	0.0263	0.9923	2.8563	0.5642
23	0.0164	0.9952	3.0124	0.5583
24	0.0121	0.9971	2.7555	0.5775
25	0.0318	0.9904	3.3832	0.49
26	0.0134	0.9962	3.0255	0.5592
27	0.01	0.9977	2.8618	0.5758
28	0.0081	0.9981	2.9056	0.5692
29	0.0022	1.0000	2.8814	0.5783

Table 13.b Low CI accuracy

Class	Baseline	Trained
n03692522	26	34
n03476684	26	40
n04286575	26	38
n03045698	26	24
n01740131	24	52
n04008634	24	56
n04270147	24	12
n04264628	24	58
n03016953	20	76
n04356056	20	14
n03532672	20	2
n04591157	20	30
n03866082	20	32
n03658185	18	22
n02123159	16	58
n04152593	16	0
n04355933	16	10
n03710637	16	70
n04525038	14	28
n03832673	12	28

A.5 Random

Table 14.a Random classes training

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.485	0.2587	3.4595	0.23
2	1.8581	0.4104	2.3265	0.4175
3	1.8581	0.4104	2.3265	0.4175
4	1.3845	0.5481	1.7598	0.4825
5	1.2021	0.5987	1.6527	0.5083
6	1.0452	0.6425	1.6391	0.53
7	0.8675	0.7079	1.8676	0.5267
8	0.7085	0.76	2.4066	0.4783
9	0.6043	0.7931	1.6244	0.5567
10	0.4878	0.8304	1.5957	0.5967
11	0.367	0.876	2.0344	0.5467
12	0.2761	0.9056	2.1512	0.56
13	0.2172	0.9227	1.5953	0.6342
14	0.1682	0.9442	1.8916	0.6067
15	0.1284	0.959	2.0958	0.61
16	0.0923	0.9727	1.9115	0.6142
17	0.0873	0.9708	2.7229	0.565
18	0.0967	0.9677	1.9194	0.625
19	0.0494	0.9842	1.8287	0.6492
20	0.0549	0.9808	2.4264	0.57
21	0.0747	0.9748	2.2205	0.6142
22	0.0917	0.9696	2.221	0.615
23	0.0374	0.9883	1.946	0.6608
24	0.037	0.9869	2.1902	0.6258
25	0.0414	0.9871	2.2147	0.5858
26	0.0439	0.985	2.0671	0.6183
27	0.054	0.9825	2.3125	0.6175
28	0.0228	0.9927	2.0141	0.65
29	0.0358	0.9883	2.1322	0.6283

Table 14.b Random Classes accuracy

Class	Baseline	Trained
n01740131	24	36
n01742172	76	40
n01744401	30	14
n07753592	84	58
n04376876	56	34
n03761084	56	84
n03908618	60	50
n02107908	30	62
n02105855	60	58
n04033995	54	50
n07747607	74	78
n04200800	68	56
n09288635	98	90
n04505470	76	76
n02965783	92	90
n09229709	78	56
n07831146	74	88
n02102040	92	66
n02412080	68	0
n04552348	76	90

A.6 Random 2

Table 15.a Random classes training 2

Epoch	Loss	Accuracy	Val_loss	Val_accuracy
1	2.5408	0.2221	7.5304	0.1375
2	2.0118	0.3371	4.6658	0.1433
3	1.7384	0.4304	2.5767	0.2883
4	1.5574	0.4773	2.3611	0.3167
5	1.3826	0.5265	2.3943	0.3475
6	1.202	0.5777	1.5829	0.5025
7	1.0399	0.6479	1.6425	0.4925
8	0.8649	0.7002	1.833	0.4925
9	0.7387	0.7469	1.7559	0.525
10	0.5755	0.7952	1.9372	0.5283
11	0.4519	0.8454	1.8955	0.5558
12	0.3621	0.8754	1.8891	0.555
13	0.2934	0.8963	2.062	0.545
14	0.1942	0.9346	2.077	0.5717
15	0.1686	0.9456	2.1727	0.5767
16	0.1607	0.946	2.096	0.5817
17	0.1146	0.9617	2.4329	0.5558
18	0.1312	0.9579	2.2998	0.5592
19	0.0951	0.9698	2.2633	0.6175
20	0.076	0.9744	2.5155	0.56
21	0.0382	0.9879	2.2838	0.6092
22	0.042	0.9875	2.6469	0.585
23	0.0332	0.9896	2.4138	0.6042
24	0.0421	0.9873	2.9106	0.5533
25	0.0586	0.9819	2.52	0.5958
26	0.038	0.9873	2.5132	0.5917
27	0.0418	0.9885	2.489	0.5875
28	0.0278	0.9896	2.5635	0.5892
29	0.0223	0.9925	2.2978	0.6025

Table 15.b Random classes 2 accuracy

Class	Baseline	Trained
n03838899	70	40
n04141076	68	32
n03372029	32	36
n11939491	98	84
n12057211	98	94
n09246464	62	0
n09468604	82	60
n09193705	50	0
n09472597	68	54
n09399592	44	34
n09421951	58	34
n09256479	82	82
n09332890	54	28
n09428293	42	34
n09288635	98	72
n03498962	50	30
n03393912	94	80
n03895866	54	52
n02797295	74	38
n04204347	74	56

B AoA mapped to ImageNet with AoA-rating

ImageNet class	Class Name	AoA-rating
n04254777	sock	3,4
n02346627	cup	3,4
n02190166	fly	3,6
n07753592	banana	3,6
n02782093	balloon	3,7
n07747607	orange	3,8
n03938244	pillow	4
n02422106	bee	4
n07745940	strawberry	4,2
n03961711	plate	4,3
n02834397	bib	4,5
n09229709	bubble	4,5
n04371774	swing	4,5
n01608432	kite	4,6
n02799071	baseball	4,7
n03775071	mitten	4,7
n07697313	cheeseburger	4,8
n03814906	necklace	4,9
n01773549	barn	4,9
n01806143	peacock	4,9
n02137549	goose	4,9
n03661043	library	5
n12267677	corn	5
n04592741	wing	5
n04127249	safe	5,1
n07749582	lemon	5,1
n02980441	castle	5,1
n07714990	broccoli	5,2
n01514859	hen	5,2
n04133789	sandal	5,2
n03179701	desk	5,2
n02879718	bow	5,2
n02391049	zebra	5,3
n04465501	tractor	5,3
n02802426	basketball	5,3
n04330267	stove	5,3
n03804744	nail	5,4
n02843684	birdhouse	5,4
n01944390	snail	5,5
n11939491	daisy	5,5
n04026417	purse	5,5
n03868863	mask	5,5

ImageNet class	Class Name	AoA-rating
n07802026	hay	5,6
n02870880	bookcase	5,6
n02363005	beaver	5,7
n03742115	chest	5,7
n02906734	broom	5,7
n03481172	hammer	5,7
n04579432	whistle	5,7
n02342885	hamster	5,8
n03000684	chain	5,8
n02119789	ox	5,9
n02443114	pole	5,9
n01945685	slug	5,9
n04507155	umbrella	5,9
n04584207	wig	6
n03125729	cradle	6
n04208210	shovel	6
n03690938	lotion	6,1
n04476259	tray	6,1
n04325704	stole	6,1
n02701002	ambulance	6,2
n04154565	screwdriver	6,2
n07715103	cauliflower	6,2
n03627232	knot	6,2
n03876231	paintbrush	6,2
n04398044	teapot	6,2
n03291819	envelope	6,3
n02007558	flamingo	6,3
n07734744	mushroom	6,4
n03877845	palace	6,5
n04273569	speedboat	6,5
n02730930	apron	6,5
n02088632	tick	6,5
n02229544	cricket	6,5
n02091635	otter	6,6
n04311174	eel	6,6
n12267677	acorn	6,6
n01910747	jellyfish	6,6
n03109150	screw	6,7
n02910353	buckle	6,7
n04442312	toaster	6,7
n09472597	volcano	6,7
n02971356	carton	6,8

ImageNet class	Class Name	AoA-rating	ImageNet class	Class Name	AoA-rating
n03794056	mousetrap	6,8	n03733131	maypole	8,1
n07695742	pretzel	6,8	n02787622	banjo	8,1
n04522168	vase	6,8	n07875152	potpie	8,1
n07565083	menu	6,9	n02699494	altar	8,2
n02326432	hare	6,9	n04004767	printer	8,2
n04296562	stage	6,9	n03841143	dome	8,2
n01833805	hummingbird	7	n02051845	pelican	8,2
n04429376	throne	7	n04525038	velvet	8,2
n07860988	dough	7	n07753113	fig	8,3
n02106030	collie	7,1	n03825788	nipple	8,4
n04540053	volleyball	7,1	n04317175	stethoscope	8,5
n02951358	canoe	7,1	n02410509	bison	8,5
n03388043	fountain	7,1	n03100240	convertible	8,5
n03530642	honeycomb	7,1	n04040759	radiator	8,5
n04009552	projector	7,2	n02437616	llama	8,6
n02749479	rifle	7,2	n03773504	missile	8,6
n02109961	ski	7,2	n02815834	beaker	8,6
n02669723	gown	7,2	n04355338	sundial	8,7
n04270147	spatula	7,3	n01843383	toucan	8,7
n03482405	hamper	7,3	n02666196	abacus	8,7
n03871628	packet	7,4	n02102318	cock	8,7
n01784675	centipede	7,4	n04251144	snorkel	8,7
n04606251	wreck	7,4	n02276258	admiral	8,7
n03141823	crutch	7,4	n04067472	reel	8,7
n03045698	cloak	7,4	n03933933	pier	8,7
n07932039	eggnog	7,5	n03980874	poncho	8,8
n04456115	torch	7,5	n01818515	macaw	8,8
n02978881	cassette	7,5	n03874599	padlock	8,8
n03255030	dumbbell	7,6	n01580077	jay	8,9
n03944341	pinwheel	7,6	n03803284	muzzle	8,9
n02447366	badger	7,7	n04523525	vault	9,1
n03662601	lifeboat	7,7	n04259630	sombrero	9,1
n01774750	tarantula	7,8	n03720891	maraca	9,1
n03250847	drumstick	7,8	n01616318	vulture	9,1
n02950826	cannon	7,8	n03498962	hatchet	9,1
n01770393	scorpion	7,8	n02804414	bassinet	9,2
n02108089	boxer	7,8	n04485082	tripod	9,3
n02012849	crane	7,9	n03785016	moped	9,4
n02012849	crane	7,9	n04336792	stretcher	9,5
n03127925	crate	7,9	n02423022	gazelle	9,6
n02441942	weasel	7,9	n02137549	mongoose	9,6
n03495258	harp	7,9	n03956157	planetarium	9,6
n04423845	thimble	8,1	n04332243	strainer	9,6
n04487394	trombone	8,1	n01806567	quail	9,6
n02486410	baboon	8,1	n03633091	ladle	9,7

ImageNet class	Class Name	AoA-rating	ImageNet class	Class Name	AoA-rating
n03782006	monitor	9,7	n03786901	mortar	11,5
n01592084	chickadee	9,8	n02088364	beagle	11,6
n02454379	armadillo	9,9	n03467068	guillotine	11,8
n01807496	partridge	9,9	n07613480	trifle	11,8
n03527444	holster	10	n02794156	barometer	11,9
n03868242	oxcart	10	n03680355	Loafer	11,9
n03447447	gondola	10,1	n04147183	schooner	12,4
n02113186	cardigan	10,1	n02490219	marmoset	12,5
n09288635	geyser	10,1	n01847000	drake	12,5
n02859443	boathouse	10,2	n04136333	sarong	12,9
n03781244	monastery	10,3	n02091134	whippet	13,1
n04376876	syringe	10,4	n03788195	mosque	13,2
n02804610	bassoon	10,4	n03297495	espresso	13,3
n02442845	mink	10,4	n04532670	viaduct	13,3
n01582220	magpie	10,5	n03837869	obelisk	13,7
n01943899	conch	10,5	n04501370	turnstile	13,7
n03443371	goblet	10,7	n02361337	marmot	13,9
n04277352	spindle	10,7	n02389026	sorrel	14
n01883070	wombat	11,1	n04141327	scabbard	14,1
n02790996	barbell	11,2	n02011460	bittern	14,5
n07768694	pomegranate	11,2	n02981792	catamaran	15,6
n04111531	rotisserie	11,3	n02018795	bustard	15,8
n03617480	kimono	11,4	n03146219	cuirass	15,9
n04612504	yawl	11,4	n02006656	spoonbill	16
n09193705	alp	11,5	n01560419	bulbul	17,2

C Training code

```
import tensorflow as tf
from tensorflow.keras.callbacks import Callback
#from tensorflow.keras.layers import Conv2D, MaxPooling2D, Dropout, Dense, Flatten, UpSampling2D,Conv3D,Lambda,Reshape,Permute,Input,Add, ConvLSTM2D,Subtract, UpSampling2D
#from tensorflow.keras.layers import BatchNormalization, TimeDistributed, LeakyReLU, concatenate,ReLU,Multiply,Lambda, GlobalMaxPool2D,LSTM,GRU,SpatialDropout2D, RepeatVector
from tensorflow.keras.layers import Dense,Input
from tensorflow.keras import backend as K
from tensorflow.keras.models import Model
import numpy as np,sys
from tensorflow.keras.preprocessing import image
from tensorflow.keras.applications.resnet50 import decode_predictions
import os
import random


def Train():

    NoOfClasses = 1000
    Epochs = 29
    Batch_size = 8
    AmountOfImages = 6000
    Val_split = 0.2

    #Prepare the classes to integer number
    ids = {}
    f = open('./ILSVRC2017_CLS-LOC/mappedclasses.txt','r') #mappedclasses.txt can be found in Appendix D
    lines = f.readlines()

    for i in lines:
        temp = i.strip()
        temp = temp.split(' ')
        ids[temp[0]] = int(temp[1])

    #get the baseline resnet model to build layer ontop of
    resnet = tf.keras.applications.ResNet50(weights='imagenet',include_top=False, pooling='avg')

    #Adapt the resnet output as the input for the new layers
    input = Input((224,224,3))
    features = resnet(input)

    #create two Dense layers
    fc1 = Dense(2048,activation='relu')(features)
    fc2 = Dense(NoOfClasses,activation='softmax')(fc1)

    #Create the model with the extra layers
    AoA_model = Model(inputs=input,outputs=fc2)
    AoA_model.compile(optimizer = tf.keras.optimizers.Adam(amsgrad=True), loss = 'sparse_categorical_crossentropy',metrics=['accuracy'])


```

```
    #initialize empty arrays to fill with images and labels for training
    TrainImages = []
    TrainLabels = []

    #Create or load an array with the classes to train on (e.g.: TrainCats = ['n03782006','n01592084','n02454379','n01807496','n03527444','n03868242','n03447447','n02113186','n09288635','n02859443','n03781244','n04376876','n02804610','n02442845','n01582220','n01943899','n03443371','n04277352','n01883070','n02790996'] )
    TrainCats = []

    for i in range(1,AmountOfImages+1):
        #Load a random image from any of the classes in TrainCats
        folder = random.choice(TrainCats)
        file = random.choice(os.listdir('./ILSVRC2017_CLS-LOC/train/'+folder+'/'))
        img = image.load_img('./ILSVRC2017_CLS-LOC/train/'+folder+'/'+file, target_size=(224, 224,3))

        #Load the image to an array to preprocess it for ResNet50
        img = image.img_to_array(img)
        img = tf.keras.applications.resnet.preprocess_input(img)
        img = np.expand_dims(img,0)

        #Append the image and the appropriate label to the trainin arrays
        TrainImages.append(img)
        TrainLabels.append(ids[folder])

    #Stack the images vertically to make the keras.fit() recognise them
    TrainImages = np.vstack(TrainImages)

    #Reshape the labels array in the same way
    TrainLabels = np.array(TrainLabels)
    TrainLabels= np.reshape(TrainLabels,(6000,1))

    #Create a checkpoint system that saves the model and it's weights, based on the best validation accuracy
    checkpoint = tf.keras.callbacks.ModelCheckpoint("best_model_29.hdf5", monitor='val_accuracy', verbose=1,
        save_best_only=True, mode='auto', period=1,histogram_freq=0)

    #Actually train the model
    AoA_model.fit(x=TrainImages,y=TrainLabels,batch_size=Batch_size,epochs=Epochs,validation_split=Val_split,callbacks=[checkpoint])
```

Listing 1: Training program

D Mappedclasses.txt

Mappedclasses.txt:

n02119789 278
n02100735 212
n02110185 250
n02096294 193
n02102040 217
n02066245 147
n02509815 387
n02124075 285
n02417914 350
n02123394 283
n02125311 286
n02423022 176
n02346627 334
n02077923 150
n02110063 249
n02447366 362
n02109047 246
n02089867 166
n02102177 218
n02091134 172
n02092002 177
n02071294 148
n02442845 357
n02504458 386
n02092339 178
n02098105 202
n02096437 194
n02114712 271
n02105641 229
n02128925 290
n02091635 175
n02088466 163
n02096051 191
n02117135 275
n02138441 299
n02097130 197
n02493509 380
n02457408 364
n02389026 339
n02443484 359
n02110341 251
n02089078 165
n02086910 157
n02445715 361
n02093256 179
n02113978 268
n02106382 233
n02441942 356
n02113712 266
n02113186 264
n02105162 225
n02415577 349
n02356798 335
n02488702 375
n02123159 282
n02098413 204
n02422699 352
n02114855 272
n02094433 187
n02111277 256
n02132136 294
n02119022 188
n02091467 174
n02106550 234
n02422106 351
n02091831 176
n02120505 280
n02104365 223
n02086079 154
n02112706 262
n02098286 203
n02095889 190
n02484975 370
n02137549 298
n02500267 384
n02129604 3
n02090721 170
n02396427 342
n02108000 241
n02391049 340
n02412080 5
n02108915 245
n02480495 365
n02110806 253
n02128385 288
n02107683 239
n02085936 153
n02094114 185
n02087046 158
n02100583 211
n02096177 192
n02494079 382
n02105056 224
n02101556 216
n02123597 284
n02481823 367
n02105505 228
n02088094 160
n02085782 152
n02489166 376
n02364673 338
n02114548 270
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E Validation code

```
import os
import sys
from pathlib import Path
import matplotlib.pyplot as plt
import numpy as np
import tensorflow as tf
import tensorflow_datasets as tfds
from keras.preprocessing import image
from tensorflow.keras.applications.resnet50 import decode_predictions
import keras.applications
import random
from xml.dom import minidom
from tqdm import tqdm
import cv2

#Load or create an array with each class in ImageNet (e.g.: imagenet = ['n02119789', 'n02100735', 'n02110185', 'n02096294',....])
imagenet = []

#Create an empty dictionary to create a map of all classes and tha accuracy of the validation images
classdict = {}
#insert the classes with an empty array
for k in imagenet:
    array = []
    classdict.update({k:array})

#load array from file with all the correct classes mapped to each image (e.g. Image ILSVRC2012_val_00000001 correspond to class n01751748, so the first line in the file is n01751748)
labels = []
f = open('./ILSVRC2017_CLS-LOC/val/ILSVRC2012_validation_ground_truth.txt','r')
lines = f.readlines()
for i in lines:
    labels.append(i.strip())
labels = np.array(labels)

#load the model to validate
ValModel = tf.keras.models.load_model('ModelToLoad.hdf5')

#iterate over each image (50k validation images)
for i in range(1,50001):

    #load image and preprocess
    fname = './ILSVRC2017_CLS-LOC/val/ILSVRC2012_val_'+ str(i).zfill(8)+'.JPEG'
    img = image.load_img(fname, target_size=(224, 224,3))
    img = image.img_to_array(img)
    img = tf.keras.applications.resnet.preprocess_input(img)
    img = np.expand_dims(img,0)

    #Use the ValModel to predict the class
    pred = ValModel.predict(img)
    decodedPred = np.squeeze(decode_predictions(pred, top=1))  ### decodedPred = [id,name,prob]

    #check if prediciton is correct
```

```
    correct = 0
    if decodedPred[0] == labels[i-1]:
        correct = 1

    #get the correct class' array
    arr = classdict.get(labels[i-1])
    #add whether the prediction was correct (1) or incorrect (0)
    arr.append(correct)
    #re-enter the new array to that class
    classdict.update({labels[i-1]:arr})

    #This results in a dictionary with 50.000 entries with their own array
    containing 50 ones and zeros

#Create a new dictionary to house each class and it's accuracy
accdict = {}

for k in imagenet:
    CorrectArray = classdict.get(k)
    TotalPredictions = len(CorrectArray)
    #Filter all the 0 values out of the array
    CorrectArray = [i for i in CorrectArray if i != 0]
    #This gives a percentage of how many images were predicted accurately
    accdict.update({k:((len(suc)/totaal)*100)})

#Write this dictionary to a file to save for results
file = open('AccuracyPerClass.txt',"w")
str_dictionary = repr(accdict)
file.write(str_dictionary)
file.close
```

Listing 2: Validation program