

Object Classification in Road Images



UNIVERSITY *of* LIMERICK

O L L S C O I L L U I M N I G H

Final Year Project 2019

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Abstract

This project will be a research-oriented project centred around the use of Convolutional Neural Networks for object detection in images from the perspective of a self-driving car. The concept of self-driving cars is a rapidly expanding field, with significant investments having taken place over the past several years in this area. Many companies have chosen to use cameras as one of the primary sensors deployed on their prototype cars in conjunction with other sensors such as LIDAR, radar etc. to allow a vehicle to understand its environment and orient itself appropriately. This project will focus on the way these cameras can allow the vehicle to classify different objects in its environment. An important challenge within the field of machine vision in self-driving cars is reliably classifying multiple objects at once within an image. The current standard Machine Learning class of algorithms for object classification are CNNs (Convolutional Neural Networks). This project will use Convolutional Neural Networks as well as some Computer Vision techniques to analyse colourised 2D images that depict typical scenes presented to a self-driving car and classify the different objects within them. The initial goal is to research and outline the basics of how Convolutional Neural Networks operate, then choose a particular Convolutional Neural Network paradigm and train a classifier using this paradigm. The classifier should be able to reliably classify major obstacles that are important to the function of a self-driving car such as other vehicles, pedestrians etc. The classifier should aim to be robust to adverse conditions creating noise within the images such as rain, snow etc. This project should then investigate the effects of parameter tuning and the consequences this reflects in the accuracy of the model.

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Chapter 1

Overview

1.1 Introduction to Problem Area

This project deals with the area of classifying multiple objects within an image, specifically from the perspective of images presented to a self-driving car. A typical use case for a Machine Learning algorithm within the field of Computer Vision is image classification, whereby an image is presented to an algorithm and the algorithm decides which class that the image belongs to from a set of classes. For example, if an algorithm that is trained to tell the difference between dogs and cats is provided an image of a dog or a cat it should return a label for the image of either dog or cat.

A more complex problem however is the concept of object detection. If in the previous example an image that contains both a cat and a dog is supplied to the algorithm, it will typically label the image with the label that corresponds to the most prominent object within the image. A Machine Learning algorithm for object detection must be able to take in this image and correctly label both the dog and the cat within the image.

This class of machine Learning algorithm is particularly useful in the field of self-driving cars. A self-driving car will typically be provided images which contain multiple objects, all of which must be correctly classified in order for the vehicle to function safely.

The standard type of Machine Learning algorithm that is utilised for image based problems is the Neural Network, a class of Machine Learning

algorithm modelled off the neural pathways of the brain. Within this class of algorithm, a class known as Convolutional Neural Networks (CNN's) has become increasingly popular. Both Neural Networks and CNN's will be explained further in this paper.

The overall aim of this project is to leverage CNN's to train an object classifier on a dataset extracted from cameras mounted on cars that consists of images containing multiple different objects such as pedestrians, vehicles etc.

1.2 Objectives

1.2.1 Primary Objectives

Utilise a Convolutional Neural Network for Object Classification

The core concept of this project is the use of Convolutional Neural Networks in the classification of objects within images. As such, the primary objective for this project is to research and implement a Convolutional Neural Network that will return an acceptable level of accuracy on the testing data. The success metric for this objective is to have a working classifier that can classify all the different objects labelled in the dataset to a reasonable degree of accuracy. As there is no significant degree of research available on the dataset, there is no hard accuracy level that could be defined as a target. However any overall accuracy above 50% will be considered acceptable for this project.

Adjust and tune the Neural Network

There are many different approaches that can be taken with regards to achieving the highest accuracy for an object classifier. Part of the project will involve researching and documenting several of these techniques. Once this has been done, a primary objective for this project will be to investigate how different approaches change the accuracy of the classifier. The success metric for this objective will be to have carried out several different approaches to the architecture and parameters of the classifier in order to improve its performance and to have the results documented.

1.2.2 Secondary Objectives

Investigate and document the concepts behind Convolutional Neural Networks

As this is a research-based project, a large amount of the work involved will be around the investigation of how Convolutional Neural Networks operate and the different approaches that one can take when designing a Convolutional Neural Network. The success metric for this objective will be the ability to make an educated choice when tuning and adjusting the classifier, as well as having documented this research.

Investigate and gain an understanding of Computer Vision techniques and concepts and how they apply to the accuracy of the Neural Network

When working with any kind of image classifier that takes in real-world image data, an important part of the process of creating a classifier is to apply Computer Vision techniques to transform the images in order to give the image classifier an easier time achieving high accuracy. The success metric for this objective is to research, document and apply different techniques that can be used to preprocess the images that are then provided to the classifier.

1.3 Contribution

1.4 Methodologies

1.5 Project Plan

1.5.1 Table

Chapter	Section	Est. Completion Date
Introduction	Intro to Problem Area	12/10/2018 - wk5
	Motivations	12/10/2018 - wk5
	Objectives	05/10/2018 - wk4
	Contribution	End?
	Methodologies	12/10/2018 - wk5
	Project Plan	05/10/2018 - wk4
Background Research	Intro to ML	19/10/2018 - wk6
	Intro to Neural Networks	26/10/2018 - wk7
	Intro to CNN's	26/10/2018 - wk7
	Intro to Computer Vision	02/11/2018 - wk8
	Technology Investigation	19/10/2018 - wk6
Empirical Studies	CNN Architectures	16/11/2018 - wk10
	Image Processing	30/11/2018 - wk11
Classifier Implementation	Requirements	14/12/2018 - wk13
	System Design	
	Implementation	
	Analysis	
Final Conclusion	Review of Research	
	Reflections	

1.6 Motivations

The main motivation behind this project for me is working within the field of self-driving cars. I find this particular area fascinating due to the broad range of technologies present within these cars. I have previously worked a summer internship at Jaguar Land Rover in Shannon working within the ADAS (driver assistance) team. I was exposed to a broad range of different technologies, from Computer Vision and Machine Learning based teams to Big Data pipelines concerned with offboarding data from test cars. This internship and the potential to work with the company further down the line has really motivated me to further my study within this field. I have found that these technologies are much more interesting to me than many more conventional potential areas of work. With ever increasing amounts of automotive manufacturers investigating this field, I feel like a final year project focusing on self-driving cars could be very beneficial to my career going forward.

I am also very interested in self-driving cars due to the far-reaching safety implications of the technology. Hundreds of people die on Irish roads every year, with driver error being the primary cause of fatalities. Self-driving cars have the potential to save countless lives in the future, and I find it very motivating to work within a field that has the potential to produce very tangible positive changes in the daily lives of many people.

Chapter 2

Background Research - 10 Pages

2.1 Introduction to Machine Learning

A general definition of Machine Learning: “[Machine Learning is the] field of study that gives computers the ability to learn without being explicitly programmed“ - Arthur Samuel, 1959.

One of the goals for Machine Learning algorithms is automatically observing structures in data and fitting these structures to a model in order to allow people to interact with the data in a way that is humanly intuitive. Development within the field has progressed to the point where people interact with Machine Learning algorithms multiple times in their daily lives without noticing. Areas such as email spam detection, Facebook image tagging suggestions and voice-to-text are all examples of a broad range of Machine Learning algorithms that are commonly used.

Machine Learning can be roughly divided into two categories - Supervised and Unsupervised.

2.1.1 Supervised Learning

In Supervised Learning, algorithms are provided with some labelled input data which they attempt to learn patterns from. The algorithms will then attempt apply this learned experience to new unseen data and attempt to create their own labels for the data, with varying degrees of success.

Prominent examples of the Supervised category of Machine Learning include Support Vector Machines, Linear Regression and the focus of this project, Convolutional Neural Networks (O'Shea and Nash, 2015).

2.1.2 Unsupervised Learning

Unsupervised Learning algorithms differ from Supervised Learning algorithms in that they are given data with no labels. They must then attempt to find some structure in this input data themselves with no given direction or explicit programming. Popular Unsupervised Learning examples include clustering algorithms.

2.1.3 History of Neural Computing

Neural Networks are not a new concept - they were first proposed in 1943 by neurophysicists in the form of a primitive electrical circuit. The concept was studied up until the 1960's until it fell out of favour with researchers. Bold claims had been made by many researchers about the vast potential of the field, however a failure to back up these claims led to widespread skepticism about the true potential of Neural Computing. The area was in part hampered by the technology of the time - processing power available to researchers was very low. Additionally, in 1969 a paper entitled "Perceptrons: An Introduction to Computational Geometry" was published introducing the XOR problem, which will be explained later. The paper stated that the research being carried out at the time on Neural Networks was fundamentally flawed and that the field would not experience any major successes. A revival was seen in the 1980's, when the concept of using multiple layers of neurons to create a network began to emerge, and the issues presented by the XOR problem were solved. From 1989 to 1994 Yann LeCun developed the LeNet architecture, one of the first examples of a CNN, which was used to recognise handwritten postal addresses. In around the 2010 the field of Deep Learning (explained below) experienced a surge in popularity, primarily due to the increase in processing power made available through GPU's. In 2012, Alex Krizevsky won the ImageNet competition, a popular image recognition competition. The architecture he used, known as AlexNet, achieved an error rate of 15%, which was approximately 10% better than the closest competition at the time. His architecture essentially scaled up the LeNet architecture into a larger, more

complex network (Krizhevsky, Sutskever, and Hinton, 2012). This architecture caused a widespread adoption of CNN's within image based Machine Learning, and CNN's are now the de facto standard for many image processing tasks (O'Shea and Nash, 2015).

2.2 Introduction to Neural Networks and Deep Learning

Artificial Neural Networks (ANN's) are a particular Machine Learning paradigm modelled after the neural pathways present in the brain. The building blocks for every Neural Network is the perceptron or node, an artificial neuron. It receives inputs with weights associated with them that show the importance of each input relative to the others. The node applies a particular activation function to the weighted sums of the input, and an output is generated, as shown in Figure 2.1 (Géron, 2017). A single Perceptron is only able to classify linearly separable data (Kotsiantis, Zaharakis, and Pintelas, 2007). In order to classify data that is not linearly separable, techniques such as Multilayer Perceptrons must be used. These will be explained in a following section. Linear separability refers to the ability for a single line to separate all members of a given class A from all members of a given class B. This is illustrated in Figure 2.3.

There are several different types of activation function, however every activation function takes in a single number as input and performs a certain mathematical operation on the number. The three most common activation functions generally encountered are ReLU, tanh and sigmoid. Rectified Linear Unit, or ReLU, takes in an input and replaces negative numbers with zero. The tanh function squashes the input to between the range between -1 and 1. Finally the sigmoid activation function takes the input and squashes it to the range between 0 and 1. In the field of CNN's ReLU is commonly used, as training times are significantly better when using this activation function. (Krizhevsky, Sutskever, and Hinton, 2012). These different types of activation function are visualised in Figure 2.2.

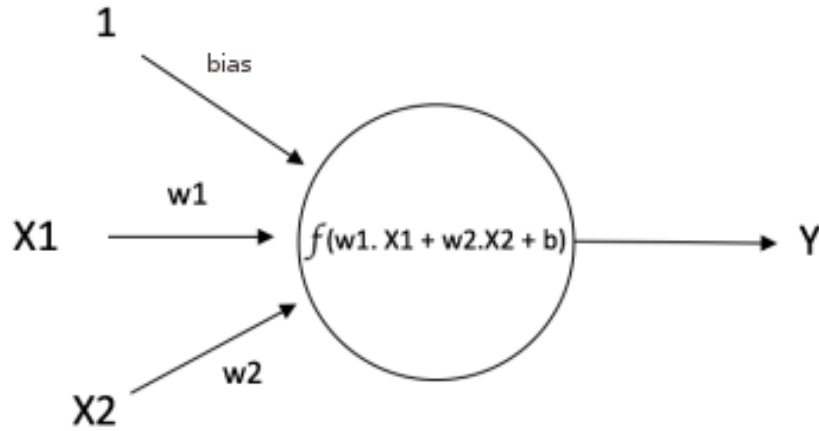


Figure 2.1: An Artificial Neuron

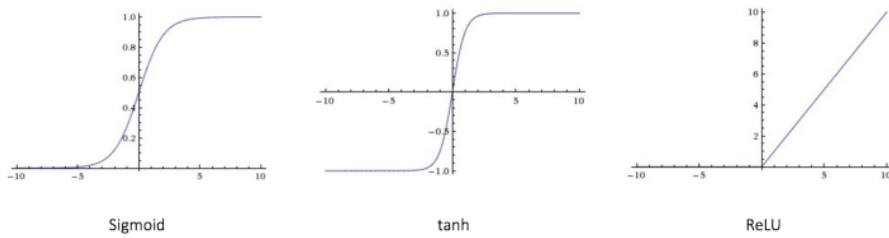


Figure 2.2: Activation Functions Visualised

A Neural Network consists of a series of interconnected layers of these artificial neurons, with the output of each layer of neurons serving as input for the next layer of neurons. The simplest and most common type of Neural Network is the feedforward neural network. It consists of multiple layers of neurons, with connections to all of the neurons in the preceding layer. Each connection or edge has a weight associated with it. There are three types of nodes - input nodes, hidden nodes and output nodes. As the name suggests, data in a feedforward neural network only moves forward through the network - into the input layer, through the hidden layers and then on to the output layer.

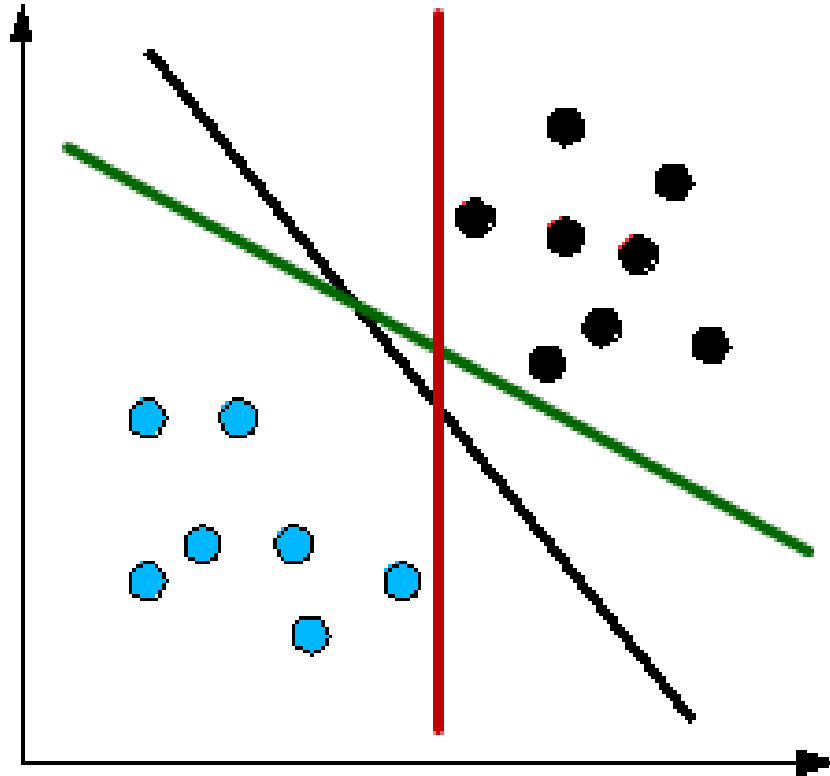


Figure 2.3: Linearly Separable Data

2.2.1 Input Nodes

Input nodes take in the input data fed into the network without performing any computation and pass the data on to the hidden nodes. These nodes make up the input layer of a neural network.

2.2.2 Hidden Nodes

The hidden nodes perform the actual computation, taking data from the input nodes and providing information to the output nodes. There can be multiple or zero hidden layers in a network, whereas there will only ever be one input and output layer.

2.2.3 Output Nodes

Like the input nodes, the output nodes do not perform any computation on the data - they simply take information from the hidden layers and expose this to the outside. This will generally consist of a prediction.

2.2.4 XOR Problem

In the paper mentioned above, "Perceptrons: An Introduction to Computational Geometry", the Xor problem was first introduced. Xor is a function that given two binary inputs returns 0 if the inputs are equal and 1 if they are not. Xor is a classification problem with known expected results, therefore it is appropriate to utilise a Supervised Learning approach to solving it. However, the Xor problem is an example of a problem that is not linearly separable. As mentioned previously, a single perceptron is not capable of predicting data that is not linearly separable, therefore a single layered architecture of perceptrons is simply not capable of solving this problem. The only way for a Neural Network to solve this problem is to expand the number of layers in the architecture, adding a hidden layer. This type of architecture is known as the Multilayer Perceptron.

2.2.5 Multilayer Perceptron

A Multilayer Perceptron (MLP) consists of an input layer, an output layer and one or more hidden layers, as seen in 2.4. MLP's are feedforward neural networks. The MLP architecture solves the Xor problem by introducing linear separability (Singh and Pandey, 2016).

Deep Learning is when there is more than one hidden layer present in a network (O'Shea and Nash, 2015). MLP's encounter issues when attempting to carry out classification tasks on large input images. As will be explained later, each pixel of an input image must correspond to an input node in the network. As every node is connected to every other node in its preceding layer, large images quickly require a large amount of nodes in the network. A small image of size 28x28 such as the images found in the MNIST dataset will require a network with 784 input nodes. Images sourced from the Apollo dataset are of 1920x1280, which would require an input layer consisting of 2457600 nodes. This will quickly cause issues due to overfitting and network training time.

Learning takes place in a MLP through changing the connection weights for each perceptron in the network based on the error between the expected and true output of each perceptron. This is carried out through a concept known as backpropagation.

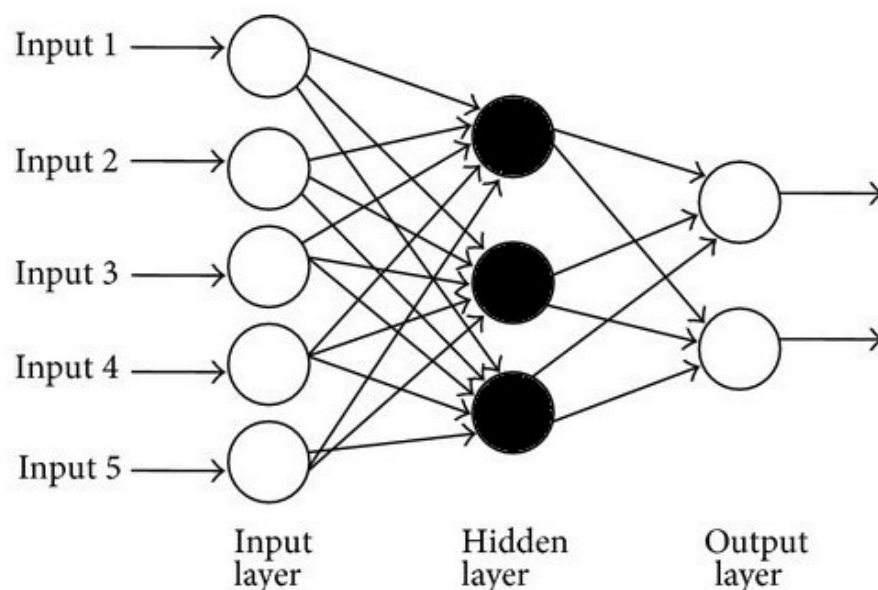


Figure 2.4: Multilayer Perceptron Architecture

2.2.6 Gradient Descent and Backpropagation

Gradient descent is an algorithm used to optimise the weights between neurons in such a manner that creates the least possible amount of error. When the network is training, a cost function is used to keep track of how the network is performing. The cost function looks at the discrepancies between the training output and the true values to determine an error. When the network trains, the goal is to therefore get this cost function as low as possible to ensure the lowest possible error. The way the cost function is minimised in an MLP is through gradient descent and backpropagation.

Every time the weights must be updated, the derivative of the cost function with regards to the weight itself scaled to a learning rate is subtracted. As the network trains the derivative should decrease. This is known as gradient descent.

The backpropagation algorithm works in conjunction with this by starting at the output layer of the network and stepping back through all the layers, updating the weights for each neuron as it goes. This is in an attempt to minimise the overall error. These steps should allow the network to reduce its error and converge on an optimal solution over time as the network trains.

2.2.7 Overfitting

An important point to consider when training any Machine Learning model is how well the model generalises to new data (Domingos, 2012). An algorithm should be able to apply concepts learned from the training data to any previously unseen data in the problem domain in order to make accurate predictions. Overfitting is the concept of a model learning the details and noise in the training domain too well, and thus failing to provide accurate predictions on new data. Overfitting tends to occur when a model learns noise and randomness in the training data as concepts that it attempts to apply to data in the problem domain. These concepts will not apply to the new data however, and poor accuracy generally results. Although a noisy dataset will increase the severity of overfitting, it is not simply a result of a noisy dataset and can occur in any dataset (Domingos, 2012). Within the field of Neural Networks, a common approach to avoid severe overfitting is to keep the network architecture relatively simple. The less parameters required to train the model, the lower the overall chance that the network will overfit and fail to generalise (O'Shea and Nash, 2015). However, this approach is not always feasible when dealing with large and complex datasets, and other approaches must also be taken. Another popular method to reduce overfitting is the introduction of dropout in the network. Dropout is when nodes are randomly dropped from the network along with their connections (Srivastava et al., 2014). This serves to constrain the adaptation of the network while it trains in order to prevent the model from over-learning the training data.

2.3 Introduction to Machine Vision

Images are represented as matrices of values, with each value corresponding to a pixel in the image. Images can be broadly broken down into two groups, grayscale and colour. A grayscale image will be represented as a 2D array of values ranging from 0 to 255, with each value representing the intensity of that pixel, as seen in Figure 2.5. A value of 0 represents black and a value of 255 represents white. In grayscale images, each pixel therefore represents one colour channel (gray). In colour images however we have multiple different channels for red, green and blue. In order to represent this, a colour image will be represented as a 3D array of pixel values, with each pixel having 3 values between 0 and 255 associated with it. These three values represent the intensity of the three colour channels at that pixel. The idea is that a CNN should be able to receive these image representations as input data and return values for the probabilities of different classes.

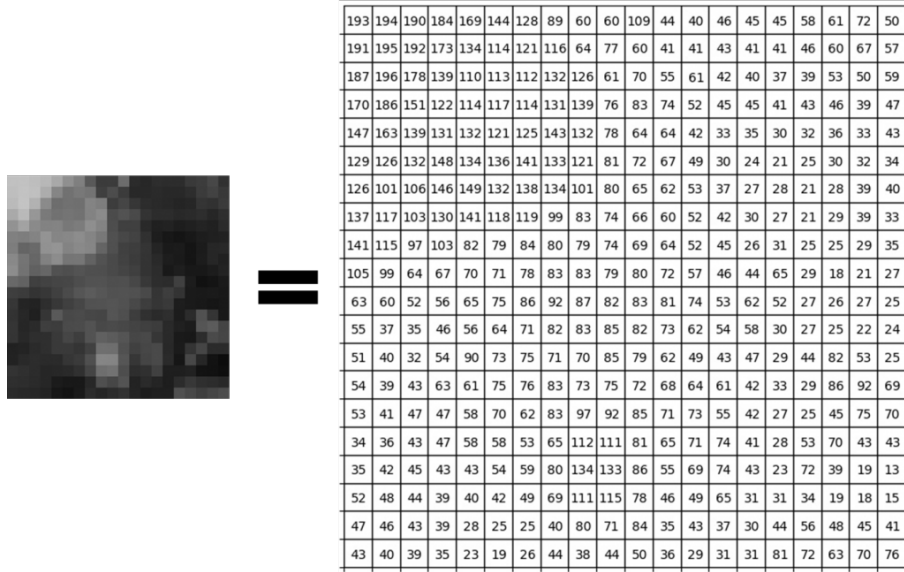


Figure 2.5: Pixel Representation of Grayscale Image

When humans look at an image of say, a dog, we automatically extract the features that make a dog unique in order to allow us to recognise it. For

example, we may see a tail, fur and a snout and recognise that we are looking at a dog. At an extremely high level this what a CNN will do - it will look for certain low-level features such as curves and edges and build these up into more abstract concepts such as a leg or a tail in order to classify the object (LeCun and Bengio, 1995).

Interestingly enough, CNN's do take some inspiration from how the brain processes images. The visual cortex of the brain contains many fields that are sensitive to different specific elements of the input. Some groups of neurons will only respond when certain elements of the input are present, for example certain vertical edges, and other groups of neurons will respond to different elements, such as horizontal edges (Hubel and Wiesel, 2011). The concept of distinct groups of neurons looking for certain features is one that has translated very well into Machine Vision through the use of CNN's.

2.4 Introduction to Convolutional Neural Networks

Convolutional Neural Networks have recently become the standard Neural Network used within the field of image-based Machine Learning tasks (O'Shea and Nash, 2015). They follow essentially the same architecture as a standard Multi Layer Perceptron, except that they include extra layers of Convolution and Pooling. When these layers of Convolution and Pooling are stacked with the Fully-Connected layers of the MLP, a CNN architecture has been formed. Once Convolution and Pooling has been performed the fully-connected layer will compute the overall class scores, resulting in a final output of $1 \times 1 \times n$, where n is the number of possible classes.

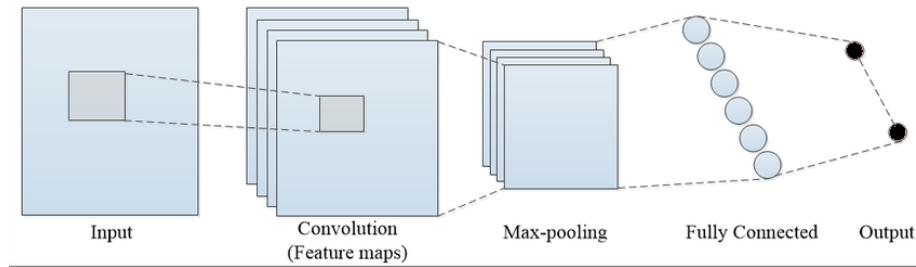


Figure 2.6: CNN Architecture

2.4.1 Convolution Layer

There are three important points of note regarding the Convolution layer: the input image, the feature detector and the feature map. The input image is the image which the CNN is given. The feature detector is a matrix (usually 3×3 or 7×7), also called the kernel or filter, which is multiplied with the matrix values of the input image to create the feature map. The aim of this is to capture important features of the image, maintaining these important features while losing some unimportant elements and reducing overall image size. The way this works is the feature detector slides over the whole image. The particular point on the image that the feature detector is over is known as the receptive field. The parameter known as the stride is the value of the number of pixels by which the feature detector slides over the input image. For example, a stride of 2 will slide the feature detector over the input image jumping 2 pixels at a time. As the feature detector slides around the input image, the pixel values of the feature detector are multiplied against the pixel values of the input image. These multiplications are all summed to give a single value, as shown in Figure 2.7. The higher the value, the higher the likelihood that the particular feature represented in the feature detector is present in that section of the input image. The feature detector then slides on to carry out this process for every section of the input image.

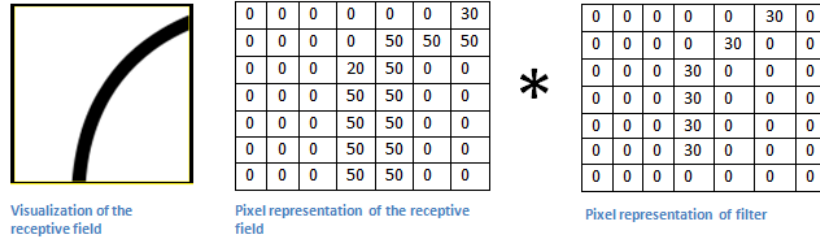


Figure 2.7: Convolution Layer

2.4.2 Pooling Layer

The pooling layer performs downsampling to extract key important features and reducing the number of parameters. The pooling layer operates over every feature map and by pacing a matrix over the feature map and selecting the min value, max value or mean value, depending on the type of pooling being utilised, as shown in Figure 2.8. These extracted values form the pooled feature map. Pooling helps to reduce image size while also extracting important features.

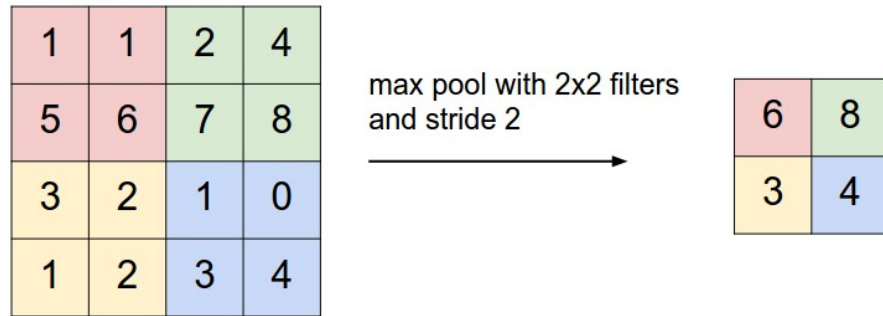


Figure 2.8: Pooling Layer

2.5 Tensorflow Introduction

This section is dedicated to the background work done in order to gain an understanding of how to implement CNN's using tensorflow. The experi-

ments illustrated in this section were carried out during the completion of the Complete Guide to TensorFlow for Deep Learning with Python course on Udemy (*Complete Guide to Tensorflow for Deep Learning with Python* 2018). This section consists of two experiments carried out on the MNIST and CIFAR-10 datasets. The first experiment is sample code provided as part of the course to illustrate the concepts learned during the course. The second experiment is an exercise for the course carried out to implement an understanding of these concepts.

2.5.1 MNIST Experiment

The first experiment carried out was the implementation of a very simple CNN. The architecture of the CNN consisted of two layers of Convolution, two pooling layers and a fully-connected layer. After carrying out 5000 training steps with a batch size of 50, a final accuracy of 98.75% was achieved.

Code Breakdown

The functions displayed in Figure 2.9 are all helper functions. The `init_weights` function initialises the random weights for fully connected or convolution layers, with the shaper of the layer passed in as a parameter. The `init_bias` function performs the same operation for the bias. The `conv2d` function creates a convolution using a built in function from tensorflow. The `max_pool_2by2` function creates a max pooling layer, also using built in tensorflow functions. The `convolutional_layer` function uses the `conv2d` function to return an actual convolutional layer with a ReLu activation function. Lastly, the `normal_full_layer` returns a normal fully connected layer.

The functions displayed in Figure 2.10 are used to create the convolution and pooling layers of the network. In creating `convo_1`, we can see that a 6x6 filter is used from the parameters. An output value of 32 is used to represent the number of filters used. The parameter of 1 represents the original input of the image. This carries down to the other layers, with `convo_2` taking in an input image of 32 from `convo_1`.

```

def init_weights(shape):
    init_random_dist = tf.truncated_normal(shape, stddev=0.1)
    return tf.Variable(init_random_dist)

def init_bias(shape):
    init_bias_vals = tf.constant(0.1, shape=shape)
    return tf.Variable(init_bias_vals)

def conv2d(x, W):
    return tf.nn.conv2d(x, W, strides=[1, 1, 1, 1], padding='SAME')

def max_pool_2by2(x):
    return tf.nn.max_pool(x, ksize=[1, 2, 2, 1],
                          strides=[1, 2, 2, 1], padding='SAME')

def convolutional_layer(input_x, shape):
    W = init_weights(shape)
    b = init_bias([shape[3]])
    return tf.nn.relu(conv2d(input_x, W) + b)

def normal_full_layer(input_layer, size):
    input_size = int(input_layer.get_shape()[1])
    W = init_weights([input_size, size])
    b = init_bias([size])
    return tf.matmul(input_layer, W) + b

```

Figure 2.9: Creating Helper Functions

The code displayed in Figure 2.11 shows the model being trained. A tensorflow session is created and data is read n from the dataset. The session is ran to begin model training. The current training step and current error calculated from a loss function is displayed as output as the model trains.

```

convo_1 = convolutional_layer(x_image,shape=[6,6,1,32])
convo_1_pooling = max_pool_2by2(convo_1)

convo_2 = convolutional_layer(convo_1_pooling,shape=[6,6,32,64])
convo_2_pooling = max_pool_2by2(convo_2)

convo_2_flat = tf.reshape(convo_2_pooling,[-1,7*7*64])
full_layer_one = tf.nn.relu(normal_full_layer(convo_2_flat,1024))

# NOTE THE PLACEHOLDER HERE!
hold_prob = tf.placeholder(tf.float32)
full_one_dropout = tf.nn.dropout(full_layer_one,keep_prob=hold_prob)

y_pred = normal_full_layer(full_one_dropout,10)

```

Figure 2.10: Creating Layers

2.5.2 CIFAR-10 Experiment

The second experiment was carried out on the CIFAR-10 dataset, and the architecture used was consistent with the first experiment, consisting of two layers of Convolution and Pooling. After 5000 training steps with a batch size of 100, a final accuracy of 72% was reached.

2.5.3 Initial Findings

The first two experiments were carried out using CNN's of the same architecture, however an accuracy discrepancy of 26.75% was observed. Both datasets contain images labelled into 10 classes. The differences arise in the dataset size and image complexity. Firstly, the CIFAR-10 dataset contains 50,000 training images, whereas the MNSIT dataset contains 60,000 training images. The images in the MNSIT dataset are grayscale, whereas images in the CIFAR-10 dataset consist of 3 colour channels. The images in the CIFAR-10 dataset are also of a higher complexity compared to the handwritten digits in the MNIST dataset. The CIFAR-10 images contain more complex real-world images with noisy backgrounds. These discrepancies between the datasets may explain the discrepancies in the accuracy achieved by the classifiers.


```

steps = 5000

with tf.Session() as sess:
    sess.run(init)
    for i in range(steps):
        batch_x , batch_y = mnist.train.next_batch(50)
        sess.run(train, feed_dict={x:batch_x, y_true:batch_y, hold_prob:0.5})

        # PRINT OUT A MESSAGE EVERY 100 STEPS
        if i%100 == 0:
            print('Currently on step {}'.format(i))
            print('Accuracy is:')
            # Test the Train Model
            matches = tf.equal(tf.argmax(y_pred,1),tf.argmax(y_true,1))
            acc = tf.reduce_mean(tf.cast(matches,tf.float32))

            print(sess.run(acc, feed_dict={x:mnist.test.images, y_true:mnist.test.labels, hold_prob:1.0}))
            print('\n')

```

Figure 2.11: Training the Model

2.6 Technology Investigation

Chapter 3

Empirical Studies

3.1 Convolutional Neural Network Architectures

3.2 Image Processing Techniques

Chapter 4

Classifier Implementation

4.1 Requirements

4.2 System Design

4.3 Implementation

4.4 Analysis

Chapter 5

Final Conclusion

5.1 Review of Research

5.2 Reflections on Implementation

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