Seeing Eye-to-Eye?
A Comparison of Object Recognition Performance in Humans and Deep Convolutional Neural Networks under Image Manipulation

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Abstract

For a considerable time, deep convolutional neural networks (DCNNs) have reached human benchmark performance in object recognition. On that account, computational neuroscience and the field of machine learning have started to attribute numerous similarities and differences to artificial and biological vision. This study aims towards a behavioral comparison of visual core object recognition between humans and feedforward neural networks in a classification learning paradigm on an ImageNet data set. For this purpose, human participants (n = 65) competed in an online experiment against different feedforward DCNNs. The designed approach based on a typical learning process of seven different monkey categories included a training and validation phase with natural examples, as well as a testing phase with novel shape and color manipulations. Analyses of accuracy revealed that humans not only outperform DCNNs on all conditions, but also display significantly greater robustness towards shape and most notably color alterations. Furthermore, a precise examination of behavioral patterns highlights these findings by revealing independent classification errors between the groups. The obtained results endorse an implementation of recurrent circuits similar to the primate ventral stream in artificial vision models as a way to achieve adequate object generalization abilities across unexperienced manipulations.

1 Introduction

Similar to other fields of artificial intelligence, technological progress in computer vision has initiated the highly philosophical discussion about a possible successor of the human brain. Artificial vision is attracting widespread and interdisciplinary interest, as for some it is believed to provide a revolutionary step towards intelligent machines in allowing them to perceive, process, and interact with the external world [1]. Primates including humans have mastered a skill crucial to higher-level cognition. It is the ability to exceed at labeling a sheer infinite number of objects at first glance, independent of latent variables such as position, size, pose, or
illumination [2, 3, 4] that has awarded some species numerous evolutionary advantages over others. In a way, view-invariant core object recognition serves as a foundation for many learning processes where classification of chaotic incoming visual stimuli into meaningful constellations forms retrievable categories [5]. For many years, neuroscience has attributed this ability to a chain of visual perception areas from retinal ganglion cells (RGC), to lateral geniculate nucleus (LGN), most important ventral stream visual areas (V1, V2, and V4), as well as inferior temporal cortex (ITC) [6, 7, 8, 9]. However, in the last few years, upcoming feedforward deep convolutional neural networks (DCNNs) have been used to emulate this process as a result of matching performance and attested representational similarities [5, 10, 11, 12, 13]. To this day, mechanisms of core object recognition in the primate brain have not been fully uncovered. However, computer science has managed to engineer biology-inspired artificial replicas, which currently serve as current state-of-the-art models, without a more extensive understanding of the underlying coherences [14].

In line with earliest pioneers of machine intelligence such as Alan Turing, performance optimization towards defined benchmarks is still cherished in the field. Today, both biological and artificial information processors undoubtedly compete on the same level in organized events such as the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [15]. An arms race of modeling ‘in silico’ vision has resulted in accuracies undreamt-of. The development can be demonstrated by the winners of milestone events such as AlexNet in 2012 [16], GoogLeNet in 2014 [17], and ResNet in 2015 [18] with corresponding top-5 error rates of 18.9 % up to 3.57 %. DCNNs have since proven themselves repeatedly to achieve respectable results in image recognition tasks [1, 19]. Similar to primate visual areas, feedforward multilayer neural networks are hierarchically structured with many layers of nodes, the technical abstraction models of biological neurons. These nodes compute weighted sums of incoming signals depending on the visual input at hand. In this way, the network optimizes its weights using a learning algorithm called ‘backpropagation’ to adjust according to a gain function for optimal label prediction [11, 20]. While the backpropagation learning algorithm is widely considered as biologically implausible [21], other simple operations performed in individual layers appear, at least theoretically, implementable in biological circuits [22].

Although, up to date DCNNs are capable of outperforming their human prototypes in recognizing natural images when trained on sufficient data [16, 18, 23, 24, 25], these same systems fail at more abstract and atypical examples, which do not pose a problem to their creators. Unlike primates, feedforward neural networks are extremely sensitive to distribution shifts, such as random noise or blur [26, 27, 28], and can be fooled by a simple change of background [29, 30], object rotation [31], object texture [32], or by shift of a few pixels only [33]. Nevertheless, an extensive body of literature suggests that many of these phenomena are not the result of lacking generalization abilities [28, 34, 35, 36], but rather a consequence of artificial systems falling for unintended, nonhuman shortcut learning strategies, which in turn lead to undesirable results [14].

As the field of neuroscience uses DCNNs as a scientific multitool for prediction, explanation, and exploration simultaneously [22], a heated debate about the coherence of primate brain areas and artificial neural networks in visual perception has emerged. Findings suggest that both processing systems may share similar ways of representing visual information, as early and late
layers of neural networks predict low- and high-level visual brain areas, respectively [37]. Moreover, better performing neural networks were found to be more similar to ITC with more clustered between-category representation patterns [38, 39, 40, 41], as well as greater within-category dissimilarities. Here, another key aspect is supervised learning, as neural networks require an enormous amount of labeled data in order to acquire decent representations. Through the process of providing neural networks with important categorical distinctions found in biological vision, such as animate versus inanimate, and faces versus other objects, labeling accuracy and explanation of ITC data were both found to increase [10].

In contrast, recent studies propose representational differences of visual information as only early layers of neural networks seem to capture the structure of associated lower visual areas [42]. Previous work of Kar et al. (2019) [43] compared performance of humans, monkeys, and well-studied AlexNet in a core object recognition task using electrophysiologically assigned ‘early-’ and ‘late-solved’ images. Here, the population of emerging activity in monkeys’ ITC was noticeably slower (~ 30 ms) for ‘late-solved’ challenge images, agreeing with the assumption that neural timing in mid- and high-level visual brain areas operates in a most non-linear fashion [44]. Additionally, performance results show that a highly recurrent primate ventral stream outperforms a strictly feedforward DCNN predominantly at these ‘late-solved’ challenge images. As can be seen here, a considerable amount of literature suggests that in addition to simple feedforward mechanisms, challenging images might need extra processing steps performed by recurrent circuits [45] with neurons interconnected to loops [46]. Since feedforward neural networks are missing recurrent connectivity as naturally occurring in the primate visual system [47, 48, 49], these networks should have no memory and therefore exhibit serious problems with previously unexperienced shape and color manipulation of natural images.

Therefore, the presented work aims towards testing hypotheses generated in accordance with this extensive body of literature on biological and artificial image recognition performance under commonly studied manipulations. As shown by numerous examinations DCNNs should perform indistinguishable on natural images when compared to human observers. However, their accuracy for shape and color manipulated challenge images should be worse due to missing recurrent computations needed to classify these predominantly ‘late-solved’ examples. Additionally, humans are thought to display great robustness towards color alterations [50], which could be regarded as a key feature of astonishing core object recognition abilities but also as a result of the higher order processes of abstraction and imagination. Consequently, behavioral classification patterns between recurrent ‘in vivo’ systems and non-recurrent ‘in silico’ replicas are assumed to diverge with uncorrelated classification errors.

2 Materials and Methods

2.1 Data Set

In order to draw a behavioral comparison in performance of human participants and the three feedforward neural networks AlexNet, GoogLeNet, and ResNet-50, a general classification learning paradigm including a training, validation, and testing phase was adopted.
Presented images were all part of a subset included in the ImageNet database consisting of seven different monkey species. An approach regarding both sufficient variance as well as participants’ attentional and motivational capabilities was decided as most appropriate for this investigation. Consequently, less categories with higher similarity and in turn higher difficulty were selected. The initial sample consisted of 30 labeled and randomly drawn images for each of the seven subsets ‘gorilla’, ‘chimpanzee’, ‘orangutan’, ‘gibbon’, ‘spider monkey’, ‘baboon’, and ‘Madagascar cat’. Of the 30 images per class, 15 were used for training, 3 for validation, and 12 for testing purposes. Hence, the data set consisted of 210 images in total, splitting up to 105 training images, 21 validation images, and 84 testing images. Moreover, challenge images for testing were randomly assigned to three increasing levels of shape distortion and a color alteration with three primary color variations (see Figure 1). All images were preprocessed using the pixel-based image manipulation program GIMP (Version 2.10, The GIMP Development Team) in a standardized way by centering towards the dominant object as well as thoroughly checking for and eliminating examples with multiple dominant objects and replicas (i.e. drawing or statue). Finally, challenge images were compiled using a shape manipulation called ‘whirl effect’ at the three intensity levels 50 %, 150 %, and 250 % (hereafter ‘shape50’, ‘shape150’, and ‘shape250’) distorting the image in a concentric way, and a color manipulation overlaying 100 % intensity of a random, equally distributed primary color (hereafter ‘color’) to the entire image [51].

**Figure 1 | Examples of the obtained ImageNet data set.** Letters show chosen ImageNet subsets (A: ‘gorilla’, B: ‘chimpanzee’, C: ‘orangutan’, D: ‘gibbon’, E: ‘spider monkey’, F: ‘baboon’, G: ‘Madagascar cat’) and numbers show levels of manipulation (1: ‘training/natural’, 2: ‘validation/natural’, 3: ‘testing/shape50’, 4: ‘testing/shape150’, 5: ‘testing/shape250’, 6: ‘testing/color’).

[1]https://www.gimp.org
2.2 Participants and Deep Neural Networks

2.2.1 Human Participants

A total of 65 human participants were recruited for the online experiment ‘Object recognition – biological and artificial neural networks’. The representative sample consisted of 34 individuals identifying as women and 31 as men. The anonymous observers were between the ages of 19 and 65 (M = 30.49; SD = 13.95) and reported normal or corrected-to-normal vision without any problems of color perception. Participants had to complete the study on a computer with a keyboard and were advised to do so in a quiet and undisturbed environment. Instructions informed about the importance of adequate brightness and avoidance of reflecting light on the screen. Participation was rewarded with 0.5 accredited study completion hours for the 31 psychology students. All procedures were in alignment with the declaration of Helsinki and agreed to by participants with informed consent.

2.2.2 Human Experiments

In a 15-minute online study, participants had to complete all three stages of a typical classification process with images of the data set in randomized order. First, in the training phase, 15 consecutive sample images of each of the seven classes were presented for 1500 ms on a blank white screen with respective labels shown as a caption. In-between trials, subjects had to focus on a fixation cross for 500 ms. After individual category sets, in order to advance, participants had to press a button. This sequence was implemented to improve compliance with the instructions. Second, in the validation phase, presented natural images had to be labeled by pressing a corresponding number on the keyboard. Adequate feedback including the correct answer was provided for 1500 ms. Last, in the testing phase, this process was continued for manipulation images without any feedback (see Figure 2). Classification decisions in both validation and testing phase were self-paced and participants were informed by the instructions to complete the task according to their individual speed. This approach was chosen over a rapid classification task with set time limits in order to ensure careful conduction without confounding reaction time aspects. As a result, performance data for a total of 6825 trials were recorded. The online study was implemented in German and programmed using the open source graphical experiment builder OpenSesame (Version 3.2.8, OpenSesame, Amsterdam, The Netherlands)².

²https://osdoc.cogsci.nl
2.2.3 Deep Neural Networks

In order to investigate DCNN performance, the three neural networks AlexNet, GoogLeNet, and ResNet-50 were trained and tested entirely in MATLAB with Deep Learning Toolbox (Version 9.8, R2020a, The MathWorks Inc., Natick, MA, USA). All networks were acquired as pretrained models of the ILSVRC data subset with more than 1.2 million training images, 50000 validation images, 150000 testing images, and 1000 classes [16]. In a fine-tuning process, the last layers of the networks were replaced to reduce classification to the seven classes preexistent in the data. Subsequently, the models were trained on clean control images with a smaller learning rate of 0.0001 to conserve weights in early and solely adjust in later layers. Training parameters were standardized for all networks and the process was stopped as soon as the loss on the validation set did not decrease further than a pre-set accepted error. While the chosen networks share most of their architecture, they can be characterized by a few individual structural differences. In comparison to 8-layer AlexNet, 22-layer GoogLeNet benefits from so called ‘inception modules’ which drastically reduce the number of parameters [17], and 50-layer ResNet-50 uses residual learning with ‘skip connections’ inspired by pyramidal cells in the cerebral cortex [18].

Figure 2 | Experimental setup of the online study. At first, in the training phase (A), participants were shown 15 control images per category for 1500 ms with a fixation cross in-between trials for 500 ms. Then, in the validation phase (B), participants classified 3 control images per category following individual feedback for 1500 ms. Finally, in the testing phase (C), participants continued labeling 12 challenge images per category in randomized order.
2.3 Statistical Analysis

Statistical analyses were performed with IBM SPSS Statistics (Version 26, IBM Corp., Chicago, IL, USA) and R (Version 3.6.1, R Core Team, Vienna, Austria) using the package ggplot2 [52] for data visualization. As several tests (Kolmogorov-Smirnov, visual inspection of distributions) revealed that performance data were not normally distributed (p < .05), in an attempt to replicate published findings under novel manipulations, several non-parametric tests were conducted. To control for outliers, two participants with results two standard deviations below mean performance (64.28 %) were dropped from further analysis. One-sample Wilcoxon signed-rank tests with r as effect size [53] were performed to investigate between-group differences comparing the human observer sample to each one of the three tested neural networks for all stages of manipulation, respectively. For main analyses, this method was chosen over the idea to treat artificial neural networks as a population of their own to explore possible differences based on architecture. Later on, for reasons of clarity and comprehensibility, DCNNs were treated as a group allowing statistically equal comparisons. Within-group differences for both manipulation types were explored using Friedman’s ANOVA with Kendall’s W as effect size followed by multiple Bonferroni-corrected pairwise comparisons. Furthermore, in order to contrast typical human and DCNN classification behavior across manipulations, confusion matrices of true and predicted labels were computed based on groups’ average performances. Additionally, special confusion difference matrices were calculated to highlight striking distinctions in classification behavior, and similarity of errors by humans and neural networks was investigated using Spearman’s rank order correlation with Spearman’s r as effect size. Aside from that, pretrained networks without a fine-tuning process were analyzed to guarantee a suitable methodological approach for comparability of the presented learning paradigm.

3 Results

3.1 Accuracy for Control and Challenge Images

As anticipated, even on a rather underpowered training data set of only few instead of many hundred newly learned examples per category, fine-tuned DCNNs achieve respectable results on natural images. Nevertheless, in the present study design all tested neural networks clearly miss performance statistically comparable to human observers (see Table 1). Remarkably, top-performing GoogLeNet reaches an accuracy of 80.95 % outperforming both AlexNet and ResNet-50 with 76.19 %, respectively. Generally speaking, our results show that the novel manipulations undoubtedly affect recognition accuracy and lead to performance drops in both groups alike. However, as apparent in Figure 3, human participants (Mdnhuman = 73.81) outperform all three fine-tuned neural networks (MdnAlexNet = 47.62; MdnGoogLeNet = 52.38; MdnResNet-50 = 46.43) by a significant margin at all levels of manipulation.

⁴https://ggplot2.tidyverse.org
Table 1 | Image recognition performance under different conditions. One-sample Wilcoxon signed-rank tests comparing individual neural networks to human participants. Median accuracy across levels with interquartile ranges for human sample and fixed values for neural networks. Test statistic W and standardized test statistic z are reported with a significant difference at the .05 level (*) and at the .001 level (**).

|         | natural | manipulated | shape50 | shape150 | shape250 | color  |
|---------|---------|-------------|---------|----------|----------|--------|
| humans  | Mdn     |             |         |          |          |        |
|         | 85.71   | 73.81       | 80.95   | 76.19    | 61.90    | 80.95  |
|         | interquartile range | 19.05 | 17.09   | 14.29    | 14.28    | 14.29  | 19.04  |
| AlexNet | Mdn     | 76.19       | 47.62   | 66.67    | 52.38    | 33.33  | 38.10  |
|         | W       | 1489.00     | 2013.00 | 1648.00  | 1888.00  | 2016.00| 2016.00|
|         | z       | 5.66**      | 6.88**  | 5.41**   | 6.79**   | 6.92** | 6.92** |
|         | p-value | <.001       | <.001   | <.001    | <.001    | <.001  | <.001  |
| GoogLeNet | Mdn    | 80.95       | 52.38   | 76.19    | 52.38    | 28.57  | 52.38  |
|         | W       | 1028.00     | 2002.00 | 958.00   | 1888.00  | 2016.00| 1949.00|
|         | z       | 2.78*       | 6.81**  | 2.16*    | 6.79**   | 6.92** | 6.83** |
|         | p-value | <.001       | <.001   | <.001    | <.001    | <.001  | <.001  |
| ResNet-50 | Mdn    | 76.19       | 46.43   | 71.43    | 61.90    | 28.57  | 23.81  |
|         | W       | 1489.00     | 1952.00 | 1440.00  | 1655.00  | 2016.00| 2016.00|
|         | z       | 5.66**      | 6.84**  | 3.88**   | 6.21**   | 6.92** | 6.92** |
|         | p-value | <.001       | <.001   | <.001    | <.001    | <.001  | <.001  |

Figure 3 | Performance of humans and DCNNs on control and challenge images. Human observers outperform tested DCNNs on both control and challenge images by a significant margin. Performance for challenge images is averaged over levels of shape and color manipulation. Error bars indicate 95 % confidence intervals for human participants only, as DCNNs show fixed values without any variance.
3.1.1 Shape

With increasing distortion of shape properties, recognition ability decreases significantly for human participants ($\chi^2(3) = 122.65, p < .001, W = .65$). As additional post-hoc tests for human performance highlight, the effect is significant between all levels of intensity. Interestingly, these results can also be observed in fine-tuned neural networks, as their performance gradually decreases over levels of increasing distortion ($\chi^2(3) = 9.00, p < .029, W = 1$) (see Figure 4 A). In both groups statistical tests indicate large effects of shape manipulation. However, in contradiction to human performance, accuracy of neural networks is statistically indistinguishable between individual consecutive levels (see Table 2). As an exceptional case, GoogLeNet ($\text{Mdn} = 76.19$) accomplishes surprisingly solid performance on shape50 images in comparison to human benchmark capability ($\text{Mdn} = 80.95$) although this difference still reaches a significant level ($W = 958.00, z = 2.16, p = .031, n = 63, r = .27$).

Table 2: Multiple pairwise comparisons between individual levels of manipulation. Standardized test statistics are shown. Median accuracy is significantly different at the .05 level (*) and at the .001 level (**). Dropped significant p-values after Bonferroni correction are indicated (†).

|       | natural | shape50 | shape150 | shape250 |
|-------|---------|---------|----------|----------|
| humans | natural | 1       | 2.52     | 5.28**   | 10.28**  |
|       |         |         | <.012†   | <.001    | <.001    |
| shape50 | 1       | 1       | 2.76*    | 7.76**   |
|         |         |         | .035     | <.001    |
| shape150 | 1       | 1       | 5.00**   |
|         |         |         | <.001    |
| shape250 | 1       | 1       | 1        |

|       | natural | shape50 | shape150 | shape250 |
|-------|---------|---------|----------|----------|
|       | 1       | .95     | 1.90     | 2.85*    |
|       | .343    | .058    | .004     |
|       | 1       | .95     | 1.90     |
| DCNNs |         | .343    | .058     |
|       |         | 1       | .95      |
|       |         |         | .343     |
|       |         |         | 1        |

3.1.2 Color

Further examination suggests that in comparison to control images ($\text{Mdn}_{\text{human}} = 85.71; \text{Mdn}_{\text{DCNN}} = 76.19$) challenge images with an overlaying primary color ($\text{Mdn}_{\text{human}} = 80.95; \text{Mdn}_{\text{DCNN}} = 38.10$) are found to be recognized with significantly lower accuracy in human observers ($W_s = 121.00, z = -.518, p < .001, n = 63, r = -.65$), while the group of tested neural networks did not show a statistically significant decrease ($W_s = 3.00, z = -.160, p = .109, n = 3, r = -.93$). However, this should be a consequence of high intergroup variance between architectures. Again, statistical tests display large effects of color manipulation in both groups. Nonetheless, in line with our hypotheses, human subjects share strikingly greater robustness
towards color manipulation, as their accuracy only decreases by 8.09 % while neural networks’ performance seems to be heavily affected in a sharp decline of 39.68 % (see Figure 4 B).

3.2 Confusion

As a way to explore behavioral classification patterns of the two groups for individual conditions in-depth, confusion matrices were computed. These visualizations are commonly used in the field of machine learning to examine possible issues underlying misclassification. Typically, as in the present case, true labels of images are plotted against predicted labels assigned by the observer, whereby a visualization with diagonally correct and off-diagonally incorrect responses becomes apparent. As indicated by Figure 5, average human responses (A-D) show a diagonally correct classification pattern slightly dissolving across shape distortion but staying nearly untouched by color manipulation. In addition, details suggest that observers occasionally seemed to confuse the categories ‘gibbon’ and ‘spider monkey’. In contradiction to their human prototypes, DCNNs (E-H) display much more confusion across shape manipulation as the diagonal dissolves rapidly. Here, it is clearly visible that even color manipulation severely disrupts recognition ability in feedforward neural networks as the matrix illustrates poor performance with lots of confusion and accuracy close to chance level.

Figure 4 | Performance of humans and DCNNs over levels of manipulation. Human observers outperform DCNNs across all levels of shape manipulation (A) and color manipulation (B) by a significant margin. Both groups experience significant recognition difficulties with increasing intensity of manipulation. Error bars indicate 95 %-confidence intervals for human participants only, as DCNNs show fixed values without any variance.
As this paper focuses on the comparative aspects, further steps proceed very much in the same way as work by Geirhos et al. (2017) [54] with calculation of confusion difference matrices. This method is based on visualizing the difference between human and neural network behavioral patterns as the groups’ mean performances are subtracted in a way to result in positive human (red) and negative DCNN (blue) occurrence entries. Surprisingly, as displayed in Figure 6, even though neural networks performed significantly worse on challenge images across all individual shape manipulations, they still seem to classify a few categories better than human observers under heavy distortion (see i.e. ‘gorilla’ and ‘baboon’).

Figure 5 | Confusion matrices for humans and DCNNs. Computed matrices show mean counts for predicted labels plotted against true labels with diagonally correct and off-diagonally incorrect entries. Classification patterns of human participants (A-D) reveal slightly increasing confusion across shape distortions and still great robustness towards color manipulations. In contrast, DCNNs (E-H) experience heavy confusion across shape and in particular color alterations.

Figure 6 | Confusion difference matrices for human versus DCNN occurrence. Computed matrices show classification occurrence on combinations of predicted and true labels. While positive (red) entries indicate preferred choice by humans, negative (blue) entries denote preferred choice by DCNNs. Difference matrices for shape distortions (A-C) suggest that neural networks generally experienced more misclassifications as most blue entries can be found off-diagonally. However, in some categories DCNNs still outperform human participants. The difference matrix for color alterations (D) clearly highlights a human predominance on images with a color overlay.
3.3 Error Correlation

Further statistical procedure confirms divergent misclassification patterns as several Spearman’s rank correlations offer no compelling evidence for significantly correlated errors made by humans and DCNNs in most manipulations (see Table 3). Interestingly, against our expectations, correlation of committed classification errors suggest no significant coherence between AlexNet and the two other tested feedforward neural networks. However, careful attention must be exercised in interpreting these results, as the computed correlations may not be reliable for lower levels of distortion due to a small number of committed errors.

### Table 3

| shape50     | humans | AlexNet | GoogLeNet | ResNet-50 | DCNNs† |
|-------------|--------|---------|-----------|-----------|--------|
| humans      | 1      |         |           |           |        |
| AlexNet     | .23    | 1       |           |           |        |
| GoogLeNet   | .07    | .09     | 1         |           |        |
| ResNet-50   | .13    | .02     | .33*      | 1         |        |
| DCNNs†      | .15    | .64**   | .54**     | .63**     | 1      |

| shape150    | humans | AlexNet | GoogLeNet | ResNet-50 | DCNNs† |
|-------------|--------|---------|-----------|-----------|--------|
| humans      | 1      |         |           |           |        |
| AlexNet     | .38*   | 1       |           |           |        |
| GoogLeNet   | .25    | -.01    | 1         |           |        |
| ResNet-50   | .22    | -.02    | .29       | 1         |        |
| DCNNs†      | .46*   | .56**   | .67*      | .59**     | 1      |

| shape250    | humans | AlexNet | GoogLeNet | ResNet-50 | DCNNs† |
|-------------|--------|---------|-----------|-----------|--------|
| humans      | 1      |         |           |           |        |
| AlexNet     | .26    | 1       |           |           |        |
| GoogLeNet   | .30    | .08     | 1         |           |        |
| ResNet-50   | .07    | -.23    | .42*      | 1         |        |
| DCNNs†      | .29    | .49**   | .70**     | .61**     | 1      |

| color       | humans | AlexNet | GoogLeNet | ResNet-50 | DCNNs† |
|-------------|--------|---------|-----------|-----------|--------|
| humans      | 1      |         |           |           |        |
| AlexNet     | .25    | 1       |           |           |        |
| GoogLeNet   | -.04   | -.17    | 1         |           |        |
| ResNet-50   | -.06   | -.18    | .49**     | 1         |        |
| DCNNs†      | .14    | .45*    | .61**     | .69**     | 1      |

3.4 Pretrained Deep Neural Networks

Further tests carried out on pretrained DCNNs without a fine-tuning process encourage the selected study design and point towards findings assumed but unproven in preceding analyses. As ResNet-50 (Mdn = 80.95) achieves performance indistinguishable from human observers
(Mdn = 80.95) on shape50 examples (Ws = 636.00, z = -.71, p = .480, n = 63, r = -.09) without previous learning history of these distortions, generally accuracy of pretrained neural networks decreases drastically across levels of manipulation (see Figure 7). Pretrained neural networks frequently link consequences of applied distortion with image features learned from the data of 1000 classes and therefore fall for unintended classifications (i.e. shape manipulations as ‘snail’ or ‘coil’, and green color manipulations as ‘cucumber’) due to the absence of category rules like ‘all images show 1 of 7 species of monkeys’.

4 Discussion

The presented attempt to compare performance of human participants’ biological vision and feedforward neural networks’ artificial vision in core object recognition of natural and manipulated images aims towards understanding the underlying characteristic differences and similarities between the two systems. Therefore, in the anticipated overarching hypotheses, selected DCNNs were thought to be a match for human performance in natural examples, and yet to be surpassed by their accuracy in novel manipulation images. Even though the expected results for control images from the ImageNet data set differ from numerous findings prevalent in the field of computer vision [1, 19, 55], as all three DCNNs fell short of achieving performance statistically comparable to human participants, additional analysis on pretrained models as well as prevalent underpowered training conditions hint at the existence of uncovered

Figure 7 | Performance of humans and pretrained DCNNs over levels of shape and color manipulation.
Performance of pretrained DCNNs shows a sharp decline across manipulations, as networks start to confuse consequences of manipulation with object features due to missing limitation of classes. Error bars indicate 95% confidence intervals for human participants only, as DCNNs show fixed values without any variance.
effects. Our results are consistent with most previous work [26, 27, 54] as image manipulation leads to performance decreases in both visual processing systems, while humans outperform DCNNs in all shape and color conditions by a significant margin. These findings fit with the assumption that humans share great robustness towards color variation as object categorization does not rely on color cues [50], while also being affected by shape distortion as it scales down both image quality and real-world fit.

That aside, correspondence between the brain and feedforward neural networks is still a matter of debate. Generally, as two different approaches ask different notions of this question, they may have to be answered in different ways. In the field of computational neuroscience, the question ‘Do they work in the same way?’ has to be answered with ‘Not quite’ for manipulations. Even though early visual processing in the brain seems to share vast similarities with feedforward neural networks in control images [42], numerous work has pointed out the importance of recurrent connectivity, as in ITC or vPFC, that seems to equip primates with the ability of core object recognition in challenge images. As neural networks experience severe problems with these ‘late-solved’ images, the primate brain simply requires additional computation time in higher visual processing regions [43, 45]. More interestingly, a recent study by Kar and DiCarlo (2020) [56] verified this by proposing that drug-induced inactivation of these same prominently recurrent regions makes the primate brain behave more like a feedforward neural network. The list of processes involved in biological vision is long and exceeds limitations of neural networks modelling feedforward sweeps of signals as next to local and long-range feedforward, lateral recurrent, as well as local and long-range feedback connections are required [21]. It has to be noted that most neural network models are oversimplifications of the primate visual system as they start at the level of V1 and therefore neglect most precortical processing units such as RGC and LGN [57].

In the field of machine learning, the question ‘Do they perform on the same level?’ concerning images including unexperienced manipulations would clearly have to be answered with ‘Not yet’. In this way, the existing performance differences postulated by previous studies for a wide spectrum of manipulations can be supported and extended by our findings. Theoretically, it could be argued that nonstop data collection in a continuous stream of perception and consciousness could give the brain an unfair advantage over artificial neural networks, which are just fed with a sparse selection of examples. While this definitely could be the case for color alterations, as human observers might have possibly seen a painted version of a blue gorilla at some point in their life, it is certainly impossible for not naturally occurring, unseen types of distortion. Therefore, we claim that effects observed for shape manipulations withstand this possible point of criticism similarly to novel eidolon distortion experiments [27, 54]. Another aspect that might seem difficult to manage in a behavioral comparison is the human ability to guess. In this particular case, the chosen study design eliminates this problem as fine-tuned neural networks use a process similar to human guessing when taking their best prediction of many calculated probabilities for a confined spectrum of categories.

However, it is certainly plausible that a number of limitations might have influenced the obtained results. First, as the study was designed as an online experiment, it is difficult to guarantee conduction under controlled conditions. Second, the tested data set contained only few images per category, which could have negatively impacted the fine-tuning process of
DCNNs. Unfortunately, it is hard to reconstruct to what extent neural networks profited from features learned as pretrained models on great quantity of ImageNet data and how much features had to be newly acquired. Therefore, further data collection on a larger number of examples would be needed to determine exactly how image manipulation affects core visual object recognition under controlled conditions. On a final note, it has to be mentioned that human object categorization involves many cognitive processes [58] which can be attributed to attention, memory, generalization, abstraction, and possibly even creativity.

Interestingly, it seems that network architecture is more important for robustness towards novel manipulations than simple network depth. While the by far deepest 50-layer ResNet architecture performed poorly on most of the experiments, the shallower 22-layer GoogLeNet was found to stand out. This implies that its architecture with built-in inception modules, reducing the number of parameters by learning among other things from self-computed image distortions, could have given the network a head start. We hope that future research will concentrate on the rather different recurrent neural networks (RNNs) as they provide extremely promising arguments for neuroscientific explanation and engineering construction of visual systems. One key advantage of RNNs could be found in their capability to memorize previous input through ‘long short-term memory’ units (LSTM) [59], allowing them to adequately process sequential data. This so called ‘reservoir computing’ [60] through numerous reciprocal connections enables dynamic and complex interfering patterns more similar to electrophysiological brain activity. Therefore, one important consideration might be that in comparison to most deterministic ‘in silico’ networks, ‘in vivo’ biological systems are stochastic. As a logical consequence, deep neural networks with implemented stochastic sampling and spiking mechanisms show first signs of success [61, 62, 63]. In image recognition, RNNs could master object manipulation effectively as they would remember preceding examples and offer more complex and better separated representations.

To sum up, we can say that there are two implications that could further artificial models when it comes to visual processing. Most importantly, it appears that local and long-range recurrent connectivity is more important than straight forward network depth. Further work needs to be done in order to establish RNNs as dependable models in the field of computer vision, and in addition, a key factor in resolving issues concerning the sheer amount of required training data could be found in unsupervised learning.

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