Neural Networks Project
CIFAR-10 Image Recognition

EE4305 Introduction to Fuzzy/Neural Systems

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1 Introduction

T. M. Hayden & M. Gini

Machine learning and especially artificial neural networks (ANN) have been the object of intense research over the last few decades. It has produced tangible useful results over many different fields, from achieving superhuman performance in the game Go (see Section 2.2) to allowing users of social networks to automatically tag their friends in photo albums (see Section 3.3). Whilst there is a lack of the theoretical foundations behind ANN, it is still regarded as the state-of-the-art in many application areas.

The object of this assignment is to give us some exposure into how machine learning - especially ANN - can be applied to practical problems. This report will focus on how a multi-layer perceptron (MLP) can be trained on the CIFAR-10 dataset to perform image classification tasks. The CIFAR-10 data set contains 60000 32*32 RGB images labeled into 10 classes. It is a popular benchmark for image classification algorithms. Due to its relatively small size, training takes a relatively short amount of time which makes it suited for our project.

In the following sections of the report, we give a brief overview of general applications of ANN as well as some some notable recent accomplishments. The state-of-the-art algorithms developed for the CIFAR-10 dataset are reviewd as well. After that, Section 4 summarizes our work implementing a MLP and Section 5 presents the results of implementing a convolutional neural network (CNN) which is a more advanced network architecture. Naturally, the report finishes with a conclusion.

2 Literature Review on Artificial Neural Networks

M. Gini

This section gives a literature review on the broad topic of ANN. A more specific review on ANN designed to classify the CIFAR-10 dataset is found in Section 3. The significance and applications of ANN will be reviewed in Section 2.1 while recent trends and accomplishments are discussed in Section 2.2.

2.1 Significance and Applications of Artificial Neural Networks

This subsection will illustrate the significance and applications of ANN. Increasing computer power shifted the focus of research towards deep ANN and similar architectures which are coined under the term "deep learning". These powerful deep ANN are nowadays used in a variety of applications[1] [2].

ANN are significant because they can work as a black box model. The performance can be improved by data preprocessing, augmentation and mainly by finding an appropriate network architecture and training process. No a-priori knowledge of the classification process itself is required. This makes deep ANN suited for applications where such knowledge is difficult to obtain. Character and speech recognition are such difficult problems, as well as image classification. In speech recognition, deep ANN have been shown to outperform other methods on a variety of speech recognition benchmarks, sometimes by a large margin[3]. In the field of image classification, the 2012 ILSVRC (ImageNet Large-Scale Visual Recognition Challenge) marks an important turning point because a convolutional neural network (CNN) architecture won the competition for the first time - by a large margin[4]. In both fields, ANN are now widely accepted as the most powerful approach.

However, the fact that ANN do not incorporate much a-priori knowledge can also backfire. In consequence, a trained model gives little insight into its inner workings and optimal network architectures are basically found through a trial-and-error process. Most design guidelines for deep learning methods are therefore rather based on empirical knowledge than on theoretical foundations.

New methods are developed to better understand the computations deep ANN perform at each layer. The resulting visualizations reveal the process of extracting high level features out of raw input data[5] [6]. In general, each layer extracts higher level features of the input the previous layer provides such that the features are highly abstract after a few layers. The last layer then classifies the input into one of the output categories.

2.2 Recent Trends and Accomplishments

Recent trends and accomplishments of ANN are described in this section. Two recent accomplishments are looked at in detail: The AlphaGo computer program and adversial examples. AlphaGo is a great example to illustrate the great capabilities of ANN. Adversial examples can easily fool very different kinds of neural networks which is a good way to exemplify the limitations the present ANN still possess.

The game Go is a complex board game with the impressive number of around 10^{170} legal positions[7]. Due to its enormous search space and difficulty to evaluate board positions, it is viewed as the most challenging of the classical games for artificial intelligence. A victory of a computer program over a professional human player has been considered to be at least a decade away. However, the computer program AlphaGo beat the European Go champion 5-0 in 2015[8].

AlphaGo makes extensive use of ANN. It consists of a ”value” and a ”policy” network to separately evaluate the board position and select moves. It is trained in a combination of supervised learning from human expert games and reinforcement learning through self-play. The training of such big networks requires notable computation resources. In a recent trend, dedicated hardware to train deep ANN is developed. Besides other adaptions, it is designed to speed up matrix multiplications which are one of the main components of the training process. The most notable example is the Tensor Processing Unit which achieves a 15- to 30-fold performance compared to a contemporary GPU or CPU[9]. It is important to note that the development of deep learning is closely connected to the ever improving available computing power[10].

AlphaGo received considerable media coverage and is considered as one of the most impressive feats of deep learning. In a follow-up paper, a further improved version of AlphaGo is presented, AlphaZero[11]. It uses a single neural network and trains solely through reinforcement learning with self-play, starting with random play. It is only provided with the rules of Go. After only days of training, it defeated all previous versions of AlphaGo and achieved a never seen before playing strength. It is quite intriguing that even for such a complex task, the network can achieve superhuman performance without any provided knowledge besides the rules of the game.

As a second recent trend, adversarial examples recently surprised a lot of researches and became a hot topic of interest. To generate an adversarial example, a slight perturbation is applied to a correctly classified image. The classification process is then repeated and the perturbation is adapted such that the prediction error is *maximized.* A slight perturbation which is not recognizable by a human is already enough to let the neural network misclassify an image with a high confidence level[12]. It has been shown that adversarial examples trained on one model are likely to be misclassified by another model as well, i.e. they possess a transferability property[13].

It is very likely that a randomly selected input to a neural network built from linear parts is processed incorrectly and the models only behave reasonably on a very thin manifold encompassing the training data[14]. This result questions the generalization abilities of ANN. Furthermore, the transferability property allows potential attacks on systems using ANN[15] [16]. For example, stop signs could be slightly modified with stickers such that they are misclassified by autonomous vehicles which then behave unexpectedly. Further research is required to develop defense strategies against such attacks. Only then, ANN can deployed in safety critical applications.

3 Literature Review on the CIFAR-10 Dataset

T. M. Hayden

The CIFAR-10 dataset[17] is a well established dataset in the machine learning community. It is challenging because it is a relatively small dataset. Even so, excellent results, even exceeding human performance, have been obtained using a variety of CNN architectures[1]. At the time of writing, the highest published result on the CIFAR-10 dataset was achieved in 2015 with accuracy of 96.53%. This is considerably better than human performance which has an accuracy of around 94%[18].

3.1 Data Augmentation

Like many other machine learning problems, image classification will almost always benefit from additional data[19]. However, even when restricted to a particular dataset such as CIFAR-10 it is possible to generate more data using a technique called data augmentation[20]. Data augmentation manipulates existing images to create 'new' data for use in training.

Common methods to augment images for use in machine learning include mirroring, rotation and image translation[4]. Using these techniques it is possible to train on a dataset that can be several times larger than the original dataset. The leading architectures all made heavy use of data augmentation[21] [22] [23].

3.2 Leading Architectures for Classifying the CIFAR-10 Dataset

In this section, the results of several different CNN architectures are presented. It should be noted that these architectures were not designed specifically to perform on the CIFAR-10 dataset. As such, they may not be fully optimised and it is likely that they could be improved slightly.

3.2.1 Fractional Max-Pooling

In a standard CNN, convolutional layers are often interspaced with 2x2 max-pooling layers. These max-pooling layers serve to downsample the data. This allows the CNN to be somewhat spatially invariant to the locations of the features and improve accuracy. However each max pooling layer also removes 75% of the data[21]. This in effect reduces the maximum depth of the CNN due to the disjoint nature of the max-pooling regions.

By using a new approach known as fractional max-pooling, it is possible to max-pool using a non-integer mask size. In this manner, the size of the hidden layers is reduced by a lesser

[1]`http://rodrigob.github.io/are_we_there_yet/build/classification_datasets_results.html`

amount and it is possible to create deeper networks without having to add consecutive convolutional layers. This is important as generally deeper networks will lead to stronger classifiers[24]. However, deeper networks are also in general more expensive to train.

An architecture based on fractional max-pooling currently has the highest published classification accuracy on the CIFAR-10 dataset at 96.53%. This architecture also made heavy use of data augmentation. Additionally, the model was 'fine-tuned' after initial training by re-training on the original dataset for a few epochs using a low learning.

3.2.2 The All Convolutional Net(ALL-CNN)

In this architecture[23] a CNN consisting entirely of convolutional layers is proposed. Max-pooling layers are instead replaced with convolutional layers with increased stride. These increased stride layers act in a similar way to max-pool layers in that they downsample the data and allow the CNN somewhat invariant feature location. This architecture has an accuracy of 95.59% which is the 2nd highest published result. This architecture also makes heavy use of data augmentation.

3.2.3 Layer-Sequential Unit-Variance (LSUV) Initialization

LSUV initialisation provides a method to initialise deep CNN. This produces networks with better accuracy than uninitialised networks. In addition LSUV greatly accelerates the training of CNNs. An architecture based on the LSUV method machine managed to achieve an accuracy of 94.16%. Note that this only used a moderate amount of data augmentation.

It is important to stress the use of data augmentation when looking at these results. Table shows the results of the three leading architectures along with the amount of data augmentation. Moderate data augmentation consists of mirroring in the horizontal axis and small translations in each axis. Extreme data augmentation involves upscaling the images to 126 $\times$ 126 pixel images and performing a variety of operations such as shearing, colour augmentation, rotation, translation and scaling. It may be the case that with additional data augmentation, LSUV outperforms the max-Pooling approach.

Data Augmentation	Fractional Max-Pooling	ALL-CNN	LSUV
None	-	90.92%	-
Moderate	-	92.75%	93.94%
Extreme	96.53%	95.59%	-

Table 1: Table showing the results of the leading CIFAR-10 architectures.

3.3 Application Areas of Image Recognition Algorithms

There are numerous applications of image recognition algorithms across many different fields. However in order for neural networks to be effective, large amounts of labeled data must first be collected. In practice labelling and uploading of images is mostly done by users of the application by 'tagging' images. For example in a stock image database such as Shutterstock[2], users would be prompted to tag uploaded images with the image contents. This provides Shutterstock with an enormous amount of data perfect for machine learning. This has allowed Shutterstock to develop powerful new tools to label images using machine learning. For example

[2]`https://www.shutterstock.com/`

the newly released compositionally aware search which allows users to search for images with specific objects in different locations of the image[25].

Another application of image recognition is to automatically tag recognised faces when uploading photos onto social media websites. This is useful as it is often tedious to tag each image in large albums. Automatic tagging algorithms have been developed using machine learning to automatically tag faces with accuracy as high 99%[26]. This allows users to upload entire albums without having to tag each photo individually.

4 Multi-Layer Perceptron Classifier

M. Gini & T. M. Hayden

This section presents the MLP classifier designed to classify the CIFAR-10 dataset. It is organized as follows: Section 4.1 introduces the software setup used to implement the MLP classifier. Section 4.2 discusses the data preprocessing and augmentation. Section 4.3 analyzes the effect of different network structures on performance. Section 4.4 analyzes the effect of different hyperparameters. Finally, Section 4.5 presents the optimized MLP classifier.

4.1 Software Setup

MATLAB's Neural Networks toolbox is employed to implement the MLP classifier. The toolbox provides convenient algorithms and applications to design the MLP. A network training function with a convenient graphical user interface (GUI) to observe the progress is included as well. Figure 1 shows the GUI.

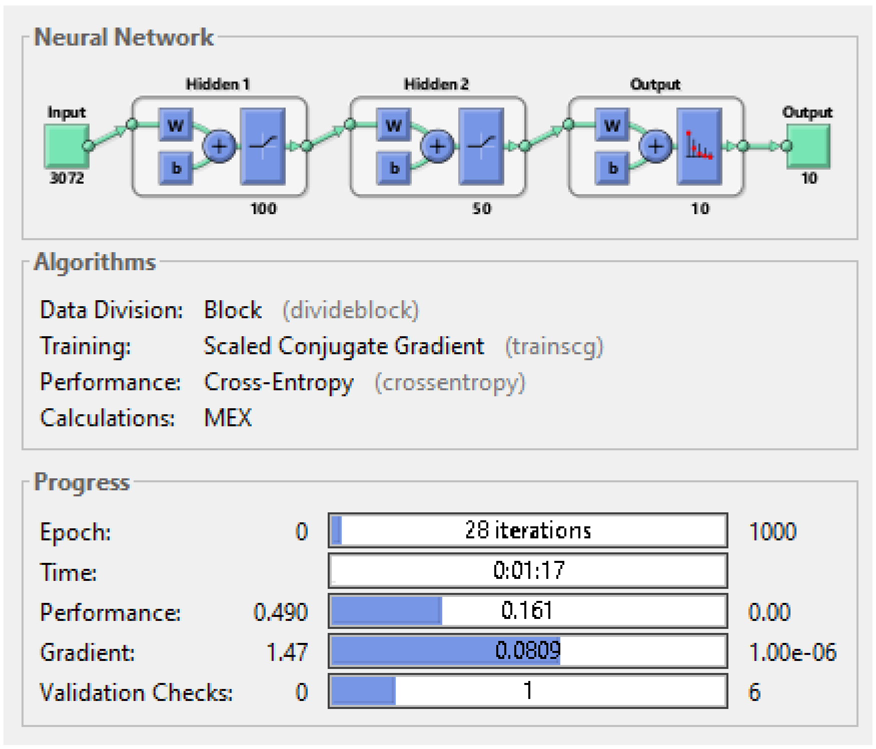
Since this is a classification problem, parts of the network structure are given. The output of the MLP should be a prediction of to which class the input belongs to. This is accomplished with the help of the softmax function, also called normalized exponential function. Equation 4.1 shows the formula of such a function. A softmax layer is then used as the last layer. It gets a K-dimensional input vector $\boldsymbol{z}$ of arbitrary real values and "squashes" it into a K-dimensional output vector $\sigma(\boldsymbol{z})$ of real values in the range $[0, 1]$. In our case, $K = 10$ and the output values represent the probabilities that the input belongs to the respective class. The class with the highest probability then constitutes the predicition of the MLP.

$$\sigma(\boldsymbol{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for} \quad j = 1, \ldots K. \tag{4.1}$$

Every ANN will have at the very least one input layer and one output layer. The size of the input layer simply depends on the size of the input data vector. In the case of the CIFAR-10 dataset, the input size is $1 * 3072$, the number of pixels per image. Since the dataset is to be classified into 10 categories, the output layer is a softmax layer with 10 nodes.

The other hidden layers consist of standard MLP. The input to the MLP are the pixel values of the image. Preprocessing and augmentation as described in the next section is done before the pixel values are fed into the network. MATLAB offers lots of adjustable settings for the MLP. Unless mentioned otherwise, the following settings are employed as default settings:

- Training function: 'trainscg', the scaled conjugate gradient method.
- Loss function: 'crossentropy'
- Activation function: 'tansig'
- As a default network structure, two hidden layers are employed with 100 and 50 neurons.



Algorithms

Data Division: Block (divideblock)
Training: Scaled Conjugate Gradient (trainscg)
Performance: Cross-Entropy (crossentropy)
Calculations: MEX

Progress

Epoch:	0	28 iterations	1000
Time:		0:01:17	
Performance:	0.490	0.161	0.00
Gradient:	1.47	0.0809	1.00e-06
Validation Checks:	0	1	6

Figure 1: Screenshot of MATLAB's nntraintool.

- Weight initialization: The weights of the neurons are randomly initialized. Since this leads to slightly different performance for each run, for the performance analysis each configuration is run five times and then the test accuracy is averaged. The standard deviation of the different runs is then plotted as well.
- The training batch size is set to 20000 images. This constitutes a compromise between a good performance and a reasonable training time. 80% are used for training and 20% are used for validation.
- The testing batch consisting of 10000 images is employed for testing of the MLP.

4.2 Data Preprocessing and Augmentation

Data preprocessing and augmentation take place before the data is fed into the network. In the preprocessing step, the data is normalized and centered around the mean. In the augmentation step, the amount of data is augmented through operations like image flipping.

4.2.1 Data Preprocessing

Each image of the dataset is represented by a 32*32*3 array, which results in 1024 pixel values per color channel. To be processed by the MLP, it is transformed into a 1*3072 array. The pixel values are integers in the range [0,255]. For normalization, the data is divided by 255 to lie within the range [0,1]. Accordingly, the datatype changes from the integer type to double. In a second step, the mean per pixel over the whole training set is subtracted. This centers the data per channel.

Data preprocessing also includes the division of the complete dataset into appropriate training, validation and test data batches. There are 50000 images available for training. With the default splitting into training and validation dataset (80% for training and 20% for valida-

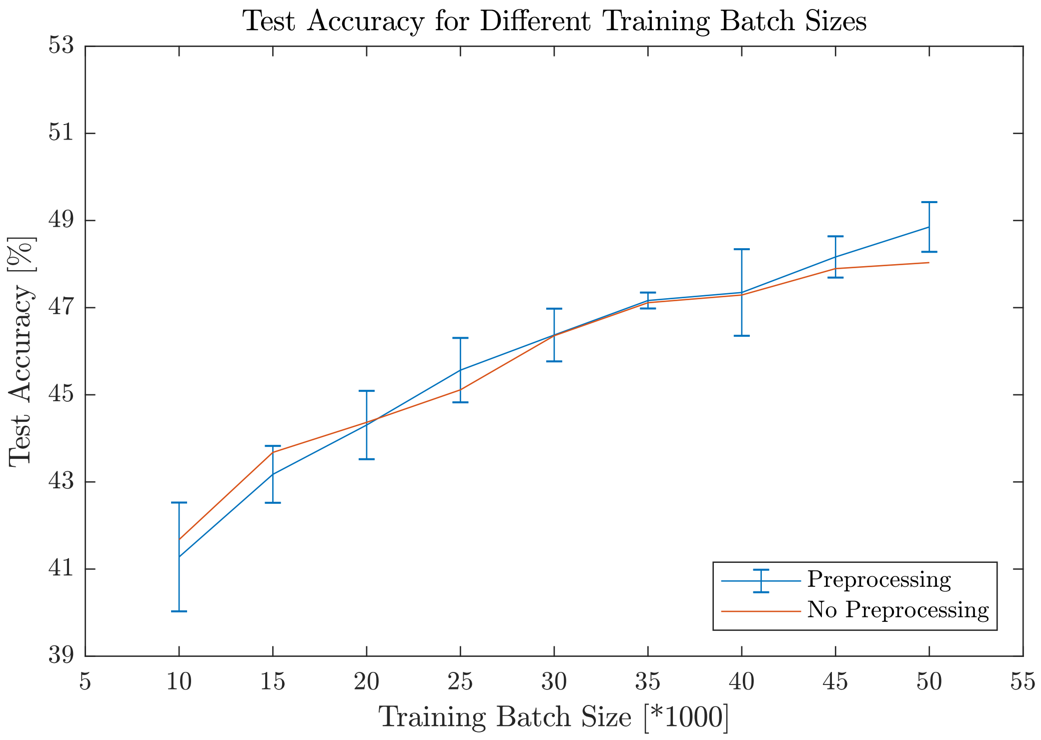


Figure 2: Comparison of network performance with and without data preprocessing. The errorbars represent one standard deviation. The default MLP classifier is used.

tion), Figure 2 shows the effect of varying the training batch size as well as employing data preprocessing.

As intuitively expected, the test accuracy increases for an increasing training batch size. However, the data preprocessing does not lead to a significant increase of performance. The normalization and mean subtraction do not have a big influence in the specific case of the CIFAR-10 dataset since the input values already lie in a well defined range and the mean per pixel is also a almost constant value over all pixels.

4.2.2 Data Augmentation

Figure 2 above shows that a larger training batch size leads to an increased performance. A natural approach is therefore to artificially increase the training batch size. Image flipping and image rotation are implemented. Figure 3 illustrates the performance gain from vertical image mirroring. The test accuracy is significantly increased for all training batch sizes by around 3 %.

Figure 4 illustrates the data augmentation process on a cat image. The image is mirrored and rotated three times by 90 degrees. This results in a 8-fold increase of the training batch size.

4.3 Optimization of Network Structure

Choosing the correct architecture of a neural network remains an area of study which is still not fully understood[27]. For a given problem, there is a variety of valid MLP architectures. Approaches to choose an architecture are mostly based on heuristics and therefore not fool-proof[27].

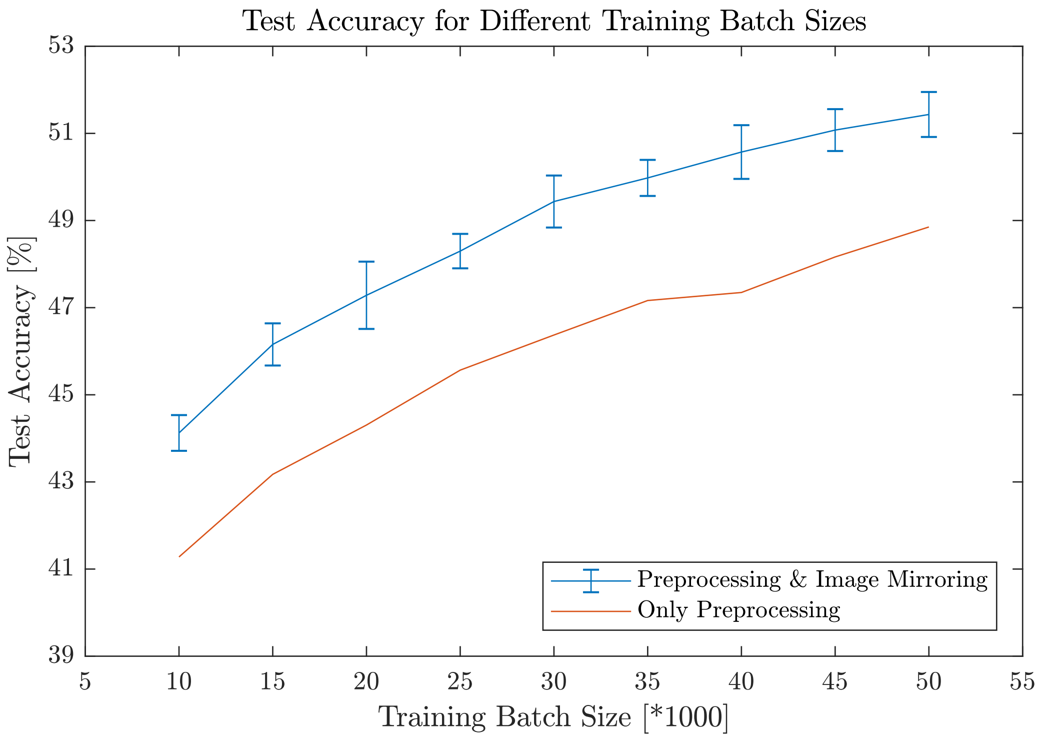


Figure 3: Comparison of network performance with and without data augmentation. The errorbars represent one standard deviation.

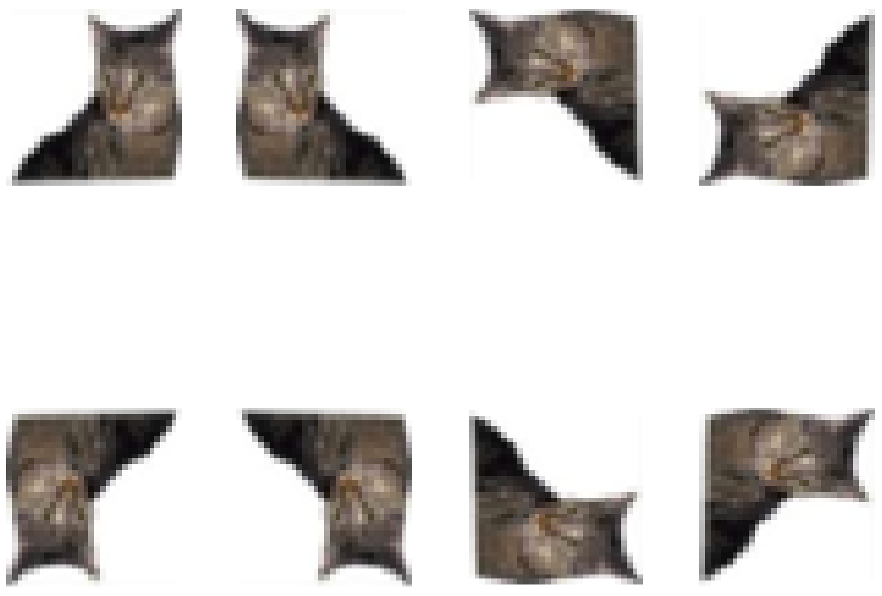


Figure 4: Illustration of the data augmentation process on a cat image. Image mirroring and rotation is employed.

4.3.1 Number of Hidden Layers

In general, a MLP can have an arbitrarily large number of hidden layers. However, MLP architectures with a large number of hidden layers are not common. Additionally, adding more layers increases the chance that the classifier finds a local minimum[28]. Figure 5 shows the effect of varying the number of hidden layers of the default MLP classifier. Note that the test accuracy remains almost constant for more than two hidden layers.

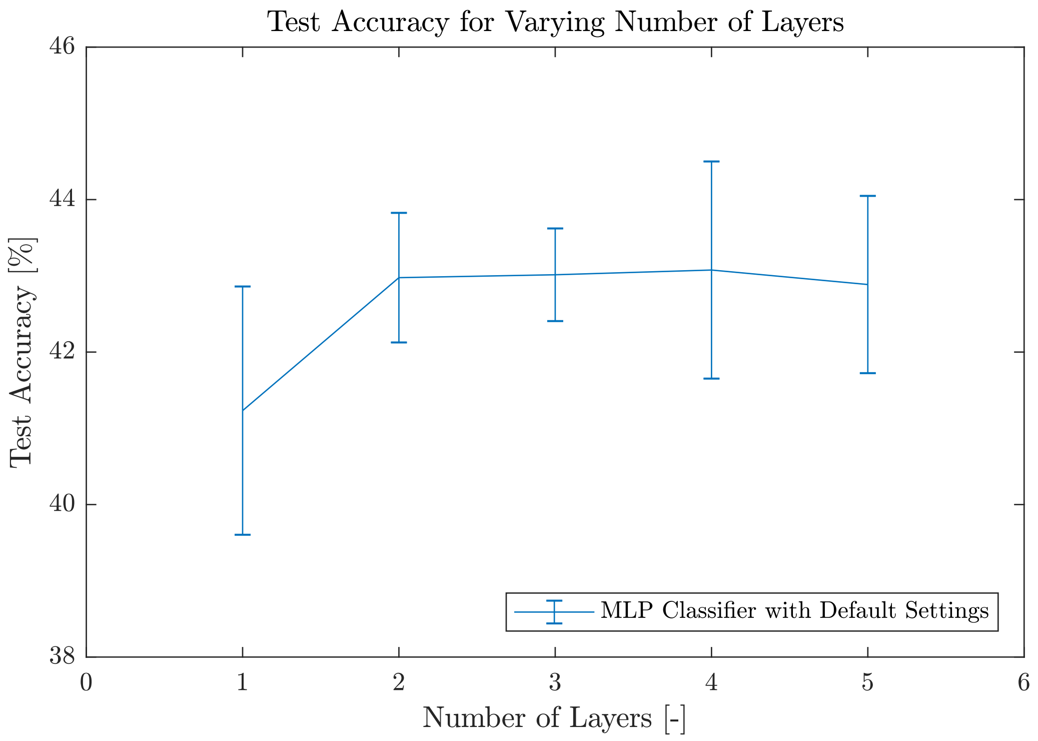


Figure 5: Effect of varying the number of hidden layers of the default MLP classifier. The errorbars represent one standard deviation of the averaging process.

4.3.2 Number of Neurons

Choosing the optimum number of neurons per layer is a challenging task when designing any MLP architecture. Even in modern archetectures, the number of neurons is generally first estimated using empirical rules and then optimised for the particular dataset[29]. This is especially the case when using noisy datasets such as CIFAR-10.

Figure 6 shows the result of varying the number of neurons in the case of two hidden layers. The results show that the number of neurons in the first layer have very little effect on the test accuracy. In addition, the results also show that increasing the number of neurons beyond around 70 had very little to no effect. Increasing the number of neurons also increased the time to train. The number of neurons in the second layer also has a much stronger impact on the time taken to train than the number of neurons in the first layer.

4.4 Optimization of Network Hyperparameters

Hyperparameter selection for ANN such as MLP has become an active field of research with various algorithms being used to estimate optimal parameters[30]. However, since these algorithms rely on performing many trials and updating the parameters accordingly, they proved unsuitable for our purposes due limited computational resources. Instead, a few parameter are varied while using the default MLP structure. Optimal parameters are then estimated from these trends.

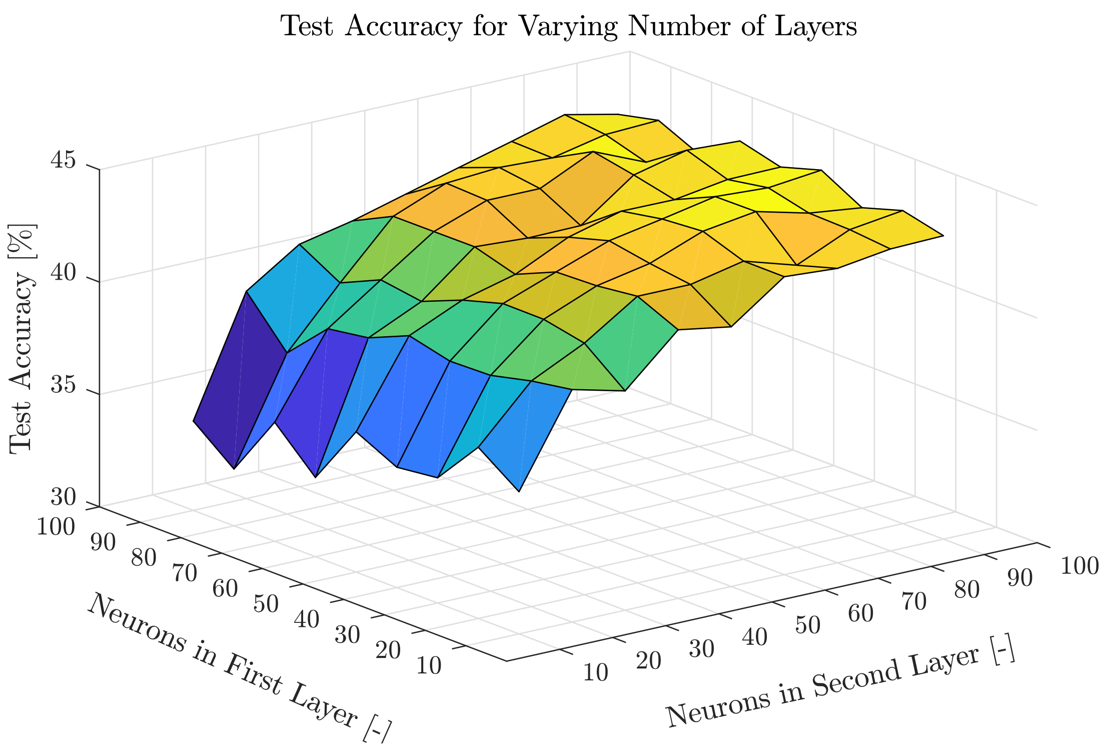


Figure 6: Hello Boy2

4.4.1 Performance Function

The performance function is used to measure the error that a specific input produces in the network. The error expression is then used in the training algorithm which usually is a variation of the backpropagation method[31]. MATLAB offers the following different performance functions:

- SAE, the sum absolute error function
- SSE, the sum squared error function
- MAE, the mean absolute error function
- MSE, the mean squared error function
- Crossentropy error function

As Figure 7 shows, three performance functions result in a similar performance: MSE, SSE and Crossentropy. SAE and MAE result in a slightly lower performance. An explanation might be that these two functions take the absolute error instead of the squared error. Using the squared error leads to a stronger penalization of larger errors. The best performance is achieved using the crossentropy performance function. This performance function heavily penalizes large errors with very little penalty for small errors. It is also recommended by MATLAB for classification tasks.

4.4.2 Activation Function

The activation function controls the firing of a single neuron. After multiplying the input with the weight and bias vector, the result is fed into the activation function. The output of the activation function constitutes the output of the neuron. Again, MATLAB offers a variety of

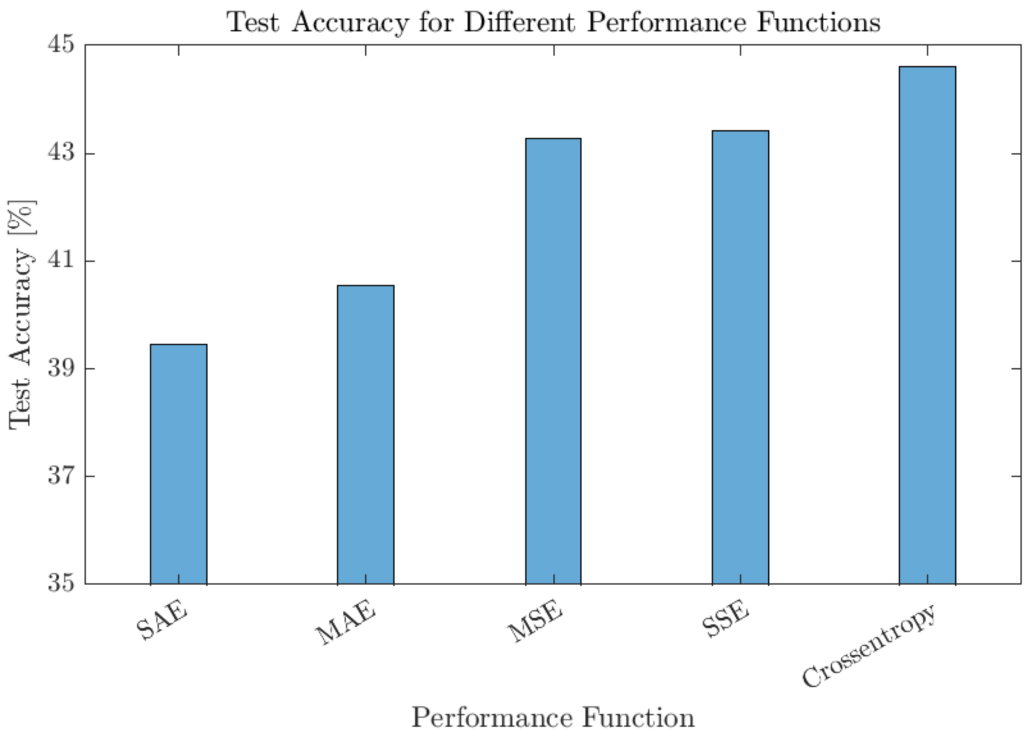


Figure 7: Comparison of the test accuracy of the default MLP using different performance functions.

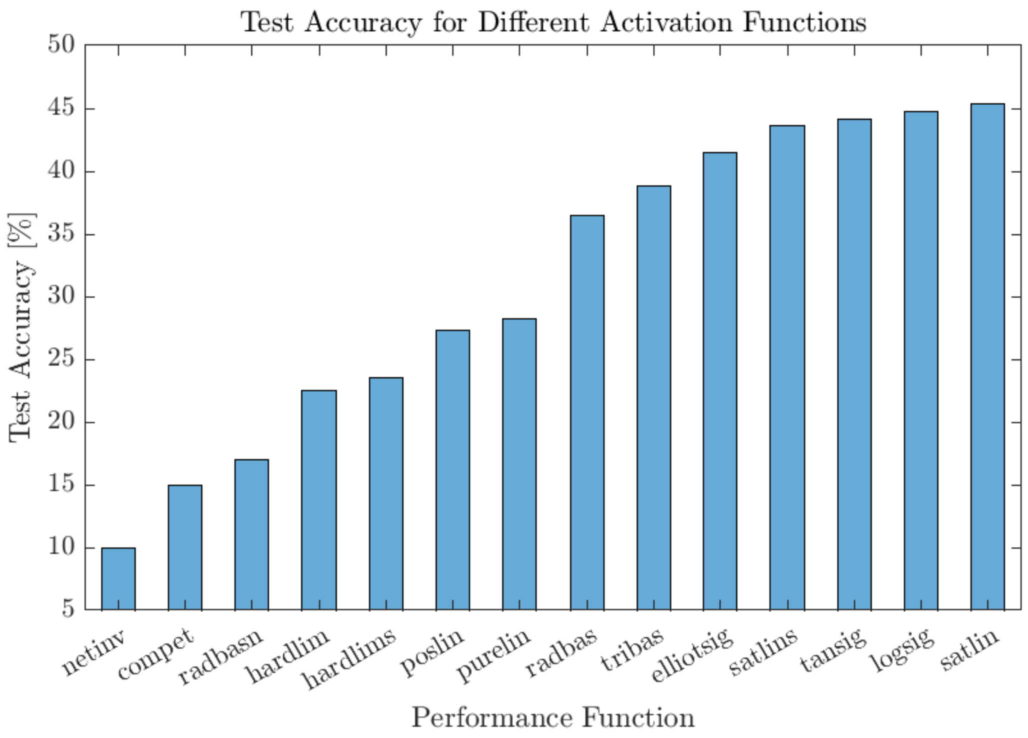


Figure 8: Comparison of the test accuracy of the default MLP using different activation functions.

different activation functions. For the sake of completeness, all activation functions are tested with the default MLP. The result is displayed in Figure 8.

It can be seen that several activation functions are not suited for a MLP classification problem, e.g the 'netinv' and 'compnet' type. Furthermore, there is a class of activation functions which are very similar and all perform well on that specific problem. Specifically, sigmoid shaped activation functions seem to be the appropriate choice for our problem setting. 'tansig' and 'logsig' are quite similar and 'satlin' and 'satlins' can be viewed as linear approximations of those nonlinear activation functions. It is interesting to note that using the 'satlin' type results in the best performance.

4.4.3 Training Function

The training function is the algorithm that dictates the training process of the network. Once again, MATLAB offers a wide selection of training algorithms. Most are variations of the backpropagation algorithm. Figure 9 shows the results of using various training algorithms on the default MLP structure.

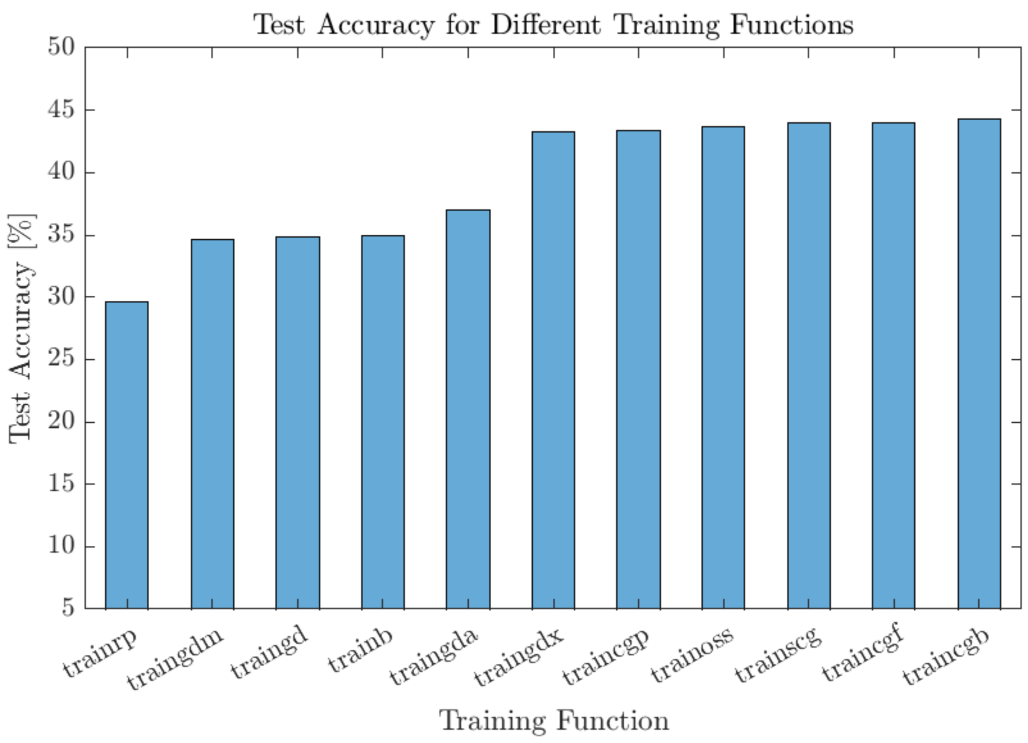


Figure 9: Comparison of the test accuracy of the default MLP using different training functions.

All variations of the conjugate gradient backpropagation algorithm[32] achieve good performance. It is interesting that the performance is superior compared to variations of simple gradient backpropagation. 'traindx' which uses momentum is the only gradient backpropagation variation which achieves similar performance than conjugate gradient backpropagation.

An advantage of conjugate gradient backpropagation algorithms is that they do not require a learning rate parameter. Since our investigations show that they are superior over other backpropagation methods, no further analysis on finding optimal learning rates is conducted.

4.5 Optimized Classifier

5 Convolutional Neural Network Classifier

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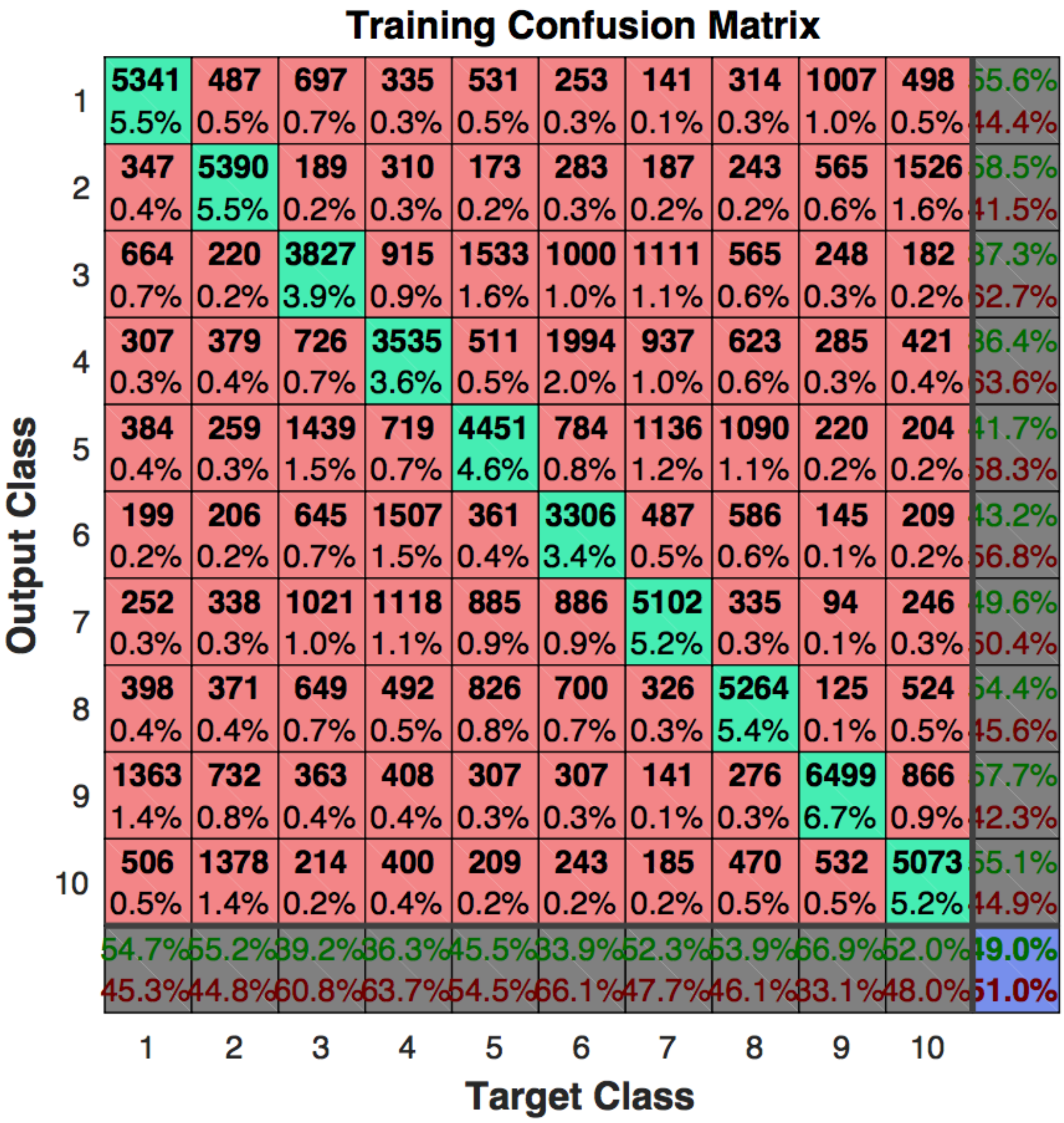
CNN is a more advanced architecture compared to a MLP network. Similarly to a MLP, it consists of an input as well as an output layer, as well as several hidden layers. The hidden layers



Training Confusion Matrix

Output Class \ Target Class	1	2	3	4	5	6	7	8	9	10	
1	5341 5.5%	487 0.5%	697 0.7%	335 0.3%	531 0.5%	253 0.3%	141 0.1%	314 0.3%	1007 1.0%	498 0.5%	55.6% 44.4%
2	347 0.4%	5390 5.5%	189 0.2%	310 0.3%	173 0.2%	283 0.3%	187 0.2%	243 0.2%	565 0.6%	1526 1.6%	58.5% 41.5%
3	664 0.7%	220 0.2%	3827 3.9%	915 0.9%	1533 1.6%	1000 1.0%	1111 1.1%	565 0.6%	248 0.3%	182 0.2%	37.3% 62.7%
4	307 0.3%	379 0.4%	726 0.7%	3535 3.6%	511 0.5%	1994 2.0%	937 1.0%	623 0.6%	285 0.3%	421 0.4%	36.4% 63.6%
5	384 0.4%	259 0.3%	1439 1.5%	719 0.7%	4451 4.6%	784 0.8%	1136 1.2%	1090 1.1%	220 0.2%	204 0.2%	41.7% 58.3%
6	199 0.2%	206 0.2%	645 0.7%	1507 1.5%	361 0.4%	3306 3.4%	487 0.5%	586 0.6%	145 0.1%	209 0.2%	43.2% 56.8%
7	252 0.3%	338 0.3%	1021 1.0%	1118 1.1%	885 0.9%	886 0.9%	5102 5.2%	335 0.3%	94 0.1%	246 0.3%	49.6% 50.4%
8	398 0.4%	371 0.4%	649 0.7%	492 0.5%	826 0.8%	700 0.7%	326 0.3%	5264 5.4%	125 0.1%	524 0.5%	54.4% 45.6%
9	1363 1.4%	732 0.8%	363 0.4%	408 0.4%	307 0.3%	307 0.3%	141 0.1%	276 0.3%	6499 6.7%	866 0.9%	57.7% 42.3%
10	506 0.5%	1378 1.4%	214 0.2%	400 0.4%	209 0.2%	243 0.2%	185 0.2%	470 0.5%	532 0.5%	5073 5.2%	55.1% 44.9%
	54.7% 45.3%	55.2% 44.8%	39.2% 60.8%	36.3% 63.7%	45.5% 54.5%	33.9% 66.1%	52.3% 47.7%	53.9% 46.1%	66.9% 33.1%	52.0% 48.0%	**49.0% 51.0%**

Figure 10: Confusion Matrix for the final MLP classifier

typically consist of convolutional layers, pooling layers, fully connected layers and normalization layers. Due to that, CNN are usually much deeper than MLP networks.

However, CNN require significantly more computing power to train. Even though MATLAB supports training on the GPU, some quick maths reveal that our computational resources are insufficient for extensive parameter search of a CNN.

5.1 Network Structure

Since the number of hidden layers of a CNN can be quite large, even more hyperparameters could be explored than for an MLP. This takes unreasonable amounts of time. Therefore, this section only presents the final version of our CNN which is found through small trial-and-error tests. It consists of 16 layers which are summarized below.

- **Input Layer**
  For a color image, the channel size is 3, corresponding to the RGB values. You do not need to shuffle the data because trainNetwork, by default, shuffles the data at the beginning of training.

- **Output Layer**
  The output layer consists of a softmax layer as described earlier together with a classification layer which simply chooses the class that obtained the highest prediction by the softmax layer.

Convolutional Layer In the convolutional layer, the first argument is filterSize, which is the height and width of the filters the training function uses while scanning along the images. In this example, the number 3 indicates that the filter size is 3-by-3. You can specify different sizes for the height and width of the filter. The second argument is the number of filters, numFilters, which is the number of neurons that connect to the same region of the input. This parameter determines the number of feature maps. Use the 'Padding' name-value pair to add padding to the input feature map. For a filter size of 3, a padding of 1 ensures that the spatial output size is the same as the input size. You can also define the Stride and learning rates for this layer using name-value pair arguments of Convolution2DLayer.

Batch Normalization Layer Batch normalization layers normalize the activations and gradients propagating through a network, making network training an easier optimization problem. Use batch normalization layers between convolutional layers and nonlinearities, such as ReLU layers, to speed up network training and reduce the sensitivity to network initialization. Use BatchNormalizationLayer to create a batch normalization layer.

ReLU Layer The batch normalization layer is followed by a nonlinear activation function. The most common activation function is the rectified linear unit (ReLU). Use ReLULayer to create a ReLU layer.

Max-Pooling Layer Convolutional layers (with activation functions) are sometimes followed by a down-sampling operation that reduces the spatial size of the feature map and removes redundant spatial information. Down-sampling makes it possible to increase the number of filters in deeper convolutional layers without increasing the required amount of computation per layer. One way of down-sampling is using a max pooling, which you create using MaxPooling2DLayer. The max pooling layer returns the maximum values of rectangular regions of inputs, specified by the first argument, poolSize. In this example, the size of the rectangular region is [2,2]. The 'Stride' name-value pair argument specifies the step size that the training function takes as it scans along the input.

Fully Connected Layer The convolutional and down-sampling layers are followed by one or more fully connected layers. As its name suggests, a fully connected layer is a layer in which the neurons connect to all the neurons in the preceding layer. This layer combines all the features learned by the previous layers across the image to identify the larger patterns. The last fully connected layer combines the features to classify the images. Therefore, the OutputSize parameter in the last fully connected layer is equal to the number of classes in the target data. In this example, the output size is 10, corresponding to the 10 classes. Use FullyConnectedLayer to create a fully connected layer.

5.2 Test Accuracy Results

Here, the results of a few tests are presented.

6 Conclusion

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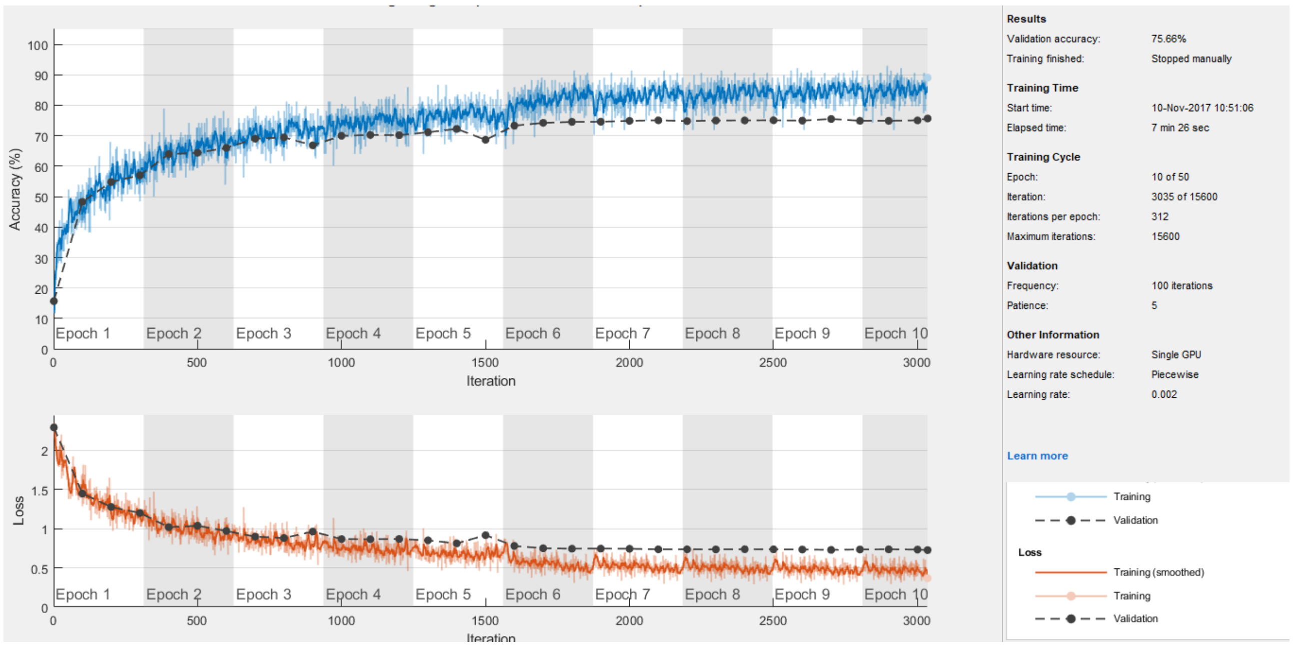
Two literature reviews gather a considerable amount of knowledge about ANN.



Results

Validation accuracy:	75.66%
Training finished:	Stopped manually

Training Time

Start time:	10-Nov-2017 10:51:06
Elapsed time:	7 min 26 sec

Training Cycle

Epoch:	10 of 50
Iteration:	3035 of 15600
Iterations per epoch:	312
Maximum iterations:	15600

Validation

Frequency:	100 iterations
Patience:	5

Other Information

Hardware resource:	Single GPU
Learning rate schedule:	Piecewise
Learning rate:	0.002

Figure 11: MATLAB GUI for training CNN.

A MLP is implemented using MATLAB. Several parameter searches over the network structure and its hyperparameters are conducted.

The random initialization of the weights provides another possibility to explore the parameter space.

Furthermore, a CNN is implemented as well. A few different architectures are tested and a performance exceeding the MLP performance is achieved. Due to the computational limitations, the main focus of this report is laid on the MLP classifier.

The excessive use of quick maths also improved our network architecture.

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