MINI PROJECT REPORT

SEMESTER 5

Analysis of different neural architectures in predicting acute intercranial brain haemorrhage

by

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SHRI MATA VAISHNO DEVI UNIVERSITY, KATRA

Faculty of Engineering & Technology

Department of Computer Science Engineering

Certificate

This is to certify that this project report entitled "Analysis of different neural architectures in predicting acute intercranial brain haemorrhage" by Krishna katyal (17bcs030) submitted in fulfilment of the requirements for the degree of Bachelor of Technology in COMPUTER SCIENCE & ENG INEERING under Faculty of Engineering & Technology of Shri Mata Vaishno Devi University Katra, during the academic session 2019-20, semester 5, is a bona-fide record of work carried out under my guidance and supervision.

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Krishna Katyal (17bcs030)

ABSTRACT

Artificial intelligence (AI) has the potential to help tackle some of the world's most challenging problems and when coupled with popular tools and technologies for development and betterment of our society, what the point of technology when it can't help the needy and save lives. Deep learning helps us to build robust, scalable and effective solutions which can be adopted by everyone even in remote corners of the world and detection of Intercranial brain haemorrhage is one of the problems which Deep learning has help to tackle.

WHO recommends 1 doctor per 1000 people whereas India has 1 doctor per 10189 people. There are ten lakh cases of brain haemorrhage in India per year. Intracranial haemorrhages account for approximately 10% of strokes Intracerebral haemorrhage accounts for 8-13% of all strokes.
Traumatic brain injuries could cause intracranial haemorrhage (ICH). intracranial haemorrhage could lead to disability or death if it is not accurately diagnosed and treated within short span of time.

Bleeding in the brain region is various types, bleeding within or around the brain is cerebral haemorrhage (or intracerebral haemorrhage), bleeding happening due to cracked or oozing blood vessels is a haemorrhagic stroke. All bleeding inside the skull is mentioned as intracranial haemorrhage.

Haemorrhages that occur within the skull or brain commonly occur abruptly, from either external or internal causes. Since intracranial haemorrhages are a comparatively common condition that has many causes ranging from trauma, stroke, aneurysm, vascular abnormalities, elevated blood pressure, prohibited drugs, and blood clotting dysfunctions. The neurologic outcomes also differ widely depending upon the extent, nature of haemorrhage and location ordering from headache to death.

Radiological Society of North America (RSNA®) hosted a challenge on Kaggle.com to build an algorithm to detect acute intracranial haemorrhage and its subtypes. The image dataset provided by the in collaboration with members of the American Society of Neuroradiology and MD.ai was used.

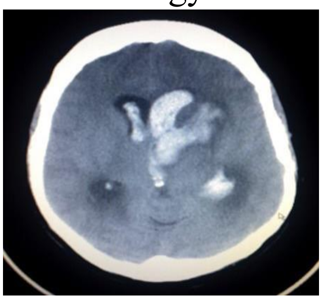

Figure : Brain with intercranial haemorrhage.

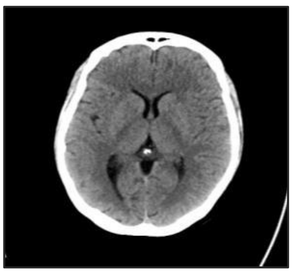

Figure : Normal brain CT with and without contrast, with axial, coronal and sagittal reformats.

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Abbreviations:

ICH: Inter Cranial Haemorrhage

1.0 Introduction

When a patient shows acute neurological symptoms such as severe headache or loss of consciousness, highly trained specialists review medical images of the patient’s cranium to look for the presence, location and type of haemorrhage. The process is complicated and often time consuming.

1.1 Causes of intracranial haemorrhage?

Intracranial haemorrhage has a number of causes, including:

Head trauma, such as that caused by a fall, car accident, sports accident, etc
Hypertensive (high blood pressure) damage to blood vessel walls that causes the blood vessel to leak or break

Blockage of an artery in the brain by a blood clot that formed in the brain or travelled to the brain from another part of the body, with subsequent leakage from the damaged artery

Ruptured cerebral aneurysm (a weak spot in a blood vessel wall that balloons out and bursts)

Build-up of amyloid protein within the artery walls of the brain (cerebral amyloid angiopathy)

Leaking of malformed arteries or veins (arteriovenous malformation)

Treatment with anticoagulant therapy (blood thinners)

Bleeding tumours

Smoking, excessive alcohol use, or use of illegal drugs such as cocaine

Conditions related to pregnancy or childbirth, including eclampsia, postpartum vas culopathy, or neonatal intraventricular haemorrhage

1.2 What are the symptoms of intracranial haemorrhage?

Sudden tingling, weakness, numbness, or paralysis of the face, arm or leg, particularly on one side of the body Sudden, severe headache

Difficulty with swallowing or vision

Loss of balance or coordination

Difficulty understanding, speaking (slurring nonsensical speech), reading, or writing
Change in level of consciousness or alertness, marked by stupor, lethargy, sleepiness, or coma

2.0 Deep learning

2.1 WHAT IS DEEP LEARNING?

According to Forbes "The field of artificial intelligence is essentially when machines can do tasks that typically require human intelligence. It encompasses machine learning, where machines can learn by experience and acquire skills without human involvement. Deep learning is a subset of machine learning where artificial neural networks, algorithms inspired by the human brain, learn from large amounts of data. Similarly, to how we learn from experience, the deep learning algorithm would perform a task repeatedly, each time tweaking it a little to improve the outcome. We refer to 'deep learning' because the neural networks have various
(deep) layers that enable learning. Just about any problem that requires "thought" to figure out is a problem deep learning can learn to solve."

2.2 HOW CAN WE PREDICT DISEASES USING DEEP LEARNING?

We first start with some piece of diagnostic data whether be it MRI Scan, CT SCAN, X-Ray or a blood smear test.

In our case, it is a DCM file is an image file saved in the Digital Imaging and Communications in Medicine (DICOM) image format.

We then want to take this image, feed it to an algorithm which tells us whether the presence of haemorrhage and its subtype.
In this project a convolutional neural network was used

It is a type of neural network that is specially tailored for images. We utilize a technique called transfer learning

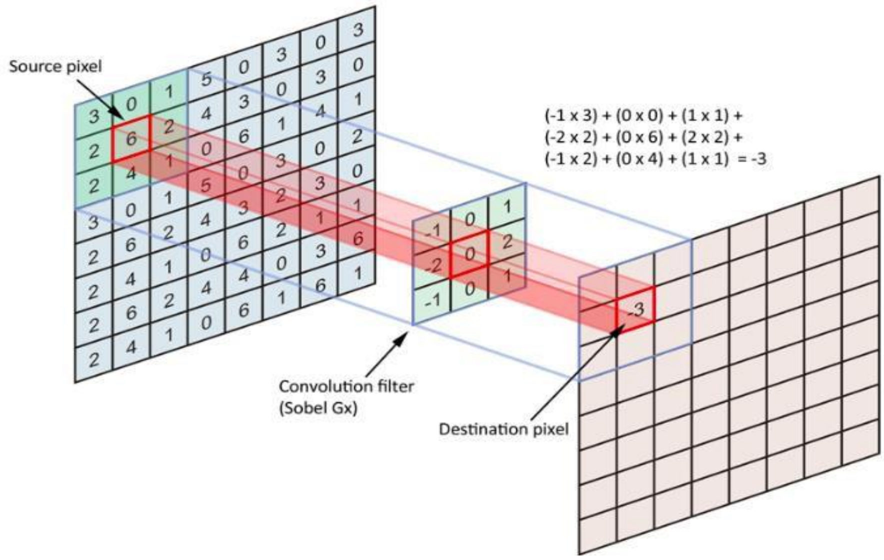
2.3Convolutional neural Networks

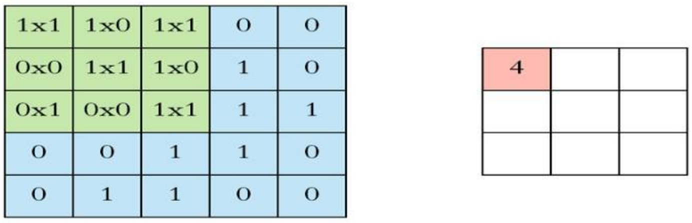
2.3.1 Convolution and convolution layers

A convolutional filter is sided all over an image as shown here.

The values of the filter, called weights, help in extracting meaningful information out of the image.

2.3.2CNN Pooling





* Image Credit: https://towardsdatascience.com/applied-deep-learning-part-4convolutional-neural-networks-584bc134c1e2

2.3.3 Max Pooling

Like a convolution, but no weights.
We just take the maximum value from the patch.
Helps in dimension reduction, and consequently saves computation

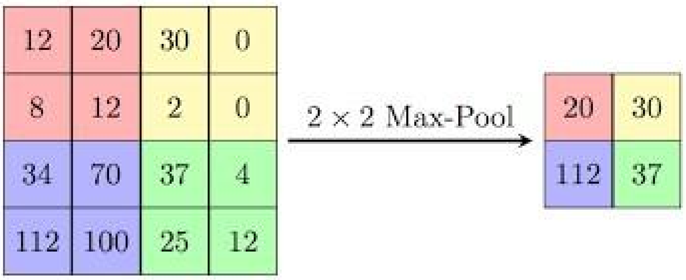
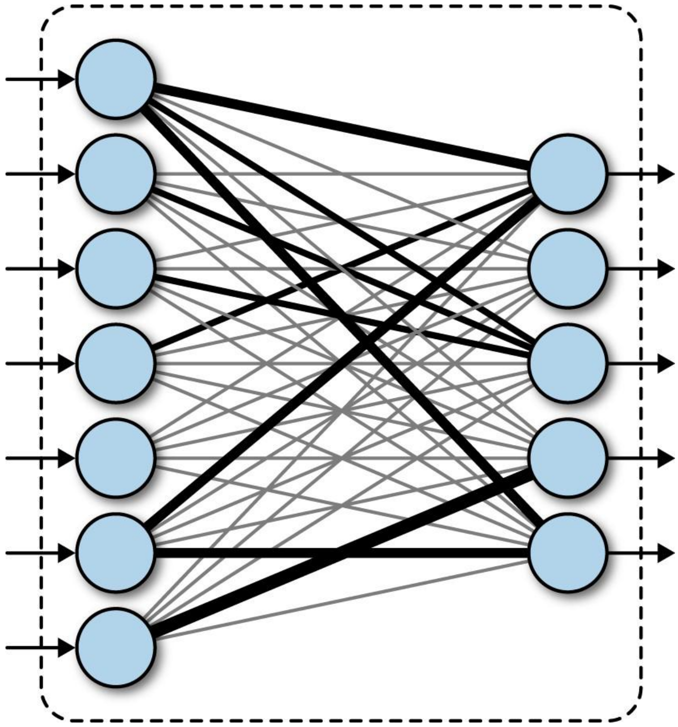


*Image credits:https://computersciencewiki.org/index.php/Max-pooling_/_Pooling

2.3.4 Fully Connected Layer

A fully connected layer connects each neuron in one layer to each neuron in the other layer.
Each connection has a weight

It allows global aggregation of information.
Much more computationally expensive than a convolutional layer.



* Image Credit: TensorFlow for Deep Learning by Reza Bosagh Zadeh, Bharath Ramsundar, O'reilly Publications

2.4 Working of a Convolutional Neural Network:

A typical Convolutional Neural Network consists of convolutional layers, interspersed with max pooling layers and fully connected layers at the end.

Each Convolutional Layer may have more than one filter. The feature maps produced by one-layer act as input for the next.

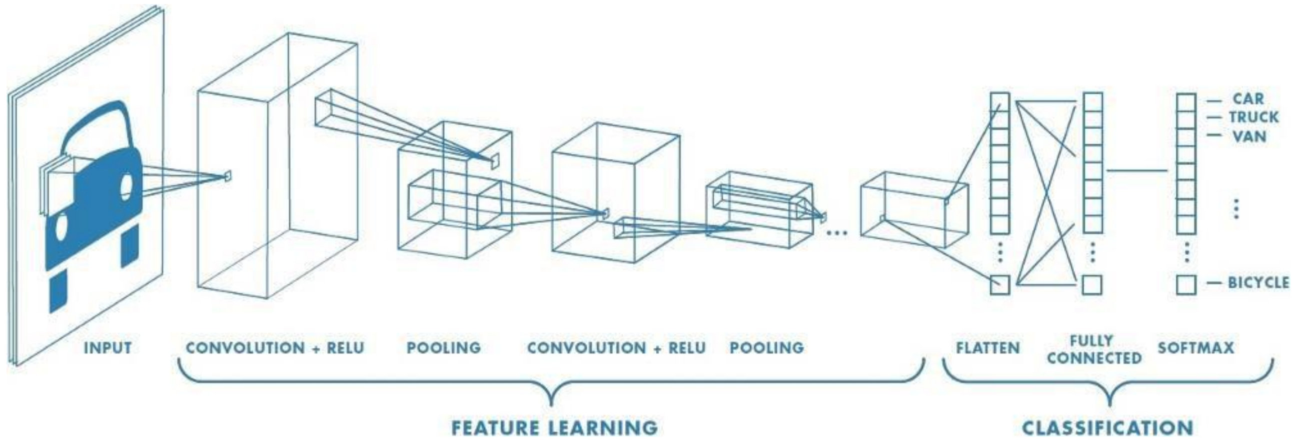
Convolutional layer act as generalized feature extractors. These computed features are used by fully connected layers to predict the information.

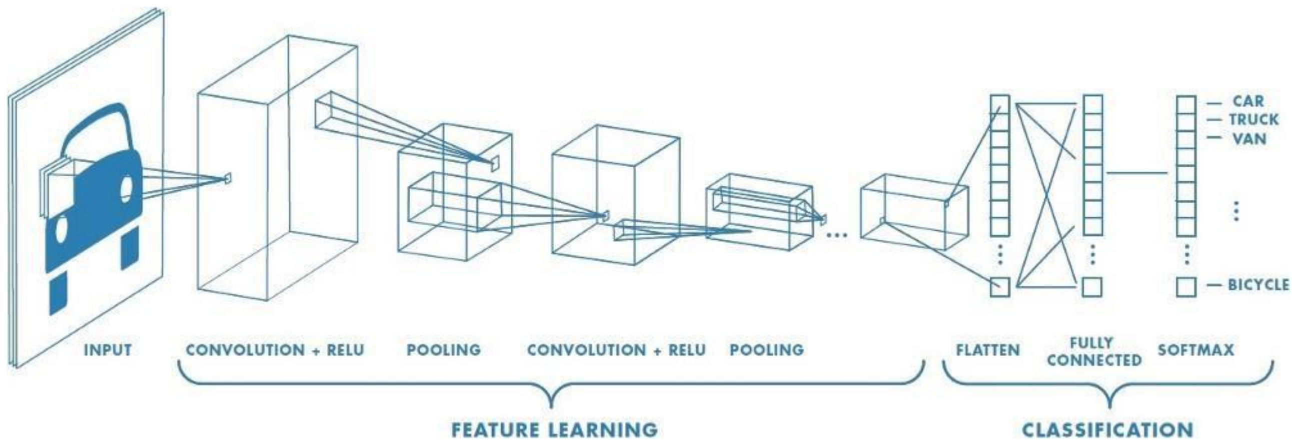
2.5 Transfer Learning: An Analogy

You don’t learn how to see and classify sparrows from scratch. You are already aided with a fully developed visual system thanks to years of evolution.

In a way, you have transferred whatever you gained during years of evolution to the sparrow classifying problem. Hence the name Transfer Learning.

We take a model pretrained on a huge dataset of images and we use transfer learning to train it on our malaria classification task.





Pretrained on Wide-ranging General Image

Trained to classify hemorrhage or not

I have used transfer learning in all of my neural networks trained weights helps in faster training.

3.0 Deep learning on acute detecting intracranial haemorrhage and its subtypes.

When patient displays acute neurological implications like sharp headache or impairment of consciousness, qualified specialists analyse medical images of the patient's cranium to scan for the presence, position, and nature of haemorrhage. The method is complicated and often takes a lot of time. This work can be done with an algorithm which will be faster and will have better accuracy

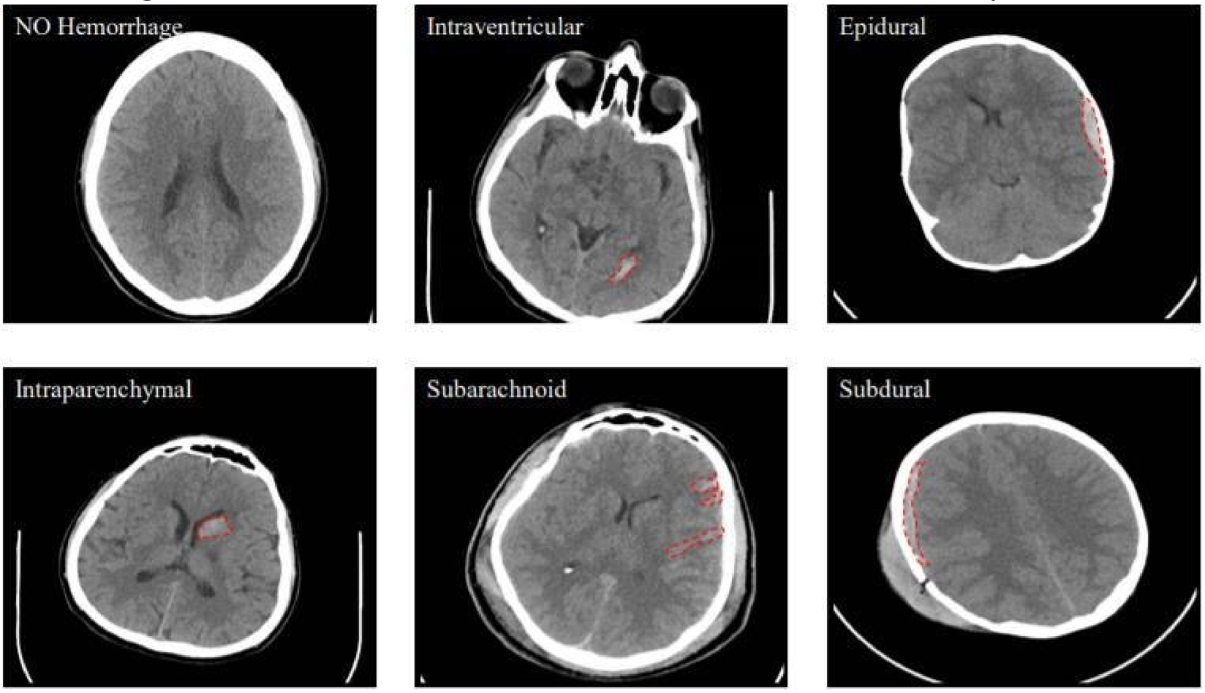


Figure: subtypes of haemorrhage

While all acute haemorrhages appear dense on computed tomography, the primary imaging features that help Radiologists define the subtype of haemorrhage are the location, shape, and vicinity to other structures

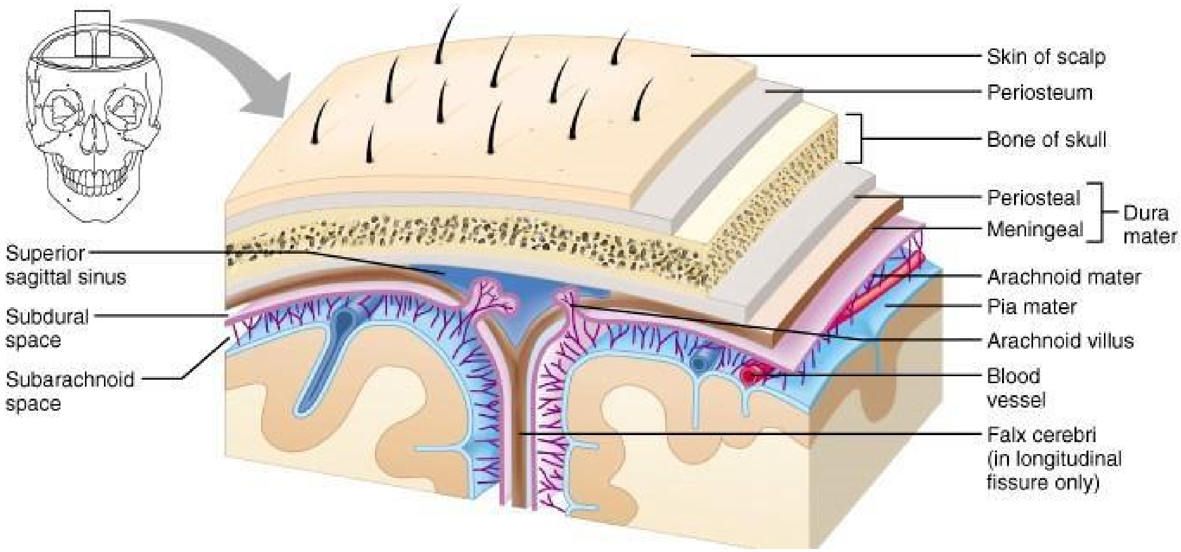


Figure: The coverings of the brain observed in frontal section

Intraparenchymal haemorrhage is blood that is positioned entirely inside the brain itself; intraventricular or subarachnoid haemorrhage is blood that has oozed into the spaces of the brain that usually contain cerebrospinal fluid. Extra-axial haemorrhages are blood that accumulates in the tissue coverings that surround the brain. Patients may manifest more than one type of cerebral haemorrhage, while small haemorrhages are less morbid than large haemorrhages typically, yet a small haemorrhage can lead to death because it is a symbol of another type of serious deformity

3.1SUBTYPES OF ICH

Name: Intraparenchymal

Location: Inside the brain

shape: Typically rounded presentation: Acute (sudden onset of headache, nausea, vomiting)

Mechanism: High trauma, blood pressure,

arteriovenous malformation,

tumour, etc.

source: Arterial or Venous

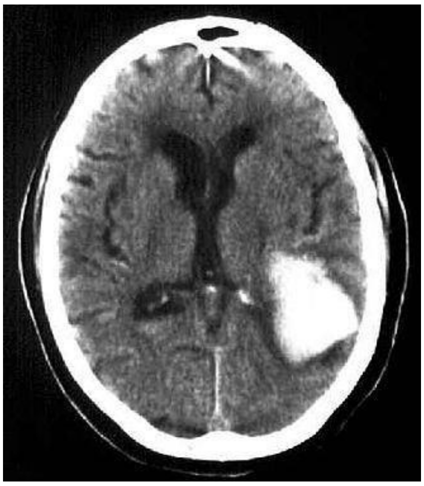


Figure: CT-scan of Intraparenchymal haemorrhage

3.1.2 Name: Interventricular

Location: Inside the ventricle

Mechanism:Canbe

associated with both

intraparenchymal and

subarachnoid haemorrhage

source: Arterial or Venous

shape: Conforms to ventricular shape

Presentation: Acute (sudden onset of headache, nausea, vomiting)

Figure: CT-scan of Intraparenchymal haemorrhage

3.1.3Name: subarachnoid

Location: Between the arachnoid and pia mater

Mechanism: Rupture of aneurysms or arteriovenous malformations or trauma

source: Predominantly Arterial

shape: Tracks along the sulci and fissures

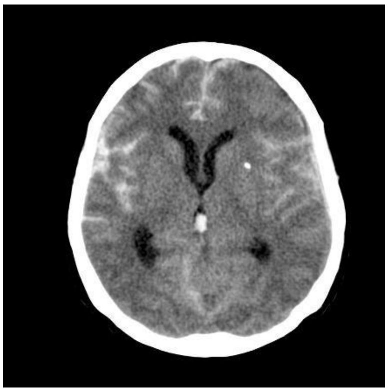


Figure: CT-scan of subarachnoid haemorrhage

3.1.4 Name: Subdural

Location: Between the dura and arachnoid

Mechanism: Trauma

source: Venous (bridging veins)

shape: Crescent

Presentation: Acute (worsening headache)

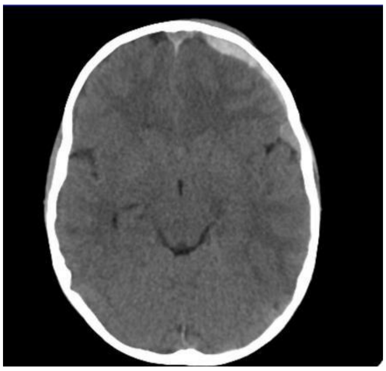


Figure: Traumatic subdural Haemorrhage in a child:

3.1.5 Name: Epidural

Location: Between the dura and skull

Mechanism: Trauma or after surgery

source: Arterial

shape: Lentiform

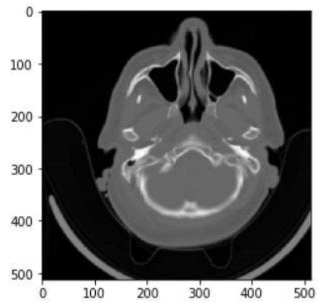
Presentation: Acute (skull fracture and altered mental status)

Figure: CT-scan of Epidural haemorrhage

4.0 Analysing the dataset

Medical images are saved in a distinctive format known as DICOM files (*.dcm). They contain a blend of header metadata as well as raw image arrays for pixel data.

The pydicom module was used to access and manipulate DICOM files

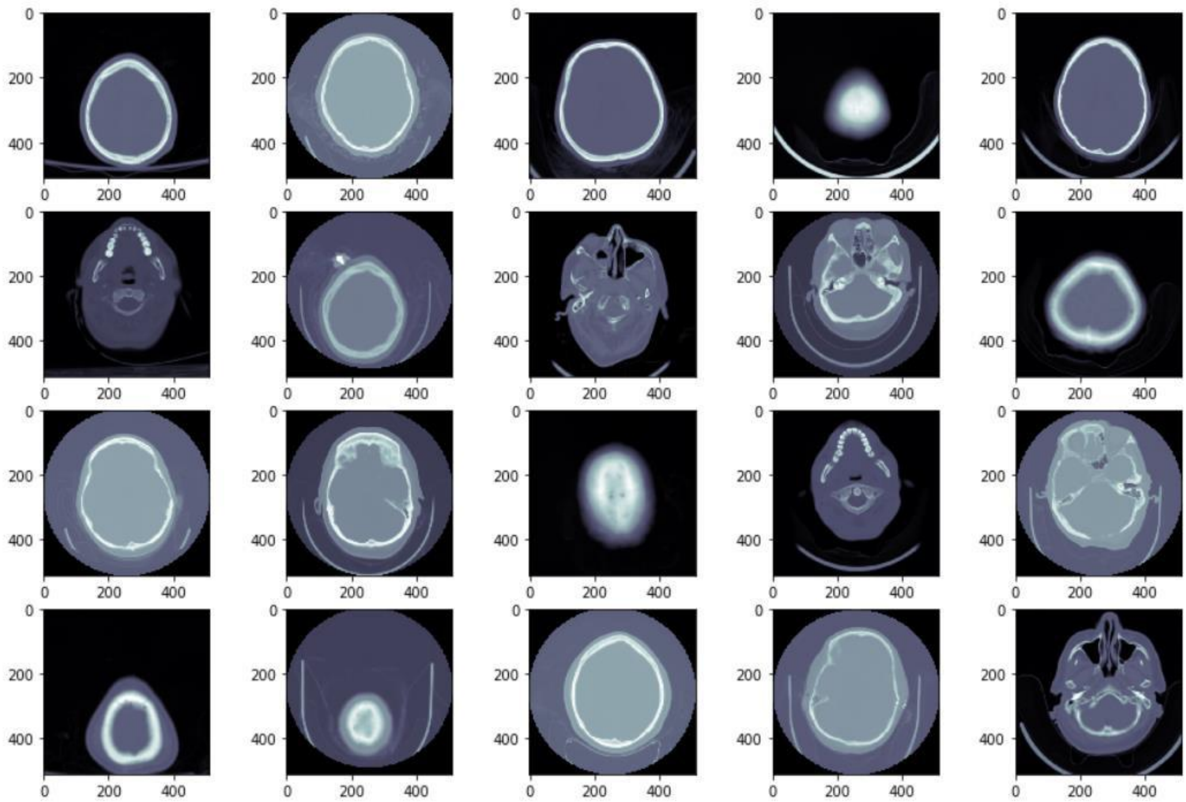


4.1 Data Analysing of stage_2 data set

Label	count
0	4260600
1	256242

Table 1: labels and counts

4.1.1Display of Twenty images from the dataset (After some pre-processing)



Subtype	Label

any	107933
epidural	3145
intraparenchymal	36118
intraventricular	26205
subarachnoid	35675
subdural	47166

Table 2: subtypes occurrences

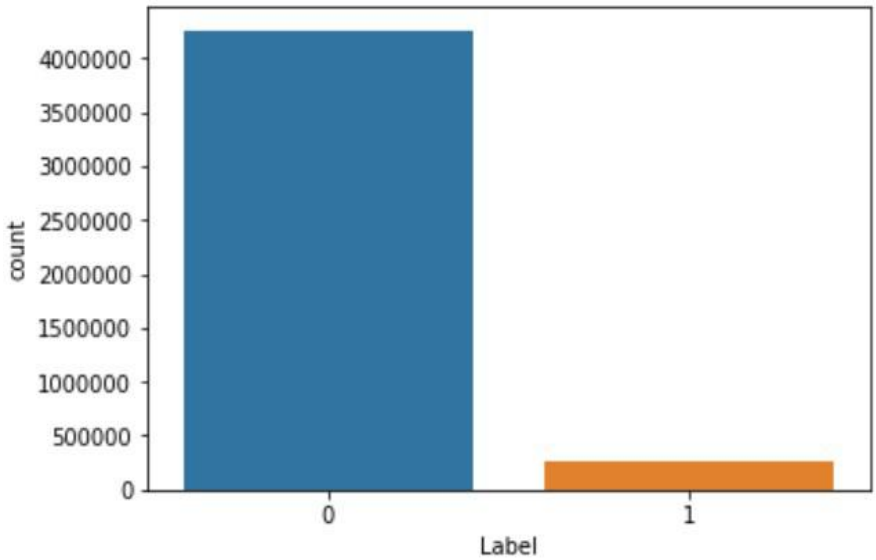


Figure: count plot

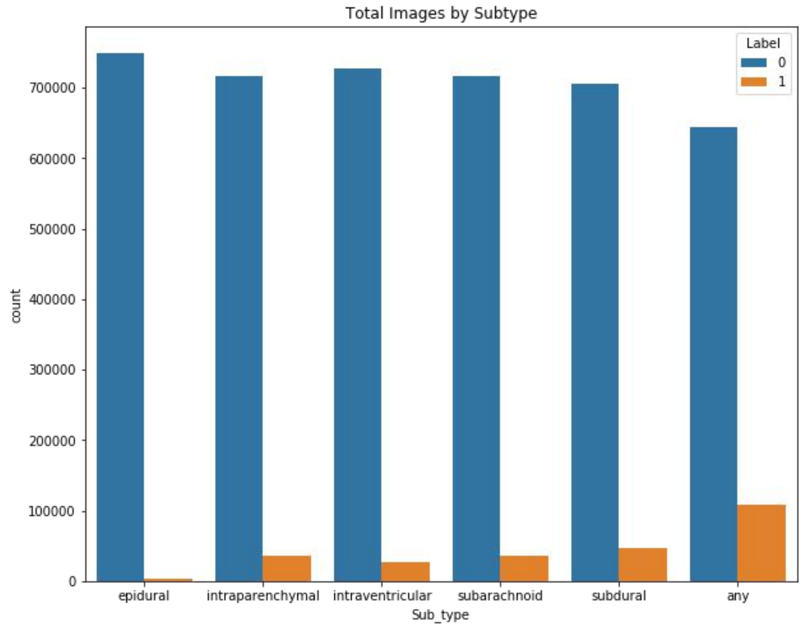
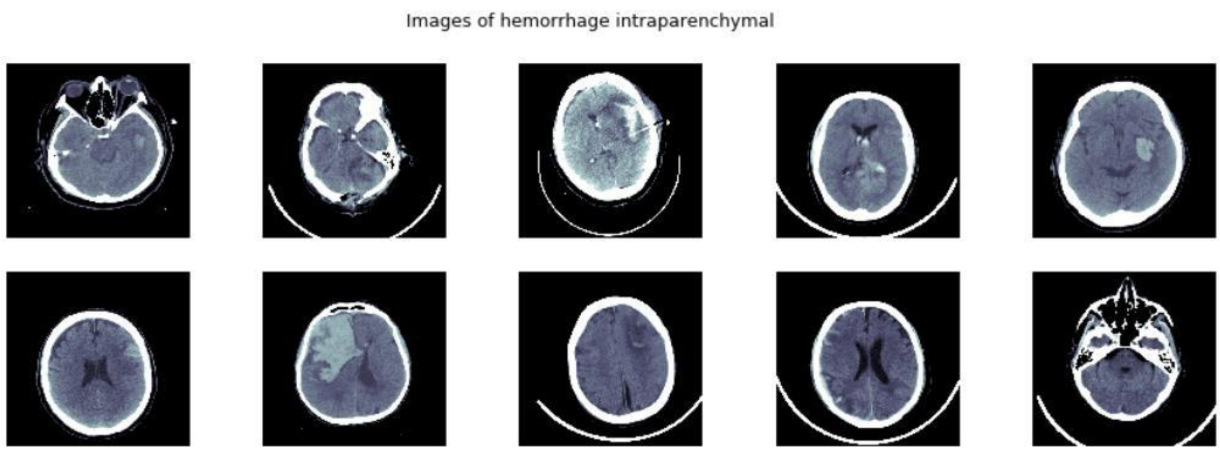


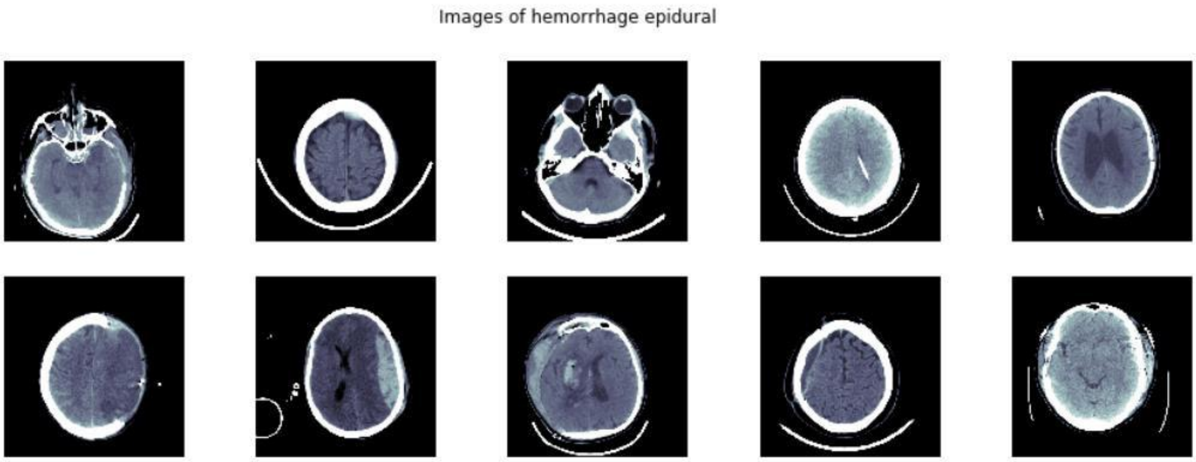
Figure: count plot of labels per subclass

4.2 Visualisation of subtypes

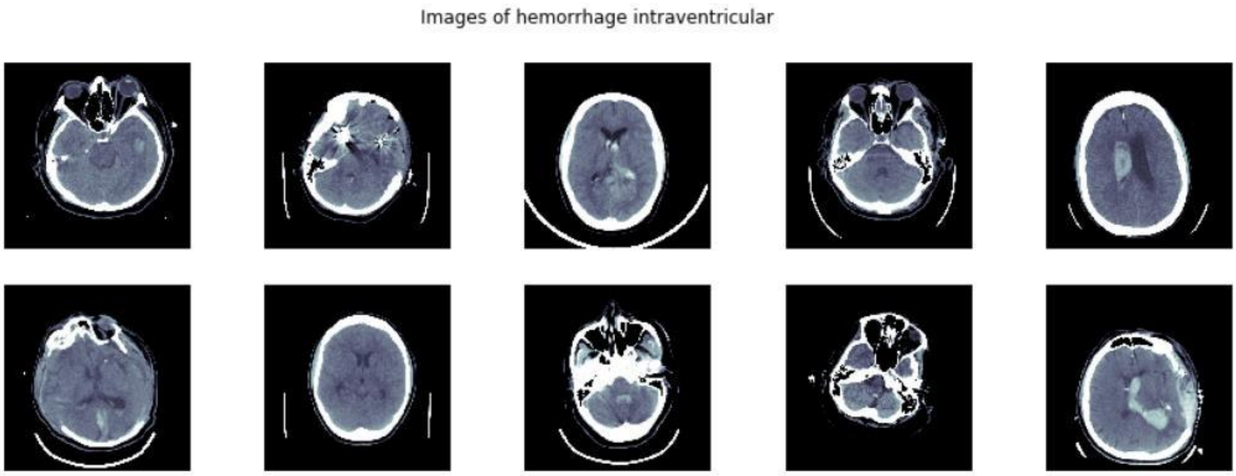
Intraparenchymal



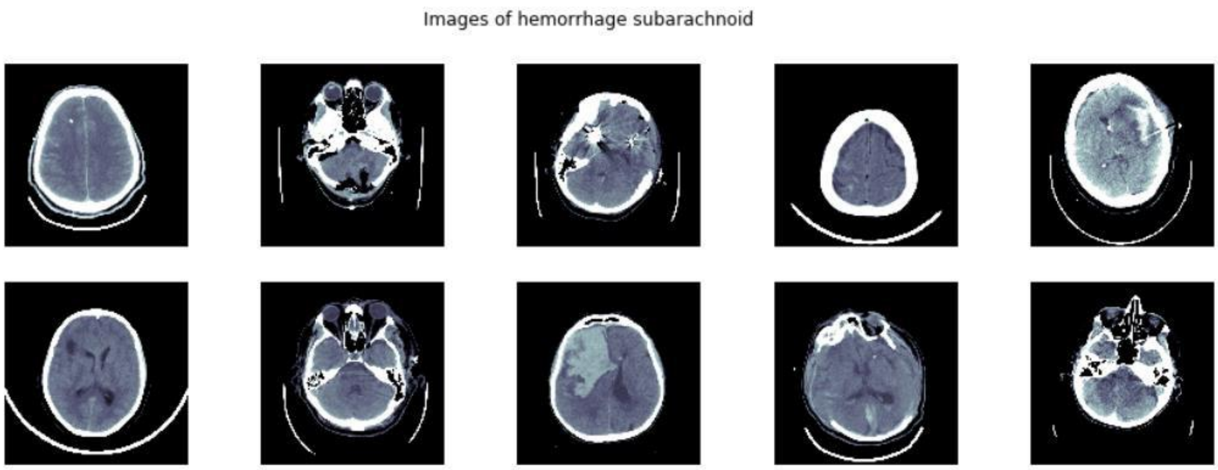
Epidural



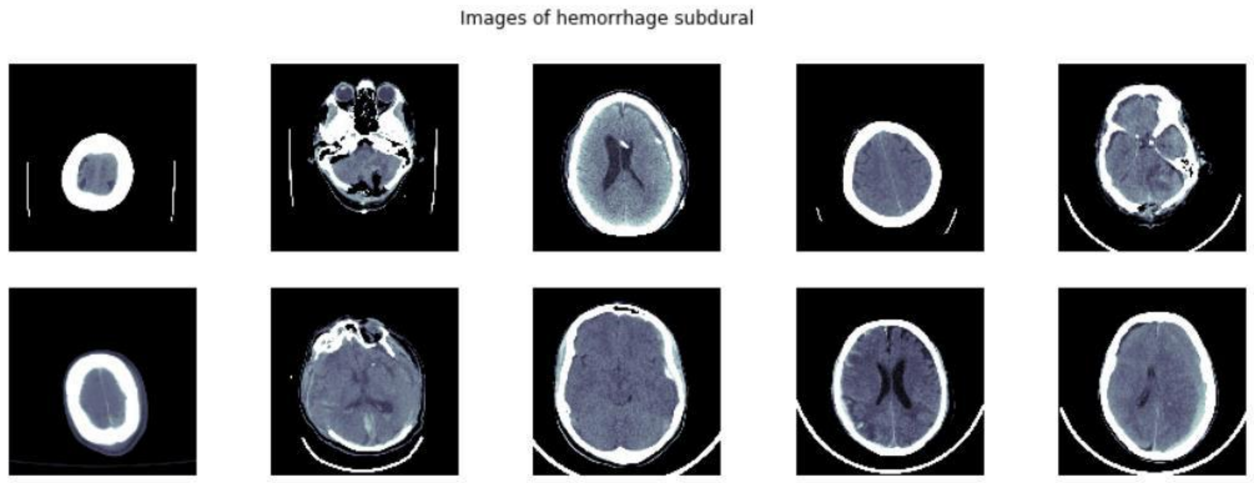
Interventricular



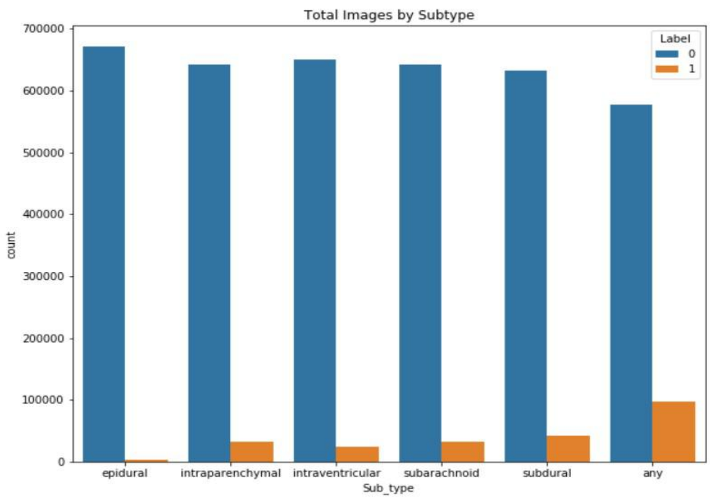
Subarachnoid



Subdural



4.3 Data Analysing of stage 1 data set



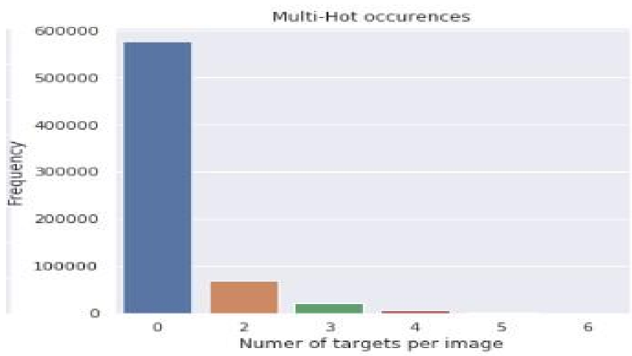


Figure: count plot of labels per subclass

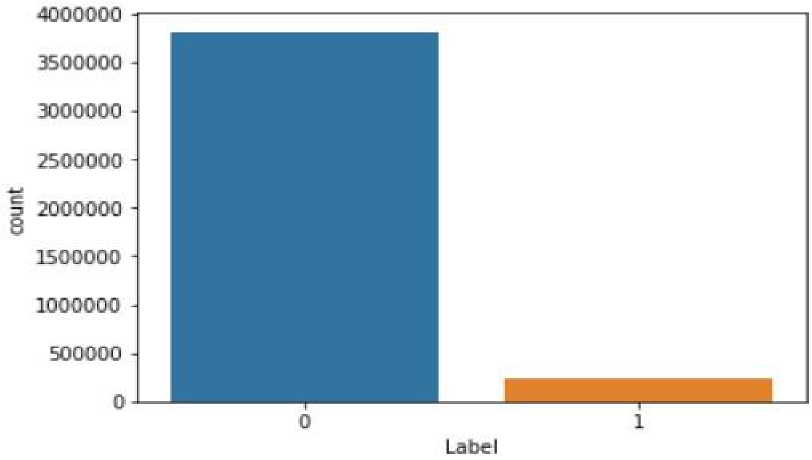
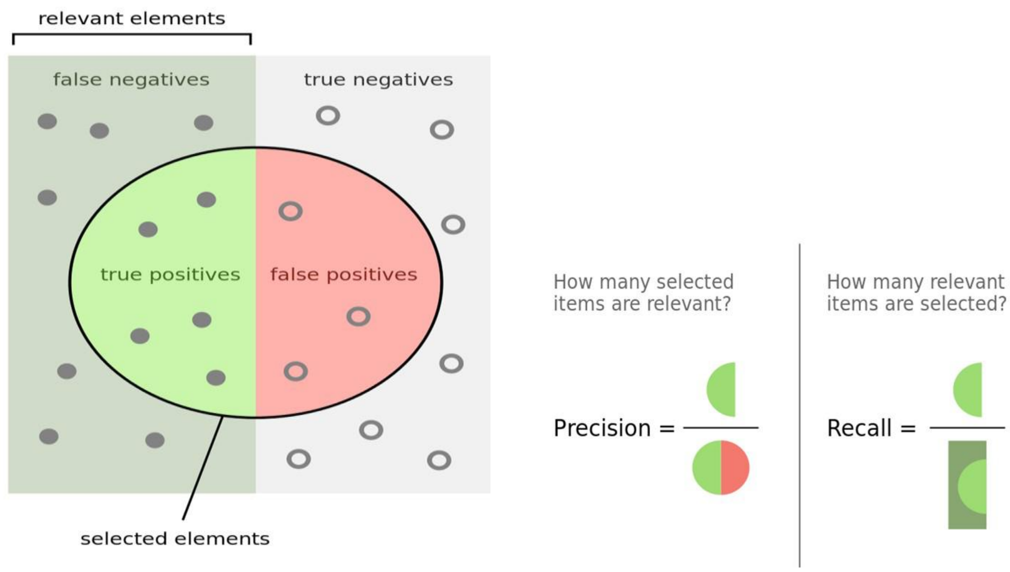


Figure: count plot of labels occurrence

5.0 Evaluation of results



* Image Credit: https://en.wikipedia.org/wiki/Precision_and_recall

Precision tells us how likely we are to classify an patient as a positive case. Recall tells us how likely a patient we diagnose as positive will have the disease. We should keep the both high. Low precision can cause us to miss cases while low recall can lead to insurance companies losing money on covering tests for false alarms.

$$\text{Precision} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

$$\text{Recall} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

Submissions are evaluated using a weighted multi-label logarithmic loss. Each haemorrhage sub-type is its own row for every image, and it is expected to predict a probability for that sub-type of haemorrhage.

There is also an any label, which indicates that a haemorrhage of ANY kind exists in the image. The any label is weighted more highly than specific haemorrhage subtypes.

Accuracy may not be the best metric especially if the data is imbalanced.
Suppose 98 percent of our data comes from patients who are not affected. A dumb classifier that calls every case negative is still correct 98% times

5.1 Multi weighted Loss

For each image Id, it must submit a set of predicted probabilities (a separate row for each sub-type). We then take the log loss for each predicted probability versus its true label. Finally, loss is averaged across all samples.
In order to avoid the extremes of the log function, predicted probabilities are replaced with max(min(p,1−10−15),10−15)max(min(p,1−10−15),10−15).

5.2 Multilabel Focal loss

$$ln, s = \alpha s \cdot tn, s \cdot ln(yn, s) + (1 - \alpha s) \cdot (1 - tn, s) \cdot ln(1 - yn, s)ln, s$$
$$= \alpha s \cdot tn, s \cdot ln(yn, s) + (1 - \alpha s) \cdot (1 - tn, s) \cdot ln(1 - yn, s)$$

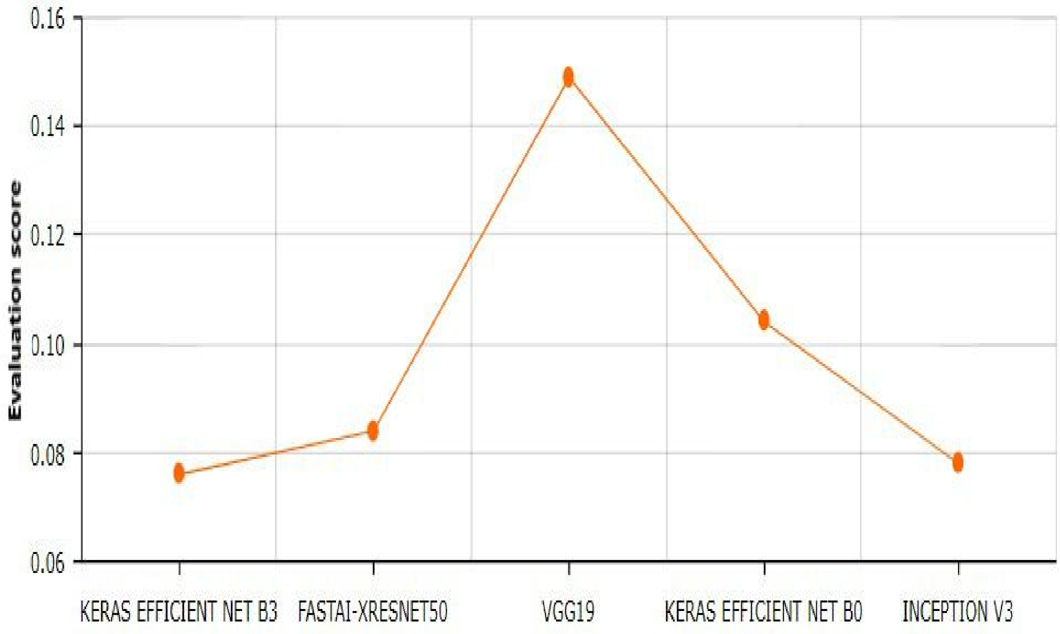
$$L = -1N\sum n = 1N\sum s$$
$$= 1Sws \cdot [(1 - \alpha) \cdot (1 - yn, s)\gamma \cdot tn, s \cdot ln(yn, s) + \alpha \cdot y\gamma n, s \cdot (1 - tn, s)$$
$$\cdot ln(1 - yn, s)]L = -1N\sum n = 1N\sum s$$
$$= 1Sws \cdot [(1 - \alpha) \cdot (1 - yn, s)\gamma \cdot tn, s \cdot ln(yn, s) + \alpha \cdot yn, s\gamma \cdot (1 - tn, s) \cdot$$
$$ln(1 - yn, s)]$$

$$L = -1N\sum n = 1N\sum s = 1Sws \cdot [(1 - \alpha t)(1 - yn, s, t)\gamma \cdot ln(yn, s, t)]L = -1N\sum n = 1N\sum s$$
$$= 1Sws \cdot [(1 - \alpha t)(1 - yn, s, t)\gamma \cdot ln(yn, s, t)]$$

6.0 Results Comparison of Neural Architectures

BASE LINE MODEL COMPARISON ON STAGE 1 DATA SET ON

ARCHITECTURE	EVALUATION SCORE
KERAS EFFICIENT NET B3	0.076
FASTAI-XRESNET50	0.084
INCEPTION V3	0.078
KERAS EFFICIENT NET B0	0.104
VGG19	0.149



6.1Figure: Evaluation score per model

Keras Efficient net b3 provides the best evaluation score Lower the score better the results.

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- https://www.kaggle.com/jesucristo/rsna-introduction-eda-models
- https://www.kaggle.com/srinesh/baseline-vggnet
- https://www.kaggle.com/c/rsna-intracranial-hemorrhagedetection/notebooks?sortBy=hotness&group=everyone&pageSize=20&compet itionId=13451&tagIds=13207
- https://www.kaggle.com/niranjankumarc/rsna-fastai-baseline-model
- https://www.kaggle.com/jhoward/cleaning-the-data-for-rapid-prototypingfastai
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Image references:

- 1: By Glitzy queen00 - http://en.wikipedia.org/wiki/Image:Intracerebral_heamorrage_2.jpg, Public Domain, https://commons.wikimedia.org/w/index.php?curid=2957370
- 2: Case courtesy of A. Prof Frank Gaillard, Radiopaedia.org, rID: 37008
- 3: Murtadha D. Hssayeni, Muayad S. Croock, Aymen Al-Ani., Hassan Falah Al-khafaji, Zakaria A. Yahyaa and Behnaz Ghoraani: https://arxiv.org/pdf/1910.08643.pdf
- 4: Benjamain cummings, an imprint of addison wesley longman INC
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- 6: Case courtesy of Dr Jeremy Jones, Radiopaedia.org, rID: 6216
- 7: Case courtesy of Dr David Cuete, Radiopaedia.org, rID: 22770
- 8: Case courtesy of Dr Nikos Karapasias, Radiopaedia.org, rID: 25426
- 9: Case courtesy of A. Prof Frank Gaillard, Radiopaedia.org, rID: 3428