MRI Images: Hemorrhage Classification

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Abstract

Many different machine learning techniques have been developed to handle problems of image classification. The different methods and models can have varying degrees of success, measured through accuracy, depending on the given classification problem. Intracranial hemorrhages are a serious medical concern, as they can lead to brain damage, and be life-threatening. Accurate and automated identification of the type of hemorrhage can positively impact a patient's recovery. This paper will focus on implementing and comparing multiple different machine learning models for classifying intracranial hemorrhages based on MRI images.

1 Introduction

Medically, a hemorrhage is defined as bleeding with a damaged blood vessel as the source[3]. While hemorrhages can occur in many areas of the body, the focus of this paper will be intracranial hemorrhages, commonly referred to as brain bleeds. Brain bleeds are very serious medical concerns, as they can cause brain damage and be fatal.

The ability to identify the type of hemorrhage based on CT images is integral to patient care and outcome. Correct classification of a hemorrhage is necessary to determine cause, location, severity, risk, and treatment plan[6]. Automatic classification of hemorrhage type using machine learning can aid physicians in providing the best care possible for patients, creating more favorable outcomes.

The Zeta Surgical company was started by a team of Harvard graduates and academics. Their mission is to democratize access to accurate, safe and fast image guidance, to unlock the use of image guidance directly at the point of care, and to enable new treatments in cases such as emergencies and bedside procedures. For this project, the company has provided us with a dataset consisting of various brain CT scan slices, each of which has a hemorrhage (bleeding) within it. The hemorrhages have been segmented and labeled in some of the images. These hemorrhages are divided into different types: intraparenchymal, intraventricular, subarachnoid, subdural, epidural, and category for images with multiple sources of bleeding. Additionally, a large selection of images without any bleeding were included.

This paper will discuss techniques in machine learning, facilitated through python, to complete classification for hemorrhage types of the given MRI images. A comprehensive list of methods will be applied and compared, in order to determine the most effective model for this problem. Models that will be studied in this paper include: Linear Discriminant Analysis, Quadratic Discriminant Analysis, Support Vector Machine, a simple Neural Network, a Convolutional Neural Network, and a pre-trained model, ResNet50. Each of these models will attempt to classify images into the given hemorrhage types: intraparenchymal, intraventricular, subarachnoid, subdural, epidural, multiple (for multiple hemorrhage types within one scan), and normal (no signs of hemorrhaging). Both accuracy and efficiency will be taken into consideration in the final analysis and comparison of these techniques.

2 Related work

Ker[5] proposed a 3D Convolutional Neural Network that classified CT scans into four different classes - one "Normal" class, and three different hemorrhage classes. However, this approach yielded non-impressive results. The main success of this work was the alternate classifier, which used a 3D Convolutional Neural Network to classify the scans into just two classes - "Normal" and "Abnormal". On the other hand, Phan[2] used a Convolutional Neural Network to classify MRI scans into four different hemorrhage types, and had an accuracy of 95%.

Alfonse[7] used a Support Vector Machine (SVM) algorithm for the classification of brain tumors from MRI images. This process involved a combination of image preprocessing, image segmentation, feature selection, and finally classification with SVM. The Radial Basis Function (RBF) kernel was used. With a data set of 100 512x512, images, and only 16x16 features used, the method was able to achieve an accuracy of almost 99%.

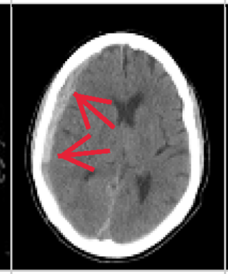
	Intraparenchymal	Intraventricular	Subarachnoid	Subdural	Epidural
Location	Inside of the brain	Inside of the ventricle	Between the arachnoid and the pia mater	Between the Dura and the arachnoid	Between the dura and the skull
Imaging					
Mechanism	High blood pressure, trauma, arteriovenous malformation, tumor, etc	Can be associated with both intraparenchymal and subarachnoid hemorrhages	Rupture of aneurysms or arteriovenous malformations or trauma	Trauma	Trauma or after surgery
Source	Arterial or venous	Arterial or venous	Predominantly arterial	Venous (bridging veins)	Arterial
Shape	Typically rounded	Conforms to ventricular shape	Tracks along the sulci and fissures	Crescent	Lentiform
Presentation	Acute (sudden onset of headache, nausea, vomiting)	Acute (sudden onset of headache, nausea, vomiting)	Acute (worst headache of life)	May be insidious (worsening headache)	Acute (skull fracture and altered mental status)

Figure 1: *The different types of intracranial hemorrhages*

3 Data

Zeta Surgical provided MRI images for many examples of each type of hemorrhage, along with examples of multiple hemorrhages and "normal scans", which contained no bleeding. For each scan, there were four available windows: "Subdural", "Max Contrast", "Brain", and "Brain Bone". Additionally, there was a folder containing segmentation data of bleeding regions for a subset of the data. This contained segmentations of some images from each category, along with their labels, and a glossary of terms.

To clean the data, first, a DataFrame including only the files which were previously already segmented was created. Each file was labeled with the respective hemorrhage type through the name of the folder containing the segmentation data. For "normal" images, in which there were no hemorrhages, a subset of 5000 images was added into the data for training and testing. These were randomly selected. The number 5000 was chosen to maintain the original ratio of normal scans to scans with hemorrhaging. For training images, only the "Max Contrast Window" was utilized, in order to simplify the input data. Lastly, any segmented scans that could not be found within the render folders were removed from the dataframe, along with any other missing files. These steps left us with a data frame that has the desired files with their locations so they could easily be loaded into arrays/tensors for different models.

4 Models

4.1 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA), while originally designed as a dimension reduction algorithm, is often used in supervised classification problems. It is favored over Logistic Regression for cases involving more than two classes. In classification applications, the algorithm assumes equal covariance between all classes, leading to the creation of linear boundaries between these classes. Additionally, the algorithm relies on the assumption that each variable in data follows a Gaussian distribution. LDA functions by estimating the probability that a new set of inputs falls within each possible class. This is done with Bayes Theorem, and the final prediction for an input is the class with the highest probability.

For the classification of MRI images into hemorrhage types, the algorithm for LDA was implemented using packages from Scikit Learn. The data was normalized prior to implementing the algorithm. Using a train/test split of 80/20, the model achieved an accuracy of 75%. Most of the incorrect predictions centered around the "Normal" class of hemorrhages. Many images were falsely classified as "Normal". Specifically, almost half of the Intraparenchymal samples were incorrectly classified as "Normal". Additionally, many "Normal" samples were mislabeled as one of the other

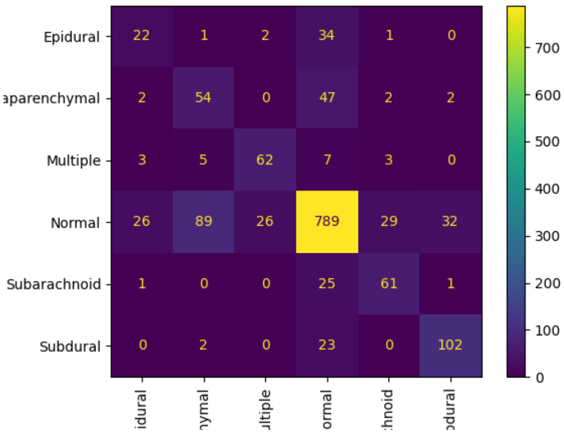


Figure 2: *Confusion Matrix of test data results for the LDA model*

classes, although this was fairly evenly distributed.

4.2 Quadratic Discriminant Analysis

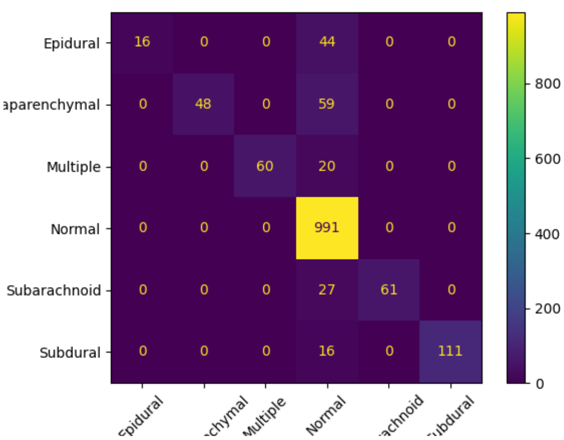


Figure 3: *Confusion Matrix of test data results for the QDA model*

Quadratic Discriminant Analysis (QDA) is an extension of LDA. It removes the assumption of equal covariance between classes, and instead, each class has an individual covariance estimate. This leads to the potential for quadratic boundaries between classes, and is more flexible than traditional LDA. Prior to running the model on the MRI image data, we predicted that this would yield better results than LDA due to the nature of the data.

For the classification of MRI images into hemorrhage types, the algorithm for QDA was implemented using packages from Scikit Learn. The data was normalized prior to implementing the algorithm. Due to the nature of the model, QDA was expected to perform better than LDA. Using a train/test split of 80/20, the model achieved an accuracy of 88%, which was a noticeable increase from the LDA model. All of the classification errors are MRI's with hemorrhaging being misclassified as "Normal". Unfortunately, this is not an ideal scenario, as misdiagnosing a patient such that they do not have any brain bleeding when they do is dangerous, and results in the patient not receiving necessary treatment.

4.3 Support Vector Machine

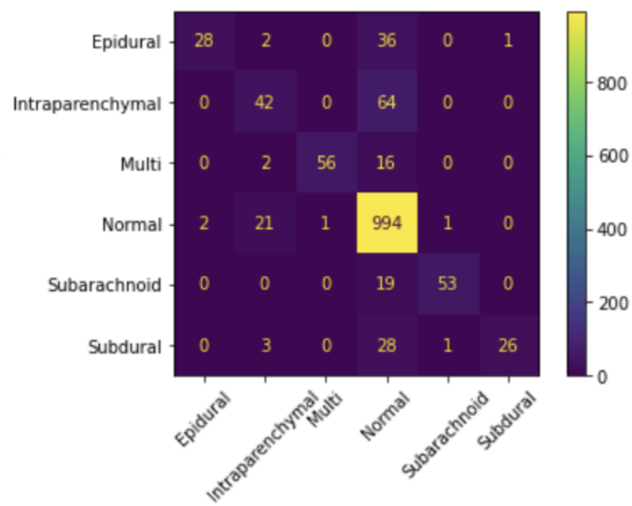


Figure 4: *Confusion Matrix of test data results for the SVM model*

A support vector machine (SVM) is a computer algorithm that learns by example to assign labels to objects. For instance, an SVM can learn to recognize fraudulent credit card activity by examining hundreds or thousands of fraudulent and non fraudulent credit card activity reports. SVM models can also learn to recognize handwritten digits by examining a large collection of scanned images of handwritten zeroes, ones and so forth. SVM algorithms have also been successfully applied to an increasingly wide variety of biological applications. For our purposes we will be using an SVM on our MRI Scans to try and label them by type.

For our initial trial of the SVM we ran the model in its base form without changing any of its parameters, using an 80/20 train/test split on the data. This yielded decent results with the accuracy score being 77.6% on our initial model run. Later we revisited this model and fine tuned the parameters for this model. Our testing yielded the best parameters to be:

- C: 10
- Learning Rate: 0.001

- Kernel: rbf'

These parameters yielded much better results with our test accuracy topping out at 87.33% after tuning. This is a great exemplification of why parameter tuning is so important in machine learning. We were able to yield a 10% increase after tuning our model to better fit the situation. Similarly to both the LDA/QDA, this model seems to struggle the most with misclassifying scans that do have bleeds as normal. This would not be acceptable in the medical applications of these models, and seems to be an issue present no matter what modelling methods we are using.

4.4 Simple Neural Network

A simple neural network model was computed using packages from tensorflow and keras. The inputs were an array of flattened MRI images, downscaled by a factor of 16, along with their given classification labels. The network consisted of 4 total layers, and was run with the following parameters:

- Batch Size: 128
- Optimizer: Stochastic Gradient Descent
- Loss: Sparse Categorical Cross Entropy
- Epochs: 10
- Train/Test Split: 75/25

This model resulted in an overall accuracy of 67%, under performing all of our previous models. Increased accuracy could be achieved with additional layers, but at the cost of increased computational time. Increased accuracy could also be achieved by downscaling by a smaller factor

4.5 Convolutional Neural Network

A Convolutional Neural Network (CNN) is a deep learning algorithm that can take in an input image and assign importance to different parts of the image. It can differentiate different types of hemorrhages and segment the areas. The architecture of a CNN mimics the connectivity pattern of neurons in the human brain. Neurons respond to stimuli in a respective field of vision and they have overlap, this fills the image. For the model, the following parameters were used:

- Batch Size: 240
- Activation Function: ReLU
- Optimizer: Stochastic Gradient Descent
- Epochs: 20
- Training Size: 960
- Testing Size: 240
- Train/Test Split: 80/20

This resulted in an accuracy of 32%. With increased compute time and resources, a stronger accuracy could be achieved.

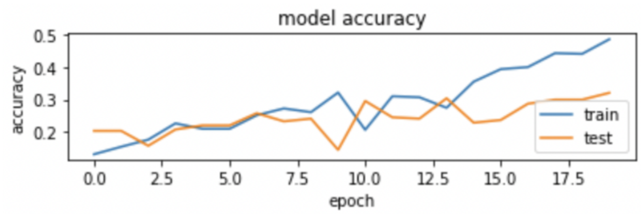


Figure 5: *Accuracy of CNN model over each epoch.*

4.6 Pre-trained Model: ResNet-50

ResNet-50 is a convolutional neural network that is 50 layers deep. You can load a pre-trained version of the network trained on more than a million images from the ImageNet database. The pre-trained network can classify images into 1000 object categories, such as keyboard, mouse, pencil, and many animals. As a result, the network has learned rich feature representations for a wide range of images. The network has an image input size of 224-by-224. You can use classify to classify new images using the ResNet-50 model.

For the purposes of our data we will be using the middle layers of this model by freezing them and using their pre-trained parameters to evaluate the labels for our MRI Images. This makes it so we simply need to load in our images and resize them, then we use the middle layers already trained in ResNet-50, and then finally output the results using a final Softmax layer to calculate the likelihood of each label.

For our model runs we used the following parameters on the model:

- Batch Size: 32
- Learning Rate: 0.001
- Optimizer: Adam
- Loss: Sparse Categorical Cross Entropy
- Epochs: 15
- Train/Test Split: 80/20

This yielded a best accuracy of 79% on the training data over 15 epochs. Interestingly enough, the accuracy only improved by about 2% from the first epoch to the last one despite the fact that there was a notable decrease in the loss function for every epoch. This suggests that some further parameter tuning could possibly be done for this model or perhaps we could try and use different views of scans in this model to reveal some more information about each image.

5 Discussion on Classification Models

Let us compare the results of our models in light of their limitations and capacities to draw reasonable conclusions. The Linear Discriminant Analysis (LDA) achieves an accuracy score of 75%. Even better, the Quadratic Discriminant Analysis (QDA) model achieves an accuracy of 88%! The initial run of the SVM gives an accuracy score of 77.6%. Rerunning with parameter tuning after gives an 10% increase to 87.33%, which demonstrates the importance of parameter tuning. The Simple Neural Network was run for 10 epochs at a batch size of 128 and achieved an accuracy score of 67%. On the other hand, the CNN runs for 20 epochs at a batch size of 240 and achieves accuracy 32%. Lastly, we applied the ResNet-50 pre-trained model. This achieved an accuracy score of 79%, over 15 epochs. The largest surprise was that accuracy only went up 2%. This is all subject to limitations in compute and resource availability. What we may draw from these is that for the given project simple methods performed the best, with the QDA getting a great 88% accuracy! This suggests for our given compute resources QDA is the best model. With increased compute power and parameter tuning the ResNet-50 model would perform the best, but this requires further research.

6 Image Segmentation

Using the labeled data for different hemorrhage types, we were able to begin the process for image segmentation. Accurate image segmentation of MRI scans into areas of "normal" or healthy brain tissue, compared to regions in which there is bleeding, will be incredibly helpful in the treatment of patients with brain hemorrhaging.

The labeled data provided by Zeta surgical included the coordinate bounds of polygons indicating the regions on the scans in which bleeding was visible. Through a combination of string formatting operations and list comprehension, we were able to transform this information into polygons that could be plotted on top of the original MRI scans, showing where professionals had determined there were bleeding regions. From there, a mask was created that differentiated which regions of the image were either bleeding or not bleeding.

From here, the next steps will be to implement the images and masks as training and testing data in a tensorflow image segmentation model[4]. One such model that may be a good fit for the data is a modified U-Net model. This model consists of an encoder, which downsamples the images, and a decoder, which upsamples the images. A pre-trained model such as ModifiedNetV2 could be incorporated as the encoder for strong results. This is available through Keras.

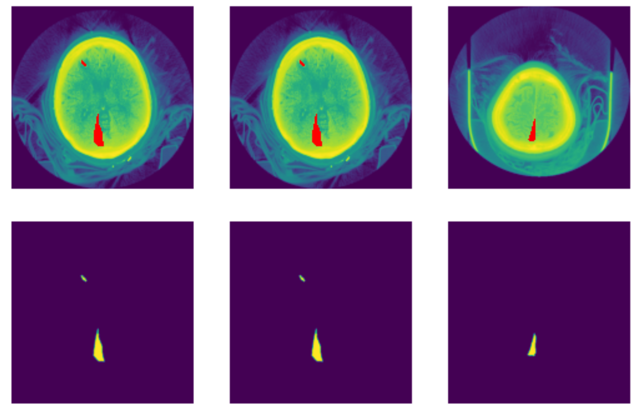


Figure 6: *Above are example MRI Scans, with labeled hemorrhage data in red. Below these, are the corresponding image masks of hemorrhaging regions.*

7 Limitations and Future Work

The most significant limitation in this project was computational capacity and resources. With additional computational resources, many improvements to the models could have been achieved. This includes but is not limited to: additional epochs on the neural network models, additional hidden layers in neural networks, and the ability to train on images that have not been downscaled. Also, additional segmented images could supplement the training data for higher accuracy. Future work could include testing other models, such as additional pre-trained neural networks, or even other simple machine learning algorithms such as Random Forest or a K Nearest Neighbor classifier. Additionally, dimension reduction could be incorporated to make the models more efficient, possibly through the use of processes such as Principle Component Analysis (PCA). Lastly, as discussed in the previous section, image segmentation could be implemented through a U-Net model to map areas of possible bleeding on MRI scans.

8 Acknowledgement

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