UNIVERSITY OF BOLTON

BSc Computing / Computing & Website Development / BSc Computer Networks & Security (Level HE6)

COURSEWORK SUBMISSION FORM

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COURSEWORK TITLE: 001 – Major Project Literature Review

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**Literature Review: Pain recognition using a neural network.**

**For Major Project, B.S.C Computing Top-Up.**

**Lee Disley.**

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# Abstract

The aim of this report is to introduce the reader to how pain on a human face can be recognised by a neural network. Through a review of current literature, an understanding of the previous work done in this field, the aims of the project will be addressed, as well as any suggestions to the use of pain recognition in a medical setting.

# Introduction

The use of neural networks to not only recognise human faces, but to also determine the emotions that the face is displaying are being used already. Disney uses Ai technology to recognise if people are enjoying watching films at trial screenings instead of filling out forms (Gilliland, 2018). Firms such as Affectiva provide services for companies to use during market research, identifying the effect of advertising on customers for example (Gilliland, 2018). But when it comes down to recognising a specific emotion for a less lucrative area the progress seems to be stuck at research, especially with regards to pain recognition, which progresses to the point just before creating a neural network to perform the task. This literature review will look at what research has been undertaken in this and other relevant areas, and how it has informed my project.

# Scope

During this literature review I will be assessing material relating to pain detection in human faces. I will also be looking at literature associated with emotion recognition, face recognition and image processing. All these areas have a bearing on my project in developing my neural network. I will also be reading material on programming the neural network and recognition technology into the Python programming language.

# Literature Review

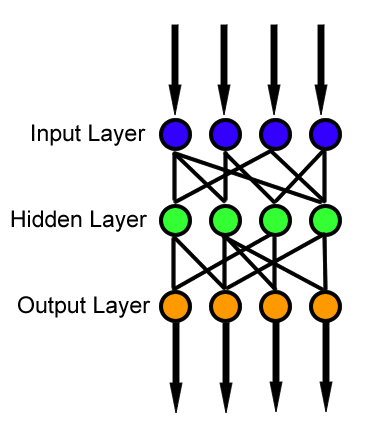
## Neural Networks – An Introduction

Neural networks, as described by James Chen (2018) are “…*a series of algorithms that endeavours to recognize underlying relationships in a set of data through a process that mimics the way the human brain operates*”.

As a neural network works like a human brain, it has neurons, which are called Units, these are mathematical functions that collect and classify information (Chen, 2018).

As can be seen in figure 4 there a three types of neural network units, input, hidden and output.

Image from: https://becominghuman.ai/artificial-neuron-networks-basics-introduction-to-neural-networks-3082f1dcca8c



*Figure 1*

The input units accept information that the neural network can learn about, the output units signal how the neural network has responded to the information. In the middle are the hidden units which form the ‘brain’. There can be several layers of each type of unit depending on the complexity of the problem the neural network is solving.

Neural networks learn the same way as a human brain, by learning from mistakes. This is done by the neural network comparing its results with expected results to tweak the values (known as weights) of the units. This is known as Backpropagation:

“*This involves comparing the output a network produces with the output it was meant to produce, and using the difference between them to modify the weights of the connections between the units in the network, working from the output units through the hidden units to the input units—going backward, in other words*” (Woodford, 2018).

The process of showing a neural network data and comparing results is known as training. After enough training has been performed then the neural network can be introduced to new information without comparison and it should work out what it is ‘seeing’.

**Types of neural networks**

There are several types of neural network or architectures. These are summarised in the table below.

|  |  |
| --- | --- |
| Neural Network | Description |
| Feed Forward | The simplest type of neural network. The information passes through the input units to the output units. There may or may not be a hidden layer. They are used in computer vision and speech recognition, where classification is complicated. |
| Radial Basis Function | Radial basic functions consider the distance of a point from the centre. RBF functions have two layers, in the first layer features are combined with the Radial Basis Function, and then the output of these features is taken into consideration while computing the same output in the next layer. These have been used in power restoration systems to prioritise repairs. |
| Convolutional (CNN) | A deep learning neural network normally applied to visual processing. They use a type of multilayer perceptrons to provide quicker processing of images. This tries to mimic how the brain translates and recognises images. CNNs do not need pre-processing and learns the filters for processing the image rather than being told, as in other neural networks. They are used in image recognition, medical analysis and language processing. |
| Recurrent (RNN) | This neural network works like the feed forward network but feeds the output back to the inputs to help predict the outcome of the layer (backpropagation). This neural network is used in speech recognition. |
| Modular (MNN) | Modular neural network is a combination of neural networks working together to solve a problem. The problem is split into areas that each neural network is best at. Although the neural networks do not interact with each other, but it breaks down large tasks into smaller chunks taking less computational power. |

## Algorithms

Algorithms are the mathematical functions that a neural network basically is, that help it to mimic the human brains processes. “*The procedure used to carry out the learning process in a neural network is called the training algorithm. There are many different training algorithms, with different characteristics and performance*” (Quesada, n.d.).

The learning process of a neural network is shown in the minimisation of a loss function. This is composed of error and regulation terms. The error term defines how the neural network fits the data set, the regulation terms prevent over fitting of the data set by controlling the neural networks complexity. The loss function relies on the parameters of the neural network such as weights and synapse weights. At each stage of the neural network the loss will decrease by adjusting the parameters, thus ‘learning’ which is right and wrong.

There are five algorithms favoured for neural networks: Gradient descent, Conjugate gradient, Newton method, Quasi newton and Levenberg Marquardt. Each has its own merits and detractions. Deciding which to use depends on the number of parameters that neural network must process.

Each of the algorithms have different computational speed and memory requirements. The below diagram shows the five popular algorithms for training neural networks and their demands.

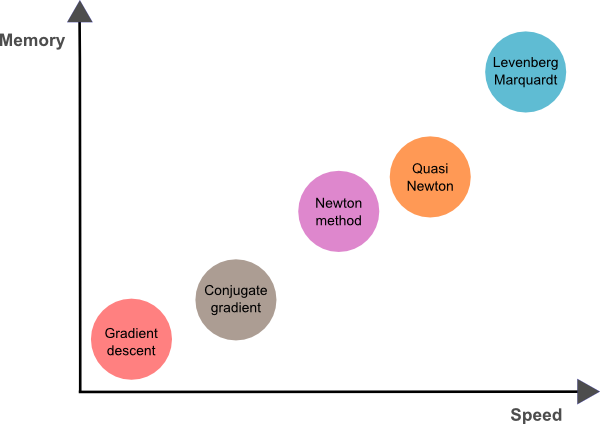


Image from: https://www.neuraldesigner.com/blog/5\_algorithms\_to\_train\_a\_neural\_network

If we have many parameters to process, then an algorithm that uses less memory at the sacrifice of speed would be best. Other algorithms provide high speeds but use more memory, and if we are using many parameters then the amount of memory needed would increase.

## Current Pain Scales

Pain scales are used in hospitals to assess a patient’s pain in situations where the patient can self-report. They can be used at admission at hospital, visiting the doctor or after surgery. Doctors use the pain scales to understand a patient’s pain type, which helps them with diagnosis, to create pain management systems and measure how well the pain is being managed (Cirino, 2017).

Current pain scales are either designed using number scales or using pictorial scales. Examples of both are shown in the diagram below. The major one used is the pictorial scale, known as the Wong-Baker scale, and is the one I will be using to create points for the neural network.

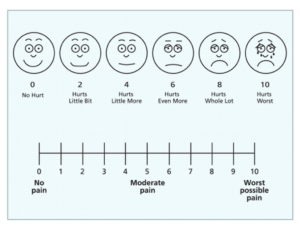


Figure 2

Image From: <http://edwinleap.com/even-dogs-get-pain-scales/>

These pain scales are typically paper based and are given to the patient as an easy to understand measurement of their pain. Understanding a patient’s pain level has serious implications on what pain management (pain relieving drugs, physiotherapy and monitoring these) they receive, having an accurate indication of their pain levels makes diagnosis more suitable for them. In some countries, such as the U.S.A, the pain scale has been moved to a touch screen device, “…*computer-based assessment of pain has come up. Palm-top computers make it possible to use VAS on a touch screen allowing electronic data assessment*” (Elfering, 2005). This has made the electronic recording easier and clearer as well as making use by a patient easier.

Although these scales are the main way of identifying pain in a patient there are problems with them, namely with accuracy and not being able to use them with a patient (e.g. when the patient is unresponsive). The accuracy of visual rating scales (VRS) has been compared to numerical rating scales (NRS) in a paper by Brunelli et al (2010) where they compared the two scales on 240 advanced cancer patients. They found that NRS was a better scale for relaying pain levels “*Our results suggest that in the measurement of cancer pain exacerbations, patients use NRS more appropriately than VRS and as such NRS should be preferred..*.” (Brunelli-et-al, 2010).

When the patient is unresponsive or incapable of giving an indication of their pain levels (e.g. children), then it is left to the healthcare professionals to decide on what pain is being experienced. To do this there is material provide on facial points to look for that indicate pain, shown in figures 2 and 3.

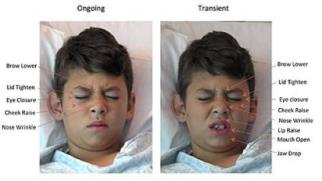


Figure 3

The above pictures are used to monitor pain in unresponsive patients whether they be children or adults.

A more comprehensive list of points to look for is shown below, especially relevant to infants.

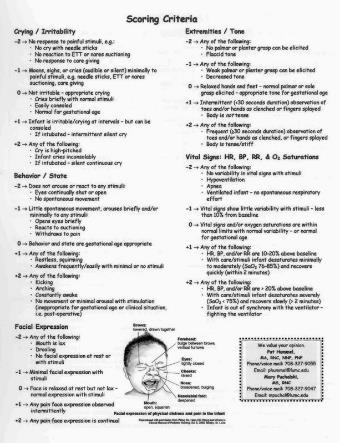


Figure 4

This above list (figure 3) also shows other ways to show pain, such as vital signs, behaviour and crying. And even though these are there to help the health professional, it does not allow an accurate measurement of pain in patients that cannot get the message across.

## Computer Based Techniques

These figures (1 & 2) do have some commonalities in that they have pictures that show facial reactions to pain that a patient will have, and these reactions are what a neural network can be trained to recognise and provide automatic identifying and monitoring of pain in a patient, known as Action Units.

This collection of facial reactions or cues have been used in other studies to see if computer based techniques can be used to help make pain recognition more accurate. The analysis of these shown in Table 1.

|  |  |  |
| --- | --- | --- |
| Author/Year | Technique(s) Used | Accuracy |
| Ashraf et al./ 2009 | AAM & SVM | 82% |
| Lucey et al./ 2009 | AAM & SVM | Not stated |
| Lucey et al./ 2011 | AAM, SVM, and LLR | 79.66% |
| Kaltwang et al./ 2012 | DCT, LBP, RVR | 92% |
| Hammal et al./ 2012 | AAM, Log-normal filters and SVM | 73% |

Table 1

**In Ashraf et al**., an Active Appearance Model (AAM) on videos containing pain expressions and then a machine learning procedure was used to classify between pain and no pain. This had the advantage of representing live changes.

**In Lucey et al**. a revised AAM and Support Vector Machine (SVM) were used to develop an automatic system for frame level pain detection in two ways: first from the facial features directly and second using individual Action Unit (AU) detectors.

Action Units (AU), to clarify, come from the Facial Action Coding System, and are derived from muscle movements of the face, created by Carl-Herman Hjortsjö in 1970, and further developed by Paul Ekman and Wallace Friesen. Pulling the identifying movements of the face for the detection of pain requires the use of a proven system:

“*Using FACS, we are able to determine the displayed emotion of a participant. This analysis of facial expressions is one of very few techniques available for assessing emotions in real-time*” (Bryn Farnsworth, 2016).

More on AU later in the review.

**In Lucey et al**., they extended their work in 2009 to detect pain from a patient’s face using an AAM approach on a frame-by-frame basis. They showed that joining AAM together with linear logistical regression (LLR) provides better performance for detection of pain and action units in frame.

**Kaltwang et al**. proposed a different shape of facial landmarks and appearance features; Discrete Cosine Transformation (DCT), Relevance Vector Regression (RVR) and Local Binary Pattern (LBP) and then joined these features, showing that together these features lead to a better estimation of pain level as compared to estimation of pain intensity from a single facial landmark.  
**Hammal et al**. used AAM as well, to get the canonical normalized appearance of a face (CAPP) and then passed it through a set of Log-Normal filters. After, an SVM classifier is used to detect pain on a frame-by-frame level.

These studies concentrated on the possibility of creating a system to automatically detect pain. The studies showed their use of techniques to identify pain only at certain points, and not created with an end-product in mind that could be used in a medical situation. One of the stumbling blocks to achieving this seems to be the lack of people who understand what is needed for pain recognition and who also could put it into practice, relying on several people with different knowledge/skills in a team.

(Awaiting reply for people on researchgate.net to allow permission for me to include their work in this review dated from 2016 to present)

## Facial Recognition and Image processing

As well as recognising pain in a human face, the ability of a neural network to identify a face as in the first instance human, and then to standardise the image it receives is an important part of ensuring the neural network performs correctly. Correctly identifying a face as human first and then processing the image so all images are standard (e.g. in size or orientation) would prevent errors from occurring. An article in the Image and Vision Computing journal by Ashraf AB (2009) shows the sorts of image processing that needs to be done before any type of facial neural network processing can be done:

“…*first detects the fully frontal face using a Viola and Jones face detector, and then rigidly registers the face in 2D using a similarly designed eye detector. Visual features are then extracted using Gabor filters which are selected via an AdaBoost feature selection process*” (Ashraf AB, 2009).

As there has been plenty of work done on face recognition and image processing and there are a variety of APIs and pre-written Python and C# codes that can be used with a neural network that will make it quicker to program a workable neural network. Books, such as Python Machine Learning by Leonard Eddison, and Advanced Machine Learning by Thomas Farth are good guides to using the pre-written parts of python with a neural network, especially using tenserflow and other AI libraries.

## Using AUs to recognise pain

AUs have a list of 20 facial muscle movements and several lower body movements and these can be mapped to the figures for the neural network, this hyperlink goes to a website that lists all the AUs from the facial coding system: [facial-action-coding-system](https://imotions.com/blog/facial-action-coding-system/)

The AUs I will be using are listed in table 2 below against a point from the transient picture in figure 1 as well as a description of the AU.

|  |  |  |
| --- | --- | --- |
| Picture Point | AU # | AU Description |
| Brow Lower | 4 | Brow lower |
| Lids Tighten | 44 | Squint |
| Eye Closure | 43 | Eye closed |
| Cheek Raised | 6 | Cheek raiser |
| Nose wrinkle | 9 | Nose wrinkle, also shows slight AU4 and AU 10 |
| Lip Raised | 10 | Upper lip raise, also shows slight AU 25 |
| Mouth Open | 25 | Lips apart |
| Jaw Dropped | 26 | Jaw drop, with AU25 |

Table 2

These show the definite points of someone in pain at the top of the Wong-baker scale (number 10 face). Working out the intervening points to zero face on the Wong-Baker scale, will provide more points for the neural network.

Specific emotions can also be included which help distinguish them from actual pain, these are shown in table 3.

|  |  |
| --- | --- |
| Emotion | AU Numbers |
| Happiness/Joy | 6 + 12 |
| Sadness | 1, 4, 15 |
| Surprise | 1, 2, 5, 26 |
| Fear | 1, 2, 4, 5, 7, 20, 26 |
| Anger | 4, 5, 7, 23 |
| Disgust | 9, 15, 16 |
| Contempt | 12, 14 (On one side of face) |

Table 3

The next steps for the AUs is to get the points for a resting or happy face (0 on the Wong-baker scale) and work out the changes shown for each of the other points (1-9) on the Wong-baker scale.

Another consideration is that neural networks are known to struggle with deciding between pain and the emotions of happiness and disgust. In Katharina Blandina Weitz Master’s thesis she has shown that a CNN could identify disgust emotions correctly the most but struggled identifying happy as happy, where 57% of the happy faces were classed as pain (WEITZ, 2018). Also, in her thesis Katharina discovered that pain faces were mis-classified as disgust (17%). During Katharina’s thesis she used a way to visualise what the CNN was doing which identified that the differences between happiness and pain are quite small, and that muscle changes around the eyes and nose can help differentiate between pain and happiness. When predicting pain, the muscles around the eyes and nose should be concentrated on, for happiness focus shifts towards the eyes (WEITZ, 2018).

This provided me with an extra area to focus on and will help towards creating the differing levels of pain against the Wong-Baker scale, and of how difficult it could be.

## Programming Language

I have chosen Python as the programming language for the neural network. There were several reasons for this choice. I have experience of programming with Python. And after researching which language I could use, Python was the obvious choice.

Throughout researching languages to use, it became clear that there were two ways of creating a neural network; using a language to create a network from the ground up, or using simulators to model the neural network and sort out the programming for the model (Davison Andrew, 2009). There are a large number of simulators to use which have been reviewed in (Hines et al., 2009) but the main problem with using a simulator is due to the myriad of languages that they use, and this causes problems with communication between insterested parties and people who wish to add functionality to the program or building on work done (Davison Andrew, 2009).

Python brings not only many libraries for Artificial Intelligence but can also be used with several of these simulators, allowing for easier building on the work done in the future.

# Conclusion

There is a large amount of literature on neural networks, especially on the theory of how they work and potential uses. With regards to pain recognition and neural networks, there is a smaller range of literature. Pain recognition was just another emotion to detect, lately it has become more important to research pain recognition as more uses are being researched in ways to make detecting pain more accurate and less open to human error.

This literature review has shown what a neural network is, what pain recognition techniques are currently used, facial recognition and image processing and programming languages used. I used this research not only reinforce my knowledge of neural networks, but also to inform my decisions for my project, which were:

1. Not to use a convoluted neural network (CNN) but to use landmarks and a back propagation neural network. This is because I do not need a neural network just to recognise an image, but to process certain points which requires a neural network that can be trained on the whole process.
2. To use the PYTHON programming language because of the availability of neural network libraries and the ease of sharing my work and its transferability to other frameworks.
3. Selecting an algorithm to use based on the number of parameters that the neural network will have to process.
4. The importance in having several algorithms to try with the neural network and to see which provides the most accurate results after training. This will require the need to run training several times before allowing the neural network to proceed on images it hasn’t seen before.

# Bibliography

al., M. L. H. e., 2009. NEURON and Python. *frontiers in Neuroinfomatics,* Volume 3, pp. 1-12.

Ashraf AB, L. S. C. J. C. T. A. Z. P. K. S. P., 2009. The painful face-pain expression recognition using active appearance models.. *Image and vision computing,* 27(12), pp. 1788-1796.

Brette, R. R. M. C. T. H. M. B. D. B. J. M. .. .. .. D. A., 2007. Simulation of networks of spiking neurons: A review of tools and strategies. *Journal of Computational Neuroscience,* 23(3), pp. 349-398.

Brunelli-et-al, 2010. Research Comparison of numerical and verbal rating scales to measure pain exacerbations in patients with chronic cancer pain. *Health and Quality of Life Outcomes,* 8(42).

Bryn Farnsworth, P., 2016. *Facial Action Coding System (FACS) – A Visual Guidebook.* [Online]   
Available at: https://imotions.com/blog/facial-action-coding-system/  
[Accessed 05 01 2019].

Chen, J., 2018. *Neural Network.* [Online]   
Available at: https://www.investopedia.com/terms/n/neuralnetwork.asp  
[Accessed 25 01 2019].

Cirino, E., 2017. *What is a pain scale, and how is it used?.* [Online]   
Available at: https://www.healthline.com/health/pain-scale  
[Accessed 19 12 2018].

Davison Andrew, B. D. E. J. K. J. M. E. P. D. P. L. Y. P., 2009. PyNN: a common interface for neuronal network simulators. *Frontiers in Neuroinformatics,* Volume 2, pp. 1-11.

Eddison, L., 2018. *Python Machine Learning.* s.l.:s.n.

Elfering, M. H. a. A., 2005. *Pain assessment.* [Online]   
Available at: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC3454549/  
[Accessed 04 01 2019].

Farth, T., 2018. *Advanced Machine Learning, Advanced Machine Learning with Python.* s.l.:s.n.

Gilliland, N., 2018. *How brands are using emotion-detection technology.* [Online]   
Available at: https://econsultancy.com/how-brands-are-using-emotion-detection-technology/  
[Accessed 19 12 2018].

Hammal Z, C. J., 2012. Automatic detection of pain intensity. *Proceedings of the 14th ACM international conference on Multimodal interaction,* pp. 47-52.

Jadhav, A., 2017. *Emotion Detection and Recognition Market,* London: Allied Market Research.

Kaltwang S, R. O. P. M., 2012. Continuous pain intensity estimation from facial expressions. In: s.l.:Springer, pp. 368-377.

Kumar Praveen, T. L., 2014. Challenges in pain assessment: Pain intensity scales. *Indian Journal Of Pain,* 28(2), pp. 61-70.

Levine, D. S., 2007. Neural network modeling of emotion. *Physics of Life Reviews ,* Issue 4, pp. 37-63.

Lucey P, C. J. L. S. M. I. S. S. P. K., 2009. Automatically detecting pain using facial actions. *3rd International Conference on Affective Computing and Intelligent Interaction and Workshop,* pp. 1-8.

Lucey P, C. J. P. K. S. P. M., 2011. Painful data: The unbc-mcmaster shoulder pain expression archive database. *International Conference on Automatic Face & Gesture Recognition and Workshops ,* pp. 57-64.

Pharma, O., 2018. *Scales and assessment tools for optimising PAD mangement.* s.l.:Orion Pharma.

Quesada, A., n.d. [Online]   
Available at: https://www.neuraldesigner.com/blog/5\_algorithms\_to\_train\_a\_neural\_network  
[Accessed 18 02 2019].

Sascha Gruss, R. T. P. W. H. C. T. S. C. A. A. S. W., 2015. Pain Intensity Recognition Rates via Biopotential Feature Patterns with Support Vector Machines. *22nd International Conference on Pattern Recognition,*, 16 10, pp. 4582-4587.

WEITZ, K. B., 2018. *Applying Explainable Artificial Intelligence for Deep Learning Networks to Decode Facial Expressions of Pain and Emotions.* Bamberg: s.n.

Woodford, C., 2018. *Neural networks.* [Online]   
Available at: https://www.explainthatstuff.com/introduction-to-neural-networks.html  
[Accessed 25 01 2019].