Blocks World Revisited:
The Effect of Self-Occlusion on Classification by Convolutional Neural Networks

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Abstract

Despite the recent successes in computer vision, there remain new avenues to explore. In this work, we propose a new dataset to investigate the effect of self-occlusion on deep neural networks. With TEOS (The Effect of Self-Occlusion), we propose a 3D blocks world dataset that focuses on the geometric shape of 3D objects and their omnipresent challenge of self-occlusion. We designed TEOS to investigate the role of self-occlusion in the context of object classification. Even though remarkable progress has been seen in object classification, self-occlusion is a challenge.

In the real-world, self-occlusion of 3D objects still presents significant challenges for deep learning approaches. However, humans deal with this by deploying complex strategies, for instance, by changing the viewpoint or manipulating the scene to gather necessary information. With TEOS, we present a dataset of two difficulty levels ($L_1$ and $L_2$), containing 36 and 12 objects, respectively. We provide 738 uniformly sampled views of each object, their mask, object and camera position, orientation, amount of self-occlusion, as well as the CAD model of each object. We present baseline evaluations with five well-known classification deep neural networks and show that TEOS pose a significant challenge for all of them. The dataset, as well as the pre-trained models, are made publicly available for the scientific community under https://data.nvision.eecs.yorku.ca/TEOS/.

1. Introduction

Over most of the last decade, computer vision was pushed by efforts put into deep learning. The exact advent of this deep learning dominated era is often dated to the ImageNet challenge ([Russakovsky et al., 2015]) in 2012. Since then, the performance of models on various tasks has been improving at unparalleled speed; for instance, image classification on the ImageNet dataset surpassed the reported human-level performance in 2015 ([He et al., 2015]). Two of the enablers for the recent successes are faster computers, specifically graphic processors, and the availability of large scale and often well-curated data sets to learn from.

The deep learning paradigm is omnipresent, and, with it, the need for data with specific statistics to work in certain domains. [Kuznetsova et al., 2020] goes as far as saying that "Data is playing an especially critical role in enabling computers to interpret images as compositions of objects, an achievement that humans can do effortlessly while it has been elusive for machines so far."

Many domains exist in which one would like machines to perform visual tasks ([Carroll and Others, 1993]). One of these is object classification, which is defined as whether a particular item is present in the stimulus ([Tsotsos et al., 2005]).

Object classification is an essential capability of humans, as well as for any robotic system whose goal is to be a real-world assistant; in a factory, hospital, or at home, just to name a few. Even though very successful in many domains, deep learning methods are challenged with occlusion ([Koporec and Pers, 2019]), which is inevitable in real-world scenarios. Here, we go a step further and show that deep learning methods are also challenged with the self-occlusion of objects, hence not generalizing to objects’ 3D structure.

The problem of understanding the 3D structure from a 2D description, for instance, a line drawing, was first put forward independently by [Huffman, 1971] and...
[Clowes, 1971], and they both showed that the necessary critical condition for a line drawing to represent an actual arrangement of polyhedral objects was labelability. As the human brain is very efficient at reconstructing a scene’s 3D structure from a single image with no texture, colour or shading, efforts have been concentrated on computational complexity issues; one might think an efficient solution exists (e.g. polynomial-time). [Kirousis and Papadimitriou, 1988], however, proved that this problem is NP-Complete, also for simple cases like trihedral, solid scenes. To further research in this field, [Parodi et al., 1998] proposed a method to generate random instances of line drawings with useful distribution to investigate questions related to complexity of understanding images of polyhedral scenes. More recently, [Solbach et al., 2018] provided a 3D extension with controllable camera parameters and two different light settings. It is designed to enable research on how a program could parse a scene if it had multiple and definable viewpoints to consider. An example of a polyhedral scene from [Solbach et al., 2018] is shown from three different viewpoints in Figure 2.

![Figure 2](image)

**Figure 2.** Six polyhedral scenes from three different viewpoints with increasing complexity ([Solbach et al., 2018]).

With the increasing successes, contemporary computer vision approaches show a healthy trend away from artificial problems and provide solutions to real-world problems, already deployed in many domains ([Andreopoulos and Tsotsos, 2013]), for example, optical character recognition, industrial inspection systems, medical imaging, and biometrics. However, at the same time, a disparagement of artificial domains can be seen ([Slaney and Thiébaux, 2001]). At the very least, these domains can support meaningful systematic experiments. Here we revisit one such artificial domain; the Blocks World.

In visual perception, the basic physical and geometric constraints of our world play a crucial role. This idea goes back at least to Helmholtz and his argument for unconscious inference. This theme of visual perception can be traced back to the early years of the discipline of computer vision. Larry Roberts argued that "the perception of solid objects is a process which can be based on the properties of three-dimensional transformations and the laws of nature" ([Roberts, 1965]). Roberts’ popular Blocks World was an early attempt to build a system for complete scene understanding for a closed artificial world of textureless polyhedral shapes by using a generic library of polyhedral block shapes. This toy domain that has remained as a staple of the AI literature for over 30 years but has fallen into disrepute since then. This is due to a superficial understanding of it, leading to insufficient experimental methodology, and therefore, failing to extract useful results from it ([Slaney and Thiebaux, 2001]).

![Figure 3](image)

**Figure 3.** Example of the objects by [Shepard and Metzler, 1971] which are used as an inspiration.

In this paper, we present TEOS: The Effect of Self-Occlusion. TEOS is a Blocks World based set of objects with known complexity, controlled viewpoints, with a known level of self-occlusion and 3D models. TEOS shares similarities in appearance with the so-called Shepard and Metzler Objects ([Shepard and Metzler, 1971]), which are widely used in the literature for mental rotation tasks. See Figure 3 for an illustration of two such objects. Similarities are for instance, the strict ninety-degree angle of elements making up an object, the use of only cuboids, the use of mainly one primitive (except for the base plate).

However, with TEOS, we present a set of objects that go beyond the Shepard and Metzler objects. Specifically, our objects have a known complexity, share a common coordinate system, and empirical results have shown that they are challenging for visual tasks using state-of-the-art classification algorithms.

Our contributions are an investigation of the effect of self-occlusion for object classification. To accomplish this, we provide a novel set of objects, a carefully created dataset, including an in-depth explanation of the objects and generated data with a focus on self-occlusion and a baseline evaluation with state-of-the-art classification algorithms. The remainder of the paper is structured as follows. First, we will explain in detail the objects we have created for TEOS. We then continue by giving an overview of related work, describing the data acquisition, presenting our self-occlusion measure, evaluating the dataset against state-of-the-art classification algorithms, and finally finishing with our conclusions and future directions.
2. Related Work

To the best of our knowledge, self-occlusion has not attracted much attention in the literature. However, occlusion caused by other objects has. In addition to several datasets, a number of approaches were introduced to deal with occlusion.

2.1. Occlusion Datasets

A burden of deep learning is its need for vast mounts of training data. Even though occlusion and its effect on vision tasks has been addressed for some time ([Hsiao et al., 2010], [Ouyang and Wang, 2012], [Brachmann et al., 2014], [Hsiao and Hebert, 2014]), datasets created are usually too small to be used to train successful deep learning models. Furthermore, to our knowledge, datasets, if considering occlusion, mostly introduce various levels of clutter but lack to define occlusion in a generic way. For instance, the CMU Kitchen Occlusion dataset (CMU KO8) by [Hsiao and Hebert, 2014] consists of 1,600 images of eight kitchen objects, such as backing pan, scissors, etc., which only yields 200 examples per class. The dataset has explicitly been designed to challenge object recognition algorithms with strong viewpoint and illumination changes, occlusions and clutter. Besides a novel dataset, an occlusion reasoning module is also proposed (further details in Section 2.2).

With the ICCV 2015 Occluded Object Challenge ([Hinterstoisser et al., 2013], [Brachmann et al., 2014]), a dataset with eight objects positioned in a realistic setting of heavy occlusion is presented. The objects can be described as being of different domains, ranging from animals, over office supplies, to kitchenware. However, neither a definition of occlusion nor a metric is given. Figure 4 shows an example image of the dataset.

![Figure 4](image)

Figure 4. A scene with different objects under occlusion taken from the ICCV 2015 Occluded Object Challenge.

The majority of occlusion datasets, however, deal with the occlusion of pedestrians. Specifically, in the context of autonomous driving, detecting pedestrians, even if occluded, is crucial to detect potential collisions. It is argued that most existing datasets are not designed for evaluating occlusion. For instance, the Caltech dataset ([Dollár et al., 2012]) only contains 105 out of 4250 images with occluded pedestrians. The CUHK Occlusion Dataset ([Ouyang and Wang, 2012]) is specifically designed as a pedestrian dataset with occlusion. The authors selected images from popular pedestrian datasets and recorded images from surveillance cameras and filtered them mainly for occluded pedestrians. The dataset contains 1,063 images with binary classification to indicate whether the pedestrian is occluded or not.

2.2. Occlusion Reasoning

Reasoning about occlusion has been used in many areas, from object recognition to tracking and segmentation. Reported in ([Hsiao and Hebert, 2014], the literature is extensive, but there has been comparatively little work on modelling occlusions from different viewpoints and using 3D information until recently. Further, occlusion reasoning is broadly classified into five categories; inconsistent object statistics, multiple images, part-based models, 3D reasoning, and convolutional neural networks. The first category includes classical approaches, which use inconsistent object statistics to reason about potential occlusion. In general, occlusions are modelled as regions that are inconsistent with object statistics. For instance, [Meger et al., 2011] use inconsistencies in 3D sensor data to classify occlusions. [Girshick et al., 2011] introduce an occluder part in their grammar model when all parts cannot be placed. [Wang et al., 2009] use a scoring metric based on individual HOG filter cells. [Hsiao and Hebert, 2014] incorporate occlusion reasoning in object detection in a two-stage manner. First, in a bottom-up stage, occluded regions are hypothesized from image data. Second, a top-down stage is used that relies on prior knowledge to score the candidates’ occlusion plausibility. Extensive evaluation on single, as well as multiple views show that incorporating occlusion reasoning yields significant improvement in recognizing texture-less objects under severe occlusions. The use of multiple images characterizes the second category. For these approaches, a sequence of consecutive images is necessary to disambiguate the object from occluders. For instance, [Ess et al., 2009] detects the objects and extrapolates the state of occluded objects using an Extended Kalman Filter. Reliable tracklets that are used in a temporal sliding window fashion are generated to disambiguate occluded objects in [Xing et al., 2009]. One of the largest categories are approaches using part-based models. A challenge of global object templates is occlusion as their performance degrades with its presence significantly. A popular solution to this problem is to sepa-
rate the object into a set of parts and detect parts individually. This approach generally yields more robust detections towards occlusion. For example, [Shu et al., 2012] analyze the contribution of each part using a linear SVM and train the classifier to use unoccluded parts to maximize the probability of detection. [Wu and Nevatia, 2009] go a step further and use multiple part detectors to maximize the joint likelihood. Binary classification of parts is introduced by Vedaldi and Zisserman, 2009. They decompose the HOG descriptor into small blocks that selectively switch between an object and an occlusion descriptor.

More recent work using 3D information for occlusion reasoning has been introduced. Hsiao et al. argue that having 3D data provides richer information of the world, such as depth discontinuities and object size. Pepikj et al., 2013 train multiple occlusion detectors on mined 3D annotated urban street scenes that contain distinctive, reoccurring occlusion patterns. Wang et al., 2013 use RGB-D information and an extended Hough voting to include object location and its visibility pattern. Radwan et al., 2013 addresses precisely the problem of self-occlusion in the context of human pose estimation and adds an inference step to handle self-occlusion to an off-the-shelf body pose detector to increase its performance under self-occlusion. The solution leverages prior knowledge about the kinematics and orientations of the human pose to deal with self-occluding body parts.

Lastly, convolutional neural networks have shown promising results when it comes to different visual tasks like object classification, recognition, segmentation and 3D pose estimation. However, occlusion and, as will be shown in this work, self-occlusion pose significant challenges. Reddy et al., 2019 introduce a framework to predict 2D and 3D locations of occluded key points for objects to mitigate the effect of occlusion on the performance. Evaluated on CAD data and a large image set of vehicles at busy city intersections, the approach increases the localization accuracy of MaskRCNN by about 10%. A self-occlusion example can be seen in Figure 5. [Li et al., 2019] uses deep supervision to fine-grain image classification. In their approach, they simulate challenging occlusion configurations between objects to enable reliable data-driven occlusion reasoning. Occlusion is modelled by rendering multiple object configurations and extracting the visibility level of the object of interest. With the work of Kortylewski et al., 2020) a convolutional neural network is combined with the idea of part-based models. The authors introduce CompositionalNets. It is proposed to replace the fully-connected classification layer with a differentiable compositional model. The idea of CompositionalNets is to decompose images into objects and context, and then decompose objects into parts and objects’ pose. Using various CNN backbone shows that the approach can learn features that are invariant to occlusion and discard occluders during classification, hence increasing performance, especially under occlusion. However, a trade-off is pointed out that a good occluder localization lowers classification performance because classification benefits from features that are invariant to occlusion, where, on the other hand, occluder localization requires a different type of features. Namely, ones that sensitive to occlusion. It is pointed out that it is essential to resolve this trade-off with new types of models.

3. Object Definitions

In this Section, we will talk about the creation of the objects, as well as their characterization.

With TEOS, we present in total 48 objects, split into two sets; $L_1$ and $L_2$. The idea of having two sets is to support the different needs of research. $L_1$ consists of 36 objects in 18 complexity levels, hence tailored towards research exploring the effect of finely grained complexity changes. $L_2$, on the other side, is made up of 12 objects in three complexity levels based on $L_1$, so made up of complexity groups.

![Figure 6. The building blocks used to create the objects of TEOS; cuboid (left) and base (right).](image-url)
with ten elements, and hard with 18 elements. For each complexity level, we have constructed three more objects with the same amount of elements but changing the orientation of one of the elements to have four distinct objects for each level. We will now continue to explain the elements used to assemble the objects and describe the objects’ typical characteristics.

All objects consist of the following two elements:

- One 20mm x 60mm x 120mm base (Figure 6 right)
- \( n \) 20mm x 20mm x 60mm cuboids (Figure 6 left)

The complexity of an object is simply calculated as

\[
\text{compl} = n + 1
\]

Where \( n \) is the number of cuboids used.

The base has five connection points for cuboids to be attached to. All cuboids are only attached upright, sitting flush with the bottom of the base. This also makes it simple to define a coordinate system. See Figure 8 for an illustration.

All objects share the same coordinate system, which is crucial for any research that looks at the effect of the orientational difference of 3D objects. The coordinate system is defined as depicted in Figure 8; the Y-Axis is running orthogonal out of the base, the X-Axis running through the base from its center of gravity towards the end with three cuboids connectors, and the Z-Axis runs orthogonal to the Y- and X-Axis with the positive direction through the side of the base with two cuboid connections.

Building up the objects, a cuboid has eight connectors at which another cuboid can be attached. Consecutive cuboids are always orthogonally and never aligned in their direction, which is one of the differences to the Sheppard and Metzler objects. Furthermore, cuboids never intersect or touch neighbouring cuboids, hence avoiding geometrical loops. Creating the objects for \( L_1 \), we focused on making the complexity comparable by consecutively adding one cuboid per complexity level to the object of the previous complexity level.

The objects can also be characterized in four stages of height. Each stage adds one perpendicular cuboid. For TEOS, four height-stages were introduced. Consequently, the number of height-stages presents another way of expressing the complexity of an object. An illustration of the different stages is given in Figure 9.

Lastly, having the objects characterized, we present the \( L_1 \) and \( L_2 \) object sets. The \( L_1 \) objects can be seen in Figure 10 and consist of 36 objects split into 18 complexity levels. There is a distractor object of the same complexity for each object that differs only in one small detail; one of the items is oriented differently. The introduction of the distractor objects is intended to support research in visual recognition,
Figure 11. Illustration of $L_2$ with all 12 objects, split into three different complexity levels.

where merely counting the number of elements would reveal the object class.

On the other side, the $L_2$ set of objects is designed with less variation in complexity but more variation within a complexity. Twelve objects are evenly split into three complexity levels. To stick with the analogy of the distractors of the $L_1$ set, each complexity level of $L_2$ has three distractors; the same amount of elements but slight changes in assembling them. As described in the introduction of this Section, we chose the complexity levels based on empirical studies of visual recognition tasks. The $L_2$ objects can be seen in Figure 11.

Figure 12. Illustration of viewpoints used to render each object of $L_1$ and $L_2$. Views are evenly distributed on a sphere around an object (blue points) and point towards the object (light red). In total 768 views are taken.

An emphasis in designing these datasets was put on the ability to use them for self-occlusion studies. To accomplish this, all objects are built around a common coordinate system, share the same base and progressively add elements to increase the complexity and level of self-occlusion. Figure 12 shows how an increase of complexity of the $L_1$ dataset also increases the average amount of self-occlusion among all viewpoints. However, worth noting, with an increasing amount of complexity, the self-occlusion distribution per class decreases. Further information about our self-occlusion measure will be explained in Section 5.

4. Dataset Acquisition

$TEOS$ is a dataset that is designed to be used in the virtual as well as the real world. For the former, one can use the rendered images and provided 3D Models (.STL file). For the latter, the objects are designed to be printable with a 3D printer. For this, we have prepared the 3D Models to be readable by many 3D printing slicing software. However, in this Section we want to focus on the generation of the rendered dataset images for which we have used Blender ($Blender, 2020$), a free and open-source 3D computer graphics software toolset. For $TEOS$, each object was rendered from 768 views – Totalling 36,864 images. To achieve realistic renderings of the objects, we used the Cycles Path Tracing rendering engine, created a white, smooth, plastic imitating material, set six light sources in the rendering scene and used 4096 paths to trace each pixel in the final rendering.

Figure 13. Illustration of viewpoints used to render each object of $L_1$ and $L_2$. Views are evenly distributed on a sphere around an object (blue points) and point towards the object (light red). In total 768 views are taken.

Each object is rendered from the same set of views. To determine the views, we used the Fibonacci lattice ($Stanley, 1988$) approach. This approach allows distributing points on a sphere uniformly. Other approaches, for example, using radial distance, polar angle and azimuthal angle, will result in an unevenly sampled sphere; dense on the poles and sparse closer to the equator. Figure 13 illustrates the chosen views to generate the dataset. Each blue-coloured point represents a location where the camera is placed and oriented to the center where the object (red) is. We chose a sphere radius of two such that the object is
view-filling but not cropped in any view.
Further, as it is sometimes practiced in the machine learning
community ([Everingham et al., 2010, Lin et al., 2014,
Matthey et al., 2017, Kabra et al., 2019]), we also provide
the object mask and renderings with a dark and bright back-
ground for data augmentation purposes. The annotation file
contains the object-type, view-id, bounding box information,
object and camera positions and orientations, and ob-
ject dimensions.

5. Self-Occlusion Measure

It seems evident that if we see less of an object, it is
harder to classify it. Regions of the object that are occluded
to us might hold distinct features to tell object X apart from
object Y. In other words, occlusion for visual classification
plays an important role. However, it is not only dependent
on the view but also on the object. Let us take, for exam-
ple, a sphere. No matter from which angle we look at it, we
always observe 50% of it. On the contrary, for a complex
polygonal shape, this cannot be answered as quickly as it is
dependent on its geometry.

[Gay-Bellile et al., 2010] distinguishes two kinds of occlu-
sions; “external occlusion” and “self-occlusion.” “Exter-
nal occlusion” is caused by an object entering the space
between the camera and the object of interest and “self-
occlusion ” which describes the occlusion caused by the ob-
ject of interest to itself. For TEOS, we are interested in the
latter, as we always have one object in the scene. To our
knowledge, no standard self-occlusion measure is used for
computational approaches; therefore, we aim to specify our
own intuitive measure as:

$$SO_{c_i} = \frac{A_\phi}{A_\sigma}$$

(2)

Where $A_\phi$ is defined as the occluded (not visible) surface
area of the object and $A_\sigma$ stands for the total surface area of
the object.

![Figure 14](image1.png)

Figure 14. Examples of different objects (Object 10 and 13 of $L_1$)
and poses causing the same amount of occlusion but different ap-
pearances.

An object might have different views from which it
causes the same amount of self-occlusion, resulting in per-
haps a considerably different appearance. Figure 14 shows
an example of two objects from two different views with the
same amount of occlusion. Therefore, we also consider the
camera’s point of view with $c_i$ as the camera pose. Here, $c_i$
is defined as the camera position $c_i = (x_i, y_i, z_i)$. There-
fore, we also consider the camera’s point of view with $c_i$
as the camera pose. Here, $c_i$ is defined as the camera posi-
tion $c_i = (x_i, y_i, z_i)$ and computed based on the Fibonacci
lattice approach (see Figure 13). The camera orientation is
automatically set such that the object is in the centre of the
viewpoint.

![Figure 15](image2.png)

Figure 15. Examples of object viewpoints and their corresponding
$SO_{c_i}$.

For evaluation purposes, we also define a function that
maps a camera position ($c_i$) onto one of the eight regions
of the octahedral viewing-sphere placed at the centre of an
object. Figure 16 illustrates a mapping example for two
camera-positions.

![Figure 16](image3.png)

Figure 16. Visualization of the octahedron based projection used
to map camera positions. Bottom: two example camera poses ($c_i$
and $c_j$) mapped to $oh_1$ and $oh_3$.

We represented the viewing sphere around an object as
a spherically tiled octahedron, resulting in eight uniformly
distributed triangles. To map a viewpoint $c_i$ to a tile, we
perform a determinant check to see in which tile a given
camera pose $c_i$ is located.
In our rendered data set, the self-occlusion was calculated
by using the following steps:
1. Iterates over all faces of the object with valid normals and calculate the \( (A_\sigma) \).

2. Subdivide the objects into many thousand elements.

3. Position the camera at a given location and pointing it at the object (see Figure 13).

4. Select all vertices that are visible through the camera view-port.

5. Divide the object into two objects: visible and not-visible.

6. Iterate over all faces of the not-visible object with valid normals and calculate \( (A_\phi) \).

7. Lastly, calculate Self-Occlusion (Equation 2).

Figure 17. Illustration of the self-occlusion distribution for \( L_1 \) and \( L_2 \) (top), as well as the distributional relation between viewpoint mapping and self-occlusion for \( L_1 \) and \( L_2 \) (bottom).

Figure [15] shows eight examples of the same object (object-7) from different viewing angles and sorted based on their amount of self-occlusion. As can be seen in the illustration, a single object can cast many different appearances based on the viewing angle and a significant change in the amount of what is observable of it.

Figure [17] illustrates the self-occlusion distribution for \( L_1 \) and \( L_2 \) (top) and the distributional relation between viewpoint mapping and self-occlusion for \( L_1 \) and \( L_2 \) (bottom). Self-Occlusion for \( L_1 \) ranges from 49.99% to 95.16% with a mean at around 68% and \( L_2 \) from 54.08% to 87.5% with a mean at 61% (Easy), 63% (Medium), and 71% (Hard). The lower half of the Figure shows that different octahedron viewpoints result in varying amounts of self-occlusion. For both \( L_1 \) and \( L_2 \), a sweet-spot with the least self-occlusion is at \( oh_5 \), presumably resulting in the best classification result.

6. Baseline Evaluation

In this Section, we discuss how well state-of-the-art classification approaches perform on \( TEOS \). We have chosen five deep learning models with different properties, carefully trained and evaluated them on \( TEOS \).

6.1. Model-Selection

We have chosen Inception-V3 ([Szegedy et al., 2016]), MobileNet-V2 ([Sandler et al., 2018]), ResNet-V2 ([He et al., 2016]), VGG16 ([Simonyan and Zisserman, 2014]) and EfficientNet ([Tan and Le, 2019]) as reference networks for \( TEOS \). Their trained version of \( TEOS \) will be made publicly available. Table 1 shows more details about the networks in ascending order of their parameter count.

| CNN          | Layers | Parameters (mil.) |
|--------------|--------|-------------------|
| MobileNet-V2 | 53     | 3.4               |
| Inception-V3 | 48     | 24                |
| ResNet-V2    | 152    | 58.4              |
| EfficientNet-B7 | 813   | 66                |
| VGG16        | 152    | 138               |

With \( TEOS \)'s unique characteristics, it is not trivial to tell which CNN architecture will perform better or worse. Therefore, we chose networks with varying numbers of parameters and different numbers of layers.

6.2. Training-Parameter

Besides the architecture of CNNs, a crucial element is the choice of training-parameters and so-called hyperparameters. In our case, we have looked at the input size, input noise, dropout rate, learning rate, optimization algorithm and lastly, the difference between learning from scratch and fine-tuning the networks. Hyperparameters such as input noise, drop rate, learning rate were determined using the hyperparameter optimizer Hyperband by [Li et al., 2017]. The remaining parameters were empirically determined. Table 2 presents the parameters used to establish the baseline of \( TEOS \).

6.3. Training Data Preparation

To prepare the data for training, we chose a 20% validation split and augmented the remaining 80% with standard data augmentation techniques ([Shorten and Khoshgoftaar, 2019]). See Table 3.
Table 2. Chosen Training Parameters

| Parameter      | Value                                                                 |
|----------------|-----------------------------------------------------------------------|
| Input Size     | 224 x 224 – 800 x 800 (dependent on CNN)                             |
| Input Noise    | Gaussian Noise of 0.1                                                 |
| Drop Rate      | 20%                                                                   |
| Learning Rate  | 1e-5                                                                  |
| Optimizer      | Adam Optimization                                                    |
| Learning Method| Fine Tuning                                                           |

Table 3. Parameters for Data Augmentation

| Data Augmentation Technique | Value   |
|-----------------------------|---------|
| Rotation                    | 0-40°   |
| Width Shift                 | 0-20%   |
| Height Shift                | 0-20%   |
| Zoom                        | 0-20%   |

6.4. Classification Results

Our results show that MobileNet-V2 performed best across $L_1$ and $L_2$. Specifically, for $L_1$, it achieved a top-1 accuracy of 17.25% and 10.83% on the $L_2$ dataset. See Figure 18 for the classification accuracies of all networks. It seems that MobileNet-V2 is the only network that was able to learn some aspects of TEOS, performing with a large ($L_1$) or small ($L_2$) margin above chance, whereas all other networks perform at around chance. This, perhaps, has something to do with the relatively homogeneous appearance of TEOS, not allowing the more complex CNNs to learn from. However, this needs to be investigated further in the future.

A closer look at the results of $L_2$ reveals that more extensive networks (VGG16 and EfficientNet-B7) were able to learn objects of class “Hard” of $L_2$; however, they could not learn “Medium” and “Easy” Objects. The smaller networks, on the other hand (MobileNet-V2 and Inception-V3), were able to learn “Easy” and “Medium” objects but not “Hard.” Except for MobileNet-V2, all networks have profound problems to learn the “Easy” Objects. See Figure 18 for details.

Figure 18. Evaluation results on $L_1$ (left) and $L_2$ (right) for five different CNNs and their accuracy across the entire datasets.

Generally, $L_2$ is more challenging to learn for CNNs than $L_1$. Even the best performing CNN is only 2.53% above chance, where this margin for $L_1$ was at about 14.5%. This is explainable with the high intra-class similarity of $L_2$ – objects of one class look very similar to each other and only vary in one small detail, which might be only observable from certain viewpoints, hence will be confused with each other.

The $L_1$ dataset, on the other side, has a low inter-class similarity – the appearance of objects varies between classes.

Figure 19. Evaluation results on $L_1$ and $L_2$ for the three top-performing CNNs. Top: Accuracy across the entire datasets with respect to self-occlusion. Bottom: Accuracy and how it is affected by the chosen viewpoint.

Regarding the connection between classification accuracy and amount of self-occlusion, it can be generally said that the classification accuracy goes down if self-occlusion increases. We have chosen the three best-performing CNNs to analyze this connection and grouped $L_1$ and $L_2$ from 50% to 85% self-occlusion in 5% intervals. < 50% captures all viewpoints with a self-occlusion of less than 50%, > 85% includes all images with more than 85%. Furthermore, we also investigated the connection between the viewpoint mapped to an octahedral viewing-sphere and accuracy. As can be seen in the example of $L_1$ and MobileNet-V2, the viewpoint does play a vital role and can result in an increase of accuracy performance by 13.28 ⇔ 22.31 = 67.99%. Across $L_1$ and $L_2$ the octahedral viewpoint resulting in the best performance was $oh_5$. This can be explained with that all objects share a common coordinate system and shows once more that the viewpoint matters and, even more, that an ideal viewpoint can exist. See Figure 19 for details.

Further, even though the CNNs are trained and validated on the entire data set, their best performance can be seen
at lower self-occlusion rates, which shows the vital role of self-occlusion for object classification performance.

7. Conclusion and Future Directions

In this work, we have presented a novel 3D blocks world dataset that focuses on the geometric shape of 3D objects and their omnipresent challenge of self-occlusion. We have created two data sets, \( L_1 \) and \( L_2 \), including hundreds of high-resolution, realistic renderings from known camera angles. Each data set also comes with rich annotations. Further, we have presented a simple but precise measure of self-occlusion and were able to show how self-occlusion challenges the classification accuracy of state-of-the-art CNNs and the viewpoint can benefit the classification. Lastly, in our baseline evaluation, we have presented that CNNs are unable to learn TEOS, leaving much room for future work improvements.

We hope to have pated a way to explore the relationship between object classification, viewpoint, and self-occlusion with this work. Specifically, we hope that TEOS is useful for research in the realm of active vision – to plan and reason for the next-best-view seems to be crucial to increase object classification performance.

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