Resiliency in Deep Convolutional Neural Networks

Faiz Ur Rahman

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Resiliency in Deep Convolutional Neural Networks

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Faiz Ur Rahman

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A Thesis Submitted in Partial Fulfillment of the Requirements for the Degree of Master of Science in Computer Engineering

R·I·T | KATE GLEASON
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Resiliency in Deep Convolutional Neural Networks

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Abstract

The enormous success and popularity of deep convolutional neural networks for object detection has prompted their deployment in various real world applications. However, their performance in the presence of hardware faults or damage that could occur in the field has not been studied. This thesis explores the resiliency of six popular network architectures for image classification, AlexNet, VGG16, ResNet, GoogleNet, SqueezeNet and YOLO9000, when subjected to various degrees of failures. We introduce failures in a deep network by dropping a percentage of weights at each layer. We then assess the effects of these failures on classification performance. We find the fitness of the weights and then dropped from least fit to most fit weights. Finally, we determine the ability of the network to self-heal and recover its performance by retraining its healthy portions after partial damage. We try different methods to re-train the healthy portion by varying the optimizer. We also try to find the time and resources required for re-training. We also reduce the number of parameters in GoogleNet, VGG16 to the size of SqueezeNet and re-trained with varying percentage of dataset. This can be used as a network pruning method.
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Acronyms

2D

Two-dimensional

AdaGrad

Adaptive Gradient Descent

AID

Aerial Image Dataset

ANN

Artificial Neural Network

ARprop

ADAM Resilient Propagation

ADAM

Adaptive Moment Estimation

AlexNet

Alex Network

CNN

Convolutional Neural Network

DCNN

Deep Convolutional Neural Network

FC

Fully Connected
FFDN

Feed Forward Dense Network

GoogleNet

Google Network

MSCOCO

Microsoft Common Objects in Context

PCA

Principal Component Analysis

RMS

Root Mean Square

ReLU

Rectified Linear Unit

ResNet

Residual Neural Network

Rprop

Resilient Propagation

SqueezeNet

Squeeze Network

VGG

Visual Geometry Group

YOLO

You Only Look Once
Chapter 1

1.1 Motivation

Deep Convolutional Neural Networks (DCNNs) have become the golden standard for object detection and localization and are increasingly adopted for various applications including face recognition [1], autonomous vehicles [2] and medical diagnosis [3]. The combination of Artificial Neural Network and convolution led to solving of object recognition and other computer vision related problems that was first accomplished by AlexNet [4] architecture on ImageNet [5] challenge which incited research in deep convolutional neural networks. The research led to development of successful architecture like VGG [6], GoogleNet [7] and ResNet [8], that included deeper or more number of convolutional(hidden) layers. Such architectures became popular in the
field of computer vision especially for object recognition tasks. Over time deeper and much more efficient architectures were introduced for object detection tasks like Faster-RCNN [9] and YOLO [10] [11]. With the increase in depth of Convolutional Neural Networks increased the demand for larger GPU’s, to reduce this, smaller architectures like SqueezeNet [12] started taking the place of these larger architectures which were more suitable for mobile or embedded platform. There is also a trend in pruning the network architecture to reduce its computations which makes training easier and faster. This was first achieved by DenseNet [13] architecture which used half the number of parameters as VGG without sacrificing its performance. A comprehensive study on network speed-accuracy tradeoffs is presented in [14].

CNNs have turned out to be powerful in analyzing images and detecting objects of interest. One of the significant advantages of CNN’s is the end to end learning of features with a classifier, giving it leeway over conventional feature extractors paired with classifiers. The limitation of CNNs lies in their requirement of immense training datasets making it computationally costly. Deep learning frameworks, such as Caffe [15], Torch [16], Tensorflow [17] and PyTorch [18], have enabled training with the assistance of GPUs and have made the learning process considerably more effective. To battle the requirement for huge datasets, transfer learning is regularly utilized.
Transfer learning is a strategy used to learn new layer weights in neural network for a given dataset from a pretrained model using a standard dataset.

With the increasing use of DCNNs in real world situations, hardware or embedded implementation are placed in environments where they could suffer damage due to hardware failure like memory failure [19] or harsh external conditions or software attacks like Malware attack which is a cyber-attack that performs operations on victim’s computer without their knowledge [20] or bit-flipping, where the attacker can change the ciphertext without the knowledge of the owner [21]. However, to our knowledge, the performance of DCNNs under failure conditions has not been investigated. The objective of this thesis is to explore the resilience of six popular object detector network architectures, AlexNet [4], VGG [6], ResNet [8], SqueezeNet [12], GoogleNet [7] and YOLO [10] [11] [22], when subjected to various degrees of failure.

A potential form of failure in a DCNN is due to corruption of network weights. This type of corruption could occur at few or many nodes in the network, and is likely to result in misclassification and leading to deterioration in performance.

1.2 Literature Review
There is limited research on the performance of deep networks under various types of faults. The most relevant research is reported in [23] and [24]. In [23] the effects of coefficient quantization on network performance is examined for fixed point implementations.

In [24] examining the resilience of the network is done by dropping features randomly using a stress function (TDR-1) and performing Principal Component Analysis (PCA) which keeps the most significant features along the direction of maximum variance. The stress function is passed through the network with frozen layers and trained on SVM classifier. In addition to TDR-1, Q-2 feature compression due to quantization is applied simultaneously. The difference between quantization and stress is that quantization just tampers the numerical precision of representation [25], while stress refers to dropping the weights randomly. In [19] resiliency is explored by bit level fault injection, which imitates the faults at the hardware level i.e. memory while training and testing. The weight file is modified while training which is called static injection of errors and while testing which is called dynamic injection of faults. Whereas, our experiments involve different ways of dynamic injection of faults. Our contributions go well-beyond the work in [24], [23] and [19], by methodically examining the effects of faults in six different architectures and retraining the networks to recover some of the lost performance.
The brute force ranking method is to prune each layer, and observe how the cost changes when running on the training set. This is known as oracle ranking, the most ideal ranking of filters for limiting the system cost change. Presently to quantify the performance of other training techniques, pruning a filter is the equivalent to zeroing it out [26]. The ranks are then normalized [27].

The resilient propagation (Rprop) has been very popular for FFDN training [28]. FFDN refers to feed forward neural network where connections between the neurons do not form a loop. Combining dropout with Rprop proved to be more effective and started giving better results [29]. Rprop considers only the sign of the gradient for its weight updating independently for each of the parameters [30]. By independently, each parameter will have its own step size. So, instead of updating with the magnitude of the gradient, it updates with the step size that is defined for that weight. That step size adapts individually over time to accelerate learning in the direction needed [31]. This method is much faster than standard SGD backpropagation.

1.3 Contribution

The contributions of this thesis are summarized as follows:
1. We provide a quantitative assessment of the DCNN object detector performance due to partial failures.

2. We gain understanding of the effects of faults at various locations in the DCNN's hidden layers.

3. We explore that DCNN’s can be of optimal depth without having to compromise performance i.e. we can remove few layers without compromising performance.

4. We explore that DCNN’s can have fewer parameters (weights) without having to compromise performance.

5. We demonstrate that resiliency of DCNN’s are dependent on the architecture and not the datasets.

6. We demonstrate that Rprop is the best retraining technique for healing the network.

7. We demonstrate that DCNN’s can self-heal to overcome the effects of faults by retraining the healthy parts of the network.

8. We propose a technique for pruning DCNN’s to the desirable depth for a given problem [32].

9. We explore the effects of dataset size required for re-training.

1.4 Thesis Organization

The thesis is organized in five chapters. Brief information about each chapter is
mentioned below:

- **Chapter 1. Introduction:** This chapter gives a brief introduction to the topic of thesis, motivation behind this thesis followed by a literature review of previous work in this field finally the contribution of the thesis.

- **Chapter 2. Materials:** This chapter starts by describing the datasets that are used in this thesis in detail, followed by a detail description of convolutional neural network architecture used in this thesis.

- **Chapter 3. Proposed Methods:** This chapter starts with description of resiliency and how the network has been trained, followed by dropping of weights with and without computation of fitness of the neuron. The next section describes how the network can heal itself by re-training by using different methods. The last section is pruning VGG16 and GoogleNet to the size of SqueezeNet.

- **Chapter 4. Results:** This chapter describes how the each of CNN’s act when subjected to damages followed by how fast each of these networks can heal itself after the introduction of failure. This chapter also has results for pruning VGG16 and GoogleNet.

- **Chapter 5. Conclusion:** This chapter gives the conclusion of the thesis including which network performs well under stress and which can heal itself quickly.
Chapter 2

Materials

This chapter starts by describing the datasets that are used in this thesis in detail followed by a detailed description of the convolutional neural network architectures used in this thesis.

2.1 Dataset

2.1.1 MS COCO

COCO stands for Common Objects in Context [33]. As indicated by the name, images in the COCO dataset are taken from regular scenes and includes labels for the objects in the images. The dataset contains images of 91 objects types with a total of 2.5 million labeled instances in 328k images. Fig. 2.1 shows some examples from MSCOCO
2.1.2 AID

AID is an aerial image dataset [34]. A few examples are shown in Fig. 2.2. AID dataset consists of 30 classes including airport, railway track, waterbody and so on and total of images are 10000 images for training and testing [34]. The images in AID are multi-source, as Google Earth images [35], from various other remote imaging sensors. This presents a bigger challenge than single source images. In addition, all the example
images per each class in AID are collected from different regions, for the most part in China, the United States, England, France, Italy, Japan, Germany, and so on. They are taken at various times and seasons under various imaging conditions, which expands the intra-class variability.

![Figure 2.2 AID Dataset](image)

**2.2 Methods**
There are six different popular convolutional neural network architectures that have been used for training. The description and the architecture of each architecture is described in this section. The architectures considered in this thesis are AlexNet, VGG16, ResNet, GoogleNet, SqueezeNet and YOLO architecture. Table 2.1 shows some features of all the six architectures. The architecture of each of these networks is described below.

<table>
<thead>
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<th>Networks</th>
<th>Maximum Filter size</th>
<th>Minimum Filter size</th>
<th>Blocks</th>
<th>Residual/Inception blocks</th>
<th>FC layers</th>
<th>Hidden layers</th>
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</thead>
<tbody>
<tr>
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<td>11X11</td>
<td>3X3</td>
<td>0</td>
<td>0/0</td>
<td>3</td>
<td>6</td>
</tr>
<tr>
<td>VGG16</td>
<td>3X3</td>
<td>3X3</td>
<td>5</td>
<td>0/0</td>
<td>3</td>
<td>14</td>
</tr>
<tr>
<td>ResNet</td>
<td>7X7</td>
<td>3X3</td>
<td>25</td>
<td>25/0</td>
<td>1</td>
<td>48</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>5X5</td>
<td>1X1</td>
<td>9</td>
<td>0/9</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>3X3</td>
<td>1X1</td>
<td>8</td>
<td>0/8</td>
<td>0</td>
<td>16</td>
</tr>
<tr>
<td>YOLO</td>
<td>3X3</td>
<td>1X1</td>
<td>23</td>
<td>23/0</td>
<td>1</td>
<td>51</td>
</tr>
</tbody>
</table>

2.2.1 AlexNet

AlexNet was an innovative architecture to tackle large labeled datasets for image recognition with higher precision and efficiency. The ImageNet dataset used to train this architecture contained over 10 million images and more than 1000 image categories [4]. AlexNet introduced various key design innovations like the addition of dropout layers [36] for higher accuracy along with incorporation of distributed processing for
better scalability and faster training. Hence leveraging a multi GPU system can speed-up training as well as evaluation for large datasets. AlexNet set the premise to better image classification architectures and research using deep learning techniques and methods. Fig. 2.3 shows the architecture of AlexNet.

The architecture for the Alexnet contains 5 convolution neural layers and 3 fully-connected layers. The architecture of AlexNet used ReLU [37] [38] activation function in its neural layers to accommodate faster training over traditional activation functions like tanh [39]. The response to normalization of layer’s average data given during training to prevent stagnant learning iterations and high false positives in recognition. The max pooling layers helped reduce variance also capturing strong inputs over the network layers. Pooling layers are placed after the response normalization layers. The architecture uses overlapping pooling in its structure.
The convolutional layers are split to contain mapped kernels in the same graphical processing units. The convolutional layers reduce the image parameters producing 4096 dimensional features for the fully connected (FC) layer that are mapped into a logistic regression output containing 1000 classes.

This architecture uses various kinds of transformations for data augmentation to increase learning. These spatial transforms provide more robust training samples for the network.

### 2.2.2 VGG16

VGGNet is a neural network that performed extremely well in the Image Net Large Scale Visual Recognition Challenge (ILSVRC) in 2014. This architecture is from VGG group, Oxford. It makes the enhancement over AlexNet by replacing expensive kernel-size filters with various filters in a steady progression. Fig. 2.4 shows the VGG16 architecture. This idea of blocks/modules was introduced in VGG. The VGG convolutional layers are trailed by 3 fully connected layers. The width of the filters begins with 64 and increments by a factor of 2 after each pooling layer [40].
The images in the challenge were divided into 1000 unique classes. Given a test image, the VGG network determines a likelihood — in the range of 0 and 1 — for every one of those 1000 classes and selects the class with the highest likelihood.

*Figure 2.4 VGG16 Architecture [41]*
2.2.3 ResNet

With the advent of deep learning in various areas of research important applications were found. The major drawback of deep learning networks is the size of dataset required to train them along with the hyper parameters associated with them. Other issues include losing the learning capability due to extensive stacking of layers and overfitting. The research on residual networks was premised on tackling the problem of vanishing gradients and training efficiency between layers. The residual blocks provide mappings that preserves the transformations in the previous layers.

The architecture for ResNet illustrated in Fig. 2.5 adds identity mappings known as skip connections. These skip connections decide the depth of the neural network depending on the dataset. The network first starts training with one residual block and keeps adding the new layers by checking gradient. There is no problem of dimensional mismatch as all the filters in all the layers are of the same size. The only problem that can be inherited is the number of filters in the layer and input to the next layer. To overcome this, it uses same padding. The architecture consists of 3x3 filters with 2 strides for 24 layers respectively [40].
Figure 2.5 ResNet Architecture [42]
2.2.4 GoogleNet

The GoogleNet model, shown in Fig. 2.6, contains an essential block called inception block containing progressions of convolutional layers at various scales. For every block, we take in an arrangement of 1x1, 3x3, and 5x5 filters which can figure out how to extract features at various scales from the image. Max pooling is additionally utilized, yet with same padding to have a legitimate connection while concatenating features from the three filters [43].

The GoogleNet architecture consists of 9 inception blocks. The easiest way to improve the performance of the deep learning model is by adding more layers and increasing the data. With more parameters, the network is prone to overfit. To avoid overfitting GoogleNet exploits all the bottleneck techniques [44].
2.2.5 SqueezeNet

SqueezeNet proposes an efficient architecture that gives accuracy that is similar to AlexNet with just half the parameters of AlexNet. SqueezeNet is ten times faster and
smaller than AlexNet. The building block of SqueezeNet is called fire module, which consists of a squeeze layer and an expand layer. A SqueezeNet stacks a group of fire modules and a pooling layer after a couple of fire module. The squeeze layer reduces the feature map size and expand layer increases it, thus helps to keep the original feature map size [45].

In Fig. 2.7, the squeeze module just contains 1x1 filters, which means it works like a fully connected layer. As its name indicates, one of its benefits is to decrease the size of the feature map. Diminishing size implies that there are fewer calculations to do in the accompanying 3x3 channels. It helps the speedup as a 3x3 filters require multiple more calculations compared to a 1x1 channel [45].

2.2.6 YOLO

The YOLOV3 network architecture consist of fifty two convolutional layers followed by an average pooling layer and one fully connected layer making it a total of fifty layers with 50 hidden layers. The 52 convolutional layer is divided into five residual blocks which are repeated several times as can be seen in the Fig. 2.8. Unlike most network architectures, there are no maxpooling layers. Instead, there is an average pooling layer just before the classifier.
The complexity of architecture is directly proportional to the depth of the convolutional neural network which makes it difficult to train. The paper [46] provides empirical

Figure 2.8 YOLO Architecture
evidence that residual networks with the inclusion of dropout is much faster to train. Residual networks show significant improvements on ImageNet and MSCOCO dataset. The residual network may have deeper layers compared to its counterparts, but because of skip connections the active parameters are lesser than non-residual networks.
Chapter 3

Proposed Methods

This chapter describes how the networks have been trained from pre-trained models available in Caffe zoo. Then it describes how the weights have been dropped to determine the resiliency of the neural network, and includes self-healing of all the DCNN’s after the weights have been dropped by different methods before re-training. We also prune the most resilient networks like VGG16 and GoogleNet to the size of SqueezeNet and compare its results.

3.1 Training the CNN’s

The Deep Convolutional Neural Networks were built from scratch in Keras and PyTorch, i.e. instead of taking the model from the library in Keras, each of these neural networks has been coded so that there can be different operations performed at each layer. If the network architectures were taken from the in-built library there would be
no access to perform changes within the network. This also provided a deeper understanding of the architecture. Table 3.1 shows parameters requires for training different architectures.

Table 3.1 Parameters required for training each of the six architectures

<table>
<thead>
<tr>
<th>Network</th>
<th>AlexNet</th>
<th>VGG16</th>
<th>ResNet</th>
<th>SqueezeNet</th>
<th>GoogleNet</th>
<th>YOLO</th>
</tr>
</thead>
<tbody>
<tr>
<td>Built from scratch</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Weights</td>
<td>Caffe Model Zoo</td>
<td>Caffe Model Zoo</td>
<td>Caffe Model Zoo</td>
<td>Caffe Model Zoo</td>
<td>Caffe Model Zoo</td>
<td>YOLO website</td>
</tr>
<tr>
<td>Layers Replaced</td>
<td>3 FC layers</td>
<td>2 FC layers</td>
<td>1 FC layers and 1 residual block</td>
<td>1 Convolution Layer</td>
<td>1 FC layer</td>
<td>1 FC layer</td>
</tr>
<tr>
<td>Regularization</td>
<td>No</td>
<td>Yes</td>
<td>Yes (FC Layer)</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>Learning Rate</td>
<td>0.01</td>
<td>0.01</td>
<td>0.0001</td>
<td>0.01</td>
<td>0.01</td>
<td>0.001</td>
</tr>
<tr>
<td>Loss</td>
<td>Cross-Entropy</td>
<td>Cross-Entropy</td>
<td>Cross-Entropy</td>
<td>Mean Squared Error</td>
<td>Mean Squared Error</td>
<td>YOLO</td>
</tr>
<tr>
<td>Optimizer</td>
<td>ADAM</td>
<td>SGD</td>
<td>ADAM</td>
<td>SGD</td>
<td>AdaGrad</td>
<td>ADAM</td>
</tr>
</tbody>
</table>

3.1.1 Training AlexNet

AlexNet is the simplest architecture of all and can be implemented in Tensorflow and converted to Keras. The pretrained weights are taken from Caffe model zoo which are in the prototxt (the format used for caffe) format. However, these weights cannot be
used directly in Keras (with TensorFlow in the background). Luckily there is a tool [47] available online which can be used to convert this weight file to .h5 file which is compatible with Tensorflow. This tool maps the weights to the dimension of the filter. The tool updates the weights in the tensor format to form an nd-array of values which then stored as a file in .h5 format. These weights are uploaded in python using load_weights. The loaded weights are pre-trained weights, which have been previously trained on the ImageNet dataset. As ImageNet and MsCOCO dataset are not that different from each other, we can assume the network features will be similar to the features required by the classifier for MSCOCO dataset.

The pre-trained weights are trained on ImageNet dataset which has 1000 classes and hence, once we upload the weights and match it with the AlexNet model, our network is ready to classify 1000 objects. For transfer learning on the MSCOCO dataset, we remove the FC layers from the network and replace it with a new FC layer which has never been trained.

The next step is to train the new FC layers with the new dataset that can classify 10 object classes so its output will be 10 classes instead of 1000 classes. The loss used for training is cross-entropy loss and the optimizer used for training the network is ADAM optimizer. Dropout is included in the FC layers to prevent overfitting.
3.1.2 Training VGG16

VGG16 is a straight-forward architecture and can be implemented in Keras by using “Api” model and adding layers with its respective filter size. The pre-trained weights are taken from caffe model zoo. We follow the same procedure as described in in Section 3.1.1.

Again, the weights have been pre-trained on the ImageNet dataset. During transfer learning, we are not training the first few layers, as they just give simple features that are commonly found across datasets.

As VGG16 has a lot of parameters and hidden layers, it is prone to overfitting during transfer learning on the MSCOCO dataset. We follow three steps to train this network.

First, we remove all the FC layers and add new FC layers that are connected to the last convolution layer of VGG1. Then all the hidden layers are frozen (set to non-trainable) and just the FC layers are trained. The FC layers are overfit on the MSCOCO dataset with this training, and this can be confirmed when the validation loss keeps increasing and the training loss is very close to zero.
The next step is to regularize this overfit model by adding dropout layer (which act as an adaptive regularization technique) [35]. A dropout layer is added after each FC layer (which drops random weights after each iteration). As was done in the first step, all the hidden layers are frozen while the FC layers are trained with dropout.

The next step is to finetune the network by training it end to end just for a couple of epochs. This is done by making all the hidden layers trainable and removing all the dropout layers in the network, so all the layers in VGG16 are now trainable (can update its weights while back-propagating) [48].

The hyper parameters used in this training is SGD optimizer [49], with learning rate set to default i.e. 0.01 and using cross entropy loss [50].

3.1.3 Training ResNet

ResNet is a complex architecture and can be implemented in keras by having the residual connections and letting the network decide its own depth. The pre-trained weights are taken from caffe model zoo and converted to .h5 format using convert.py as described in the previous section.
The pre-trained weights are trained on ImageNet dataset by the authors of ResNet. These weights are trained to classify 1000 object classes. Again we perform transfer learning by replacing the last Fully Connected layer to output 10 classes as we did in previous networks. However, AlexNet and VGG16 have two fully connected layers which learn to classify objects in the image but ResNet has only one fully connected layer to give 10 class output. If just the one fully connected layer is trained then the network will learn very fast and it may skip the local minima.

This above stated problem can be overcome by including more layers for training and not just the fully connected layer. With this process, the learning parameters will have a lot more weights to update, so the learning pace is not that fast and it can converge correctly. The ResNet model’s last residual block and the Fully connected layer is now trained on MSCOCO dataset for classify 10 class objects by using dropouts in the Fully connected layer to prevent overfitting.

The hyper parameters used for training are cross entropy loss and ADAM optimizer with learning rate kept lower at 0.0001, as the ResNet accuracy if it was set to 0.01 which is the default value network accuracy is then stuck at 60% which is not what ResNet paper has given.
### 3.1.4 Training SqueezeNet

SqueezeNet is the smallest network, but it is complex because of the squeeze layer and expanding layer. It can be implemented in Keras by using “Api” model and adding layers in squeeze function and expanding functions. SqueezeNet consists of only convolutional layers and does not include fully connected layer. The last layer in SqueezeNet is 1x1 convolutional layer which acts as fully connected layer.

The pre-trained weights are trained on the ImageNet dataset. Transfer learning with SqueezeNet can be tricky because of the absence of the fully connected layer. This network may underperform or underfit on the dataset, so instead of training just the last convolutional layer, we train the all the fire block as well. For this training method no layer in the network will be frozen or all the layers in this network are set to trainable.

The last convolution layer 1X1X1000 is replaced by 1X1X10, as we have 10 classes to train. First step of training is to take the input from the fire block into the convolution layer and train just the convolutional layer along with the fire block. The next step is to include the previous fireblock and train it to 4 epochs. The last step is to train all the
layers in the network. The hyper-parameters used here are Mean-squared error, with SGD optimizer and learning rate left to default 0.01.

### 3.1.5 Training GoogleNet

GoogleNet is a complex architecture and can be implemented in keras by having the inception block with different filter sizes where the output from each of these layers are concatenated to pass it to the next inception block.

The pre-trained weights are taken from caffe model zoo. We perform the same procedure to convert the weights from .prototxt to .h5 as we did in AlexNet in Section 3.1.1. The pre-trained weights are trained on ImageNet dataset which has 1000 classes and hence, once we load the weights and match it with the GoogleNet model, our network is now ready to classify 1000 class objects. We remove the FC layers from the network and replace with a new FC layer which has never been trained and so, the weights are randomly assigned.

The next step is to perform transfer learning with the new FC layers using the COCO dataset that can classify 10 objects so its output will be 10 classes instead of 1000 classes.
The loss used here is mean squared error and the optimizer used for training the network is Adagrad. Dropout is included to prevent overfitting (by-hearting the dataset). Dropout is included only in the FC layers and not in any of the convolution layers.

3.1.6 Training YOLO

YOLO is the most complex architecture of all. It can be implemented in Keras by using “Api” model, adding layers with its respective filter size and by using residual layers as in ResNet. These residual layers use fixed padding, hence to replicate the results we need to use bilinear upsampling. The pre-trained weights are taken from YOLO website [43] which are in the .weights (the format used for darknet). Now these weights cannot be used directly in Keras (With TensorFlow in the background). To overcome this problem, there is a function called convert.py which is present in [51] that converts. weights file to .h5 file. It does this by transposing the weights from. weights file to .h5 file as it is in the transposed format of Tensorflow.
These weights are uploaded in the python file by using load_weights. Now these weights are pre-trained weights, which have been previously trained on ImageNet dataset.

The pre-trained weights have been trained on MSCOCO dataset for detection 99 classes but our objective is to detect 10 object classes which is simple as we remove the last FC layer and replace it with new FC layer with 10 class output. Dropout is not used, as the weights have been pre-trained on MCCOCO dataset. This is trained using ADAM optimizer.

3.2 Resiliency

With the increasing use of DCNNs in real world situations, hardware or embedded implementation are placed in environments where they could suffer damage due to hardware failure or harsh external conditions. However, to our knowledge, the performance of DCNNs under failure conditions has not been investigated. The objective of this thesis is to explore the resilience of six popular object detector network architectures, AlexNet, VGG, and ResNet50, SqueezeNet, GoogleNet and YOLO, when subjected to various degrees of failure.
A potential form of failure in a DCNN is due to corruption of network weights. This type of corruption could occur at few or many nodes in the network, and is likely to result in misclassification and deterioration in performance.

The resiliency of each DCNN is determined by examining the network performance after inducing such errors. The corruption of network weights is induced in random order and systematic order, to observe the effects of performance deterioration.

### 3.3 Resiliency in DCNN’s

Three types of experiments were considered. The first involves randomly dropping weights (setting them to zero) at the convolutional layers of the network. The percentage of dropped weights is varied to test the accuracy of the network under various degrees of failure. The second includes dropping weights from each convolutional layer to observe the change in test accuracy. The third set of experiments deals with re-training the network after failures have been introduced. This is a form of network self-healing that helps regain some of the performance that is lost when the network experiences failures.
3.3.1 Resiliency with faults across the network

![Network Architecture Diagram]

*Figure 3.1 Illustration of how weight damage (red) is introduced into the network architecture.*

The first step of our investigation introduces faults in the network nodes by randomly dropping weights (setting them to zero). We consider six different architectures that have been very effective: AlexNet, VGG16, ResNet50, GoogleNet, SqueezeNet and YOLO. The weights are taken from the pre-trained model [52] and then fine-tuned [53] for classification in all the six networks. Fig. 3.1 represents the weights being dropped at every convolution layer except for the fully connected(FC) layer. The dropping of weights is done by two methods, first by using in built function from keras and other by manually updating the weights to zero.
3.3.1.1 Dropping weights using in-built function

Keras drops the weights by invoking a dropout layer in keras.layers. This function sets the random fraction of the weights to zero and drops the weights randomly. The dropout layer drops particular weights for a particular iteration, but for the next iteration, different set of random weights are dropped. This is not what out experiment requires but instead, if a particular weight has been dropped it should remain dropped for all iterations. Furthermore, the dropout layer in keras works only while training but it does not work while testing, which is a big setback for the nature of our experiments. Most of our work is while testing, as we will be observing how the network performs while the weights have been damaged.

To overcome the above shortcomings, a permanent drop layer is used. This function invokes the kernel of the kers by using the Lambda function, where we set the flag for dropout during testing and the same weights are dropped for one following session of Tensorflow as Keras is working as a frontend of Tensorflow. The permanent drop function which invokes kernel layers in Keras for dropping,k refers to keras’s backend. Here we are changing the dropout function in keras in its core code. This permanent
drop function ignores the parameter and considers it to have 0 while forward propagation and backward propagation.

### 3.3.1.2 Dropping weights manually

Dropping weights manually refers to zeroing of weights by invoking each layer’s parameters. For example if a network has five layers, we call each layer’s parameters and set the weights to zero by randomly selecting the position of the weights that has to be set to zero.

![Figure 3.2 Toy example of weights (a) Represents weights before drop and (b) Represents weights after drop](image)

Fig. 3.2 is a toy example of showing the change in the weight file before and after the manual drop is invoked. This is done by calling a function get_weights in keras which will give the weights of that layer, then the random number generator function is called
which gives a random number from zero to the size of the tensor of weights. Random function generator used here is a library in python which can be called by importing a random class which has randomint() method with parameters lowest to the highest number. This function puts all the values in a tuple and shuffles. The first number in the tuple is given as the output. Then we traverse to that position of the network and set that weight to zero which can be seen in Fig. 3.2. This step is repeated for all the layers in the network. The percentage of dropped weights in all the layers remains the same. For example, in a network with 2 hidden layer, we first go to the 1st convolution layer and set 50% of weights to zero. Then we repeat the procedure on the 2nd convolution layer where again the percentage of dropped weights is 50%.

After dropping the weights, the actual weight file needs to be updated, so we use a function called set_weights in keras. Next we use save_weights to .h5 file which will be re-used.

### 3.3.2 Resilience with faults at a single convolution layer

In this experiment, the network weights are dropped successively at each convolutional layer. For example, in VGG16 there are five blocks of convolution layers,
so at each layer weights are dropped at varying degrees, from 0% to 100% as shown in Figure 3.3. The effects of dropping weights at different layers were similar. Since the last convolution layer which precedes the classifier is the most important, we consider dropping only the weights in the last layer for this experiment. The procedure for dropping weights is as described in Section 3.3.1.

Figure 3.3 Illustration of how weight damage (red) is introduced into the network architecture

3.3.3 Resilience with faults across the entire network with fitness
Finding the fitness of weights in the network requires ranking mechanism for each filter’s importance. There are different ranking mechanisms including [54]. In Keras we don’t have enough liquidity in modifying the layers and hence we use Pytorch which gives full access to each layer and allows modifications. Hence this part of the thesis is performed in Pytorch which is built on torch framework. The ranking mechanism used is Taylor Ranking.

### 3.3.3.1 Taylor Ranking

Taylor Ranking criteria does pointwise multiplication of activation in each batch with its gradient, where activations are the output features from the convolution layer. The same process is repeated for all the activations in that convolutional layer. Then we sum all the dimensions except for the dimension of the output. This will give the rank of each filter in the network and it can be dropped by zeroing the weights [55].

\[
value = \sum_{i=1}^{n} F^i \odot g^i \tag{3.1}
\]

\[
rank = normalize(value, \dim(filter)) \tag{3.2}
\]
In Equation (3.1) value gives the point wise multiplication of activation (F) and the gradient (g) which is then summed to the batch size i.e. value will have a dimension of (batch_size) x (dim(filter)) x (number of filter). By normalizing in the direction of the filter we will have a rank filter of dimension 1 x (number of filter) as can be seen in Equation (3.2).

For example in VGG16 batch size is 32, output from the activations has a dimension of 256 and the spatial dimension of the network is 112x112 and hence the dimension of the gradient will be 32x256x112x112. When the gradient and activation gets, pointwise multiplied and normalized (averaging) with the dimension of the filter, the output will be a vector with ranks of size 256, each corresponding to a filter.

### 3.4 Self-Healing by Re-training

In this Section we explore whether partially damaged DCNNs have the ability to self-heal and recover their performance by retraining. We address this question in two steps. First, we retrain the network on the entire dataset using Resilient propagation (Rprop). Rprop is a learning heuristic for supervised learning in feedforward artificial neural networks, where the learning rate is adapted for each of the parameters. The idea is to divide the learning rate for a weight by a running average of the magnitudes of recent gradients for that weight. It has been found that Rprop is efficient when
combined with dropout. Thus, we expect that it will work well when the network is subjected to faults because this resembles dropout. Furthermore, Rprop is faster than standard gradient descent back-propagation. This increase in training speed can be used for efficient retraining. Retraining was done using Keras with tensorflow at the background. After the weights were dropped at each stage, the network with Rprop as the optimizer to obtain the testing accuracy. While retraining, we carefully inspected the dropped weights to make sure they don't change. We used a permanent drop by calling the core layers of keras. A permanent drop is meant to drop weights during training and testing. There are different methods through which the network is re-trained.

### 3.4.1 Re-training with AdaGrad

AdaGrad [56] or adaptive gradient allows the learning rate to adjust dependent on parameters. It performs bigger updates for rare parameters and little updates for continuous one. Because of this, it is appropriate for sparse data, for example Natural Language Processing. Another favorable attribute is that it fundamentally disposes of the need to tune the learning rate. Every parameter has its own learning rate that is monotonically decreasing. This causes the most concerning issue: sooner or later the
Learning rate is very small to the point that the framework quits learning [57]. The equation is shown below.

\[ w^{i+1} = w^i - \eta \cdot \frac{g^i}{\sqrt{\sum_{l=1}^{i} g^l}} \times g^i \] \hspace{0.5cm} (3.3)

\[ g^i = \nabla J(w^i) \] \hspace{0.5cm} (3.4)

In Equation (3.3), \( w^{i+1} \) and \( w^i \) refers to the parameters at time step \( i+1 \) and \( i \) respectively. In the Equation (3.4), degradation of learning rate increases with every iteration. \( \nabla J(w^i) \) is the objective function which we are trying to reduce. This method would take too long to train as it keeps adding all the past gradients to reduce the learning rate. There comes a point where the learning rate is so low that the parameters stop learning.

### 3.4.2 Re-training with Adadelta

AdaDelta [58] is an expansion of AdaGrad that tries to lessen the forceful, monotonically diminishing learning rate of AdaGrad. Rather than adding all past squared gradients, Adadelta limits to average of the past gradients. Instead of
discarding the past squared gradients it recursively calculates the decaying average of
the past squared gradients [57].

\[ w^{i+1} = w^i - \frac{RMS[\nabla\theta]^t_{t-1}}{RMS[g^2]^t} \cdot g^t \]  \hspace{1cm} (3.5)

\[ RMS[g^2]^t = \sqrt{E[g^2]^t} + \epsilon \]  \hspace{1cm} (3.6)

\[ RMS[\nabla\theta]^2]^t = \sqrt{E[\nabla\theta]^2} + \epsilon \]  \hspace{1cm} (3.7)

Where RMS refers to root mean squares, \( E[g^2] \) is the decaying average over past
squared gradients. \( E[\nabla\theta] \) is the decaying average of the squared parameters. \( \epsilon \) is the
smoothing term to avoid division by zero. From the above equation, instead of keeping
the information from all the past gradients but only keeps the past squared gradients.

### 3.4.3 Re-training with Rprop

Rprop [59] refers to resilient back propagation and is a local adaptive learning scheme,
performing local batch training with multi layered neural network. The fundamental
principle of Rprop is to remove the impact of size of the derivative in each weight
step. Thus, just the sign of the derivative is considered to demonstrate the course of the
weight updates. This process requires no parameter tuning. The learning and adaptation are only affected by the sign of the partial derivative. Learning is equally spread over the network [59].

\[
\Delta w^t = \begin{cases} 
+\Delta v^t, & \text{if } d\theta > 0 \\
-\Delta v^t, & \text{if } d\theta > 0 \\
0, & \text{if } d\theta = 0
\end{cases}
\]

(3.8)

The above equation is the updating rule for Rprop where \(\Delta v^t\) refers to the Momentum and \(d\theta\) denotes the sum of gradient in a particular batch. This is a method that helps accelerate SGD in the relevant direction.

### 3.4.4 Re-training with ADAM optimizer

Adaptive Moment Estimation (ADAM) [60] is another technique that registers adaptive learning rates for every parameter. This method includes decaying average of past squared gradients like Adadelta and RMSprop, but also includes decaying average of past gradients as in the case of momentum. While momentum can be viewed as a ball
running down a slant, ADAM acts like a substantial ball with friction, which along these lines inclines toward level minima in the rough surface [57].

\[ m^t = \beta^1 + (1 - \beta^1) \times g^t \]  \hspace{1cm} (3.9) \\
\[ v^t = \beta^2 + (1 - \beta^2) \times g^t \]  \hspace{1cm} (3.10) \\
\[ \Delta m^t = \frac{m^t}{1 - \beta^1} \]  \hspace{1cm} (3.11) \\
\[ \Delta v^t = \frac{v^t}{1 - \beta^2} \]  \hspace{1cm} (3.12) \\
\[ w^{t+1} = w^t - \frac{\eta}{\sqrt{\Delta v^t + \epsilon}} \times \Delta m^t \]  \hspace{1cm} (3.13)

Where \( m^t \) refers to past squared gradient and \( v^t \) is the decaying average of the past. \( \beta^1 \) and \( \beta^2 \) refers to decay rates. The authors propose default values of 0.9 for \( \beta^1 \), 0.999 for \( \beta^2 \), and \( 10^{-8} \) for \( \epsilon \). The authors show that ADAM optimizer works best for all the training mechanism. ADAM optimizer has been the most used optimization algorithm for gradient descent.

3.4.5 Retraining with ARprop
We prepare ARprop, that combines two well used optimizing algorithms, ADAM and Rprop. The best feature of Rprop is the way it updates the weights using Manhattan Rule [42] that makes it faster than any other optimizing algorithm including ADAM optimizer. We use ADAM optimizer’s learning rate decay method and update the weight using Manhattan rule by keeping the momentum of the gradients. So the equation used is:

\[
\Delta w^t = \begin{cases} 
+\Delta p^t, & \text{if } d\theta > 0 \\
-\Delta p^t, & \text{if } d\theta < 0 \\
0, & \text{if } d\theta = 0
\end{cases}
\]  
\hspace{0.5cm} (3.14)

Where p is ADAM’s learning rate decaying method.

\[
p = \frac{\eta}{\sqrt{\Delta v^t} + \epsilon} * \Delta m^t
\]  
\hspace{0.5cm} (3.15)

The other method that was tried was using AdaGrad with Rprop which makes it faster but after a certain decay of learning rate, the network stops learning and results are not great.
3.5 Pruning

Pruning refers to deleting or eliminating the parts of the network without sacrificing performance. This is done by reducing the size of the parameters by eliminating the weights i.e. dropping the weights. In our example, we follow a procedure to prune VGG16 and GoogleNet architecture to the size of SqueezeNet by using manual drop of weights without considering the fitness of the weights. The flow diagram of this procedure is as shown in the Fig. 3.4.
In Fig. 3.4 we follow the same procedure as described in this chapter. The network is transfer learned for MSCOCO dataset. Then the network goes though the dropping of weights, as SqueezeNet consists of 1.2M parameters VGG16 must be reduced from 7M parameters to 1.2M and hence, resulting in 82% reduction in the number of its parameters. Similarly GoogleNet has 5.6M parameter so it is reduced by 78% to reach the size of SqueezeNet.

Next step is retraining the healthy part of the network. The ADAM optimizer, because of its exponential decay and momentum decay, gives the best result for retraining after 50% of weights have been dropped but it takes considerably more time than its competitors.

Advantages of pruning a network includes less computational capacity required while testing or predicting, hence the results can be faster. Memory usage is reduced thus pruning can be good for computational time and space. Disadvantage of pruning the network is transfer learning will be limited to same class objects.
This chapter describes how each of CNN's acts when subjected to failure followed by how fast each of these networks can heal itself with training. This chapter also has results of pruning VGG16 and GoogleNet.

### 4.1 Resiliency with faults across the network

Figure 4.1 shows the result of test accuracies after the weights have been dropped for AlexNet, VGG16 and ResNet. The percentage of weights dropped was varied from 0%
to 100%. Our results indicate that AlexNet is the least resilient of the three networks as it only has five layers and fewer parameters compared to the others. At just 20% of dropped weights the test accuracy reduces to 40%. On the other hand, VGG16 is the most resilient. With almost 50% of the weights dropped the network still maintains accuracy close to 80%. For ResNet50 the accuracy falls suddenly when approximately 30% of weights are dropped.

![Graph of Performance vs Test Dropout](image)

*Figure 4.1 Accuracy vs Percent of Dropped Weights across the full network in AlexNet, VGG16 and ResNet*

Even though ResNet has more layers when compared to VGG16, it is less resilient. This is probably due to its width and number of parameters in the network. Additionally,
we explored the effects of filter size and found that networks with smaller filter size are more resilient.

ResNet was introduced to tackle the problem of redundancy in deep convolutional neural network by using residual blocks or skip connections. This reduces the redundancy in the network. The network is found to be resilient when its weights are dropped. ResNet, with the help of residual blocks, already drops or skips parameters that can be considered as unimportant or redundant. For this reason ResNet remains less resilient when compared to VGG16, even though ResNet has more number of parameters.

Each of these experiments have been run 3 times and all the results were similar. So, all these experiments are performed for the fourth time and results were noted down and plotted as a graph. For the cases of 50% and 25% of faults the experiments are performed for 6 times and then the results have been averaged out.

Fig. 4.2, shows the results of performance after the weights have been dropped in SqueezeNet, GoogleNet and YOLO. The percent of weights dropped was varied from 0% to 100%. Our results indicate that SqueezeNet is the least resilient of the three networks because of the fire module which squeezes the network and reduces the filter
size to 1x1 instead of 3x3 filters and it has fewer parameters compared to the other network.

At just 30% of dropped weights the test accuracy reduces to 40%. On the other hand, GoogleNet is the most resilient network because it has the most number of parameters which excludes residual blocks and containing of redundant layers.

YOLO is a very popular convolutional neural network. Because of residual block in the network it faces the same problem as ResNet and starts to show decline in performance at just 35% of dropped weights.

Figure 4.2 Accuracy vs Percent of Dropped Weights across the full network in SqueezeNet, GoogleNet and YOLO.
GoogleNet on the other hand is the most resilient out of YOLO and ResNet because of more trainable parameters and does not include residual blocks similar to VGG16 model.

![Performance vs Test Dropout](image)

*Figure 4.3 Accuracy vs Percentage of dropped weights across the full network comparing ResNet and YOLO*

Fig. 4.3 shows the comparison of two similar networks i.e. ResNet and YOLO as both have residual blocks which means it may not redundant layers which we were trying to remove from the network. But, because YOLO has more parameters compared to ResNet and the residual blocks are only for 2 convolution layer as described in Chapter 2. Yolo performs better than ResNet.
Fig. 4.4 shows the comparison of VGG16 vs GoogleNet architecture in terms of resiliency. VGG16 architecture does slightly better compared to GoogleNet which has almost 10 times the parameters of GoogleNet. Hence 60% drop of weights in these networks would leave GoogleNet almost with 1 million parameters but the VGG16 still will be having 60 million parameters.

Fig. 4.4 shows that VGG16 remains as the most resilient of all the architectures and AlexNet is the least resilient architecture. GoogleNet comes second to VGG16 as can be seen in the figure because of the parameters that VGG16 contains. Fig. 4.5 shows the performance of all the six architectures in one graph.
4.2 Resilience with faults at a single convolution layer

Fig. 4.6 shows the performance of AlexNet, VGG16 and ResNet when weights have been dropped. AlexNet has a gradual drop in accuracy, whereas VGG16 does well until 60% of weights are dropped and has a sudden drop in accuracy after that. ResNet's last layer acts the same way as it did when the weights were dropped throughout the network. Our experiments illustrate that DCNNs start losing performance in a similar manner whether faults are introduced across the entire network Fig. 4.3 or just at a
single layer Fig. 4.6. This result indicates that networks have a high level of inbuilt resilience, due to the redundant nature of DCNN architectures.

Similar experiment were performed on GoogleNet, YOLO and SqueezeNet where the weights are dropped at varying degree from 0% to 100% from layer just before its classify. For SqueezeNet model the layer before the last convolutional layer is dropped as the filter size is 1x1 this layer acts as a fully connected layer. With YOLO the last residual block is where the errors are induced. In GoogleNet we chose the last inception layer. Figure 4.7 shows the results for SqueezeNet, YOLO and GoogleNet when weight drops take place at the last layer (or the last convolution block).
Figure 4.7 Accuracy vs Percent of Dropped Weights in last convolution layer for SqueezeNet (red), YOLO (blue), and GoogleNet (green)

SqueezeNet has a gradual drop in accuracy, whereas GoogleNet does well until 70% of weights are dropped and has a sudden drop in accuracy after that. The YOLO last layer acts the same way as it did when the weights were dropped throughout the network just like ResNet.

Our experiments illustrate that DCNNs start losing performance in a similar manner whether faults are introduced across the entire network Fig. 4.3 or just at a single layer Fig. 4.6. This result indicates that networks have a high level of inbuilt resilience.
4.3 Resilience with faults across the entire network with fitness

Fig. 4.8 shows the results of AlexNet, VGG16 and ResNet when weights were dropped considering the fitness of the weights. The percent of weights dropped was varied from 0% to 100% starting from least fit to most fit based on Taylor ranking method. Our results indicate that AlexNet gradually loses its accuracy. On the other hand, VGG16 retains its properties and gives acceptable results even after 60% of dropped weights. Then it starts losing its accuracy after 60% of weights being dropped as can be seen in
Fig. 4.8. ResNet starts losing accuracy at 35% of dropped weights, seen previously because of its residual blocks.

Fig. 4.8 shows the results of SqueezeNet, GoogleNet and YOLO when weights were dropped considering the fitness of the weights. The percent of weights dropped was varied from 0% to 100% starting from least fit to most fit. Our results indicate that SqueezeNet gradually loses its accuracy as it is the smallest network of all, while YOLO just like ResNet remains the same as in Section 4.2 because of the residual block. On the other hand, GoogleNet retains its properties and gives acceptable results even
after 50% of dropped weights, as can be seen in Fig. 4.9, as it has large number of parameters and hence it shows it can be pruned well to match the size of the other network.

### 4.4 Network Self-Healing by Retraining

We retrained each of the three networks after introducing faults ranging from 0% to 100% across the entire DCNN. In all cases, we found significant recovery of accuracy after retraining. This type of retraining is a form of self-healing that utilizes the surviving connections after parts of the network have been damaged.

#### 4.4.1 Retraining with AdaGrad Optimizer

All the three networks AlexNet, VGG16 and ResNet show significant improvement after retraining seen in the Fig. 4.10. Even though VGG16 does well while the weights have been dropped in Fig. 4.5, ResNet does remarkably well while re-training mainly because of residual layers or skip connections. The ResNet network, which had skipped redundant layers when trained without any damage, reuses those layers while re-training. VGG16 and AlexNet on the other hand cannot match ResNet’s performance because they lack skip connections.
Fig. 4.11 shows that retraining improves in the next three architecture, out of which YOLO performs remarkably well compared to GoogleNet and SqueezeNet up until 60% of the weights have been corrupted. This is because of the residual layer present in the architecture. After 60% of dropped weights the network suddenly shows a significant drop in the accuracy as can be seen in the Fig. 4.11. This is because in YOLO the network has convolutional layers after each residual block. These individual convolutional layers are very important for re-training, according to the architecture. On the other hand, GoogleNet and SqueezeNet because of their fixed parameters result
in similar curve after retraining, GoogleNet does better because it has larger number of parameters.

Figure 4.11 Performance recovery by retraining (self-healing) after weights are dropped throughout the SqueezeNet, GoogleNet, YOLO

Fig. 4.12 shows performance recovery by retraining after the weights have been dropped with fitness in all the six architectures. From Fig. 4.12(a) ResNet does performs well but just not as good as it performed when weights were dropped randomly. This is because of the ranking method which reduces the network breadthwise thus creating a bottleneck in terms of training and as it is a permanent loss of weights the network stops learning after a certain point of damage which can be seen in Fig. 4.12(a) and
4.12(b). In Fig. 4.12(b) for the same reason GoogleNet performs remarkably well compared to YOLO.

![Performance vs Test Dropout](image1.png)
![Performance vs Test Dropout after re-training](image2.png)

*Figure 4.12 Performance recovery by retraining (self-healing) after weights are dropped with fitness throughout the a) AlexNet, VGG16, ResNet, b) SqueezeNet, GoogleNet, YOLO*

Table 4.1 shows the numerical representation of the network when subjected to 50% damage with and without fitness and results after re-training using AdaGrad technique for re-training. As it can be seen VGG16 at 50% faults induced is the most resilient of all the network. Table 4.2 shows the results when the networks are at 25% of faults.
Table 4-1 Network parameters and associated test accuracy with 50% faults across the entire network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>24.3</td>
<td>34.1</td>
<td>95.4</td>
<td>95.0</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>78.7</td>
<td>82.1</td>
<td>96.1</td>
<td>95.3</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>19.6</td>
<td>23.1</td>
<td>96.3</td>
<td>94.1</td>
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<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
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<tr>
<td>GoogleNet</td>
<td>5.6M</td>
<td>98.9</td>
<td>75.1</td>
<td>78.8</td>
<td>93.1</td>
<td>90.1</td>
</tr>
<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>19.3</td>
<td>25</td>
<td>91.2</td>
<td>85.6</td>
</tr>
</tbody>
</table>

Table 4-2 Network parameters and associated test accuracy with 25% faults across the entire network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>48.8</td>
<td>85.2</td>
<td>96.1</td>
<td>96.0</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>97.4</td>
<td>97.9</td>
<td>96.3</td>
<td>96.3</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>76.6</td>
<td>91</td>
<td>96.9</td>
<td>96.1</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
<td>95.8</td>
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<tr>
<td>GoogleNet</td>
<td>5.6M</td>
<td>98.9</td>
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<td>95.7</td>
<td>95.9</td>
<td>96</td>
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<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>91</td>
<td>92.4</td>
<td>95.2</td>
<td>95.6</td>
</tr>
</tbody>
</table>

Fig. 4.13 shows examples of correct and incorrect classification of images after 50% of weights were dropped and retrained with AdaGrad. All the six CNN’s recover remarkably well using AdaGrad. But still there are some errors like, VGG16 classifies clock as mirror as shown in the figure. Most of the networks find it difficult to classify
more complex images like Person, Bike. When weights dropped with or without fitness, the output is of the same class.

50% Faults

<table>
<thead>
<tr>
<th>AdaGrad</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
</tr>
<tr>
<td>VGG16</td>
</tr>
<tr>
<td>VGG16 with Fitness</td>
</tr>
<tr>
<td>ResNet</td>
</tr>
<tr>
<td>ResNet with Fitness</td>
</tr>
<tr>
<td>SqueezeNet</td>
</tr>
<tr>
<td>SqueezeNet with Fitness</td>
</tr>
<tr>
<td>GoogleNet</td>
</tr>
<tr>
<td>GoogleNet with Fitness</td>
</tr>
<tr>
<td>YOLO</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
</tr>
</tbody>
</table>

Figure 4.13 Examples of correct and incorrect classification after 50% of dropped weights when re-trained with AdaGrad
Fig. 4.14 shows examples of correct and incorrect classification of images after 25% of weights were dropped with fitness and retrained with AdaGrad. As can be seen from
the figure almost all the networks except AlexNet and SqueezeNet misclassify the cat image to a bag. Same is the case with Giraffe image. But when there are two classes in an image AdaGrad underperforms. Even after re-training AlexNet, SqueezeNet and YOLO fail to detect that there are two objects.

4.4.2 Retraining with AdaDelta Optimizer

Fig. 4.15 shows the performance recovered after the weights were dropped in all the six architectures. The networks manage to heal after re-training with AdaDelta optimizer. As expected ResNet performs better here for the same reason as explained.
in the previous section. VGG16, GoogleNet and YOLO networks heals itself, but the only difference here is there is marginal improvement over the AdaGrad optimizer. AdaDelta is slightly faster than AdaGrad because it is not storing all the past gradients, and instead it is just averaging out the past gradients which works well in updating the learning rate.

Fig. 4.16(a)(b) shows how the network trains under AdaDelta when weights are dropped considering fitness. There is a slight improvement from the predecessors. The improvement can be seen in the Table 4.3.
Table 4-3 Network parameters and associated test accuracy with 50% faults across the entire network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>24.3</td>
<td>34.1</td>
<td>95.9</td>
<td>95.2</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>78.7</td>
<td>82.1</td>
<td>96.8</td>
<td>96.3</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>19.6</td>
<td>23.1</td>
<td>97.3</td>
<td>96.1</td>
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<tr>
<td>SqueezeNet</td>
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<td>93.1</td>
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<tr>
<td>YOLO</td>
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<td>19.3</td>
<td>25</td>
<td>91.2</td>
<td>90.6</td>
</tr>
</tbody>
</table>

The Table 4.3 shows numerical results when all six networks are subjected to 50% fault and retaining results with AdaDelta optimizer. Table 4.4 shows the results when the networks are at 25% faults.

Table 4-4 Network parameters and associated test accuracy with 25% faults across the entire network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>48.8</td>
<td>85.2</td>
<td>96.2</td>
<td>96.4</td>
</tr>
<tr>
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<td>97.9</td>
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<td>96.9</td>
<td>96.4</td>
</tr>
<tr>
<td>SqueezeNet</td>
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<td>95.8</td>
<td>79.5</td>
<td>80.2</td>
<td>94.5</td>
<td>94.4</td>
</tr>
<tr>
<td>GoogleNet</td>
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<td>95.7</td>
<td>94.9</td>
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<tr>
<td>YOLO</td>
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<td>98.7</td>
<td>91</td>
<td>92.4</td>
<td>95.8</td>
<td>96.6</td>
</tr>
</tbody>
</table>
Fig. 4.17 shows examples of the recovery of all six CNN’s when retrained with AdaDelta. The misclassification of train as bridge in VGG16 and ResNet were recovered using AdaDelta. But there are few errors, as in SqueezeNet classifies the car
image as horse and YOLO classifies it as a mirror. As can be seen, there is better recovery when weights were dropped without fitness.

<table>
<thead>
<tr>
<th>25% Faults</th>
<th></th>
<th></th>
<th></th>
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</thead>
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<tr>
<td><strong>AdaDelta</strong></td>
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</tr>
<tr>
<td><strong>Labels</strong></td>
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<td><strong>Giraffe</strong></td>
<td><strong>Person, Bike</strong></td>
<td><strong>Person, Horse</strong></td>
</tr>
<tr>
<td>AlexNet</td>
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<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>VGG16</td>
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<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
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</tr>
<tr>
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<td>Person, Horse</td>
</tr>
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<td>Cow</td>
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<tr>
<td>SqueezeNet with Fitness</td>
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<td>Car</td>
<td>Cow</td>
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<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
</tr>
</tbody>
</table>

*Figure 4.18 Examples of correct and incorrect classification after 25% of dropped weights when re-trained with AdaDelta*
Fig. 4.18 shows examples of correct and incorrect classification after 25% of dropped weights when re-trained with AdaDelta. The recovery at 25% of corruption in AdaDelta is marginally better when compared to AdaGrad. Single object images have been classified correctly by all the networks except AlexNet and SqueezeNet but there is no improvement when multiple objects are in the image.

4.4.3 Retraining with Rprop Optimizer

Fig. 4.19 shows the network performance when retrained with Rprop optimizer. As expected ResNet performs better here for the same reason as explained in the previous sections. Rprop is significantly faster than AdaDelta because of the rule it
follows for updating parameters, i.e. Manhattan rule which is explained in Chapter 3. As it turns out, it just updates with its momentum and not the gradient. Thus, for retraining we need just the momentum as it is the fastest and gives results more favorably compared to AdaGrad and AdaDelta.

![Performance vs Test Dropout after Re-training](image)

*Figure 4.20 Performance recovery by retraining (self-healing) after weights are dropped with fitness throughout the a)* AlexNet, VGG16, ResNet, *b)*SqueezeNet, GoogleNet, YOLO

Fig. 4.19(a)(b) shows how the network trains under Rprop when weights are dropped considering fitness. There is a significant improvement when trained with AdaDelta. The improvement can be seen in the Table 4.5 and 4.6.
Table 4-5 Network parameters and associated test accuracy with 50% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining with fitness</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>24.3</td>
<td>34.1</td>
<td>96.7</td>
<td>96.2</td>
</tr>
<tr>
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<td>14M</td>
<td>98.6</td>
<td>78.7</td>
<td>82.1</td>
<td>97.4</td>
<td>96.6</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>19.6</td>
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<td>GoogleNet</td>
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<tr>
<td>YOLO</td>
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<td>98.7</td>
<td>19.3</td>
<td>25</td>
<td>94.2</td>
<td>92.6</td>
</tr>
</tbody>
</table>

Table 4.5 shows numerical results when all six networks are subjected to 50% fault and retaining results under Rprop optimizer. Table 4.4 shows the results when the networks are at 25% faults.

Table 4-6 Network parameters and associated test accuracy with 25% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
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<td>48.8</td>
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<tr>
<td>VGG16</td>
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<tr>
<td>ResNet</td>
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<tr>
<td>SqueezeNet</td>
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<td>GoogleNet</td>
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<tr>
<td>YOLO</td>
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<td>91</td>
<td>92.4</td>
<td>97.8</td>
<td>98.6</td>
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</table>
Fig. 4.21 shows examples of correct and incorrect classification after 50% of dropped weights when re-trained with Rprop. Recovery of all six CNN’s is significantly better when retrained with Rprop compared to AdaGrad and AdaDelta. Some of the previously misclassified images are rectified using Rprop. ResNet starts classifying
difficult objects (2 objects image) correctly but classifying 2 class objects is still difficult in AlexNet, SqueezeNet and YOLO. On the other hand, SqueezeNet misclassifies clock to a mirror and train to a bridge. SqueezeNet also fails to detect 2 objects in an image.

**25% Faults**

<table>
<thead>
<tr>
<th>Labels</th>
<th>Cat</th>
<th>Giraffe</th>
<th>Person, Bike</th>
<th>Person, Horse</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Horse</td>
</tr>
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<td>VGG16</td>
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<tr>
<td>VGG16 with Fitness</td>
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<td>Person, Horse</td>
</tr>
<tr>
<td>ResNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>ResNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Cow</td>
</tr>
<tr>
<td>SqueezeNet with Fitness</td>
<td>Cat</td>
<td>Cat</td>
<td>Car</td>
<td>Cow</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>GoogleNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>YOLO</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
</tr>
</tbody>
</table>

*Figure 4.22 Examples of correct and incorrect classification after 25% of dropped weights when re-trained with Rprop*
Fig. 4.22 shows examples of results when each of the networks are subjected to 25% of corruption. When networks are retrained with Rprop there is a significant improvement. As can be seen in the figure cat image has been correctly classified by all the networks. When it comes to two object images there is a marginal improvement in AlexNet and YOLO but SqueezeNet still fails to detect two objects.

4.4.4 Retraining with ADAM Optimizer

![Performance vs Test Dropout after Re-training](image_url)

Figure 4.23 Performance recovery by retraining (self-healing) after weights are dropped throughout the a) AlexNet, VGG16, ResNet, b) SqueezeNet, GoogleNet, YOLO
Fig. 4.23(a)(b) shows how well the network manages to heal itself with ADAM optimizer. As expected ResNet performs better here for the same reason as explained in the previous sections. For other networks ADAM is significantly slower than AdaDelta because it updates all the parameters with momentum and gradient. The performance is better with ADAM optimizer when compared to AdaGrad, AdaDelta and Rprop but it is slower when compared to Rprop.

![Figure 4.23 Performance recovery by retraining (self-healing) after weights are dropped with fitnetss throughout the a) AlexNet, VGG16, ResNet, b)SqueezeNet, GoogleNet, YOLO](image-url)

Fig. 4.24(a)(b) shows how the network trains under ADAM optimizer when weights are dropped considering fitness. There is a significant improvement from the Rprop results. The performance can be seen in the Table 4.7 and 4.8.
Table 4.7 Network parameters and associated test accuracy with 50% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>24.3</td>
<td>34.1</td>
<td>96.6</td>
<td>95.1</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>78.7</td>
<td>82.1</td>
<td>97.1</td>
<td>95.6</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>19.6</td>
<td>23.1</td>
<td>97.9</td>
<td>96.2</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
<td>95.8</td>
<td>31.6</td>
<td>32</td>
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<td>90.5</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>5.6M</td>
<td>98.9</td>
<td>75.1</td>
<td>78.8</td>
<td>94.2</td>
<td>92.7</td>
</tr>
<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>19.3</td>
<td>25</td>
<td>93.3</td>
<td>92.6</td>
</tr>
</tbody>
</table>

Table 4.7 shows numerical results of all the six networks when subjected to 50% fault and retrained with ADAM optimizer. Table 4.8 shows the results when the networks are at 25% faults.

Table 4.8 Network parameters and associated test accuracy with 25% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>48.8</td>
<td>85.2</td>
<td>97.1</td>
<td>97.1</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>97.4</td>
<td>97.9</td>
<td>98.1</td>
<td>98.0</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>76.6</td>
<td>91</td>
<td>98.9</td>
<td>98.4</td>
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<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
<td>95.8</td>
<td>79.5</td>
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<td>96.5</td>
<td>95.4</td>
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<td>GoogleNet</td>
<td>5.6M</td>
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<td>95.2</td>
<td>95.7</td>
<td>98.9</td>
<td>97.4</td>
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<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>91</td>
<td>92.4</td>
<td>98.5</td>
<td>98.6</td>
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</tbody>
</table>
50% Faults

ADAM

<table>
<thead>
<tr>
<th>Labels</th>
<th>Clock</th>
<th>Train</th>
<th>Car</th>
<th>Person, Bike</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
<td>Mirror</td>
<td>Bridge</td>
<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>VGG16</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>VGG16 with Fitness</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>ResNet</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>ResNet with Fitness</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>Clock</td>
<td>Bridge</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>SqueezeNet with Fitness</td>
<td>Mirror</td>
<td>Train</td>
<td>Car</td>
<td>Cat</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>GoogleNet with Fitness</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>YOLO</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Bike</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
<td>Clock</td>
<td>Train</td>
<td>Car</td>
<td>Person, Horse</td>
</tr>
</tbody>
</table>

Figure 4.25 Examples of correct and incorrect classification after 50% of dropped weights when re-trained with ADAM optimizer

Fig. 4.25 shows examples of correct and incorrect classification after 50% of dropped weights when re-trained with ADAM. All the six networks recover remarkably well under ADAM when compared to AdaGrad, AdaDelta and Rprop. All the networks
start to classify difficult images correctly, except for SqueezeNet and AlexNet. The car image is correctly classified by all the networks. The train image is still misclassified by SqueezeNet and AlexNet, same as the case with clock image.

### 25% Fault

<table>
<thead>
<tr>
<th>Labels</th>
<th>Cat</th>
<th>Giraffe</th>
<th>Person, Bike</th>
<th>Person, Horse</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>VGG16</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>VGG16 with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>ResNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>ResNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>SqueezeNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>GoogleNet with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>YOLO</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
</tr>
</tbody>
</table>

*Figure 4.26 Examples of correct and incorrect classification after 25% of dropped weights when re-trained with ADAM optimizer*
CHAPTER 4: RESULTS

Fig. 4.26 shows examples of images that have been misclassified when subjected to 25% faults and their recovery. Almost all the images are classified correctly by all the networks except AlexNet and YOLO for 2 class object images. But there has been a significant improvement in the single object images, as the cat image is classified correctly by all the networks. In two class object images, AlexNet with fitness has no misclassification but AlexNet without fitness still fails to detect two objects.

4.5 Retraining with ARprop

![Performance vs Test Dropout after Re-training](image1)

![Performance vs Test Dropout after re-training](image2)

*Figure 4.27 Performance recovery by retraining (self-healing) after weights are dropped throughout the a) AlexNet, VGG16, ResNet, b) SqueezeNet, GoogleNet, YOLO*

Fig. 4.27(a)(b) shows that all six convolutional neural networks heal itself to a certain limit of faults. Fig. 4.27(a) shows that VGG16, when re-trained, performs a little better than ResNet and significantly better than AlexNet after 70% of its parameters are
faulty. Similarly, in Fig. 4.27(b) shows that the GoogleNet performance remains intact throughout the process of dropping weights (0% to 70%) and then there is significant drop in its accuracy. GoogleNet performs better than YOLO and SqueezeNet throughout the process. When GoogleNet and VGG16 is compared, VGG16 remains the most resilient of all the six networks overall, when re-trained with ARprop.

Fig. 4.28(a)(b) shows how the network trains under ARprop optimizer when weights are dropped considering the fitness of them. There is a slight improvement in its
performance when compared to AdaDelta. The results can be seen in the Table 4.9 and 4.10.

Table 4-9 Network parameters and associated test accuracy with 50% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>24.3</td>
<td>34.1</td>
<td>96.7</td>
<td>96.2</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>78.7</td>
<td>82.1</td>
<td>97.4</td>
<td>96.6</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>19.6</td>
<td>23.1</td>
<td>98.3</td>
<td>96.8</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
<td>95.8</td>
<td>31.6</td>
<td>32</td>
<td>90.4</td>
<td>89.5</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>5.6M</td>
<td>98.9</td>
<td>75.1</td>
<td>78.8</td>
<td>95.1</td>
<td>93.7</td>
</tr>
<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>19.3</td>
<td>25</td>
<td>94.2</td>
<td>92.6</td>
</tr>
</tbody>
</table>

Table 4.9 shows numerical results when all the six network when subjected to 50% fault retrained with ARprop. Table 4.10 shows the results when the networks are at 25% faults.

Table 4-10 Network parameters and associated test accuracy with 25% faults across the Network

<table>
<thead>
<tr>
<th>Network</th>
<th>Parameters</th>
<th>Accuracy without Faults</th>
<th>Accuracy with faults</th>
<th>Accuracy with faults with fitness</th>
<th>Accuracy after retraining</th>
<th>Accuracy after Retraining with fitness</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>3.7M</td>
<td>97.2</td>
<td>48.8</td>
<td>85.2</td>
<td>96.1</td>
<td>96.1</td>
</tr>
<tr>
<td>VGG16</td>
<td>14M</td>
<td>98.6</td>
<td>97.4</td>
<td>97.9</td>
<td>97.1</td>
<td>97.0</td>
</tr>
<tr>
<td>ResNet</td>
<td>25M</td>
<td>98.9</td>
<td>76.6</td>
<td>91</td>
<td>96.9</td>
<td>97.4</td>
</tr>
<tr>
<td>SqueezeNet</td>
<td>1.2M</td>
<td>95.8</td>
<td>79.5</td>
<td>80.2</td>
<td>95.5</td>
<td>94.4</td>
</tr>
<tr>
<td>GoogleNet</td>
<td>5.6M</td>
<td>98.9</td>
<td>95.2</td>
<td>95.7</td>
<td>96.9</td>
<td>96.4</td>
</tr>
<tr>
<td>YOLO</td>
<td>75M</td>
<td>98.7</td>
<td>91</td>
<td>92.4</td>
<td>97.5</td>
<td>97.6</td>
</tr>
</tbody>
</table>
Fig. 4.29 shows examples of correct and incorrect classification after 50% of dropped weights when re-trained with ARprop. All the six CNN’s recover remarkably well
using ARprop, but still there are some errors. VGG16 classifies clock as mirror. Most of the networks find it difficult to classify two object images like person, bike.

<table>
<thead>
<tr>
<th>Labels</th>
<th>Cat</th>
<th>Giraffe</th>
<th>Person, Bike</th>
<th>Person, Horse</th>
</tr>
</thead>
<tbody>
<tr>
<td>AlexNet</td>
<td>Bag</td>
<td>Horse</td>
<td>Car</td>
<td>Zebra</td>
</tr>
<tr>
<td>AlexNet with Fitness</td>
<td>Bag</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>VGG16</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>VGG16 with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Horse</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>ResNet</td>
<td>Bag</td>
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<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
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<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>SqueezeNet</td>
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<td>Person, Bike</td>
<td>Zebra</td>
</tr>
<tr>
<td>SqueezeNet with Fitness</td>
<td>Bag</td>
<td>Giraffe</td>
<td>Horse</td>
<td>Zebra</td>
</tr>
<tr>
<td>GoogleNet</td>
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<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
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<td>GoogleNet with Fitness</td>
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<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
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<tr>
<td>YOLO</td>
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<td>Giraffe</td>
<td>Person, Bike</td>
<td>Person, Horse</td>
</tr>
<tr>
<td>YOLO with Fitness</td>
<td>Cat</td>
<td>Giraffe</td>
<td>Car</td>
<td>Person, Cow</td>
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</table>

Figure 4.30 Examples of correct and incorrect classification after 25% of dropped weights when re-trained with ARprop
Fig. 4.30 shows recovery of the network when subjected to 25% of the faults. There are more misclassifications of images when compared to ADAM optimizer. ResNet misclassifies cat image as bag which was previously classified correctly when retrained with ADAM optimizer. SqueezeNet and AlexNet classify cat image as bag and person, horse image as zebra which is like Rprop results. SqueezeNet also misclassifies Giraffe image as horse.

**4.5 Dataset for Re-training**

We examine whether we need the full dataset for retraining a network after faults have been introduced. It would be beneficial to use parts of the training data for retraining to reduce memory requirements and training time. We retrained the networks with various portions of the training dataset and found that close to maximum recovery is achieved with about half of the training data when using the MSCOCO dataset and around 30% with AID dataset. Fig. 4.31 illustrates the increase in accuracy obtained when retraining VGG with larger portions of the data. This result illustrates that we don't need to have the whole dataset for retraining, but instead just part of it does the job. With about 50% of training data we achieve 98% accuracy as shown in Fig. 4.25.
4.6 Pruning

Table 4.11 Network Parameters, with its associated accuracy and number of iterations required

<table>
<thead>
<tr>
<th>Network</th>
<th>% of parameters dropped</th>
<th>Iterations required</th>
<th>% of data required</th>
<th>Accuracy after retraining</th>
</tr>
</thead>
<tbody>
<tr>
<td>GoogleNet</td>
<td>78%</td>
<td>1050</td>
<td>80</td>
<td>94.2</td>
</tr>
<tr>
<td>VGG16</td>
<td>82%</td>
<td>980</td>
<td>80</td>
<td>95.3</td>
</tr>
</tbody>
</table>

The optimizer used here is ADAM as it gives better testing accuracy, but it is slower.

The objective here is to reduce the size of the network by keeping the depth constant.

Table 4.11 shows that for the convolutional part of GoogleNet to reach the size of SqueezeNet, it should shed 78% of its parameters, while VGG16 must lose 82% of its
weights. Training with this kind of damage is hard but it yields good results with gradual decline in learning rate, i.e. using the ADAM optimizer.
Chapter 5

Conclusion

In this thesis, we present a study that explores the resiliency of six popular DCNN architectures when faults are introduced throughout the network or at a single convolution layer. Our results indicate that DCNNs are resilient to faults and their performance decreases gracefully, in most cases, as larger amounts of degradation are introduced. Out of the six networks we considered, AlexNet, VGG16, ResNet, Yolo, GoogleNet and SqueezeNet, VGG16 was found the most resilient when weights were dropped. After re-training ResNet is the most resilient to a particular limit of damage. Finally, AlexNet and SqueezeNet are the least resilient.

We find that most of the DCNN’s are over parameterized because they are built to classify a large number of object classes but most of the real-world scenarios deal with small number of classes. Preserving all the parameters would lead to computationally
intensive processing thus making the process slower. We demonstrate that bigger architectures can shed some of their parameters with little or no impact in their performance.

We also found that DCNNs have the capacity for self-healing by retraining the parts of the network that remain intact. Retraining only required about half of the data to recover the network's performance. Out of all the optimizers, the ADAM optimizer gives better result but requires increased computational cost. Rprop gives results that are very close to ADAM at almost 70% of the time. Hence Rprop can be used for retraining when there is weight damage. When pruning the network, where we focus on accuracy, we use ADAM optimizer as it gives better results when weights have been dropped above 60%. We finally demonstrate that larger architectures like GoogleNet and VGG16 can be reduced to the size of SqueezeNet while retaining. We also propose ARprop, a tweaked version of Rprop, that combines ADAM and Rprop to get results very close to Rprop at a faster rate.
Bibliography


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<th>Number</th>
<th>Reference</th>
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</table>


