Intracranial Hemorrhage Detection using Machine Learning Models

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Intracranial Hemorrhage Detection using Machine Learning Models

B Tirupati Patro

Abstract

Intracranial Hemorrhage is the internal bleeding caused in the skull and brain due to excessive intake of alcohol, stoke,etc. Radiologists sometimes miss subtle and critical findings which when detected at later stages becomes a critical concern. Previous research on this field mainly focused on feature extraction and image classification using supervised learning which produces inaccurate results due to inappropriate input data. This research work concentrates on modelling a network for detection of intracranial hemorrhage using sparse autoencoder for unsupervised machine learning for complex feature extraction then feeding to SVM classifier for Image Classification. This deep learning network was compared with other models like Random Forest, CNNs, PCA with a SVM classifier. The performance shown by sparse autoencoder with SVM classifier was better than other models.

1 Introduction

Intracranial Hemorrhage refers to the bleeding occurring in the skull or brain when blood vessels present inside the skull or brain ruptures. It is the bleeding in between the meningeal spaces and the brain parenchyma. It is a highly destructive disease. Intracranial hemorrhage is an important cause of death and disabilities. There are around 40,000 to 50,000 of intracranial hemorrhage deaths in the United States with a mortality rate of approximately 50 percent over a 30 day period, patients who survived were in continuous medication of 6 months. (Caceres and Goldstein; 2012)

The position of Intracranial Hemorrhage on CT scans of the brain and X-Ray attenuation makes them detectable and also helps the radiologists to differentiate between the types of intracranial hemorrhage.There are about five different types of Intracranial Hemorrhages such as Subarachnoid, Intraparenchymal, Subdural, Intraventricular and Epidural Haemorrhages which are differentiated based on the internal bleeding in different regions inside the skull.(Majumdar et al.; 2018)

- **Intraparenchymal Hemorrhage**: Intraparenchymal hemorrhage is bleeding that occurs within the brain parenchyma. Out of all strokes, 8 to 13 percent of the strokes accounts to Intraparenchymal hemorrhage. It usually occurs for middle aged people due to hypertension. This is caused due to unwanted proteins in the wall of arteries of brain which leads to bleeding. Excessive intake of drugs like coccaine, alcohol,etc. leads to this deadly disease.(Refer figure 1(a))

- **Intraventricular Hemorrhage**: Intraventricular hemorrhage is a disorder which is mainly seen in infants and premature babies within a weeks of their birth due to lack of oxygen flow inside the brain, blood vessels being fragile easily ruptures in a newly born baby.(Baker et al.; 2017)(Refer figure 1(b))

- **Subarachnoid Hemorrhage**: Subarachnoid Hemorrhage is the type of bleeding in the subarachnoidal space which is in the surface of the skull. Only one third of the patients with Subarachnoid hemorrhage survive , remaining one third have a disability and the rest loose their lives.This is caused due to ruptured aneursym or a head injury. The blood flowing from the arteries in the brain gets accumulated in the cerebrospinal space which is usually filled with cerebrospinal fluid under normal condition. (Lawton and Vates; 2017)(Refer figure 1(c))

- **Subdural Hemorrhage**: Subdural Hemorrhage is the bleeding that occurs outside the brain between the arachnoid layer and the outer covering of the brain called dura matter. The blood gets accumulated in this space if the bleeeding continues. This type of hemorrhage mainly happens due to severe road accidents that ruptures the blood vessels on the surface of the brain. Around 95 percent of the cases of Subdural hemorrhage is due to trauma. (Rybkin et al.; 2018)(Refer figure 1(d))

- **Epidural Hemorrhage**: Epidural Hemorrhage is the internal bleeding which occurs in outer membrane of the brain called dura matter and skull. A person with this kind of brain disorder looses consciousness and comes back to normal and then again looses consciousness. There is a lack in the blood flow within the brain which leads to subsequent death. This is mainly caused due to vehicle accidents, sport contact or collision, damage to head during a fall.This makes early detection or finding of Intracranial Hemorrhage very much necessary. (Kaoutzani and Stippler; 2019)(Refer figure 1(e))

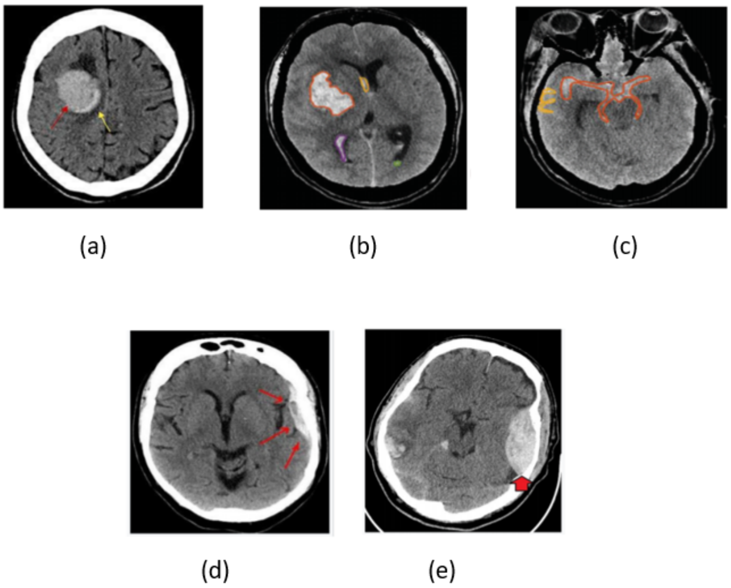


Figure 1:Types of Intracranial Hemorrhages

Even though radiologists are very good at detecting intracranial hemorrhages, a second set of eyes in finding subtle hemorrhages would add value to the quality of diagnosis provided by healthcare organisations to avoid emergency risks of patients. (Majumdar et al.; 2018)

A Deep Learning Network which can easily detect an Intracranial hemorrhage that can be installed in hospitals for early detection by integrating it with the CT(Computed

Tomography) equipment where in Images or studies captured for a specific radiology order prescribed from the CPOE by the consulting physician. The Images captured by the CT equipment is usually in the .dcm format(DICOM format).

DICOM stands for Digital Imaging and Communications in Medicine which is not only a specific image format, also a international standard in the field of medical imaging. A single CT study comprises of minimum of 1000 odd images which accounts to large amount of memory. These examinations once captured are forwarded to the Picture Archiving and Communication Systems popularly known as PACs. PACs is a server which stores,retrieves and processes the data. The pre-processing is much needed by doing image conversions for compressing the data because large data size of CT studies consume lot of memory. (Nguyen et al.; 2019)

The PACS system in radiology department of hospital is also integrated with other healthcare applications like Hospital Information System with Health Level 7(HL7) international standard. HL7 operates in the application layer of the networking protocols. It is the message format which provides interoperability between different software applications used in hospitals to maintain data integrity. DICOM images have metadata along with the pixel data which hold clinical information of the patient which helps the neurosurgeons to relate the clinical information with the findings of the radiologists. (Gupta and Gupta; 2019)

The deep learning system to be developed for detecting the Intracranial Hemorrhage can be integrated with the PACs system so that the once the brain CT images are forwarded to the PACs through the DICOM network follows a pre-processing step which does a lossless compression into one of the image formats like .jpg, .jpeg, .png,etc. which is most widely known. The compressed images of the brain once fed into the Intracranial Hemorrhage Detection System detects the type of Intracranial hemorrhage if any.

When an radiology order is prescribed by a consulting physician for a patient, the examination to be carried out for patient is send to PACs in the form of HL7 message. The scheduled examination is visible in CT equipment as it is configured with the PACs system via DICOM network. After the image capture is done by the radiology technician, image is being forwarded to PACs. ICH detection system can detect the abnormality if any and notifies the findings to Hospital Information System(HIS) by HealthLevel7(HL7) message thereby improving the quality of healthcare. This message sent to the Hospital Information System helps to change the priority from routine to stat if there is any critical finding for the patient.(refer Figure 2)

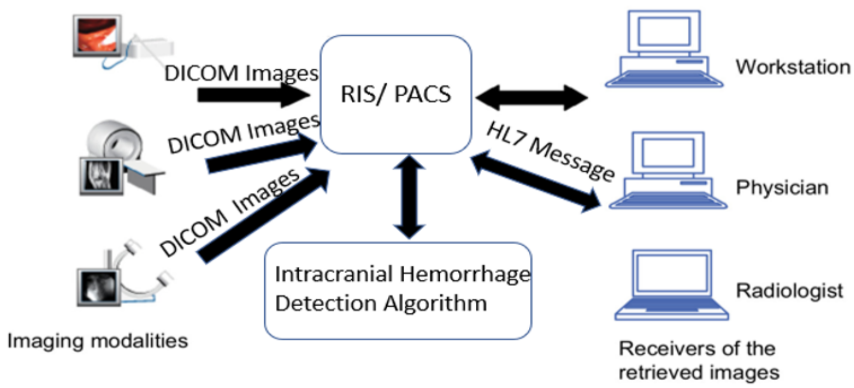


Figure 2: Interoperability of various applications in hospitals

The state-of-the-art for this research focuses on the use of autoencoders which performs high level feature extraction using unsupervised learning. (Moussavi-Khalkhali et al.; 2016) This high level features is then sent to a Support Vector Machine classifier to train the entire network with labelled data and help predicting the different types of Intracranial Hemorrhage.

1.1 Research Question

This research tries to find a solution to the following research question:

RQ: *How efficiently, accurately and quickly machine learning algorithms detect intracranial hemorrhage from brain CT images?*

2 Related Work

Image Classification has been the most fundamental tasks in field of pattern recognition and computer vision. Image classification is assigning one or more labels to an image. Initially, the feature extraction is done for the representation of each image and then training the classifier with the labels for label assignments.

2.1 Deep Learning using Convolution Neural Networks

Misdiagnosis of acute hemorrhages can lead to false patient outcomes. Majumdar et al. (2018) developed a computer aided system which detected subtle intracranial hemorrhages which involved multiple steps of image processing, feature extraction, image corrections, alignment and classification. They designed a convolutional neural network for feature learning and classification. Data Augmentation was initially performed to improve the performance by rotating the input image. Specificity was mostly improved by post-processing the output of the Convolutional Neural Network. The dataset comprises of 134 CT cases which is approximatelty closed to 4,300 images.

Many patients attending multi-speciality hospitals face a long wait for consultation with the doctor. Priority of patients treatment should be taken care off to avoid any emergency. Arbabshirani et al. (2018) have proposed a deep learning framework based on CNNs which will take various historical patient data to set the priority of patient by the computer aided system. In any radiologist workflow, this methodology can be applied to setting the priority to 'Stat' from a 'Routine' which will help doctors evaluate less complex cases later and will help the neurosurgeons to avoid any missing finding which is actually critical.

Computed tomography scans in Medical Imaging is highly considered for diagnosis of various neuro disorders like acute traumatic brain injury, brain haemorrhage, aneurysm, brain tumours. Highly qualified radiologists also miss some subtle findings which a trained deep learning model can identify to avoid any misdiagnosis. Kuo et al. (2019) proposed a convolution neural network model for predicting the acute intracranial hemorrhage trained by 4,000 brain CT images obtained from various examinations performed at the hospitals affiliated to University of California for the detection of acute intracranial haemorrhage. The model predicted the results same as 2 of 4 radiologists. The deep learning model also showed high specificity and sensitivity and therefore detect all possible critical findings. Due to the advancement in the field of computer vision and artificial intelligence, Deep learning has been productive to draw useful clinical data from the scanned medical images. The deep learning model localizes any subtle finding that would be helpful for a physician to visualize which might be missed by radiologists while examining the study manually which would be helpful for further treatment.

It is quite obvious to observe a trade-off between sensitivity and specificity to have better accuracy in the prediction. This trade-off should be maintained in such a way that the quality of prediction can be compared with radiology experts. Cho et al. (2019) trained a deep learning model by cascading two CNNs which helped in identifying internal bleeding and increasing the sensitivity by 1 percent. The cascaded network designed was based on GoogleNet is the 22 layer deep CNN which also enhanced the computation power used for the network. This network had fully convoluted neural networks popularly known as F-CNNs which was helpful in detecting different types of intracranial hemorrhage. The image data used from training the network had 100,000 brain CT images. This cascaded network rendered better accuracy in comparision to other conventional CNN and F-CNN network.

Critical care in multi-speciality hospitals shows delay in diagnosis taking lives of many individuals. Deep Learning can help overcome this issue by detecting the abnormality at early stages. Ginat (2019) designed a neural network in a academic research centre in Israel where in 2000 CT scans were used to train the deep learning CNN model. The studies used to train the deep learning model involved the data of 373 patients.Most of the cases belonged to emergency patient. Accuracy of the model was 89 percent. The deep learning network found that the performance was dependent on different types of visits for a patient.

Patient outcomes can deteriorate due to misdiagnosis in hospitals due to workload on radiologists. The percentage of error introduced can be decreased by introducing a computer-aided automated system . Rao et al. (2020) designed an CNN model which was used for a second opinion for diagnosis done by the radiologists.The system designed showed 28 studies to be positive which was tested negative by the radiologists. There was a review carried on these 28 scans by various radiologists, 16 of the whole where detected with Intracranial hemorrhage. Radiologists showed a false negative rate of 1.7 percent, but false negatives in diagnosis should be zero which can take many lives of individuals. This designed model was thus helpful for reviewing and taking a second opinion of the negative cases which were actually positive.

Technologists also used brain symmetry along with Machine Learning for the detection of intracranial haemorrhage which was integrated with the existing clinical workflow of hospitals. A Sheth et al. (2020) designed a deep learning model by considered the studies of patients who were in high risk of Acute Ischemic Stroke and where admitted in Emergency Ward. The model was trained with 568 brain CT studies.The model was then tested with an external dataset. This deep learning based model was very useful in identifying if there was any acute Intracranial Hemorrhage with an accuracy of 81 percent.

For an injured patient, Intracranial Haemorrhage Detection has become a tough task for neurosurgeons. Automated systems can detect haemorrhage which is needed to avoid invasive detection of haemorrhage for clinically stable trauma patients. Rashedi et al. (2020) have designed a machine learning model for sub clinical haemorrhage in which the vital signs remained constant before a clinically detected haemorrhage. The model was trained for investigation of non-invasive single variable machine learning model based on Electrocardiogram and its derived heart rate variability. 7 subjects of patients where used to train the ensemble classifier. Remaining 2 subjects were used to test the model. This model was then used for comparison with a machine model with multiple variables like heart rate, Electrocardiogram (ECG) and plethysmography signals (measures the change in volume of blood within a organ). The performance in prediction by a multi variable machine learning model with variable having a recall of 0.45 and a precision of 0.67.

2.2 Deep Learning using Autoencoders

Autoencoders have become widely popular in high level feature extraction using unsupervised machine learning technique by encoding the input image data and the reconstructing the image by decoder and giving the reconstructed output same as input.

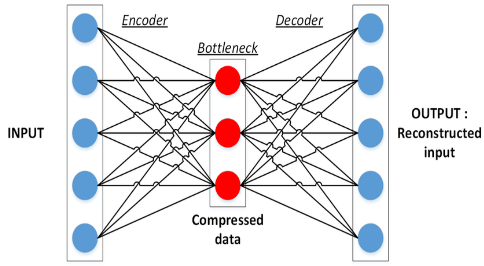


Figure 3: Basic Autoencoder Network (Sublime and Kalinicheva; 2019)

Sparse autoencoder works very well in learning in extracting high-level features from an input image data. Sparse autoencoder has also been used in nuclei classification on breast cancer histopathology images. Xu et al. (2014) proposed a deep learning network for nuclei classification which had a sparse autoencoder and a softmax classifier. These deep learning method was then compared with model formed by Principal Component Analysis and softmax classifier. The sparse autoencoder and softmax deep learning produced accuracy of 83.7 percent, F1 score 0.82 and AUC value of 0.89 which was better than a PCA+softmax network.

Autoencoders has widely gained popularity in various field of medical imaging because of its capability to reconstruct the image almost same as input by fine tuning and minimizing the reconstruction loss by removing unwanted noise in the image and doing a high level feature extraction. Lymphnode Metasis is one such abnormality whose prediction at early stages can help the oncologists take immediate action for the treatment of lung cancer. Wei et al. (2018) proposed a stacked sparse autoencoder (SAE) network for identifying the lymph node metastasis present in lung cancer. Around 100 images were fed into the image based stacked encoder network, whereas same was fed to CNN network. The performance of a image based stacked sparse autoencoder was better when compare to the CNN network. There was a 50 percent rise in AUC value for the image based stacked sparse autoencoder.

Autoencoders have also shown its importance in other medical imaging fields like retinal microaneurosym segmentation. Microaneurosym is the first visible identification of diabetic retinopathy. Diabetic retinopathy is the swelling of blood vessels caused in the back of the eye, leads the eye blindness if not detected in earlier stages. Cerrolaza et al. (2018) have proposed a autoencoder based regularized neural network model for segmentation and classification of retinal microaneurosym from image data. The proposed implementation performed segmentation multi-scale correlation filter. The neural network introduced in this framework has a multilayer neural network with an additional layer for considering the reconstruction error which works similar to a autoencoder. The performance of this modified network showed a very good improvement when compared to the conventional deep learning network. It showed promising results in comparision to existing state-of-the-art techniques.

Innovation in brain imaging technologies have also played a vital role in exploring and concentrating new brain anatomy and functional views. Mallick et al. (2019) proposed a deep neural network for image segmentation and classification. A deep wavelet encoder(DWE) is used for image compression which does the feature reduction by picking the high level features, which is used in combination with image decomposition of wavelet transformation. This combination produced a huge effect on sinking the input image data for extracting high level features, then feeding it to a deep neural network(DNN) classifier to perform a classification for cancer detection. The brain MRI image dataset considered for training the entire network. The DWA-DNN classifier outperformed the other deep neural network classifiers.

The machine learning techniques can improve both patient outcomes and automate the operations in hospitals. However, heterogeneous patient data containing vital signs and other patient demographics and poor feature learning methododology has been affecting the data analysis of patient data done using machine learning approaches. Zhou et al. (2019) proposed an feature learning approach based on unsupervised deep learning that can automatically learn various representations of patient data for efficient decision making. The dataset used was collected from nation University Hospital of Singapore to evaluate the performance of the proposed network. The performance of deep learning based feature learning framework designed with autoencoders performed better than other feature learning based networks based on Raw Feature Selection and Principle Component Analysis.

Autoencoders has also gained its popularity in predicting the need of heart transplant for a patient. Heart transplant rejection is one major threat for the survival of patients with a heart transplant. Endomyocardial biopsies are quite efficient in identifying a rejection for heart transplant way before any symptoms are captured, but this manual process is way too expensive. Due to the advances in medical imaging technology, computer vision and artifical intelligence, prediction of rejecting heart transplant using whole side image slices has been quite promising. Zhu et al. (2019) designed a network for image clustering, feature extraction, quality control and image classification. The proposed network has a stacked convolutional autoencoder to extract high level feature maps incorporated with unsupervised clustering before performing the classification task. Results proved that unsupervised clustering of input data after feature extraction can show better predictive power in a multi class classification problem.

2.3 Summary

As mentioned in subsection 2.1 about autoencoders showed better accuracy than other image classification methods like CNNs,Support Vector Machines Classifier, Random forest Classifier and is being used extensively for high level feature extraction by reconstructing the input image. As mentioned by Liu et al. (2018), autoencoders recreate the input image by removing the unwanted noise and reducing the reconstruction error. The low dimensioned data produced by encoding input data will be fed to the classifier for image Classification. Sparse autoencoders perform better dimensionality reduction than principle component analysis due to unsupervised learning. As mentioned by Xu et al. (2014) unsupervised deep learning in medical imaging was very beneficial in finding complex representation by exploring data on its own for small and critical finding which is not taken care with supervised learning.

Author(s) and Title	Aims and objective	Models Applied	Dataset	Findings relevant to the review
Arbabshirani et al. (2018) ”Advanced machine learning in action: identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration”	Predicting the intracranial haemorrhage and prioritize the radiology worklist by reducing the amount of time required for diagnosis for outpatients	CNN	37,084 training images and 9499 images for testing the model	Sensitivity and Specificity was 0.80 and Accuracy of the model was 84.6 percent
Majumdar et al. (2018) ”Detecting intracranial hemorrhage with deep learning”	Detecting the intracranial hemorrhage from brain CT images	CNN	4,300 brain CT images	Sensitivity is 0.81 Specificity is 0.98
Kuo et al. (2019) ”Expert level detection of acute intracranial hemorrhage on head computed tomography using deep learning”	Detecting the intracranial haemorrhage by deep neural network	CNN	4000 brain CT images	Showed high specificity and sensitivity and detected subtle and critical finding.
A Sheth et al. (2020) ”Automated Detection of Hemorrhagic Stroke From Non-Contrast Computed Tomography: A Machine Learning Approach”	Detecting intracranial hemorrhage with high accuracy	CNN	568 brain CT studies of emergency patients who had a risk of ischemic stroke	Accuracy of the model was 81 percent
Cho et al. (2019) ”Improving Sensitivity on Identification and Delineation of Intracranial Hemorrhage Lesion Using Cascaded Deep Learning”	Detecting different types of Intracranial hemorrhage	F-CNN	100,000 Brain CT images	Recall of 0.82 and a precision of 0.80.
Rao et al. (2020) ”Utility of artificial intelligence tool as a prospective radiology peer reviewer — detection of unreported intracranial hemorrhage”	Design a model that would predict Intracranial Hemorrhage which would help physician a second opinion diagnosis done by the radiologists	CNN	6565 head CT images	Reduced the false negative rate of the radiologists output
Rashedi et al. (2020) ”A Multivariate Learning Derived Model For Detection of Hemorrhage	To design an automated system from predicting acute intracranial haemorrhage”	Ensemble Classifer	Data of 7 subjects were used to train the model and tested by 7 two subjects	Model showed a precision of 0.63 and recall of 0.85
Ginat (2019) ”Analysis of head CT scans flagged by deep learning software for acute intracranial hemorrhage	Analyze the implementation of deep learning for worklist prioritization of acute intracranial hemorrhage”	CNN	373 head CT studies	Accuracy of model was 89 percent for inpatient and 96 percent for emergency patient
Mallick et al. (2019) ”Brain MRI Image Classification for Cancer Detection Using Deep Wavelet Autoencoder-Based Deep Neural Network”	Design a deep learning network for cancer detection using autoencoder	Deep Wavelet Autoencoder and Deep Neural Network		Autoencoder based classifier performed better than conventional CNNs
Zhou et al. (2019) Optimizing Autoencoders for Learning Deep Representations From Health Data	Design a autoencoder based deep neural network for Analyzing patients' health data	Autoencoder	Clinical patient data of Pneumonia patients	This unsupervised learning autoencoder performed feature learning better than Raw Feature Selection and Principle Component Analysis.
Wei et al. (2018) ”Predicting Lymph Node Metastasis of Lung Cancer Using Stacked Sparse Autoencoder”	Design a Deep learning network for identifying lymph node metasis in Lung cancer	Stacked Sparse Autoencoder	Around 100 images of lung cancer	The sparse stacked autoencoder network performed better than CNN network with 50 percent rise in AUC value.
Zhu et al. (2019) ”Improved prediction on heart transplant rejection using convolutional autoencoder and multiple instance learn-ing on whole-slide imaging”	Design a automated mechanism for rejecting heart transplant	Convolutional Autoencoder		Autoencoders can show better predictive power due to unsupervised learning of feature extraction in a multi class classification problem
Kasantikul and Kusakunniran (2018) ”Improving Supervised Microaneurysm Segmentation using Autoencoder-Regularized Neural Network”	Design a autoencoder based deep learning mechanism for retinal microaneurosym	Autoencoder	Retinopathic online challenge dataset	This autoencoder based network increased the classification performance than other conventional neural networks.
Xu et al. (2014) ”Stacked Sparse Autoencoder (SSAE) based framework for nuclei patch classification on breast cancer histopathology”	Design a deep learning unsupervised learning network for nuclei classification	Sparse autoencoder		83.7 percent, F1 score 0.82 and AUC value of 0.89.

Table 1: Literature Summary Table.

3 Methodology

The research methodology is based on the conclusions of the literature. This research work applied the combination of autoencoder with a classifier to brain CT DICOM images. For implementing this, a sparse autoencoder is used to derive the encoded form of image data by unsupervised learning and fed to a classifier to detect and classify a intracranial hemorrhage. The industry standard process CRISP-DM method is used for implementing this research project.(Refer figure 4). This process will be explained in further subsections.

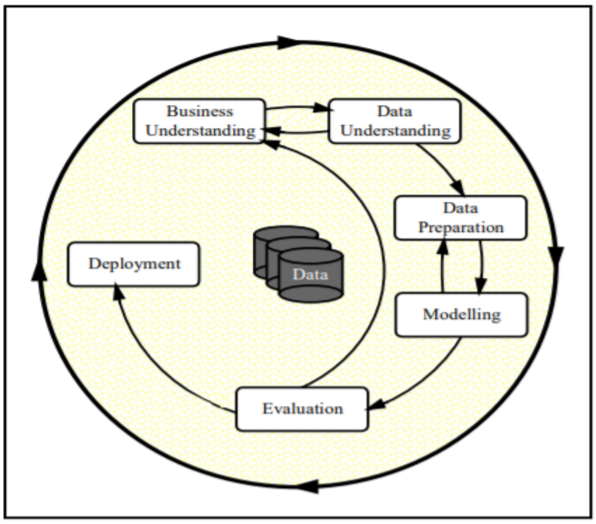


Figure 4: CRISP-DM Architecture

3.1 Business Understanding

Intracranial hemorrhage is mainly detected from brain CT(computed tomography) DICOM images. Radiologists manually evaluate the CT examination which is a time consuming process. This has impacted the radiologists and neuro surgeons in examining emergency patients or identifying any subtle finding which can be critical at later stages of diagnosis. Hence, this research project would be helpful when integrated with modalities in the existing radiologist workflow, which in turn can save many lives of individuals.

3.2 Data Understanding

Dataset used for this research project is gathered by Radiological Society of North America(RSNA), MD.ai and American Society of NeuroRadiology. The dataset used for this research is publicly available in Kaggle without any patient demographics, hence it is ethical to perform the research with this dataset. The Image dataset consists of 600,000 DICOM images which is labelled with different types of Intracranial Hemorrhages. The CT studies in DICOM format occupies large amount of memory. All the images in DICOM format has to be converted to PNG format as there is no pixel data lost. This is further discussed in data processing steps. The dataset available is split into training,testing and validation datasets.

3.3 Data Preprocessing

All modalities like CT,MRI,Ultrasound,etc. generate DICOM images. These images in DICOM format occupy a large storage space for any PACS system,so the image has to be intially converted to a format which is efficient for clinical practice without any loss in data. The radiologist usually see images in various file formats like PNG, JPEG, TIFF and GIF. All the mentioned formats have its advantages and disadvantages which is considered when images are stored and submitted for clinical practices in radiology workist applications like PACS(Picture Archiving and Communication System). Handling the image data with various aspects like maintaining the image resolution, image compression, handling the image metadata, helps the radiologist in archiving, displaying and organizing the images. These formats can also be viewed in personal computers without any high resolution dedicated viewers which helps the radiologists to perform any diagnosis remotely for emergency patients by accessing the PACS, whereas DICOM files is not recognized by personal computers as image files. (Varma; 2012)

3.3.1 Image Conversion

PNG images provide good browser compatibility and good image quality. It is quite smaller in size when compare to DICOM images. PNG images perform lossless compression without the loss of important information from the pixel data. DICOM images have associated metadata apart from pixel data which contains all the clinical information if any along. These information are mainly stored in databases to avoid the loss in clinical information after the conversion of DICOM images to PNG images.(Varma; 2012)

3.3.2 Windowing of Images

Head CT plays a important role in examining any Intracranial abnormalities like hemorrhage,trauma,stroke,etc. CT images has wider availability,sensitivity and lower in cost when compared to MR images for detecting abnormalities like acute hemorrhage, skull fracture, calcification. CT images are formed by X- rays. The tissues present in different locations of body absorb the X-rays is mapped to Hounsfield units (HU). CT image values correspond to Hounsfield units (HU). But the values stored in CT DICOM images are not Hounsfield units, but instead a scaled version. To extract the Hounsfield units we need to apply a linear transformation using slope and intercept from the Dicom tags. The HU value is higher for denser tissues because X-rays gets more attenuated. Windowing is the term used for the conversion of Hounsefield units to gray scale ([0,255]) values. The different features of tissues can be easily seen in image viewers by focussing area of interest by maximizing subtle differences among the tissues. Window level(WL) and window width(WW) are two parameters of windowing. The window width and window level is lost while conversion to PNG format. Hence, the window width,window level values are taken from DICOM tags using pydicom library which is very useful for processing DICOM images. If HU value of tissues lies in the range of specified window ([WL-WW/2, WL+WW/2]), the image is mapped to full range of gray scale. HU values greater than (WL+WW/2) is set to white and HU values less than (WL-WW/2) are set to black. Brain window and bone window are two important window settings for brain. Visual detailing of subtle lesions in skull and bone structures are provided by Bone window.Brain window is high useful in identifying differences in various bone tissues like fluid spaces, blood, brain. Brain window makes soft tissues visible which was lost in the bone window. (Refer figure 7) (Xue et al.; 2012)

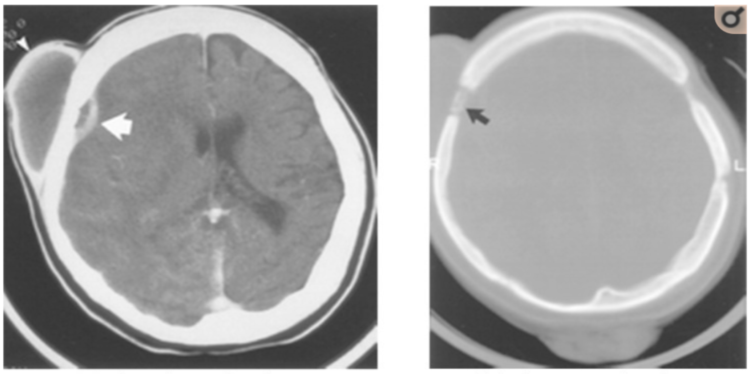


Figure 5:(a) Brain window (b)Bone window

3.4 Modelling:

The architecture of the model comprises of brain CT DICOM images taken from CT equipments, data preprocessing layer converts the DICOM images to PNG images by applying appropriate window width and window level on brain and bone settings. This preprocessed data is then fed to the sparse auto encoder which encodes the image array and reconstructs the input image.Then encoded representation is then fed to the Support Vector Machine Classifier to detect the intracranial hemorrhage.

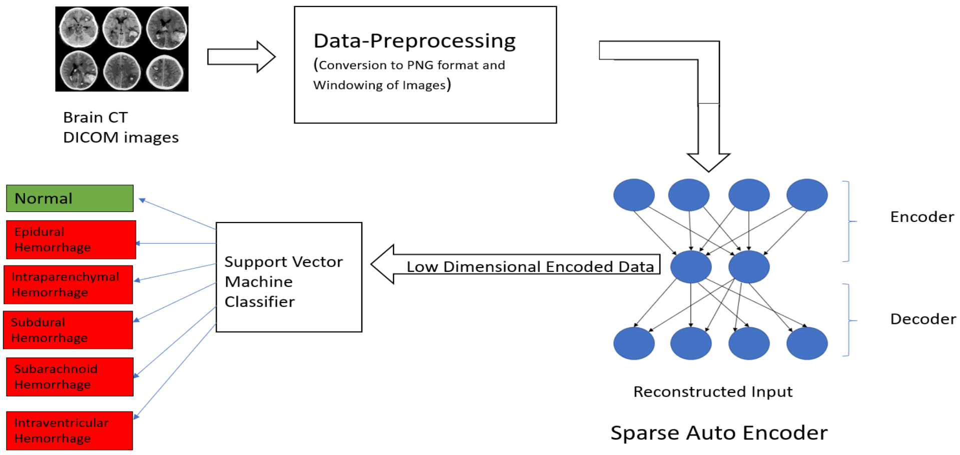


Figure 6: Model Architecture

3.4.1 Sparse Autoencoders and SVM

Autoencoders are deep learning networks whose output layer is same as input layer. Autoencoders perform compression on the Input data into low- dimensioned vector having all the essential features of input data. The low-dimensioned data is called "latent-space representation" or "compression" of the input. An autoencoder mainly consists of three parts namely encoder, decoder and code. An autoencoder consists of 3 components: encoder, code and decoder. The encoder compresses the input , the decoder then reconstructs the input only using the low dimensioned data by removing the unwanted noise from the input data. Autoencoders are the unsupervised deep learning networks which does not need any label on training data that applies back propagation and generates output same as input by reducing the reconstruction error.

Sparse autoencoders are unsupervised deep learning algorithms which automatically learns features from unlabelled data. This type of autoencoders has gained more attention due to dimensionality reduction in the field of medical imaging and identify the symptoms of patients from the low dimensioned data. As mentioned by Yang, et al., (2018), Sparse autoencoder is a deep learning algorithm used for dimensionality reduction which performs feature extraction by unsupervised learning producing high level representation of image. The sparse auto encoder tries to reconstruct the input by minimizing the reconstruction error. The loss function used in autoencoders is derived in terms mean squared error(MSE) represented by,

$$J(W, b, x) = \frac{1}{2}||hw, b(x) - x||^2 \tag{1}$$

where x is the input image, hw,b(x) is the reconstructed input image from the autoencoder.

The goal of the sparse autoencoder is to adjust the weights W and bias b by backpropagation such that the value of loss function J(W,b,x) is minimum. The low dimensioned data from encoder layer is which has all high level features obtained by unsupervised learning is fed to the Support Vector Machine Classifier.

Support Vector Machines are supervised machine learning algorithms which solves classification and regression problems. Support Vector Machines are very powerful for classification problems because of the tendency of not overfitting the model. Support Vector Machines creates a hyperplane in multi-dimensional space that helps in differentiating between different class labels. SVM performs kernel based learning by mapping the mappings the data points to multi dimensional space such that the classification becomes easier. Support Vectors are the points in the multi-dimensional space. Support Vector Machines creates a decision boundary between each class called hyperplane. The hyperplane which is of maximum distance among different classes is called Optimal Hyperplane. SVM extracts the features from the images and maps to a hyperplane based on similarity in features. This sparse autoencoder network with Support Vector Machine classifier will then be compared with supervised learning networks like CNN and random forest, dimensionsality reduction methods like principle component analysis along with SVM classifier with evaluation metrics such as Accuracy, Precision and Recall.

3.4.2 Random Forest Classifier

Random Forest Classifier is a machine learning algorithm widely used for classification and regression problems. Random forest classifier is formed by number of decision trees by randomly selecting the training data. The image classification is done by sending the image through every tree on after the other and then aggregating the votes from the leaf nodes of all the decision trees results in the final classification of the image.

3.4.3 CNN Model

Convolutional Neural Network has been giving promising results over a decade in various fields of medical imaging, image processing and computer vision. The important aspect of CNN is to abstract features when input propagates toward the layers.In image classification, the edge is initially detected by first layers and then the next layers identify the high level features. The more deeper the CNN network, better the feature extraction. Hence leading to better image classification in medical image classification and diagnosis.

3.4.4 Principal Component Analysis

Principal component analysis (PCA) is popularly known dimensionality reduction approaches in the field of machine learning and data science. Image is a matrix of numbers containing pixel values represented by RGB color values containing all the features of the image. As mentioned by Xu et al. (2014), PCA converts a high-dimensional vector to a lower dimensional feature vector by selecting the principal components and obtaining the best feature vectors which has the best of the information. This high level feature vectors fed to a SVM classifier leads to image classification.

4 Design Specification

The implementation of this research project is carried out in a 3 tier architecture. Firstly, Data gathering layer gathers all the data needed for the research project using Kaggle Api. Secondly, the business logic layer initally converts the DICOM images to PNG format. In the next step, the exploratory data analysis is done to check the spread of the dataset. The Data imbalance is removed from the dataset if any. The dataset is then splitted into training and testing datasets before applying various machine learning and deep learning algorithms. Lastly, The results and statistical analysis of various various models are shown in the presentation layer.

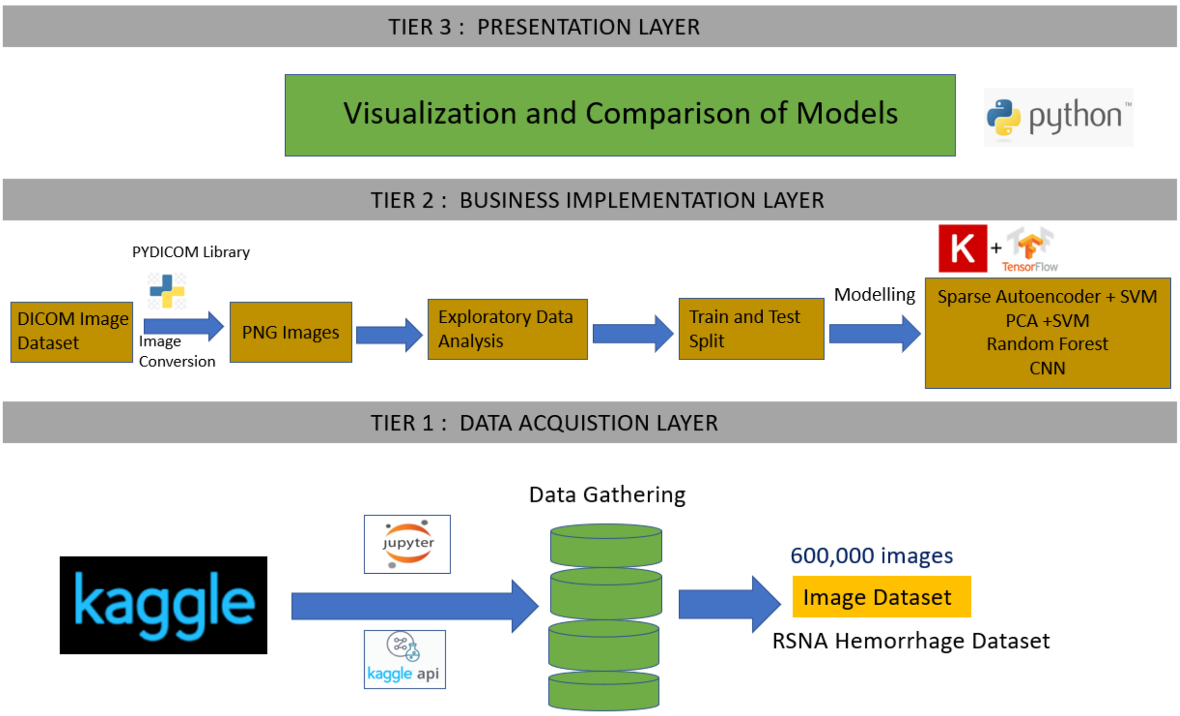


Figure 7: 3-Tier Architecture

5 Implementation

The implementation carried on this research is done by various steps based on the design specification in Section 4. This section provides the detailed information on how the models like sparse autoencoder and SVM, Principal component analysis and SVM, random forest classifier and CNN. These models are implemented to classify and detect different types of intracranial hemorrhage.

5.1 Setup

The implementation for this research project is done with a 4th Generation i5 Processor Laptop with 8 GB of Ram. The 64 bit Windows 10 operating system environment. Below is the list of software used for the purpose of this project.

- Python 3.7.4 – Python is a robust language which is easy to learn and use. This language is supported by a number of IDEs. Moreover, it has a vast community support and packages available for machine learning and other data analytic models. This encouraged the use of Python for the creation of the proposed tool.

- Anaconda Jupyter Notebook – This is an IDE which requires minimal resources to operate. It supports the use of latest version of python 3.7.

- Python Packages – Multiple python packages were used for performing operations such as data mining, cleaning, encoding and machine learning. Due to the large of images in the dataset and complexity of deep learning models,more time is required while training the various model. The implementation is carried out on the Jupyter Notebook with 500 GB drive storage, 8 GB RAM and 2.0 GB run-time GPU.For implementing deep learning models, Keras and TensorFlow python libraries are used.

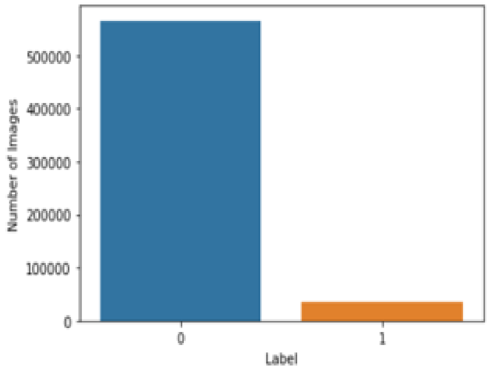
5.2 Data Gathering

Data Gathering used in this research is done by using Kaggle api to download the entire dataset containing 600,000 labelled images with six different classes namely Any, epidural, intraventricular, intraparenchymal, subdural, subarachnoid, normal.

5.3 Data Preprocessing

Data Preprocessing for CT DICOM images involves applying windowing to the CT images which is applied with default brain and bone settings and then converting DICOM into PNG images. This windowing is lost while conversion to PNG, but windowing makes soft tissues and bone very clearly visible. Image conversion is necessary due to the storage space consumed by DICOM images. PNG images have better image quality due to lossless compression. This image conversion is carried out by python's pydicom library.

The dataset used from the detection of intracranial hemorrhage is highly imbalanced. The labelled dataset is resampled using under sampling in such a way that the dataset has equal number of 0's and 1's as labels. The majority class is brought down to same size of minority class by undersampling using scikit learn python library.



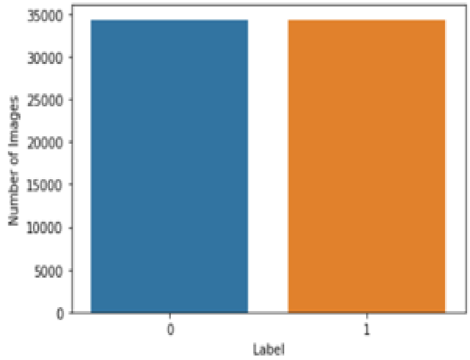


Figure 8(a): Imbalanced Data Figure 8(b): Balanced data

50,000 images of the balanced dataset is considered for modelling due to minimal hardware available for implementation. The newly obtained dataset is then split into training and testing samples. 20 percent of the dataset is used for testing the models. The models demonstrated in these research is unsupervised deep learning Sparse autoencoder with SVM classifier which is compared with supervised learning models like Random forest Classifier, PCA and SVM, CNN Model.

5.4 Baseline Approach

5.4.1 CNN model

CNN Model was implemented using keras and tensorflow libraries in python by number of maxpooling layers, convolution layers and dense layers at the output layers. The CNN model was fine tuned with 50 epochs, adding a dropout 0f 0.50 after a dense layer. Early stopping of 5 was introduced in the model so that the model stops training is there is no change in validation accuracy until 5 successive epochs.

5.4.2 Principle Component Analysis and SVM

Principal Component Analysis(PCA) is also a dimensionality reduction technique very much efficient in the field of machine learning. In this research, PCA is implemented using sklearn library in python which selects the principle components. Principle components are selected in such a way that all the useful information of the image is represented by the reduced image data. The dimensionality reduction is done from various image sizes (224*224,128*128,28*28,62*64) to extract the principle components. The reduced image array was then passed to the SVM classifier with labels to classify the intracranial hemorrhage if any.

5.4.3 Random Forest Classifier

Random forest is a machine learning algorithm used in this research implementing multi-class classification of intracranial hemorrhage. Random forest classifier is used because of its ability of make decision of classifying images based on majority of votes from decision trees. Random forest is implemented in this project using sklearn library in python. The accuracy of the model was calculated by implementing the model with 100 decision trees(estimators).

5.5 Sparse autoencoders and SVM - Newly Proposed Approach

Sparse autoencoders have are highly efficient in unsupervised deep learning which learns high level features by itself which will be useful in identifying subtle critical findings which might not be identified by unsupervised learning.Sparse autoencoders helps in dimensionality reduction and removal of unwanted noise from the image. In this research python libraries such as keras is used in building various dense layers in encoder and decoder components present in the spare autoencoder network. The initial dense layers is fed by the input image array formed by 80 percent of the image dataset. The image compression is done in this encoder part of the autoencoder where in the input image is reduced to low dimensioned image array by extracting all the high level features. This model was applied for various input image sizes. This latent representation is then fed to the decoder with various dense layers to reconstuct the image which is of same size as the input . Sparsity parameter is added to the hidden representaion to make the representations more compact so that only fewer neurons gets activated while reconstruction of the input.In Keras, Activity regularizers to add the sparsity constraint and produce an optimal reconstruction at the output and hence the latent representation of encoder input is modified to its best feature extraction by back propagation. The encoded output is reshaped to two dimensional image array as the SVM doesnot accept the image vectors with more than 2 dimensions. This transformed encoded output is then fed to the support vector machines classifier for image classification. Radial Basis function(RBF) is the kernel used in Support Vector Machines for defining non linear decision boundaries between different classes. RBF has two parameters namely gamma for decision region and C for penalty of misclassification on the training data. Regularizers used in sparse autoencoders reduced the reconstruction error, hence increasing the accuracy of the SVM classifier.

6 Evaluation

Evaluation for classification problems are mainly computed from the confusion matrix. Confusion Matrix is the method which is used to describe the performance of a classification model. Confusion matrix comprises of True Positives, False Positives, True Negatives, False Negatives.

True Positives(TP): True Positives is when the actual value is positive and the prediction by the model was also positive.

False Negatives(FN): False Positives is when the prediction by the model was negative but the actual value is positive.

False Positives(FP): False Positives is when the prediction by the model was positive but the actual value is negative.

True Negatives(TN): True Positives is when the actual value is negative and the prediction by the model was also negative.

Evaluation Metrics such as accuracy , precision,recall,f1 score are computed from confusion matrix to evaluate all the models implemented in this research project.

- **Accuracy**: The accuracy is calculated by total number correctly predicted cases upon the total cases predicted. This value shows efficiency of the model.

$$Accuracy = \frac{TP}{TP + FN + FP + TN} \tag{2}$$

- **Precision**: Precision is the total number of correctly predicted positive cases divided by total number of positive predicted cases. In this research project, precision helps in identifying how much percent of patients had intracranial haemorrhage upon number of patients who were predicted with intracranial haemorrhage.

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

- **Recall**: Recall is the total number of correctly predicted cases out of the total positive cases. Recall helps in measuring the false negatives. In this research project,Recall value shows how much percent of patients where predicted with intracranial hemorrhage with respect to patients not predicted with intracranial hemorrhage who actually where hemorrhagic.

$$Recall = \frac{TP}{TP + FN} \tag{4}$$

- **F1 score**: F1 score is the weighted average of the precision and recall values. f1 score is taken in consideration because a model can excellent precision and a terrible recall values and vice versa which can lead a model towards taking many lives of patient.

$$F1Score = \frac{2 * Recall * Precision}{Precision + Recall} \tag{5}$$

The below table shows the evaluation metrics for various models implemented in this research.

Image Size	Model	Accuracy	Precision	Recall	F1 Score
128*128	Sparse Auto Encoder + SVM	78.15	0.69	0.75	0.71
	PCA +SVM	75.50	0.73	0.78	0.75
	Random Forest	74.24	0.69	0.60	0.64
	CNN	76.66	0.59	0.77	0.67
224*224	Sparse Auto Encoder + SVM	79.00	0.62	0.79	0.70
	PCA +SVM	77.50	0.73	0.78	0.75
	Random Forest	83.29	0.79	0.81	0.80
	CNN	78.24	0.60	0.77	0.67
64*64	Sparse Auto Encoder + SVM	84.95	0.72	0.81	0.76
	PCA +SVM	80.10	0.76	0.80	0.78
	Random Forest	79.92	0.62	0.79	0.70
	CNN	81.66	0.67	0.82	0.73
28*28	Sparse Auto Encoder + SVM	87.97	0.84	0.87	0.85
	PCA +SVM	74.50	0.80	0.75	0.77
	Random Forest	84.97	0.74	0.83	0.76
	CNN	82.69	0.75	0.72	0.73

Table 2: Model Comparison Table

Based on the comparision done on different machine learning and deep learning models, it was observed that random forest showed better accuracy for 224*224 image size. But the recall value was remarkably less with a value of 0.81 which shows 19 percent of cases where predicted with false negatives from the model. In the field of healthcare, its better to reduce the false negative as much as possible. CNN network also showed better recall of random forest for 64*64 image size but precision value was 0.67 which shows that the false positives. This trade-off between precision and recall is balanced by unsupervised learning sparse autoencoder and SVM classifier which shows the best F1 score of 0.85 and accuracy of 87.97 percent.

```
[[1572   25    2   39    11    25   11]
 [   0  862   45    0    34    10   34]
 [   7   76  572   56    24     1    1]
 [  25   67    0  689     0    15   21]
 [   4  101   57   41  1481    19    0]
 [   3    0   56   21    22  1159    0]
 [   6   62    1   82     2     0  703]]
```

Figure 9: Confusion Matrix of Sparse Autoencoder with SVM Classifier Model

7 Conclusion and Future Work

Sparse autoencoder performed better dimensionality reduction than principle component analysis. The unsupervised deep learning network with sparse autoencoder and SVM identified the subtle findings upto great extent. The results showed that epidural hemorrhage, intraparenchymal hemorrhages very easily predictable. The number of false negatives predicted from the model was very less than other supervised learning methods. Unsupervised learning models where helpful in detecting subarachnoid haemorrhages which are very subtle and critical. Unsupervised learning were better in finding complex representations from the image better than supervised learning techniques. The accuracy, precision, recall, F1 score was 87.97 percent, 0.84, 0.87, 0.85 respectively which was better than supervised learning models like random forest, model formed by PCA and SVM, CNN network.

The future work to be carried on this research can be combining the whole set of images in one plane(eg. sagital) by reordering the images and creating a multi planar reconstruction of the brain(generating other two planes namely coronal and axial) and thus training the model will lead to better accuracy in results. Training the model on larger dataset in PCs with high computation power can help the model predict better.

References

A Sheth, S., Aboutaleb, P., Barman, A. and Vahidy, F. (2020). Automated detection of hemorrhagic stroke from non-contrast computed tomography: A machine learning approach, *AHA Journals* .

Arbabshirani, M. R., Fornwalt, B. K., Mongelluzzo, G. J., Suever, J. D., Geise, B. D., Patel, A. A. and Moore, G. J. (2018). Advanced machine learning in action: identification of intracranial hemorrhage on computed tomography scans of the head with clinical workflow integration, *npj Digital Medicine* **1**(1).

Baker, A. D., Perla, K. M. R., Yu, Z., Dlugash, R., Avadhani, R., Mould, W. A., Ziai, W., Thompson, R. E., Staykov, D., Hanley, D. F. and et al. (2017). Fibrinolytic for treatment of intraventricular hemorrhage: A meta-analysis and systematic review, *International Journal of Stroke* **13**(1): 11–23.

Caceres, J. A. and Goldstein, J. N. (2012). Intracranial hemorrhage, *Emergency Medicine Clinics of North America* **30**(3): 771–794.

Cerrolaza, J. J., Li, Y., Biffi, C., Gomez, A., Matthew, J., Sinclair, M., Gupta, C., Knight, C. L. and Rueckert, D. (2018). Fetal skull reconstruction via deep convolutional autoencoders, *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)* .

Cho, J., Park, K.-S., Karki, M., Lee, E., Ko, S., Kim, J. K., Lee, D., Choe, J., Son, J., Kim, M. and et al. (2019). Improving sensitivity on identification and delineation of intracranial hemorrhage lesion using cascaded deep learning models, *Journal of Digital Imaging* **32**(3): 450–461.

Ginat, D. T. (2019). Analysis of head ct scans flagged by deep learning software for acute intracranial hemorrhage, *Neuroradiology* **62**(3): 335–340.

Gupta, N. and Gupta, B. (2019). Big data interoperability in e-health systems, *2019 9th International Conference on Cloud Computing, Data Science Engineering (Confluence)*, pp. 217–222.

Kaoutzani, L. and Stippler, M. (2019). Epidural hematoma, *Neurotrauma* p. 35–44.

Kasantikul, R. and Kusakunniran, W. (2018). Improving supervised microaneurysm segmentation using autoencoder-regularized neural network, *2018 Digital Image Computing: Techniques and Applications (DICTA)*, pp. 1–7.

Kuo, W., Hne, C., Mukherjee, P., Malik, J. and Yuh, E. L. (2019). Expert-level detection of acute intracranial hemorrhage on head computed tomography using deep learning, *Proceedings of the National Academy of Sciences* **116**(45): 22737–22745.

Lawton, M. T. and Vates, G. E. (2017). Subarachnoid hemorrhage, *New England Journal of Medicine* **377**(3): 257–266.

Liu, J., Li, C. and Yang, W. (2018). Supervised learning via unsupervised sparse autoencoder, *IEEE Access* **6**: 73802–73814.

Majumdar, A., Brattain, L., Telfer, B., Farris, C. and Scalera, J. (2018). Detecting intracranial hemorrhage with deep learning, *2018 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 583–587.

Mallick, P. K., Ryu, S. H., Satapathy, S. K., Mishra, S., Nguyen, G. N. and Tiwari, P. (2019). Brain mri image classification for cancer detection using deep wavelet autoencoder-based deep neural network, *IEEE Access* **7**: 46278–46287.

Moussavi-Khalkhali, A., Jamshidi, M. and Wijemanne, S. (2016). Feature fusion for denoising and sparse autoencoders: Application to neuroimaging data, *2016 15th IEEE International Conference on Machine Learning and Applications (ICMLA)*, pp. 605–610.

Nguyen, T. T., Nguyen, N. C. and Le, T. T. (2019). Manufacturing pacs, online medical consultation system and designing security dicom web viewer software, *2019 International Symposium on Electrical and Electronics Engineering (ISEE)*, pp. 37–42.

Rao, B., Zohrabian, V., Cedeno, P., Saha, A., Pahade, J. and Davis, M. A. (2020). Utility of artificial intelligence tool as a prospective radiology peer reviewer — detection of unreported intracranial hemorrhage, *Academic Radiology* .

Rashedi, N., Sun, Y., Vaze, V., Elliott, J., Hamlin, A., Klein, S., Anderson, J., Minichiello, J., Halter, R., Paradis, N. and et al. (2020). 1786, *A Multivariate Learning Derived Model For Detection of Hemorrhage.* **48**: 867.

Rybkin, I., Kim, M., Amin, A. and Tobias, M. (2018). Development of delayed posttraumatic acute subdural hematoma, *World Neurosurgery* **117**: 353–356.

Sublime, J. and Kalinicheva, E. (2019). Automatic post-disaster damage mapping using deep-learning techniques for change detection: Case study of the tohoku tsunami, *Remote Sensing* **11**: 1123.

Varma, D. (2012). Managing dicom images: Tips and tricks for the radiologist, *Indian Journal of Radiology and Imaging* **22**(1): 4.

Wei, W., Yisong, W., Lihui, W., Caixia, S., Xinyu, C., Zhi, L., Jian, Z., Feng, Y. and Yuemin, Z. (2018). Predicting lymph node metastasis of lung cancer using stacked sparse autoencoder, *2018 14th IEEE International Conference on Signal Processing (ICSP)* .

Xu, J., Xiang, L., Hang, R. and Wu, J. (2014). Stacked sparse autoencoder (ssae) based framework for nuclei patch classification on breast cancer histopathology, *2014 IEEE 11th International Symposium on Biomedical Imaging (ISBI)*, pp. 999–1002.

Xue, Z., Antani, S., Long, L., Demner-Fushman, D. and Thoma, G. (2012). Window classification of brain ct images in biomedical articles, pp. 1023–1029.

Zhou, C., Jia, Y. and Motani, M. (2019). Optimizing autoencoders for learning deep representations from health data, *IEEE Journal of Biomedical and Health Informatics* **23**(1): 103–111.

Zhu, Y., Tong, L., Deshpande, S. R. and Wang, M. D. (2019). Improved prediction on heart transplant rejection using convolutional autoencoder and multiple instance learning on whole-slide imaging, *2019 IEEE EMBS International Conference on Biomedical Health Informatics (BHI)* .