Classification of Brain Haemorrhages in Head CT Scans

Kirsty Sant

Supervisor: Prof. Ing. Carl James Debono

Co-Supervisors: Dr. Paul Bezzina, Dr. Francis Zarb

Faculty of Information and Communication Technology

Department of Communications and Computer Engineering

University of Malta

May 2018

Submitted in partial fulfilment of the requirements for the degree of B.Sc. (Hons.) Computer Engineering

Declaration

Abstract

Acknowledgements

Table of Contents

List of Abbreviations

List of Figures

1 Introduction

2 Background and Literature Review

2.1 Medical Aspect

2.1.1 Clinical definition and types of brain haemorrhage

Brain haemorrhage is defined as a bleed in or around the brain tissue. It may be spontaneous, precipitated by an underlying vascular malformation, induced by trauma or related to therapeutic anticoagulation. [1] This can be caused by a blood vessel rupturing, typically due to high blood pressure, stroke or trauma to the head. The resulting bleeding, especially within the brain tissue, results in an increase in pressure on the part of the brain near the bleed, which pressure can potentially damage the effected brain tissue. The place of the ruptured vein, the speed at which blood flows into the brain and the volume of the bleed can all be factors of the severity of the case, potentially leading to death. The region of the brain in which the bleed occurs tends to indicate what are the functions and bodily abilities the patient might lose, such as movement of one side of the body or speech. The increase in pressure in the region where the bleed occurs is since blood irritates brain tissue thus making it swell. Although high blood pressure is often one of the main causes of brain haemorrhage, haemorrhagic stroke only amounts to roughly 20% of all stroke cases.

In the cases of head trauma, traumatic brain injury (TBI) is a possible occurrence. In the case of traumatic brain injury, the bleed in the brain is a result of an external force, such as a blow to the head in instances like motor vehicle crashes. In such cases, the brain is highly likely to move within the skull, potentially hitting the dura matter, of the innermost layer of the skull, and causing contusions, or bleeding and bruising in the brain. This thus implies that in the cases of trauma, a haemorrhage may be present even if there is no visible skull fracture. Due to the nature of this form of haemorrhage, it is most common in young adults, being considered as the highest cause of death in the 15-24 age group, and the third highest, after heart disease and cancer, in other ages. [2] For patients diagnosed with brain haemorrhage, a late or wrong diagnosis can potentially lead to disabilities or death, making the quick and correct diagnosis imperative for such cases.

There are four different types of haemorrhage. These are intracerebral haemorrhage (ICH), intraventricular haemorrhage (IVH), epidural haemorrhage (EDH), subdural haemorrhage (SDH) and subarachnoid haemorrhage (SAH). [3] The location of the bleed determines what the original source was, for instance subdural and epidural haemorrhages are usually due to experienced trauma, sometimes having a scar related to them and are located towards the side of the brain, not inside. [1] Each of these types of haemorrhage have different qualities that are used to distinguish one from the other. At a basic level, a bleed can be classified as intra-axial or extra-axial. These two classifications are the broader categories, with each having more sub-categories. Intra-axial bleeds are ones which occur within the brain itself and include ICH and IVH whereas extra-axial bleeds are those occurring within the skull but external to the brain tissue and tend to be easier to treat. Extra-axial bleeds can be further classified into 3 sub-categories, namely EDH, SDH and SAH.

<Possibly enter image of haemorrhages?>

2.1.2 Computed tomography

Computed tomography, or CT, relies on the principle of using x-rays transmitted through the body to analyse interior parts of the body in a non-invasive way, meaning without the need to operate. The underlying principle behind CT and how it works is that x-rays going through the body are absorbed to some extent, with the rate of absorption varying according to the medium it passes through. The rate of absorption is calculated by measuring the attenuation coefficient of the detected x-ray wave in comparison to the fixed emitted x-ray waves, which properties are known. The attenuation coefficient quantifies how much the detected x-ray signal is weakened after passing through a given material, and is used to calculate the density of the material. [4] This is the same principle behind conventional radiography, which is traditionally used to examine the skeletal structure for fractures and assess lung pathologies, amongst other applications [5].

The main difference between these two types of scans is that in CT a more sensitive detection system, typically making use of glass or crystal detectors as opposed to photographic film which is used in conventional radiography. This increased sensitivity gives the ability of detecting smaller changes in the absorption values can be detected, which in turn implies that finer detail, such as the distinction of density gradation within soft tissues can be observed. The detection system is connected to a computer, which is used to visualise these results, as opposed to traditional radiography which relied mainly on photographic film. [6] Another important distinction between conventional radiography and CT is that while in the former a fixed x-ray tube is used, CT uses a motorised x-ray source that rotates around the circular opening through which the patient is passed, referred to as the gantry. [7]

2.1.2.1 How CT works in general

When a CT scan is to be performed, the patient is placed such that the part to be examined is within the gantry, within which the x-ray emitter tube and detector are enclosed, opposite one another. [8] As the patient is passed through the gantry, the emitter and detector are quickly rotated, with the emitter producing a narrow x-ray beam. For every rotation, the data collected forms a cross-sectional image, known as a section or 'slice'. The typical thickness of each section is between 1 and 10mm. Given that multiple rotations are performed, a number of adjacent sections are obtained, which can then be digitally stacked to form a 3D image of the patient. The 3D image can in turn be used to identify the location of basic structures and any abnormalities in an easier way. [7] The operator of the CT machine decides the thickness of each section, considering the trade-off between accuracy and number of sections, according to the case at hand.

There are two main ways of scanning, which are the slice-by-slice, conventional CT scanning and the volume acquisition scanning, which is also referred to as 'spiral' or 'helical'. [6] In conventional slice-by-slice scanning, the patient is in a fixed position while a section is being scanned. In this way, the thickness of each section can be defined by how much the patient is moved between one complete scan and the next, and the position is defined by the position from which scanning starts. [9] The main drawbacks of this form of scanning are that it takes a longer time to scan the body section of interest, which can prove to be challenging with children and people who cannot hold still for a long time, and that the sections' position and thickness are fixed while scanning and cannot be changed afterwards. In spiral scanning, the patient is constantly moved through the scanner, while the x-ray emitter and detector move continuously in one direction such that it traces a spiral path, collecting data continuously. In this way, a shorter time is taken to scan the section in question, thus eliminating inconsistencies due to breathing or slight movements. The data collected is stored as a volume, thus any required position within the body section can be obtained from the data set, either because it was scanned at that position or via reconstruction. Furthermore, spiral scanning facilitates the reconstruction in 3D form and the possibility of reconstructing the image in a different plane. [6] [9]

2.1.2.2 Brain CT Scans

For the vast majorities of neurological disorders, CT or Magnetic Resonance Imaging (MRI) are used, since both give more information when compared to conventional radiography. [6] In CT scanning, there are three planes along which a scan is performed, which are the axial, coronal and sagittal planes. With regards to brain CT scans, the most common axis chosen is the axial plane. Should other planes be required, in some cases they can be reconstructed from the axial plane result set.

When analysing a CT scan for abnormalities, there are three main signs that one is present. These are abnormal tissue density, mass effect and enlargement of ventricles. Abnormal tissue density refers to areas in the brain tissue that have higher or lower densities, thus are seen as lighter or darker, when compared to the rest of the brain. The mass effect is the displacement of the brain's soft tissues due to an intracranial lesion [10] that was not always present and is taking up space, such as a bleed or a tumour. This can be seen in the scan as a compression or displacement in the lateral ventricles and shift in midline structures of the brain [6]. Finally, an enlargement of ventricles can be due to an increase in the volume of cerebrospinal fluid (CSF) in the brain. This can be easily noted in the scan when comparing the size of regular and abnormal lateral ventricles.

In CT scans, a fresh bleed is characterised by an area of very high intensity, and possibly surrounded by a low-density area, known as oedema, which is caused by swelling [6]. The importance of correct diagnosis of the case based on the scan is vital in determining whether the patient requires immediate surgery or not, since in some cases operating the patient could potentially be harmful. CT scans, albeit being the best initial way of detecting these bleeds, can only visualise the largest aneurysms, which are usually the source of such bleeds.

ICH in CT scans can be easily seen as a hyperdense area, or a white patch, within brain tissue, and thus gives little difficulty in diagnosis provided the bleed is large enough to detect. IVH in CT has the similar hyperdense property but the location of the bleed is within one or both brain ventricles. EDH is usually lens-shaped, distinct, hyperdense area and usually associated with a skull fracture. Its shape is heterogeneous, meaning it is not uniform. SDH classically appears as hyperdense crescent-shaped area and is situated over the surface of a cerebral hemisphere, with a skull fracture potentially present but not necessarily so. SAH is the most difficult to detect, since generally the bleeds are small and dispersed. [11]

2.2 Computer aided diagnosis – brief overview and developments

Computer aided diagnosis (CAD) is a research area which bridges the gap between technology, more specifically Artificial Intelligence (AI) and the medical world. CAD can be currently considered as a major research area in medical imaging, technology and radiology. The background idea behind CAD is for the computer to analyse a medical case in a particular field and offer a "secondary opinion" to the radiologist, who is the person taking the final decision on the case. This thus implies that the computer, using a suite of tools in multiple areas, such as image processing and classification, can reach a conclusion on whether or not there is the pathology being tested for. With the use of such software, there can be cases where the radiologist did not spot a problem, yet the computer detected a region of concern, thus possibly giving a better diagnosis. Considering the way CAD works, one can note that the concept of the system is to put equal weight on the computer result and the role of physicians and radiologists, without having one undermining the other, to reach a conclusion on whether the pathology being tested for is present or not. This alleviates some pressure from the performance of the system itself, in the sense that it is not necessary for the system to have a performance which is superior to that of the radiologist, but rather it being comparable and complimentary [12].

Although CAD has been popularised as a research area only recently, it has been around, in different forms, for quite some time. The history of computers as tools for diagnosis dates to the 1960s, where the idea of automated computer diagnosis started to emerge. The notion behind this movement was the general assumptions that computers can completely replace radiologists and physicians in identifying and diagnosing certain pathologies, given that the computer was proven to be superior to humans in other areas. This did not work out due to several factors, including the lack of sufficient computing power at the time, lack of advanced image-processing techniques and the lack of access to digital medical images. Overall, at the time, too much was being expected from computers, which led to the notion losing popularity and being deemed as unfeasible and impossible.

In the 1980s however, a different approach to automated computer diagnosis was introduced, where the system output can be used by the radiologist to help in the decision-making process, but not replace them. This system, dubbed as Computer-Aided Diagnosis was widely accepted as a concept and research interest in the area grew widely and rapidly. This was due to multiple factors, including the reduced performance expectations since the computer program's output is combined with, rather than replacing, the radiologist's expertise. This is not the case for automated computer diagnosis, where computer performance is of utmost importance given that the result is being issued solely by the computer. Performance in such cases is measured by specificity and sensitivity. For automated computer diagnosis, both of these factors are required to be very high, that is comparable or higher than that of radiologists, but given that the performance level of radiologists and physicians is much higher than that of a computer, in CAD lower specificity and sensitivity is allowed, since it is being combined with the radiologist's knowledge. [12]

CAD is currently being researched extensively in the medical imaging realm. It has proven to be a very useful tool in the industry, particularly when it comes to the detection of breast [13] [14] and lung [15] [16] cancers. These areas were of great interest since lots of screening tests are performed to check for these pathologies. Given that most screened cases are normal, it may be tedious and time-consuming for the radiologist to go through each result, thus with CAD, these results can be fed through the system, and the computer flags which results have areas of concern. Such systems are nowadays available for clinical use.

2.3 Pre-Processing, haemorrhage detection and segmentation

Once the CT scan images are obtained, the following step would be processing these images such that it can be detected if a bleed is present or not. With such techniques, one can determine if there is a region within the section which is suspected to contain haemorrhage, in this case, or any other pathology being tested for. The three main processes to detect whether there is a haemorrhage present in a CT image are pre-processing, segmentation and detection. For the purpose of this project, the procedures mentioned below have already been covered by the system that was developed by a graduate student, Mr. Napier, in his dissertation. [17]

1.1. Pre-Processing

The pre-processing part involves mainly noise removal techniques. Medical imaging is known to produce images susceptible to visual noise, which can potentially make it harder to identify the bleed from other parts of the brain, specifically the brain's white matter (WM) and gray matter (GM). Following the analysis carried out by Mr. Napier, the best noise removal technique was found to be a bilateral filter with a 5 pixel neighbourhood, colour standard deviation value of 10 and a space standard deviation of 2.5.

2.3.1 Segmentation

Segmentation is the process of extracting information from a region within an image while removing other parts of the same image that are not required. This step was carried out twice in the course of determining whether a bleed is present or not. The first segmentation step was carried out to extract the brain tissue information and discarding the part of the image representing the skull, and the second segmentation was carried out to extract the bleed from the rest of the brain tissue.

The segmentation process is initiated with the removal of the head tissue from the skull. This was accomplished by making use of thresholding and contour methods. Once this step is complete, morphological operations, namely dilation and erosion were applied on the segmented image. Incorporating these two techniques has proven to help the system achieve better results. Dilation involves convoluting an image with a kernel containing a defined anchor point, which is usually situated at the centre of the kernel. This results in regions within the image containing a particular colour value expanding, based on the description of the kernel. This process was required so as to join disconnected bone structures within the brain. Conversely, erosion is a similar process with the opposite effect obtained. With erosion, the anchor point in the kernel is replaced such that bright areas in the image are shrunk, once again based on how the kernel is implemented.

Following the segmentation process, the result was presented as an image of the brain tissue on a black background. This was achieved by detecting the largest contour in the original image and using it as a mask. In this way, any pixels within the mask are retained as in the original image, whereas all other pixels outside the mask were set to black.

2.3.2 Haemorrhage Detection

The main techniques used for the detection of the haemorrhage are clustering, thresholding and contour detection. In this step, the segmented brain image is considered, and the pixel intensities present in the image were grouped into four clusters, representing CSF, WM and GM, brain parenchyma and haemorrhage pixels respectively. Once this clustering is performed, the lower and upper pixel intensity thresholds were determined. The lower intensity threshold was set to be a value found half way through the third cluster and the upper intensity threshold was determined, through testing, to be 40 intensity levels above the lower threshold. By making use of a contour-finding algorithm, all the contours of joined pixel masses were obtained, and should the pathology be present, it is identifiable as the largest detected pixel mass.

In order to minimise the number of false positive detections, a number of features were implemented, which can be categorised in 3 different tests. The first test states that, through testing, that for a pixel mass to be considered a haemorrhage, the area of the mass must be greater than 3788 pixels, and at least 10,000 pixels smaller than the area of the original brain. The latter check was performed to eliminate the possibility of GM and WM being mistaken for haemorrhage should the skull be incorrectly segmented. Furthermore, the perimeter of the closed contour assumed to be the bleed itself must be 1.5 times smaller than the contour of the segmented brain image.

For the cases when a contour perimeter is less than 2000 pixels, the area enclosed by this contour is required to be between 2800 and 15,000 pixels and the contour perimeter of the segmented brain image is at least 4000 pixels longer than that of the haemorrhage contour.

The final test carried out takes into consideration the volume of the bleed. Should a bleed be present in the brain, it will appear in multiple consecutive slices. When the case is being processed, if a pixel mass obeys one of the two described tests, a counter is incremented. Should there be 4 or more consecutive sections containing a pixel mass corresponding to a bleed, the pathology is confirmed whereas if the consecutive slice count is less than 4, the case is considered free of haemorrhage.

2.4 Technological Aspect

2.4.1 Machine Learning

Machine learning is defined as an “application of Artificial Intelligence (AI) that provides systems with the ability to automatically learn and improve from experience without being explicitly programmed” [18]. In this area of computing, the main aim is to design software that uses a given dataset to learn and adapt itself without being hardcoded to do so. A machine learning algorithm is thus designed with the aim of finding patterns in the data given and alter the internal workings to make better decisions based on the training set provided. Machine learning algorithms can be divided into three main categories, which are supervised learning algorithms, unsupervised learning algorithms and reinforcement algorithms.

In supervised machine learning algorithms, the training dataset is clearly labelled, in the sense that for a given set of input parameters, the expected produced output is known. When the training data is fed to the algorithm, the learning algorithm develops a function that produces predictions of the output values. These predictions are then compared to the expected outputs to find errors and correct the developed model accordingly. This model is more widely used, and the majority of practical machine learning techniques use supervised learning.

In unsupervised machine learning algorithms, on the other hand, the training dataset is neither classified nor labelled. When this training dataset is fed to the algorithm, there is no right or wrong answer that is produced. This means that for the input training set, there is no expected output defined. The algorithm is designed to find similarities in the provided dataset and derive a function that defines the hidden structure within the unlabelled data, thus this technique is mainly used to learn more about the data being fed to the system.

In real applications however, the vast majority of machine learning systems incorporate a combination of these two techniques. In these applications, which are referred to as semi-supervised learning, there is a large volume of input data, with only a small subset being labelled. These applications were built given that the process of labelling all the input data is highly time-consuming and can potentially be expensive if the data labelling process requires he help of experts in the domain, while on the other hand, unlabelled data is cheap and easy both to collect and store. In some applications, and for the problem being tackled, a small dataset of labelled data can be used to train the application such that when feeding unlabelled data, a better prediction can be made based on the modifications to the model made via the labelled training data. The newly labelled data can then be fed back to the supervised learning system to further adjust the model for new unlabelled data [19].

The fourth type of machine learning algorithms is reinforcement learning. In this approach, machines and software agents determine the ideal behaviour based on the context that the application is being used for by interacting with the surrounding environment, producing an action and discovering if the said action causes a reward or error via the reinforcement signal. In these cases, machines and software agents learn, through trial and error, which is the optimal decision based on the context to provide maximum performance [18].

2.4.2 Classification

<elaborate more on classifiers if the page count is weak>

Classification is the task of labelling data from a set into one of many subsets or classes. This technique can be applied to data in different formats, such as images, audio and text. While classification is considered to be a relatively easy task for the human being, it has proved to be quite a challenging task for machines, given the complexity of the problem in itself. However, with the increase of programming power, classifiers have gained more popularity and performance power, which is leading to them being used in an ever-growing number of applications.

Image classification, in particular, refers to the task of extracting information from a raster image, and categorising all pixels in an image into one of multiple classes. The whole concept of image classification is mapping regions of an image to particular predefined classes, and with sufficient training this can be achieved quite accurately. Given that image classification is a subset of machine learning, all forms of learning algorithms can be applied to the problem. Some of the most common image classification techniques include support vector machines (SVMs) and Neural Networks (NNs).

In most applications, supervised classification algorithms are applied, either for the entire span of the network operation or as the training potion of the classification algorithm. These algorithms include Nearest Neighbour Algorithms, SVMs and NNs. In supervised classification, each case within a class tends to have common characteristics, such as the mean, covariance matrix and the minimum and maximum grey levels in the applicable class, which values are obtained by calculations during the image processing stage.

There are various classifier types that can be used for this application. The main types of classifiers can be divided into different categories such as linear classifiers, such as Naive Bayes, statistical such as logistic regression, decision trees, SVMs and NNs. The choice of which classifier to use depends on multiple factors, such as the number of cases available to train the classifier, previous knowledge of class probabilities and exactness of such knowledge, and computation complexity requirements.

Apart from choosing the classification algorithm, another decision needs to be made with regards to the evaluation methods. These methods give an estimate to the performance of the classifier by measuring the error rate. These methods describe how to use the currently available dataset to train and test the classifier. Methods such as redistribution uses full dataset to first train the classifier and then reuse the same dataset to test it, which is easy to implement yet gives a highly optimistic error rate. Other methods, which are more realistic, include partitioning the dataset into two groups for training and testing, which can be done in various ways, such as splitting the dataset once, with the training set being significantly larger than the testing set as done in data partitioning [20].

2.4.3 Classifier Types

As already mentioned in the previous section, there are various types of classification algorithms that can be employed based on a number of factors. The three most commonly used classification algorithms are KNNs, SVMs and NNs, as indicated above.

2.4.3.1 K-Nearest-Neighbours (KNN) Classifiers

The KNN algorithm is an easy, robust and versatile way of implementing classification, and is typically used as a form of comparison metric when considering other more complicated classification algorithms. Despite the algorithm being relatively simple and straight-forward to understand, it has proven to beat more complex classifiers in a number of tasks. This algorithm is considered as a supervised learning algorithm, as well as a non-parametric and instance based learning algorithm. This means that no explicit assumptions are made by the algorithm about the form of the function that eventually maps the inputs to the outputs, and that the algorithm remembers the training instances which are used as the knowledge when predicting a test case outcome, rather than an entire model. While KNNs are great as an initial form of testing on data that is to be fed into more complex systems, it is a very computationally intensive algorithm, which leads to a very long testing phase.

The algorithm makes a prediction on a test case by seeing under which class the nearest k neighbours fall, and the test case is classified in one of the classes based on the classification in which the majority of the nearest neighbours are classified in. programmatically, this is done by computing the difference between the test case and each of the training cases, selecting the K training instances that give the minimum difference. Considering the subset of K training instances, the test case is assigned to the class with the highest conditional probability, i.e. to the class in which the majority of these K neighbours belong to.

As it can be seen, the value of K is one of the most important parameters in this classifier setting. In this setup, the number of neighbours considered, K, can be any positive integer. A small value of K provides a fit with low bias but high variance, whereas a large value of K help in making the algorithm resilient to outlying points, which translates to a lower variance but increased bias. The choice of K depends on application, and a parametric analysis can easily determine the best value for K. [21]

2.4.3.2 Support Vector Machine (SVM) Classifiers

The SVM algorithm is a supervised learning algorithm which can be applied to both classification and regression. Each data point in the training set is plotted in an n-dimensional space, with the number of dimensions correspond to the number of features being taken into consideration. Following some processing, each data point is translated into a coordinate in this space [22]. The algorithm tries to find an optimal decision plane that defines the boundary between any two classes, referred to as a hyperplane. Hyperplane selection is based on two main principles: best possible class segregation and maximising the margin which is how far the nearest data points are from the hyperplane. In order to find the ideal hyperplane for a dataset, one might require the use of a kernel, which is a transformation function that converts a low-dimension space into a more complex, higher dimension space in which the dataset can be linearly separable.

This algorithm has proven to be useful in multiple cases, particularly those where a clear distinction between the classification classes exist, in highly dimensional spaces and in classification cases where there exist more dimensions than samples. However, the algorithm performs poorly when the dataset is large due to the increased training time and in cases with overlapping classification classes. Furthermore, the algorithm does not inherently provide probabilistic measures of correctness, which would have to be computed using other, computationally expensive, functions. [23]

2.4.3.3 Artificial Neural Networks (ANNs)

An ANN is a "parallel computational network made up of interconnected neurons" [24]. An ANN is formed of multiple nodes, referred to as neurons, which are connected to other neurons in previous and following layers, and were designed as a computational version of how the human brain works. The structure of a neural network is analogous to the structure of the brain, in the sense that each neuron is connected to several other neurons. [25]

In a biological neuron, the dendrites are hair-like extensions of the soma which collect inputs from other neurons connected to it, the soma processes these inputs. Following the input processing by the soma, the axon converts these processed inputs into an output, which is then sent out of the neuron via the synapses, which are the structures connecting one neuron to another, effectively passing the output of the neuron in question as an input to a set of other neurons connected to it. In a similar way, an artificial neuron is designed to incorporate these four different functions performed by the biological neurons. The inputs to the neuron are multiplied to some weight value w, which vary for each input. There weighted inputs are then summed together, and a transfer or activation function is applied to them to produce an output. This output is then fed to neurons in the successive layer or as an output to the network should the neuron be in the output layer. [26]

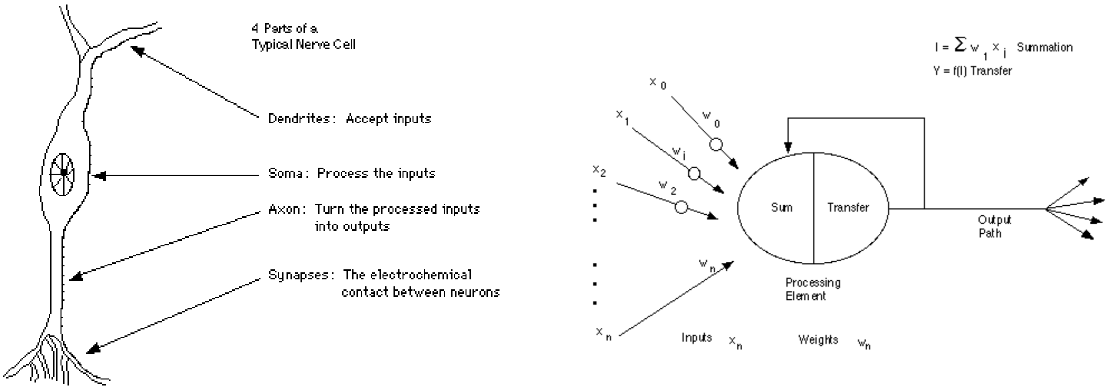

Figure 1: Analogy between a biological neuron and an artificial neuron

In an ANN, neurons are divided in a number of layers, namely the input layer, output layer and one or more hidden layers. In any one of these layers, each neuron is connected to every other neuron in the successive layer, if any, and receives inputs from every neuron in the previous layer, making the structure fully-connected. The input layer fo the neural network represents the number of dimensions in the data, whereas the output layer consists of the number of classes in which an input can be assigned to. The number of dimensions in the input are fed into the network one by one as a normalised weighted value to each of the input layer neurons. Each of the input neurons performs the weighted sum which passes through the activation function and produces an output, which is propagated into the next layer. The output propagates forward in the network in the same way until reaching the output layer, where each neuron outputs a normalised value corresponding to the probability of the given input being classified into that class.

ANNs can be designed to follow supervised learning and unsupervised learning, based solely on the data being fed and how the weights are adjusted to reach a local minimum, however the most common structure for an ANN used as a classifier is using supervised learning to train the network and backpropagation to adjust the weights after every training iteration.

One of the major advantages of neural networks over other systems is their ability to infer results based on input-output relationships and other underlying rules in the data. Even though the network requires a significant amount of training thus requiring large processing times especially for larger structures, the structure allows for information to be processed in a highly parallel way, thus speeding this process. Given that the network is designed to learn patterns in the data, the same structure can be reused for other purposes without having to alter the structure of the network within itself.

2.4.4 Previously developed systems

The task of developing an automated classification system for brain haemorrhage in CT and MR images is no new topic in CAD systems. There have been many attempts in the development of a reliable, robust system that can cater for such a need. While for MR images this was quite successful, the research in CT images still has room for improvements. Considering what was done previously in the area, one can see that there have been several attempts to address the research area, using different algorithms. The two most common classifiers used in Brain CT scan classification are the K-Nearest Neighbour Classifier and the Artificial Neural Network. Shahangian et.al. [27] compared the accuracy of KNN and ANN algorithms for classification and found that using a multilayer perceptron (MLP) neural network with 14 input nodes representing the 14 features extracted from the CT image, 12 hidden-layer neurons and 3 output neurons gave much better results when compared to using the KNN algorithm. An improvement on the obtained result was observed by applying a genetic algorithm (GA) to the input features to select the best features to be used for classification. This yielded an improvement for both the KNN and ANN classifiers. When testing the classifiers, the image set consisted of EDH, SDH and ICH bleeds mixed with normal images. 50% if the image set was used as the training set for the KNN classifier and the other 50% was used for testing, whereas the dataset distribution for the ANN structure was 70% for training and 30% for testing the system.

In another study, Sharma et.al. [3] created an ANN structure with 16 features fed as inputs, 30 neurons in the hidden layer and 3 outputs, classifying EDH, SDH and ICH. Their study used 100 brain CT images, with haemorrhage present in all images. 70% of the dataset was used to train the network and the remaining 30% were used to test the system.

In a third study carried out by Balasooriya et.al [28], an ANN structure was designed and tested. The number of input features were 3 – the number of closed-contour objects detected; 1 if SDH since the skull and brain are ‘attached’ or 2 if ICH since it is separate from the skull; the area of the first closed contour typically the brain itself, and the area of the second closed contour if applicable. For this study, the number of hidden-layer neurons was varied and it was determined by the author that 15 neurons was the best option. The number of samples available for this implementation were 50, where 80% were used for training and 20% for testing. In the table below, one can see the observed accuracy levels for each of the cases mentioned above.

Author	Classifier type	Hidden layer Neurons	Total cases	Training set	Testing set	Accuracy
Shahangian [27]	KNN without GA	N/A	No information	50%	50%	53.33%
Shahangian [27]	KNN with GA	N/A	No information	50%	50%	60%
Shahangian [27]	ANN without GA	12	No information	70%	30%	86.7%
Shahangian [27]	ANN with GA	12	No information	70%	30%	93.3%
Sharma [3]	ANN	30	100	70%	30%	97%
Balasooriya [28]	ANN	15	50	80%	20%	97.8%

Table 1: Findings from previous work

When considering all the above studies, which were the ones most relative and comparable to the study being carried out, it was noted that there seemed to be a similarity in the haemorrhage cases being analysed. As noted above, the previous research papers limited their systems to cover only ICH, SDH and in some cases EDH. This is mainly because SAH is very difficult to detect due to it being highly dispersed throughout the brain and is spotted in CT scans as numerous small patches of blood in the subarachnoid space.

2.5 Conclusion

From the analysis of previous work carried out in relation to this problem, as seen in the previous section, one can see that while there has been some research carried out, there is still room for improvement and further research. It can be clearly see from the comparison performed in the previous section that the best results thus far have been achieved using a single hidden layer ANN using several features from the CT image as inputs to the system. Considering this, one can argue that there is still room for experimentation with the type of classifier being used, with the intention of seeing if the accuracy can be increased further.

The first conclusion that can be reached following the analysis of previous work is that the types of haemorrhage being classified is not the full range of possible diagnoses. Out of the five different haemorrhage types mentioned above, one can note that only three were considered for classification in these studies. This can be due to different reasons, one of which is the potential lack of cases of the types of haemorrhage not classified. Another reason behind the lack of classification of different types could be that the developed system was not intelligent enough to recognise the haemorrhage type since not enough information was being extracted about the bleed. As Balasooriya et.al [28] mentioned in their section on further improvements, the three parameters being fed into their network were not enough to help distinguish between EDH and SDH since they both give the same number of objects and roughly the same area. For the detection of SAH, their suggestion is to take into consideration the histogram value of all objects, since such a pathology can be seen spread throughout the image.

Another conclusion that can be reached is that from the performed research thus far, the ANN structure is the most successful in classifying correctly these haemorrhage types. Considering the study that targeted the widest variety of haemorrhage detection, Sharma et.al. [3] classified between EDH, SDH and ICH with 97% accuracy, using 16 features as inputs to the designed ANN classifier. This shows that the current research is highly accurate, but there is still room for improvement.

Bibliography

[1] A. M. Naidech, "Intracranial Hemorrhage," *American Journal of Respiratory and Critical Care Medicine*, vol. 184, no. 9, pp. 998-1006, 2011.

[2] B. Pourghassem and H. Shahangian, "Automatic brain hemorrhage segmentation and classification in CT scan images," in *8th Iranian Conference on Machine Vision and Image Processing (MVIP)*, Zanjan, 2013.

[3] B. Sharma and K. Venugopalan, "Classification of hematomas in brain CT images using neural network," *International Conference on Issues and Challenges in Intelligent Computing Techniques (ICICT)*, pp. 41-46, 2014.

[4] M. Nadrljanski, "Attenuation coefficient | Radiology Reference Article | Radiopaedia.org," Radiopaedia.org, [Online]. Available: https://radiopaedia.org/articles/attenuation-coefficient. [Accessed 28 02 2018].

[5] W. |. W. H. Organization, "Who.int," WHO | World Health Organization, [Online]. Available: http://www.who.int/diagnostic_imaging/imaging_modalities/dim_plain-radiography/en/. [Accessed 28 02 2018].

[6] P. Armstrong, Diagnostic imaging, 6th edition ed., Blackwell, 2009.

[7] "Computed Tomography (CT)," National Institute of Biomedical Imaging and Bioengineering, undated. [Online]. Available: https://www.nibib.nih.gov/science-education/science-topics/computed-tomography-ct. [Accessed 28 02 2018].

[8] M. Nadrljanski, "Computed tomography | Radiology Reference Article | Radiopaedia.org," Radiopaedia.org, undated. [Online]. Available: https://radiopaedia.org/articles/computed-tomography. [Accessed 28 02 2018].

[9] P. Sprawls, "CT Image Quality and Dose Management," [Online]. Available: http://www.sprawls.org/resources/CTIQDM/. [Accessed 28 02 2018].

[10] "Acute CT Brain - Mass effect," Radiologymasterclass.co.uk, [Online]. Available: https://www.radiologymasterclass.co.uk/tutorials/ct/ct_acute_brain/ct_brain_mass_effect. [Accessed 28 02 2018].

[11] F. Gaillard, "Intracranial haemorrhage | Radiology Reference Article | Radiopaedia.org," Radiopaedia.org, [Online]. Available: https://radiopaedia.org/articles/intracranial-haemorrhage. [Accessed 28 02 2018].

[12] K. Doi, “Computer-aided diagnosis in medical imaging: Historical review, current status and future potential,” *Computerized Medical Imaging and Graphics,* vol. 31, no. 4-5, pp. 198-211, 2007.

[13] R. V. M. a. I. C. P. Raha, “Fully automated computer aided diagnosis system for classification of breast mass from ultrasound images,” in *2017 International Conference on Wireless Communications, Signal Processing and Networking (WiSPNET)*, Chennai, India, 2017.

[14] F. M. B. D. a. S. R. V. Kumar, “A hybrid computer-aided diagnosis system for abnormality detection in mammograms,” in *2017 2nd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT)*, Bangalore, 2017.

[15] F. B. S. A. F. a. M. B. A. K. AlZubaidi, “Computer aided diagnosis in digital pathology application: Review and perspective approach in lung cancer classification,” in *2017 Annual Conference on New Trends in Information & Communications Technology Applications (NTICT)*, Baghdad, 2017.

[16] M. P. P. a. S. Choomchuay, “A computer aided diagnosis system for detection of lung nodules from series of CT slices,” in *14th International Conference on Electrical Engineering/Electronics, Computer, Telecommunications and Information Technology (ECTI-CON)*, Phuket, 2017.

[17] J. Napier, *Image processing techniques for brain haemorrhage detection in head CT scans,* University of Malta, Faculty of Information and Communication Technology, Department of Communications and Computer Engineering, 2017.

[18] “What is Machine Learning? A definition - Expert System,” Expertsystem.com, [Online]. Available: http://www.expertsystem.com/machine-learning-definition/. [Accessed 28 02 2018].

[19] J. Brownlee, “Supervised and Unsupervised Machine Learning Algorithms - Machine Learning Mastery,” Machine Learning Mastery, [Online]. Available: https://machinelearningmastery.com/supervised-and-unsupervised-machine-learning-algorithms/. [Accessed 28 02 2018].

[20] N. T. N. U. Department of Computer Science and Information Engineering, “Classifier Training and Evaluation,” Department of Computer Science and Information Engineering, National Taiwan Normal University, Taiwan.

[21] K. Zakka, “A Complete Guide to K-Nearest-Neighbors with Applications in Python and R,” Kevinzakka.github.io, 2018.

[22] S. Patel, “Chapter 2 : SVM (Support Vector Machine)—Theory,” 2017.

[23] S. Ray, “Understanding Support Vector Machine algorithm from examples (along with code),” 2017.

[24] A. Cortis, “Artificial Neural Networks,” *The Collection,* vol. 7, pp. 28-33, 2003.

[25] M. A. Nielsen, “Neural Networks and Deep Learning,” 2018. [Online]. Available: http://neuralnetworksanddeeplearning.com. [Accessed 21 04 2018].

[26] U. o. Toronto, “Artificial Neural Networks Technology,” [Online]. Available: http://www.psych.utoronto.ca/users/reingold/courses/ai/cache/neural_ToC.html. [Accessed 21 04 2018].

[27] H. P. Bahare Shahangian, “Automatic Brain Hemorrhage Segmentation and classification in CT scan images,” in *8th Iranian Conference on Machine Vision and Image Processing (MVIP)*, Zanjan, 2013.

[28] U. B. a. M. U. S. Perera, “Intelligent brain hemorrhage diagnosis using artificial neural networks,” in *IEEE Business, Engineering & Industrial Applications Colloquium (BEIAC)*, Kuala Lumpur, 2012.

[29] F. Gaillard, “Subdural haemorrhage | Radiology Reference Article | Radiopaedia.org,” radiopedia.org, 2018. [Online]. Available: https://radiopaedia.org/articles/subdural-haemorrhage.

[30] F. Galliard, “Extradural haemorrhage | Radiology Reference Article | Radiopaedia.org,” Radiopaedia.org, 2018. [Online]. Available: https://radiopaedia.org/articles/extradural-haemorrhage. [Accessed 24 02 2018].

[31] “Education. Whats an MRI,” Multiple-sclerosis-research.blogspot.com, 10 01 2015. [Online]. Available: http://multiple-sclerosis-research.blogspot.com/2015/01/education-whats-mri.html. [Accessed 28 02 2018].

[32] “Spontaneous Intracerebral Hemorrhage,” Clinical Gate, 03 12 2015. [Online]. Available: https://clinicalgate.com/spontaneous-intracerebral-hemorrhage/. [Accessed 28 02 2018].

[33] “Computed tomography,” TheFreeDictionary.com, [Online]. Available: https://medical-dictionary.thefreedictionary.com/Computed+tomography. [Accessed 28 02 2018].