

# A Suite of Incremental Image Degradation Operators for Testing Image Classification Algorithms

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**Abstract:** Convolutional Neural Networks (CNN) are extremely popular for modelling sound and images, but they suffer from a lack of robustness that could threaten their usefulness in applications where reliability is important. Recent studies have shown how it is possible to maliciously create adversarial images—those that appear to the human observer as perfect examples of one class but that fool a CNN into assigning them to a different, incorrect class. It takes some effort to make these images as they need to be designed specifically to fool a given network. In this paper we show that images can be degraded in a number of simple ways that do not need careful design and that would not affect the ability of a human observer, but which cause severe deterioration in the performance of three different CNN models. We call the speed of the deterioration in performance due to incremental degradations in image quality the *degradation profile* of a model and argue that reporting the degradation profile is as important as reporting performance on clean images.

## 1 INTRODUCTION

Convolutional Neural Networks (CNNs) are increasingly criticised for being fragile, meaning that they fail on inputs that are out of the distribution (OOD) of the training data or on inputs that are deliberately altered to cause failure (Heaven, 2019). Such inputs are often known as adversarial inputs. This paper proposes a methodology for testing the robustness of CNN models for computer vision, showing how the *degradation profile* of a model can be used to measure robustness and compare one model with another. Some simple image degradation operators, which would not fool a human viewer are shown to significantly reduce model accuracy. The operators are incremental, in the sense that repeated application causes increased degradation, and we find that model accuracy falls as the level of degradation increases. What's more, the ranking of the correct label in the list of model outputs drops as an image degrades, as does the probability assigned to the correct label. We call these three measures the *accuracy degradation profile*, the *rank degradation profile* and the *probability degradation profile*. These measures degrade faster for less robust models.


Three different models are compared: ResNet50 (He et al., 2016), the B0 version of EfficientNet (Tan

and Le, 2019), and version 3 of the Inception model (Szegedy et al., 2016). The implementations readily available in Keras were utilised, using the standard weights from the Imagenet training data. No additional training was performed. These models were chosen because they are widely accessible and widely used, so their robustness is of interest. The paper is not designed as a ranking of these algorithms—they are chosen as illustrations only.

### 1.1 Background and Motivation

CNNs have become the state-of-the-art in computer vision over the past decade, performing at or even in excess of human levels of accuracy (Chen et al., 2015). They have found application in industry, security, entertainment and medicine and will play a crucial role in advances in technology such as self-driving cars. It is becoming increasingly clear, however, that current CNN models are not as robust as they need to be (Heaven, 2019), and if they are to be relied on to drive us safely home or detect cancer in a scan, then we need to be able to trust them not to make mistakes (Maron et al., 2021a), (Maron et al., 2021b), (Finlayson et al., 2019).

There are a small number of standard measures of model quality. Most papers report accuracy (the percentage of correctly classified images) and other

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derived measures such as precision, recall or f-score. These measures are calculated from a dataset that is removed from the training corpus before the modelling process begins so they are independent of that process. They are, however, generally taken from the same distribution as the training data. Recently, there has been an increased amount of work addressing the question of performance on out of distribution (OOD) examples. These are images that clearly belong to one of the target classes for the model, but which have been altered in some way to make them novel to the classifier.

Much of the recent work in this field has concentrated on adversarial images, which are images that are generated with the intention of fooling a classifier, often guided by the classifier itself. In an early example of this (Szegedy et al., 2013) used the gradients at the output layer of a classification CNN to guide small changes to the input pixels that would leave the input image visually unchanged but elicit an incorrect classification from the model. Other similar results have followed, while others have taken the opposite view and produced images that are classified with high confidence by a CNN but which are completely unrecognisable to humans (Nguyen et al., 2015). Other approaches use rendering software to produce images in which the object to be classified is in an unusual pose (Alcorn et al., 2019) or to filter images to find those that are naturally difficult for CNNs to classify (Hendrycks et al., 2019).

Some methods follow the gradients of the model and some make use of gradient free optimisation techniques (Uesato et al., 2018). Others make use of adversarial images generated using a surrogate model that was trained on a similar (or the same) data set. These are known as transfer based attacks (Papernot et al., 2017). Methods that make use of the gradients accessible in an image may be classed as white box attacks, as they are guided by access to the model. Other adversarial methods, known as black box attacks, degrade input images in a way that would not cause a human observer any difficulty in making a classification, but which can fool a CNN model. For example, (Engstrom et al., 2019) explore the effects of rotations and translations on classifier robustness. They also point out that there is a focus in the literature on finding small image perturbations (in some p-norm measure) but that humans might classify two images as being of the same class even if there are large differences in the pixel values.

Not all adversarial attacks involve manipulating an existing image. A number of researchers have produced stickers that can be used to defeat computer vision algorithms by placing them in a real world scene.

For example, (Komkov and Petiushko, 2021) show how stickers worn on a hat confuse the state-of-the-art ArcFace face recognition model. (Thys et al., 2019) developed a patch that can be printed and held by a person, which is capable of hiding them from a person detection algorithm.

We make the distinction between targeted adversarial examples and degraded examples. The assumption in a lot of the work on adversarial images is that a malicious agent generates images to fool a CNN classifier. The assumption behind degraded images is more benign: simply that variations in light, weather, image quality, occlusion and color occur naturally and may impact the performance of classifiers. Of course, images may also be degraded by malicious agents and some of the degradations proposed in this paper are both effective and trivial to apply.

We conclude that CNNs are not as robust as they need to be, that they are easily fooled into making errors and that a measure of robustness would be an important step towards addressing that issue. The rest of the paper proposes a series of such measures and illustrates their use on three popular CNN models.

## 1.2 Degradation Operators

Fourteen degradation operators were tested, each with 30 different levels of degradation from the original image. All the operators have the quality that each subsequent level of degradation increases the difference from the original image. Operators can be characterised as either **global**, where every pixel in the image is altered at each level, or **local**, where only some pixels are altered. They may also be characterised as being **deterministic**, where the same degradation has the same effect in repeated applications to the same image, or **stochastic**, where the effect of applying a degradation is drawn at random from some distribution. Operators may also be either **colour** based, where the colour palette is altered, or **pixel** based, where the alterations are to individual pixels.

Each level of a degradation has a degree to which it is applied. For example, if random pixel values are changed, the degree is the number of pixels altered at a single level. These degree parameters are chosen experimentally to produce a degradation to near zero accuracy after 30 levels.

The following sections briefly describe and characterise each degradation operator. Unless stated otherwise, the phrase *randomly selected* means that samples were drawn from a uniform distribution.

**Random Lines.** Lines of one pixel width are drawn onto the image with anti-aliasing. Lines start at a ran-

dom location on the left or top edge of the image and end at a random location on the right or bottom edge, meaning they have a location and orientation both drawn from a uniform random distribution. Two different operators are defined, one which draws white lines and one which draws black lines. This operator is local, stochastic and pixel based. A single line is added at each level of the degradation.

**Random Boxes.** Small black rectangles are drawn onto the image, with random locations and with height and width chosen from a uniform random distribution over 2 to 5 pixels. This operator is local, stochastic and pixel based. The number of rectangles added at each level of the degradation is  $(h + w)/10$  where  $h$  and  $w$  are the height and width of the image respectively.

**Global Blur.** A five by five pixel uniform blur is applied to the image by replacing each color channel value for each pixel by the average of the values in a  $5 \times 5$  square neighbourhood around the pixel. Repeated application of the operator leads to increased levels of blur. This operator is global, deterministic and pixel based.

**Local Blur.** Small rectangular areas of the image are replaced by the average value of the pixels in that rectangle (for each color channel). Rectangle locations are selected at random from a uniform distribution over the image and height and width are selected uniformly at random from  $[2, 10]$  pixels. This operator is local, stochastic and pixel based. The number of rectangles added at each level of the degradation is  $(h + w)$ .

**Random Noise.** A number of pixels, chosen at random, have their colours changed to a new, random color. This operator is local, stochastic and pixel based. The number of pixels changed at each iteration is  $wh/50$ .

**Random Pixel Exchange.** Pairs of pixel locations are selected at random and the color values of the two locations are exchanged, so that the pixels effectively swap locations. The number of pixels exchanged at each iteration is  $wh/20$ . This operator is local, stochastic and pixel based.

**Random Adjacent Pixel Exchange.** Pairs of adjacent pixels are swapped. The location of the first pixel is chosen at random and the location of the second is chosen at random from the eight adjacent locations

around the first. The number of pixels exchanged at each iteration is  $wh/20$ . This operator is local, stochastic and pixel based.

**White Fog.** Pixel locations are selected at random and the color of the chosen pixels is faded towards white. The fading is done by adding 20 to each of the colour channels and clipping each at 255. The number of pixels exchanged at each iteration is  $wh/5$ . This operator is local, stochastic and pixel based.

**Fade to Black, White or Greyscale.** The whole image has its color space altered so that it fades towards a chosen target palette, either an all black image, an all white image, or the image in greyscale. To fade towards black, each color channel of each pixel is multiplied by 0.9 and to fade to white, they are multiplied by 1.1. The move towards greyscale is achieved by converting the image to the HSV colour space, multiplying the saturation channel by 0.9, and then converting back to the RGB colour space. These operators are global, deterministic and color based.

**Posterize.** The number of colors in the palette of the image is reduced at each iteration. A simple method is used, in which each color channel is discretized separately into a chosen number of distinct values. The color range from 0 to 255 is split into  $b$  bins, each of size  $255/b$ . The color value for bin  $i$  is calculated as  $(i + 1)255/b$ . The bin count,  $b$  starts at 32 in these experiments and decreases by one each iteration until it reaches 2 at the last level. This operator is global, deterministic and color based.

**JPEG Compress.** Images are compressed using JPEG compression with increasingly high levels of compression. In this work, the `imencode()` function of the Python OpenCV library was used to encode each image, which was then reconstructed using `imdecode()` to produce a degraded image. The degree of compression over 30 iterations started at 32 and finished at 2. This operator is global, deterministic and color based.

**Model Gradient Descent.** This is the only one of the degradation operators that relies on access to the model being used to make the classifications. It follows (Szegedy et al., 2013) by following the gradients of the output probabilities from the model, back propagating them to the input layer to make small changes to the input image that move the classification away from the correct output. This operator is local, deterministic and pixel based.

### 1.3 Approximating Real World Degradation

All but one of the operators described above are applied without knowledge of the model that will be used to make classifications. They can all be applied very simply to source images in digital form. Some may also be applied to real world scenes before the scene is photographed and some are approximations to real world degradations in image quality. Placing small black or white rectangular stickers onto objects such as road signs has been shown to confuse classification models (Eykholt et al., 2018) and we approximate that with the Random Boxes operator. Similarly, it would be possible to draw thin black lines across objects that you did not want detected. The Local Blur operator is an approximation to the effects of grease or water on a lens, blurring small areas of the image. The Fade to Black operator approximates darkness and the fade to white operator approximates saturation due to bright light. Both situations occur naturally in vehicle driving situations. The White Fog operator approximates the effects of fog or smoke in a scene and the Posterise and JPEG Compression operators investigate the effects of poor quality sensors or storage compression. We include one adversarial example—the Gradient Descent—for comparison, but this paper is primarily concerned with degraded images rather than carefully designed attacks.

## 2 METHODOLOGY

The degradation profile for three popular CNN image classification algorithms was calculated. The models are the 50 layer version of ResNet (ResNet50) (He et al., 2016), the B0 version of EfficientNet (EfficientNetB0) (Tan and Le, 2019), and version 3 of the Inception model (InceptionV3) (Szegedy et al., 2016), all using the default weights trained on the Imagenet dataset. The Keras implementation of these models was used. Models were tested using a small sample of 590 images from the Imagenet training set, all selected for being correctly classified by the ResNet50 model. Three measures of performance were calculated: **Accuracy** is the proportion of correctly classified images over the dataset. **Label Rank** is the average index position of the correct label in the model output list, sorted by probability. A score of 5 suggests that the model is often incorrect, but that the correct answer is still in the top five. There are 1000 class labels in the Imagenet dataset so a model that is no better than chance would score around 500. **Label Probability** is the average probability assigned by the

model to the output label that is known to be correct. The models have a softmax at the output layer, so we expect the probability assigned to non-winning labels to be low.

For each model, the testing regime was as follows: For each degradation operator, all 590 images are presented to the model once for each of the 30 levels of degradation. The three performance measures were recorded for each level. The images are of different sizes, but the models expect an input of a fixed size, so the images were resized **before** the degradation operations were applied, meaning that the pixel based operations really did alter single pixels in the images processed by the models. That is to say that the degradations were not subject to scaling.

## 3 RESULTS

Over three models, fourteen degradation operators, 30 levels of degradation, and three performance metrics, there are many ways to analyse the results. The simplest aggregation is to calculate the average of each performance metric for each model. This gives an easily digested comparison among the models. Figures 1, 2 and 3 show the average of the three performance metrics: accuracy, ranks and probability, by level, for each of the three models. They show that InceptionV3 is the most robust across all three measures. Note that for the correct label rank measure, low values are closer to the top, so the winning label has a rank of zero.

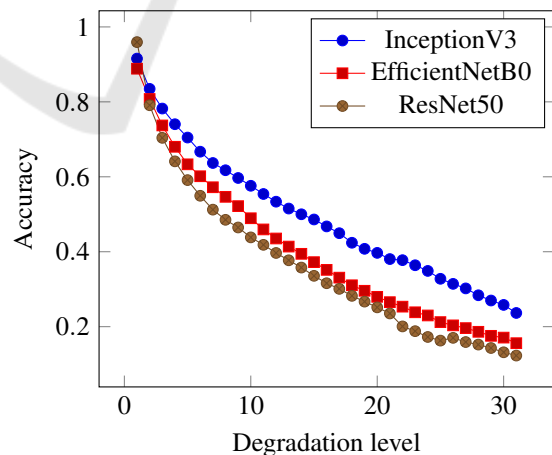


Figure 1: The accuracy degradation profile for ResNet50, EfficientNetB0 and InceptionV3 across 30 levels of input image degradation. The average is taken over 14 different degradation operators.

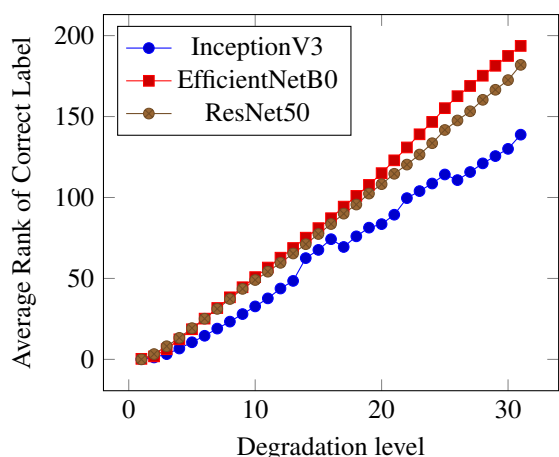


Figure 2: The rank degradation profile for ResNet50, EfficientNetB0 and InceptionV3 across 30 levels of input image degradation. The average is taken over 14 different degradation operators.

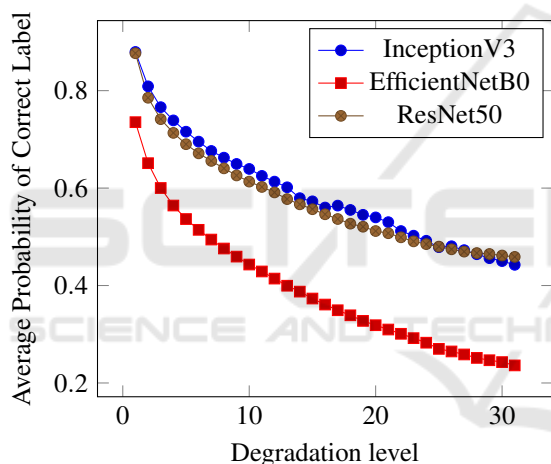


Figure 3: The probability degradation profile for ResNet50, EfficientNetB0 and InceptionV3 across 30 levels of input image degradation. The average is taken over 14 different degradation operators.

### 3.0.1 Degradation Profile by Model

The degradation profile of a model, given a test set and a degradation operator describes the performance of the model on increasingly degraded versions of the images in a data set for which it was originally capable of achieving 100% classification accuracy. The steeper the curve, the more fragile the model is judged to be. We compare the profile of each operator in turn. Figures 4, 5, and 6 show the profiles for ResNet 50, EfficientNet B0 and Inception V3. Looking at these figures, we learn that all networks are robust to changes from full colour to grey scale and all are particularly vulnerable to blurring an image or swapping the values in a few pixel pairs.

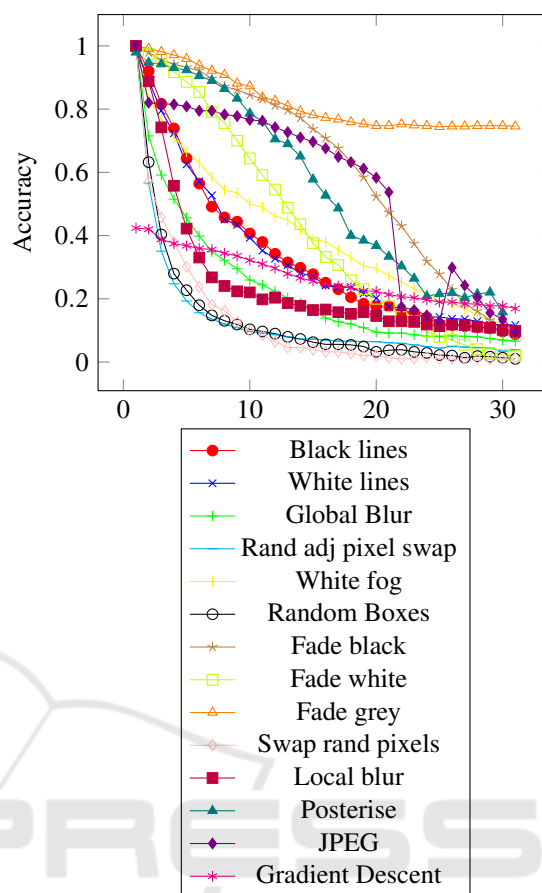


Figure 4: The accuracy degradation profile for ResNet50 for 14 different degradation operators. The y axis shows accuracy and the x axis increases with the degree of degradation. The model is particularly vulnerable to the addition of small black rectangles, the swapping of pixel locations and blurring of the image. It can also be quickly fooled using gradient descent away from the winning category.

### 3.1 Example Failure Points

In this section we investigate the degree to which an image needs to be degraded before the average accuracy of a CNN classifier drops below 50% on the test data. Tables 1, 2, and 3 describe the degree of degradation required to move each of the three models from 100% accuracy to 50% accuracy. The percentage of the pixels in the original image that are changed as a result of each degradation is given, along with a description of the change. This measure is only meaningful for the pixel based operators, as the global operators alter every pixel in an image. The three operators that require the fewest pixels to change before accuracy drops below 50% are those that draw lines or small boxes onto the image. In the case of the small boxes, for example, only 3% of the pixels need to be changed in the images in the test set be-

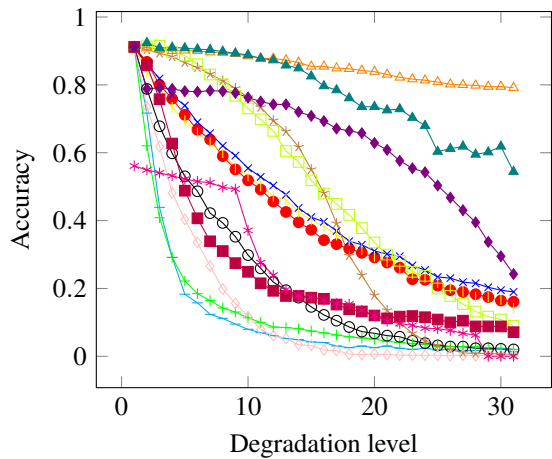


Figure 5: The accuracy degradation profile for EfficientNet B0 for 14 different degradation operators. The y axis shows accuracy and the x axis increases with the degree of degradation. The model is particularly vulnerable to the swapping of pixel locations and blurring of the image. Refer to figure 4 for the legend.

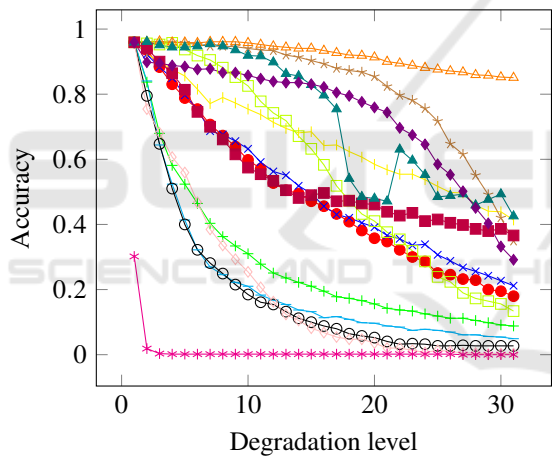


Figure 6: The accuracy degradation profile for Inception V3 for 14 different degradation operators. The y axis shows accuracy and the x axis increases with the degree of degradation. The model is particularly vulnerable to the addition of small black rectangles, the swapping of pixel locations and blurring of the image. Refer to figure 4 for the legend.

fore the accuracy drops below 50% for the ResNet50 model. The degradations that the models are most robust to are the color saturation based operators: fade to black, fade to white and fade to grey scale. All three models are very robust under a change from full color to grey scale, maintaining around 80% accuracy even when the image is reduced completely to grey scale. Similarly, the models are robust to a reduction in the number of colours in the palette. EfficientNet is particularly robust, achieving 55% accuracy when the palette is reduced to just 8 colors.

The gradient descent operator is the only one we employ that is aided by access to the model itself. By following the steepest gradient away from the winning category label, an adversarial image is generated, which is similar to the original image, but produces a different output label. A more robust model will require a greater number of steps down the classification gradient before the output class is changed. Of the three models we investigate here, ResNet50 and EfficientNetB0 are far more brittle than the Inception V3 model, with the number of steps required to change the labels on 50% of the test set being 1, 4 and 22 for the models respectively.

Table 1: The average change made to images in the test set to reduce the accuracy of the ResNet50 model from 100% to 50% on that dataset. The % Ch. column contains the number of pixels changed as a percentage of those in the image.

Degr.	Change Made	Ch.
Black Lines	6 randomly placed 1 pixel wide lines	6%
White Lines	7 randomly placed 1 pixel wide lines	8%
Random Boxes	90 boxes	3%
Global blur	4 consecutive 5×5 convolutions	100%
Local blur	1792 local blur boxes	70%
Noise	8% of pixels replaced with a random color	8%
Swap Adjacent Pixels	56% of pixels changed	56%
Swap Rand. Pixels	9% of pixels changed	9%
White Fog	Average pixel values increased: 151 to 187	86%
Fade Black	Average pixel values reduced: 151 to 18	100%
Fade White	Average pixel values increased: 151 to 250	100%
Posterise	Reduced to 151 Colors	100%
JPEG Compress	Reduced to 135 Colors	100%
Gradient Descent	1 Iteration	100%

### 3.2 Visualising the Effects of Degradation

To help the reader visualise the degree to which images need to be changed to produce a significant drop in model performance, we present some visual exam-

Table 2: The average change made to images in the test set to reduce the accuracy of the EfficientNetB0 model from 100% to 50% on that dataset. The % Ch. column contains the number of pixels changed as a percentage of those in the image.

Degr.	Change Made	Ch.
Black Lines	10 randomly placed 1 pixel wide lines	10%
White Lines	12 randomly placed 1 pixel wide lines	13%
Random Boxes	224 boxes	8%
Global blur	2 consecutive 5×5 convolutions	100%
Local blur	896 local blur boxes	70%
Noise	16% of pixels replaced with a random color	16%
Swap Adjacent Pixels	56% of pixels changed	56%
Swap Random Pixels	13% of pixels changed	13%
White Fog	Average pixel values increased: 151 to 190	89%
Fade Black	Average pixel values reduced: 151 to 31	100%
Fade White	Average pixel values increased: 151 to 253	100%
Posterise	Reduced to 8 Colors	100%
JPEG Compress	Reduced to 25 Colors	100%
Gradient Descent	5 Iterations	100%

ples. Specifically, we present examples of images that move an Inception V3 model from 100% accuracy to 90%, 50% and 10% respectively. For each degradation operator, the accuracy profile is used to find the number of times the degradation needs to be applied to first cause the accuracy to drop below the target threshold on the test dataset. A single example image is then degraded this many times to produce an example image. These images are just examples, but they illustrate to the human viewer how little or much degradation is needed to cause a drop in performance from slight to catastrophic.

#### 4 OTHER MEASURES OF ROBUSTNESS

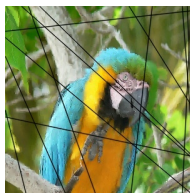
CNN models have an output layer that associates a score or probability with every possible class label. Classification is performed by identifying the label

Table 3: The average change made to images in the test set to reduce the accuracy of the Inception V3 model from 100% to 50% on that dataset. The % Ch. column contains the percentage of pixels changed in the image.

Degr.	Change Made	Ch.
Black Lines	13 randomly placed 1 pixel wide lines	14%
White Lines	14 randomly placed 1 pixel wide lines	13%
Random Boxes	176 boxes	7%
Global blur	5 consecutive 5×5 convolutions	100%
Local blur	5824 local blur boxes	77%
Noise	24% of pixels replaced with a random color	24%
Swap Adjacent Pixels	78% of pixels changed	78%
Swap Random Pixels	22% of pixels changed	22%
White Fog	Average pixel values increased: 151 to 225	100%
Fade Black	Average pixel values reduced: 151 to 8	100%
Fade White	Average pixel values increased: 151 to 253	100%
Posterise	85 Colors	100%
JPEG Compress	Reduced to 23 Colors	100%
Gradient Descent	Reduced to 22 Iterations	100%

with the highest score. A model might be considered more robust if a degradation causes the correct label to be rated as the second most probable rather than the 10th. Where the probabilities of the top rated categories are close, there are methods based on context (Chu and Cai, 2018) that might help disambiguate the confusion. Therefore, it is useful to know the probability assigned to the correct label and how far down the probability rankings a degradation moves the correct label. We measure the average probability and the average rank of the correct class across our test dataset for each degree of degradation. We call these the probability degradation profile and the rank degradation profile.

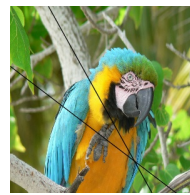
Figures 10, 11 and 12 show the rank degradation profiles for ResNet50, EfficientNetB0 and Inception V3, respectively and figures 13, 14 and 15 show the probability degradation profiles for ResNet50, EfficientNetB0 and Inception V3, respectively.



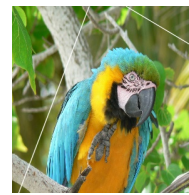
(a) Black lines.



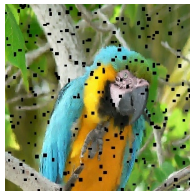
(b) White Lines.



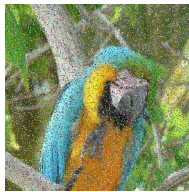
(a) Black lines.



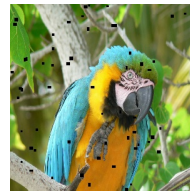
(b) White Lines.



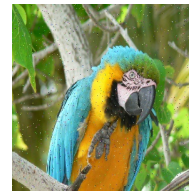
(c) Small Boxes.



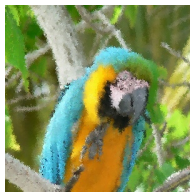
(d) Random Noise.



(c) Small Boxes.



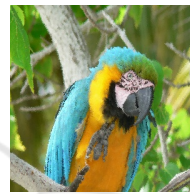
(d) Random Noise.



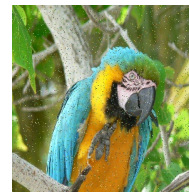
(e) Adj. Pixel Swap.



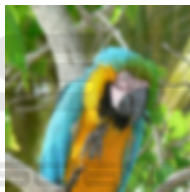
(f) Rand. Pixel Swap.



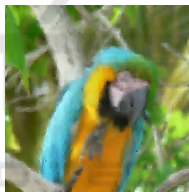
(e) Adj. Pixel Swap.



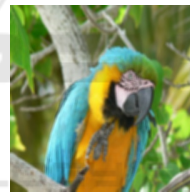
(f) Rand. Pixel Swap.



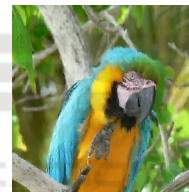
(g) Global Blur.



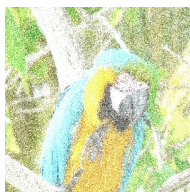
(h) Local Blur.



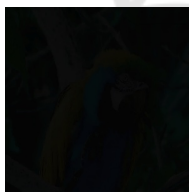
(g) Global Blur.



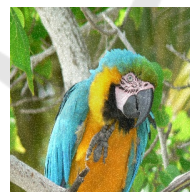
(h) Local Blur.



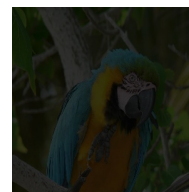
(i) White Fog.



(j) Fade to Black.



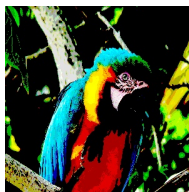
(i) White Fog.



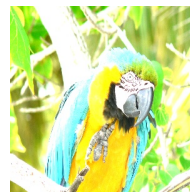
(j) Fade to Black.



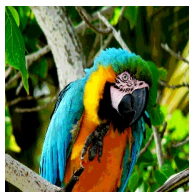
(k) Fade to white.



(l) Posterise.



(k) Fade to white.



(l) Posterise.

Figure 7: Example degraded images at the first point where the accuracy measure for our test data first drops from 100% to below 50%.

Figure 8: Example degraded images at the first point where the accuracy measure for our test data first drops from 100% to below 90%.



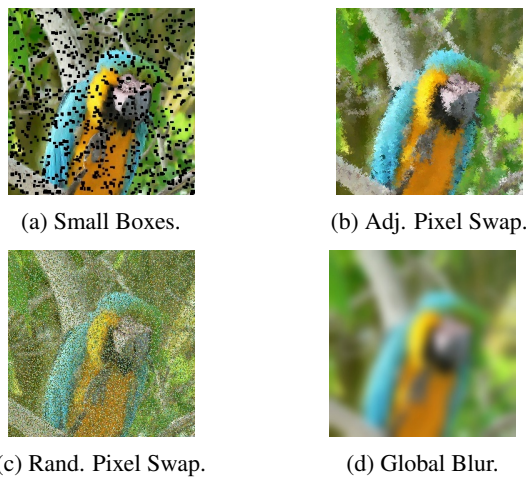


Figure 9: Example degraded images at the first point where the accuracy measure for our test data first drops from 100% to below 10%.

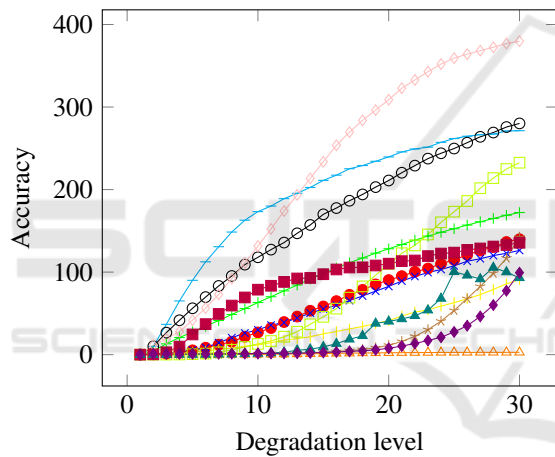


Figure 10: The rank degradation profile for ResNet50 for 14 different degradation operators. The y axis shows average ranking of the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

## 5 CONCLUSIONS AND FURTHER WORK

It is clear that some of the commonly used computer vision CNN models are easily fooled by a range of image degradations. By presenting a suite of simple degradation operators, we hope to encourage researchers to include a measure of robustness in addition to accuracy measures when presenting new algorithms or architectures. We found that three commonly used CNN architectures were robust to changes in the color palette, but that small pixel

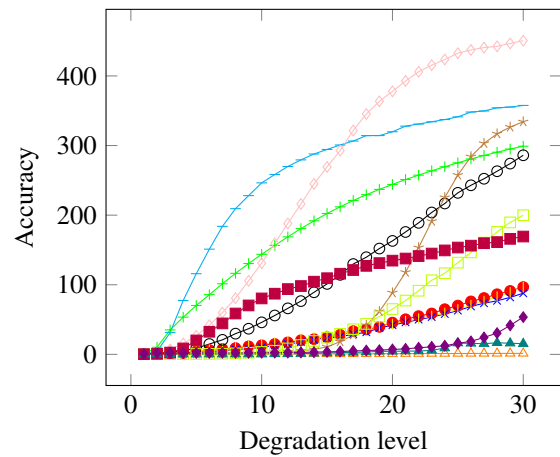


Figure 11: The rank degradation profile for EfficientNet B0 for 14 different degradation operators. The y axis shows average ranking of the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

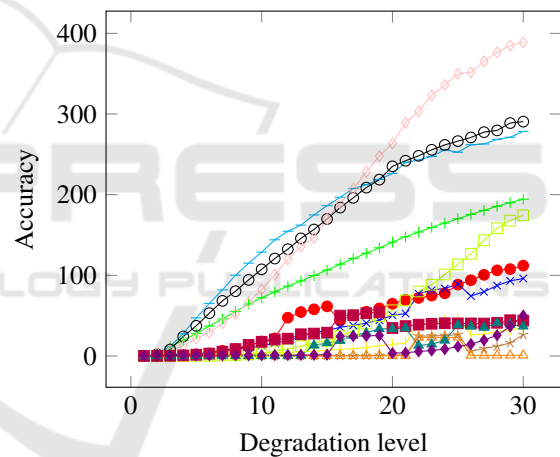


Figure 12: The rank degradation profile for Inception V3 for 14 different degradation operators. The y axis shows average ranking of the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

level changes such as drawing thin lines or swapping random pixel values cause severe degradation in accuracy. We show some examples where the accuracy of the CNN falls below 10%, and the identity of the object is still clear to the human eye. We hope that more researchers will include measures of robustness when they report the performance of new computer vision algorithms. To this end, the code to perform the image degradations and associated experiments may be found on github at <https://github.com/kevswingler/ImageDegrade>.

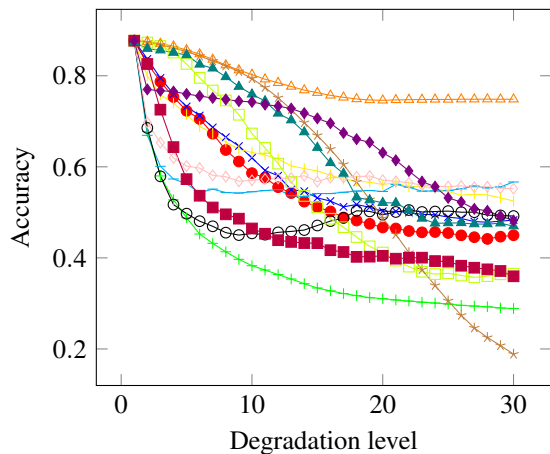


Figure 13: The probability degradation profile for ResNet50 for 14 different degradation operators. The y axis shows the average probability assigned to the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

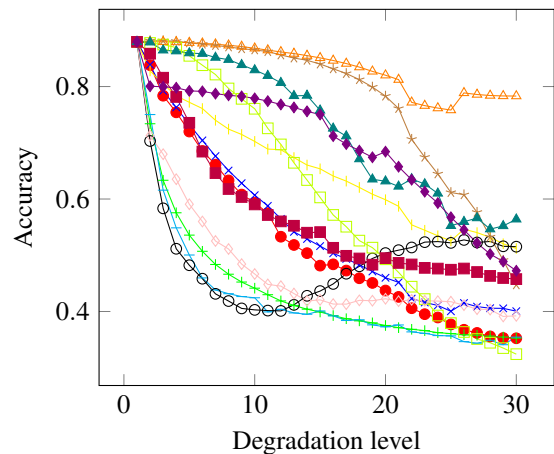


Figure 15: The probability degradation profile for Inception V3 for 14 different degradation operators. The y axis shows the average probability assigned to the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

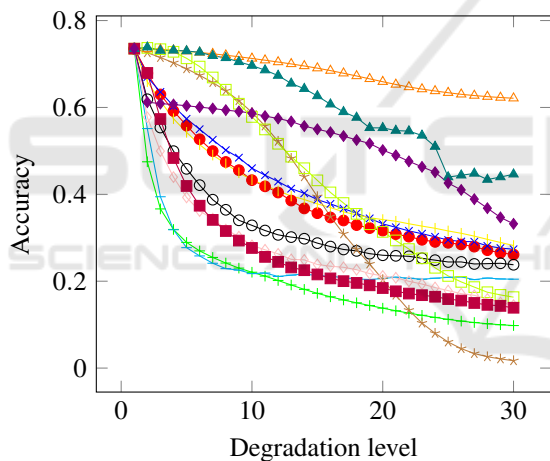


Figure 14: The probability degradation profile for EfficientNet B0 for 14 different degradation operators. The y axis shows the average probability assigned to the correct label and the x axis increases with the degree of degradation. The three most damaging degradations are swapping pixel pairs, and occluding with small rectangles. Refer to figure 4 for the legend.

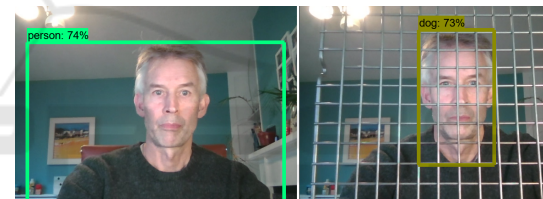


Figure 16: It is easy to fool an SSD object detector by simply holding a grid in front of yourself - here the classification changes from person to dog.

We are curious to see whether the simple degradations we propose can be used live. For example, rather than use a carefully designed patch to fool a person detector, as proposed by (Thys et al., 2019), simple props are often sufficient. The question of computer vision camouflage is the subject of ongoing work, but figure 16 shows one small example where an SSD MobileNet object detection algorithm trained on the MS-COCO dataset is fooled into labelling a person as a dog with the aid of nothing more sophisticated than

a cake cooling rack. As the robustness of models improves, the type of degradations that should be tested will evolve and we do not expect the operations described here to be challenging for long. We hope that other authors will propose further tests and that some kind of arms race will enhance the robustness of all models. We hope, of course, that the algorithm developers win the race but at the moment what is important is that they start to take part.

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