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Machine Learning Based Model for the Detection of Brain Aneurysms from MR Angiography

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ABSTRACT

A brain aneurysm is a thin or weak spot on a blood vessel wall that expands and fills with blood. Brain aneurysms are very dangerous due to the fact that in most cases, patients do not show any symptoms. Because of this, aneurysms are difficult to diagnose unless it becomes very large or ruptures, resulting in fatal hemorrhage.

Aneurysms can be detected by a number of different brain imaging methods including Magnetic Resonance Imaging (MRI), Magnetic Resonance Angiography (MRA), Computed Tomography Angiography (CTA) and other imaging methods but for the sake of this report we will only be focusing on MRA. MRA scans are optimal for the detection of brain aneurysms because they produce images that can be used to distinguish blood vessels from surrounding stationary tissue. Since aneurysms happen only in the blood vessels, MRA scans are an ideal image type to train a predictive machine learning model for our purposes.

Artificial intelligence, machine learning, and deep learning are all growing fields that are leading to breakthroughs in the medical community. For machine learning models and algorithms specifically, they have greatly helped in analyzing, locating, and predicting critical health conditions including brain aneurysms. With the help of this technology, medical professionals, such as radiologists, can greatly benefit from the predictions these models can provide. Image interpretation by human experts can be limited due to subjectivity, complexity of the image, extensive variations across different interpreters, and fatigue.

With the help of these models, physicians and radiologists will be able to make more accurate and precise diagnoses with predictive algorithms serving as a second opinion. More specifically, with the help of machine learning and MR Angiography, a predictive model can be trained to help detect brain aneurysms that might otherwise go unnoticed by radiologists. Here, we have developed four convolutional neural network (CNN) models that successfully detect aneurysm presence within MRA scans. Further investigation should be done to validate and improve these models to create a more accurate and sensitive diagnostic platform.

ACKNOWLEDGMENTS

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Chapter 1

Introduction

1.1 Background

Aneurysms are a weakened spot in blood vessels that either bulges or balloons out and then fill out with blood [1]. When an aneurysm ruptures, called a hemorrhage, hemorrhagic stroke can take place where the body begins to shut down due to large amounts of blood loss in the tissues surrounding the brain as seen in Figure 1.1. An unruptured aneurysm usually causes no symptoms and can lay dormant, unbeknownst to a person, for years. Occasionally, there can be pain above or behind the eye if the aneurysm is pressing on brain tissue or nerves. Classic symptoms of ruptured aneurysms is the sudden onset of a very severe headache [1]. Treatments for an unruptured aneurysm typically include medications to control blood pressure, or possibly surgery that clips the aneurysm from the blood vessel and removes it completely. Emergency medical care is required for a ruptured aneurysm. In most cases, brain aneurysms are not hereditary, and there is generally only a single case in a family [2]. When two or more first-degree relatives (parent, child, or sibling) have aneurysms, these are called "familial aneurysms." Individuals in these families may be at higher risk of developing aneurysms than the general population. Therefore, aneurysm screening using Magnetic Resonance Imaging (MRI) or Magnetic Resonance Angiography (MRA) is usually recommended.

MRI uses very strong magnets to generate a field that forces the body's protons to align within the field [3]. When the radio frequency moves through the patient, the protons are stimulated, move out of equilibrium, and are strained against the field. After the field is turned off, the MRI sensors can detect the proton's energy and realign it with the field from the magnets [3]. This allows for the radiologists to distinguish various tissues and bones as they all have different magnetic properties. MRA is similar to MRI but looks closer at the body's blood vessels and does not require a catheter [4]. The patient may be injected with a contrast to enhance visibility of the blood vessels.

These scans are traditionally used to produce two or three dimensional images of the brain and blood vessels to better visualize where aneurysms are located within the brain itself and the vasculature inside the brain. Small aneurysms are less than seven millimeters in diameter and are about the size of a pencil eraser, whereas large aneurysms are 11 to 25 millimeters and are about the width of a dime [5]. Small aneurysms and those less than three millimeters

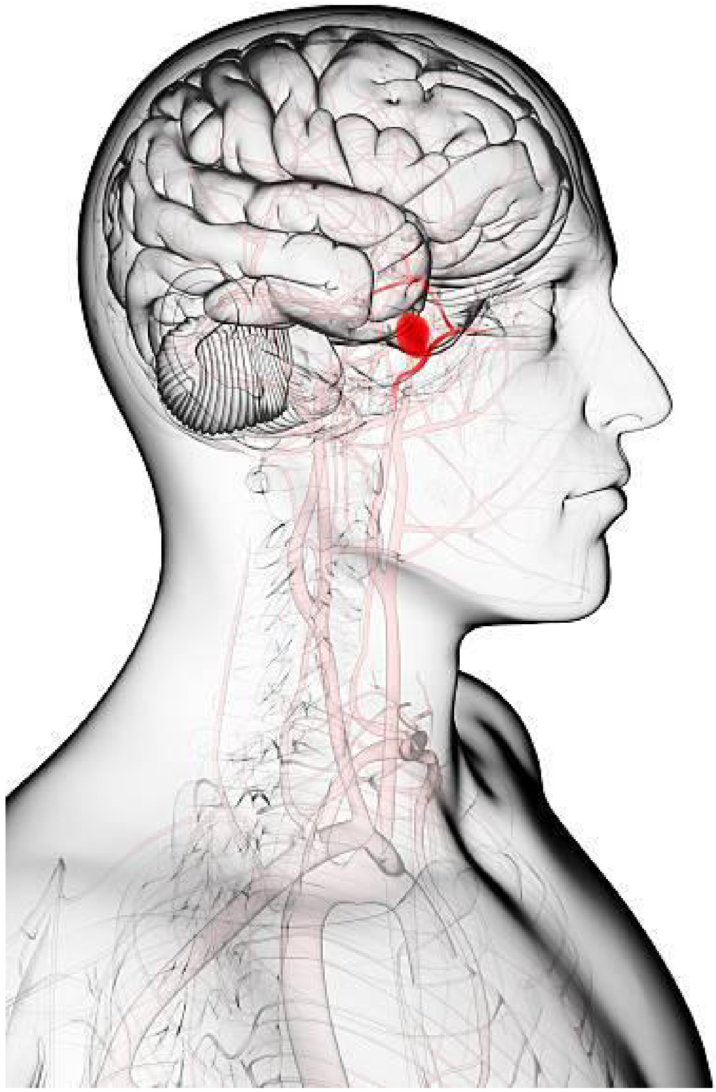

Figure 1.1: Depiction of brain aneurysm

are difficult to detect especially on maximum intensity projection images because there is overlap of the aneurysm with arteries and various flow patterns that make identification difficult [6].

1.2 Motivation

In the United States, an estimated 6.5 million people, about 1 in 50, currently live with an unruptured brain aneurysm [7]. The annual rate of an aneurysm rupture is roughly 1 in 1,000, meaning 30,000 people in the U.S each year suffer from a ruptured aneurysm. This can lead to life-threatening brain hemorrhaging and often has high fatality rates. Statistical data shows that 25 percent of patients with ruptured aneurysms do not survive within the first twenty-four hours, and an additional 25 percent die within six months due to complications [7]. It is extremely important to locate a brain aneurysm as early as possible. However, it can often be difficult for radiologists and physicians to detect small, misshapen, or obscured aneurysms in brain MRA images [8]. Our team has recognized how advanced programming technology, namely machine learning (ML) and convolutional neural networks (CNNs) for image analysis, can help in detecting the details that physicians might miss and fill the gap of misdiagnosis in often complex medical imaging. With this context in mind, our group chose to develop a convolutional neural network that would detect the presence of brain aneurysms in MRA scans with competitive accuracy as our capstone project.

1.3 Solution

Our solution will first pre-process the MRA scans in gray scale. This will increase the algorithm's ability to identify contours and edges of possible brain abnormalities and investigate that region for an aneurysm. The model will be trained on large data sets of MRA images that already contain aneurysms to learn which features to look for. The system will then accumulate knowledge about the images and their respective classification to start forming predictions on its own. After training, the algorithm is given images without knowing if an aneurysm is present or not. This will allow it to be able to search for features that are consistent with aneurysms and detect any that are present based on the previous training samples. By using an algorithm that is pre-trained with other medical images and calibrating it further using a data set of brain MRA scans with and without present aneurysms, our model will yield more accurate predictions than previous models. To improve upon previous models and make the model more accurate, data sets will be collected from a wide variety of resources to limit the potential bias within the image annotations [9]. With the large amount of data that we have and outstanding technology, our solution will be able to accurately detect aneurysms within MRA scans and provide an accurate second assessment to radiologists and physicians.

Chapter 2

Current Research

The methods in which doctors diagnose disease or conditions have significantly changed over the past twenty years, evolving from purely physician-based knowledge to now incorporating machine learning and intelligent programming [9]. These models can assist in speeding up the process of diagnosis and improve accuracy of correct diagnosis. In terms of brain aneurysms, the use of machine learning will be a crucial factor in determining patient outcome, especially in those that have a familial history or concurrent symptoms. Developing models trained to recognize aneurysms from brain scans is a revolutionary platform, as these could eventually predict exact coordinates, severity, and possible weakened blood vessel locations that should be monitored.

2.1 Preparing Medical Imaging Data for Machine Learning

Forming a complete understanding about how artificial intelligence is being increasingly used in the medical imaging field was crucial to our capstone project. Research was conducted on how algorithm data sets must be curated in order to properly train and validate them as seen in the article, Preparing Medical Imaging Data for Machine Learning [10]. The authors entail how medical imaging data is prepared for ML algorithm development step wise.

The first step in image preparation is to have the data set be approved from a local ethical committee. This is where informed consent is either determined to be given or not, as using patient data non-retrospectively requires informed consent. Other protected health information must be removed from the images before use.

The second step is accessing and querying information. The ideal way to make data accessible to AI developers is to reach an agreement with clinicians in a collaborative research effort. Querying information usually consists of strings, classification of disease codes, and terminology codes, but can also be achieved through querying software.

Next, the personal information of the patient must be removed from the medical images due to HIPAA and privacy laws. This process is called de-identification, and it may remove metadata that is useful to developers but encroaches on patient confidentiality. After de-identification, the data is transferred to a local data storage or an external data storage. Cloud computing has its drawbacks of cost and speed, but local storage limits shareability.

The data is then labeled and annotated in order to build accurate ML algorithms. Imaging data can be labeled through structured labeling, image annotations, image segmentation, and electronic phenotype. This is done as a way of diagnosing images based on expert assessment. The authors emphasize that bias in a training set should be minimized based on population prevalence, and that a large dataset is necessary for greater algorithm performance.

The main idea of this paper was to explain the steps for image preparation for algorithm implementation and describe the issue of data availability due to the human nature of medical images. Curating and labeling data is essential to the development of a high-performance model. This information is valuable to us in that it describes how our data set should be curated and how the labeling comes about.

2.2 Deep Learning for MR Angiography: Automated Detection of Cerebral Aneurysms

This article, Deep Learning for MR Angiography: Automated Detection of Cerebral Aneurysms [11], details a study conducted by Daiju Ueda to help further the development of an algorithm that used deep learning to detect cerebral aneurysms with MR angiography as a method of providing a second opinion to radiologists. This study showed that a deep learning algorithm could detect cerebral aneurysms in radiology reports with a high sensitivity and improved the rate and accuracy of detection of aneurysms that would have otherwise gone unnoticed.

The study began with the selection of a data set that would be used to train the algorithm. TOF MR angiography source images were acquired at four different medical institutions with standard protocols used with non-contrast material gradient-echo. These data sets were separated into three groups: a training set, an internal test set, and an external test set. The size of the data set was 748 aneurysms for 683 evaluations [11]. Images containing aneurysms were selected as the algorithm would serve as a second assessment.

Next, the algorithm itself was developed from an untrained architecture of ResNet-18. To detect aneurysms from the training data set, the algorithm was supervised, using patches with annotations of aneurysms. The images were first augmented by a 90 degree rotation, shift right of 10 percent, zoom 30 percent, vertical and horizontal flip within TensorFlow [11]. Then, the algorithm used the parameters of 100 epochs; base learning rate for untrained model, Nadam learning rate = 0.002, beta 1 = 0.9, beta 2 = 0.999, epsilon = 0.00000001, schedule decay = 0.004 to output a probability of an aneurysm for each patch. If the output was closer to 1, the algorithm would rank the probabilities from highest (highest being closer to 1) to lowest probability and present the aneurysm candidates from the image. The results of the algorithm sensitivity in detecting aneurysms was 91 percent (592 of 649) in the internal test data set and 93 percent (74 of 80) in the external test data set [11]. Every aneurysm detected by the algorithm was a candidate that had the highest probability to contain an aneurysm. Lowest rates in detection were for aneurysms larger than 10.0mm in the vertebral artery area and the middle cerebral artery area.

The main idea of this article was the creation of a deep learning model that would accurately detect aneurysms from MRA scans that would serve as a double check for radiologists to ensure that an intracranial aneurysm had not been missed. This study was relevant to our research as it detailed a viable way to develop an algorithm for our purposes, but also provided information on how to improve specificity: using maximum intensity projection images in the learning process, a greater amount of learning data on uncommon aneurysms, and using mixed data sets for training with and without aneurysms.

2.3 Deep Learning-Based Detection of Intracranial Aneurysms in 3D TOF-MRA

Within the article Deep Learning-Based Detection of Intracranial Aneurysms in 3D TOF-MRA, Sichtermann explains the importance of using an automated detection system to identify intracranial aneurysms [12]. Using 3D TOF-MRA examinations with the combination of DeepMedic CNN frameworks can produce a high sensitivity rating to detect the aneurysms and possibly predict aneurysms in the future.

85 MRA images were collected from 2015-2017 from their internal database. The following parameters were used on the 3T Magnetom Prisma: TR 21 ms, TE 3.42 ms, flip angle 18 degrees, FOV 200 mm, section thickness 0.5mm, matrix 348x384, acquisition time 5 minutes 33 seconds, 20 channel head/neck coil [12]. Whereas on the 1.5T Magnetom Area has: TR 28ms, TE 7ms, matrix 256x320, acquisition time 5 minutes 52 seconds, and 20 channel head/neck coil. The program uses skull stripping to remove the excess brain tissue from the images as part of the pre-processing step as seen in Figure 2.1

Sichtermann et al. used the DeepMedic model for brain lesion segmentation and catered it specifically towards intracranial aneurysms. DeepMedic is a model that can detect brain lesions based on a multi-scale 3-D deep convolution neural network (CNN) and a 3-D fully connected conditional random field. They used Rectified Linear Unit activation functions and batch-normalization to improve upon the DeepMedic model and gear it towards detection of brain aneurysms, they called this the DeepMedic hybrid sampling scheme. They then used the EvaluateSegmentation Tool to analyze the results by calculating the Hausdorff distances and the dice similarity coefficient.

The overall sensitivity of using DeepMedic hybrid sampling scheme in identifying cranial aneurysms was at 90 percent. For aneurysms with a diameter of 3-7 mm it was at 96 percent. And greater than 7mm had a sensitivity at 100 percent [12]. The larger the aneurysms the higher the sensitivity value measured. For smaller aneurysms, there are issues with having to compromise for wanting higher sensitivity ratings but smaller numbers of false positives. Overall, the study presents different methods and ways to detect the aneurysms using DeepMedic.

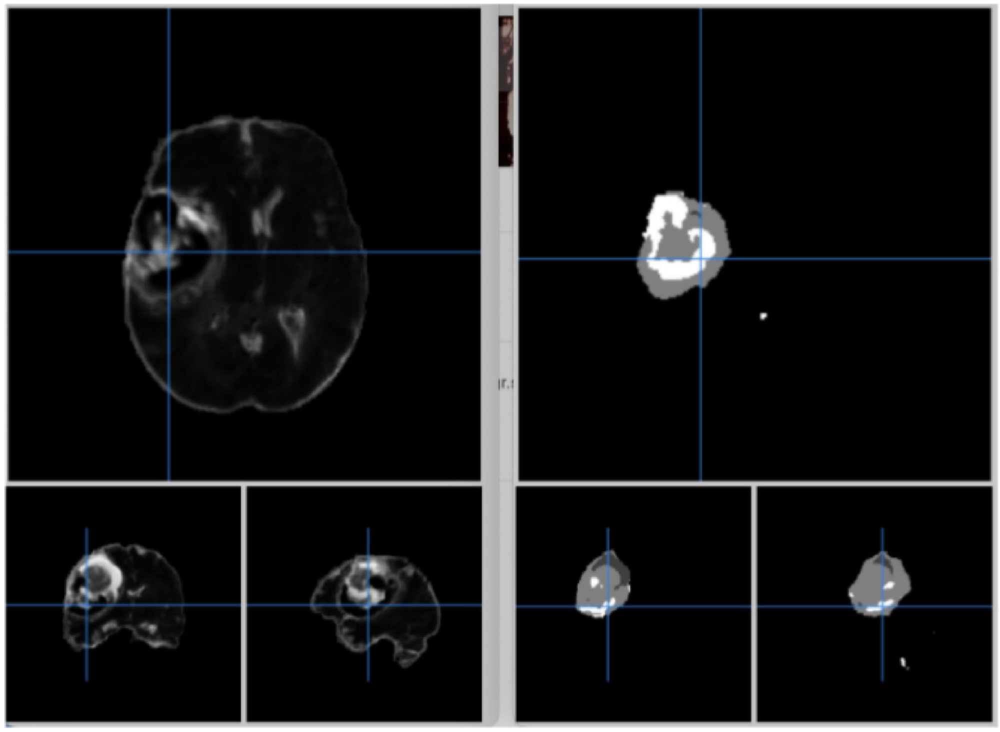

Figure 2.1: DeepMedic Scans with skull stripping

2.4 Development and Validation of Deep Learning Algorithms for Detection of Critical Findings in Head CT Scans

This article, Development and Validation of Deep Learning Algorithms for Detection of Critical Findings in Head CT Scans by Sasank Chilamkurthy, focused on developing and validating deep learning algorithms to automate detection of intracranial hemorrhages from CT scans [13]. This study demonstrated a successful algorithm development process that could accurately identify scans with abnormalities for quality of assessment. Firstly, this experiment used a dataset of 313,318 pre-processed CT head images with 2-128 slices per rotation [13]. This dataset was divided into a training and a validation test set. A natural language processing (NLP) algorithm was used to detect the abnormalities in each image. ResNet-18 with slight modification and a softmax function were used in combination with random forest methods to predict the scan confidence for hemorrhage detection. The algorithm was evaluated using confidence scores of 0 and 1. The algorithms had fairly good performance with the chosen open-source dataset.

The main idea of this article was to demonstrate that deep learning algorithms could be developed and trained with high accuracy to detect findings from CT scans. This information is meaningful in that it used multiple different algorithms and tested them against one another in order to determine if NLP or CNN could be successful in detecting brain imaging abnormalities. For our purposes, knowing that this algorithm has been trained on open-source cranial images is helpful in planning out how our algorithm should be implemented.

Chapter 3

Methods

3.1 Our Method

From our literature research, our group decided to develop convolutional neural network models with both a feature extraction and fine-tuning approach to determine which method would yield better results in detecting aneurysm presence in MRA scans. There were several key requirements that we had to keep in mind to provide the most optimal program for the doctors and radiologists at Santa Clara Valley Medical Center.

3.2 Key Constraints

3.2.1 Functional Requirements

The functional requirements for our solution are summarized below.

1. Our application is used to assist radiologists and doctors in identifying if there is an aneurysms as well as outputting the specific location.

2. Allows doctors to input MRI/MRA scans into the program

3. Allows radiologists to interact with the program to confirm the prediction was actually true or false.

4. Have radiologists give feedback to the program for correct location and size of aneurysm.

3.2.2 Non-Functional Requirements

In addition to functional requirements, we outlined and were successful in following the non-functional requirements listed below.

1. The application is compatible with desktops and laptops.

2. The application is easy to manage for the radiologists and doctors.

3. The images and results will load in a reasonable amount of time.

4. The application user face will be simple and intuitive.

3.2.3 Design Constraints

With regards to design constraints, here are the requirements given from SCVMC.

1. System is a downloadable software.

2. System must be easy to use and access at a hospital or private clinic.

3. System will be encrypted and protected against outside threats.

3.3 Methods

For our model design, we took two different approaches to train and test our model. The first approach was feature extraction with a ResNet50 base model and the second being a fine-tuned approach on a VGG-16 base model. For each method, we fed the algorithm two sets of pre-trained weights. The first weights were each model's respective pre-trained weights. The second were weights obtained from our literature research that had been trained on brain tumor images.

3.3.1 Experimental Methods

From our literature research, the state of the art model that we originally wanted to initiate a transfer learning approach from a program called DeepMedic [12]. DeepMedic is a brain lesion segmentation model that identifies lesions from TOF images with an overall sensitivity rate of 90%. Because DeepMedic processes .nifti images, which are a common medical image file type, we encountered issues with converting the program to take the .avi and .jpg files we received from SCVMC. After successfully converting the program, our dataset was found to be incompatible with DeepMedic, as the bounding box data had labels on top of the actual image, which ultimately prohibited us from using the program.

We decided to take a transfer learning approach with two different convolutional neural network models to establish our baseline. These two networks are called ResNet50 and VGG16. Transfer learning means to apply the knowledge that some machine learning model holds, which is represented by its learned parameters, to a new (but in some way related) task. We started with transfer learning using the models' pre-trained weights, then applied specifically brain related weights for improved aneurysm detection, and lastly fine-tuned the models to improve prediction accuracy.

To write the model scripts, we used a Tensorflow framework, which is a free and open-source software library for machine learning. It can be used across a range of tasks but has a particular focus on training and inference of deep neural networks. We used Keras libraries as well, which is also an open source software library that provides a python interface for artificial neural networks. It acts as an interface for the Tensorflow library.

3.3.2 Materials

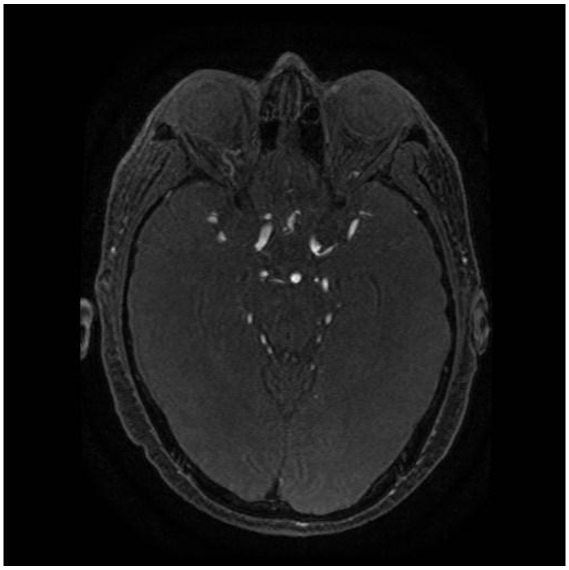

Figure 3.1: TOF image from SCVMC

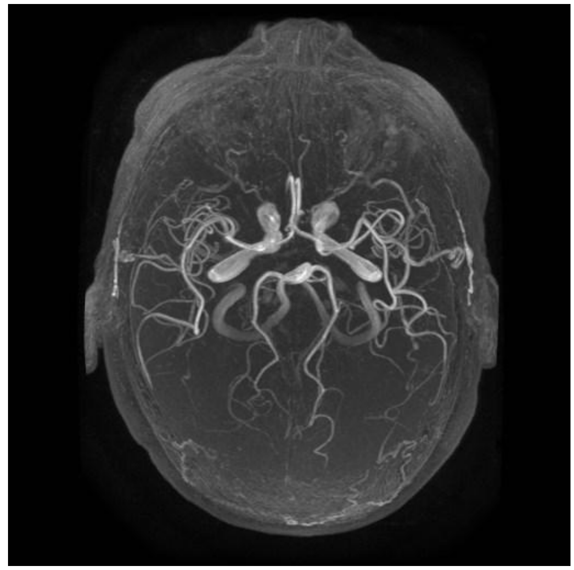

Figure 3.2: MIP image from SCVMC

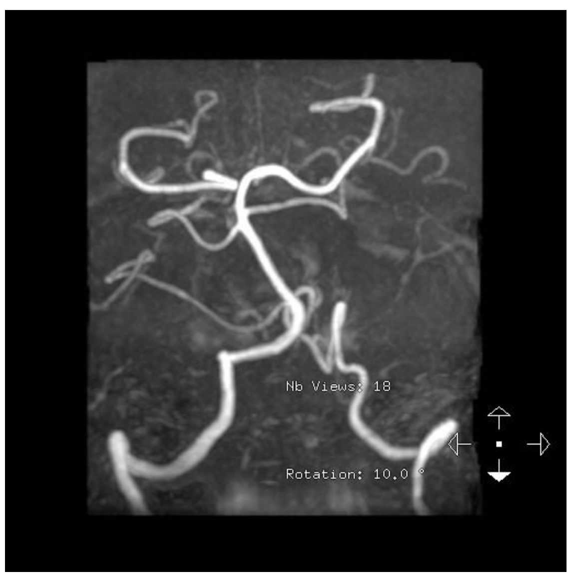

Figure 3.3: Bounding-box annotated MIP image

The project was based on images obtained from SCVMC. We obtained three data sets in total: a positive for aneurysms data set containing 80 patient files, a negative for aneurysms data set containing 98 patient files, and a combined positive and negative dataset with bounding box labels. Each patient file has 400-500 images total. We used various programs to assemble the code and be able to upload the images.

The datasets had both Time of Flight (TOF) and Maximum Intensity Projection (MIP) images. As seen in Figure 3.1, TOF images use an MRI technique to visualize the actual flow within vessels and a contrast is not needed [14]. It uses the phenomenon of flow-related enhancement of spins entering into an imaging slice. And as seen in Figure 3.2, MIP images involve projecting the voxel with the most noteworthy constriction esteem on each view all through the volume onto a 2D picture [14].

The last data set contained annotated images of the previous TOF and MIPs that had been sent over. As seen in Figure 3.3, the MIP image has been annotated to show possible aneurysm location.

In future work, we anticipate using the VGG Image Annotator to place our own bounding boxes around scans with aneurysms present to mark their location.

3.4 Pre-processing and Augmentation

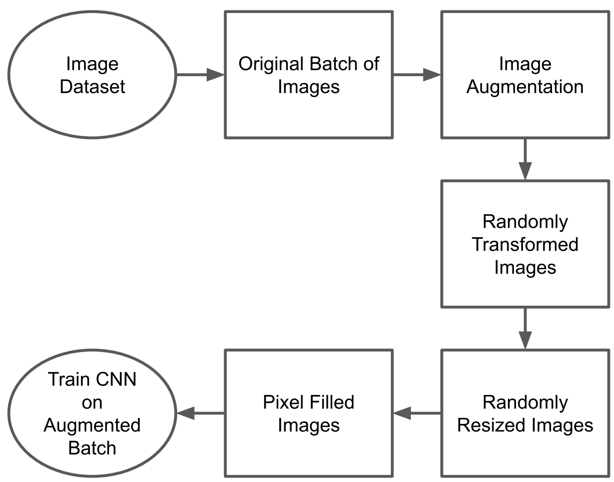

Figure 3.4: Pre-processing workflow

Before we built the model, we needed to pre-process and augment our dataset for training and validation. Firstly, we ensured that all our images were the same size and normalized the image pixel range to be between 0 and 1 for scales of black and white. For our training and validation datasets, we enlarged the images randomly by a factor of 0.3. We then rotated the images randomly by 50 degrees. Next, we translated the images randomly horizontally or vertically by a 0.2 factor of the image's width or height. After that, shear-based transformations were applied randomly and half of the images were randomly flipped horizontally. We also used the fill_mode parameter to fill in new pixels for images after we applied the previous operations to fill in any new pixels with their nearest surrounding pixel values. After these transformations and augmentations were completed, we split up our training and validation data to be fed into the programs [15].

3.5 Deep Learning Architecture

After our setbacks with DeepMedic, we decided that building convolutional neural network models with binary classification from scratch would better suit our project needs. A convolutional neural network (ConvNet/CNN), is a deep learning algorithm which can take in an input image, assign importance to various aspects or objects in the image, called weights, and is able to differentiate those objects based on their weight [16]. Neural networks are programmed and trained with an optimization process that requires a loss function to calculate the model error. Usually, a neural network model is trained using the stochastic gradient descent optimization algorithm. When training, weights are updated using the back-propagation of error algorithm. In a general sense, a model with a given set of weights is used to make predictions and the error for those predictions is calculated, and the loss function calculations indicate how "poorly" the model performed. The goal of multiple training epochs is to minimize the loss function calculation, thus reducing the error and improving the performance of the model [17].

Convolutional neural networks are made up of layers. These layers perform convolution operations. Convolutions are a multiplication of the set of weights and the input image. This multiplication is performed between an array of input data and kernel, which is a two-dimensional array of weights. The dot product of the kernel and the input is calculated. The kernel is smaller than the input as to make many multiplications at different points of the input in a systematic way, essentially scanning the whole input. This allows the kernel to identify features in the input image. The objective of the convolution operation is to extract the high-level features, such as edges, from the input image. This creates a feature map, where it is then passed through a ReLu function. These layers are typically stacked to hierarchically identify features in an input image, continuing in deeper layers to eventually extract high level features in images. Convolutional neural networks use this to identify features consistent with positive and negative images, and this is how the model learns to identify those features when given new images. ResNet50 and VGG16 are two different types of convolutional neural networks that function in this manner.

3.6 Feature Extraction

3.6.1 Overview

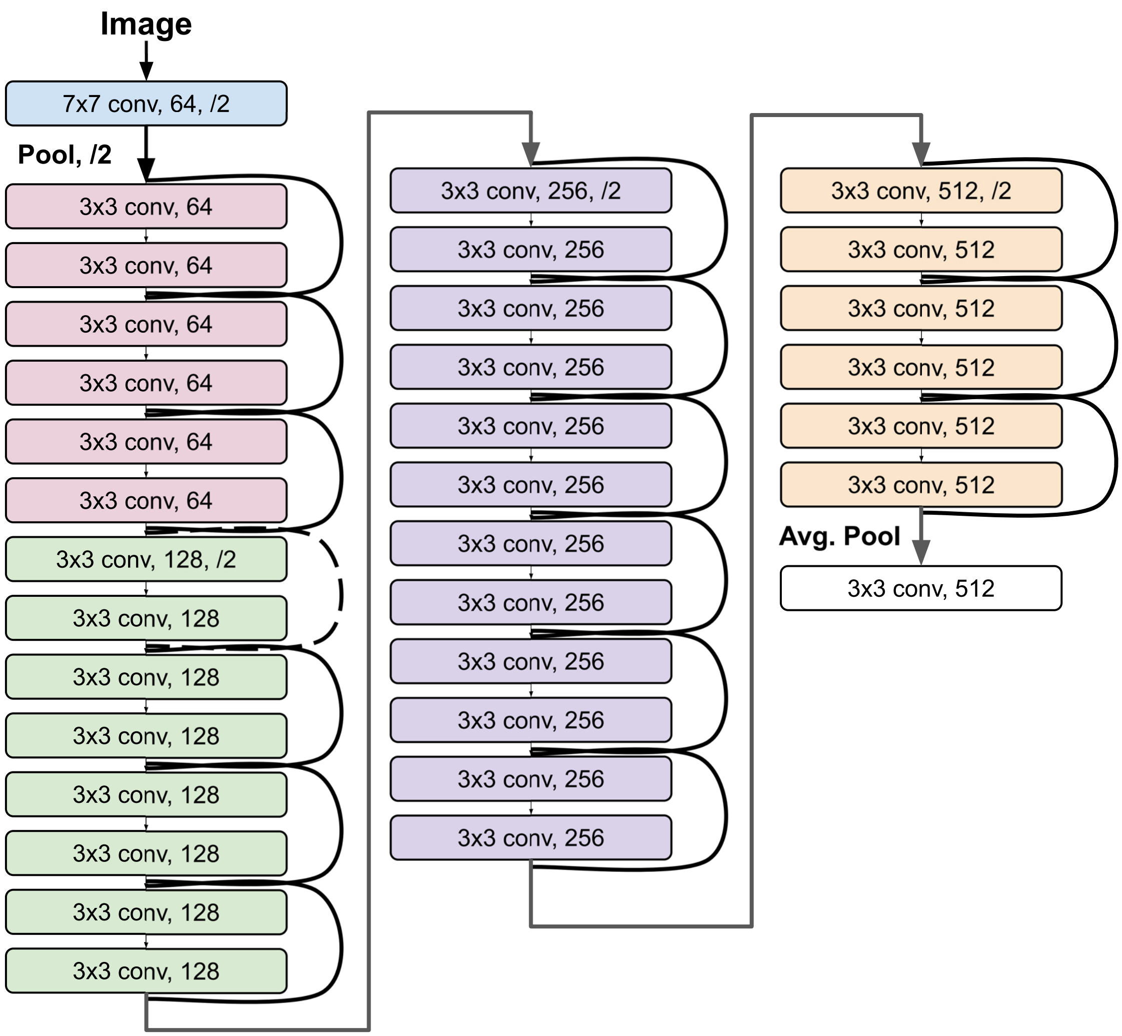

Figure 3.5: ResNet50 architecture

The first step of training our model is performing feature extraction. Feature extraction increases the accuracy of learned models by extracting features from the input data. This phase of the general framework reduces the dimensionality of data by removing the redundant features after the neural network decides which features are important and which ones are not. As seen in Figure 3.5, feature extraction works by treating the pre-trained network, for our model this is ResNet50, as an arbitrary feature extractor, allowing the input image to propagate forward, stopping at pre-specified layers, and taking the outputs of that layer as our features. Feature extraction is an important step in transfer learning to reduce error and increase accuracy based on the learned features of datasets.

3.6.2 ResNet50 Architecture

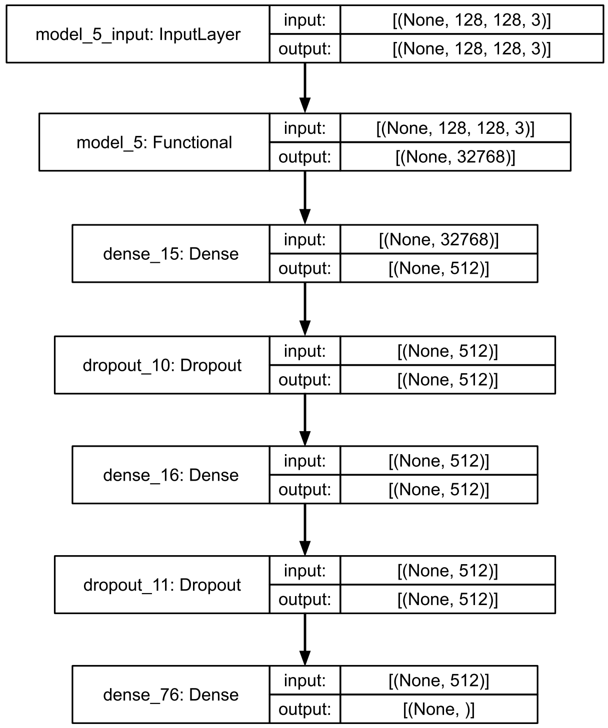

Figure 3.6: Feature extraction Architecture

For the first step of feature extraction in training our model, we loaded ResNet50's pre-trained weights as weights into our ResNet 50 model. ResNet50's architecture consists of 4 stages and takes images as inputs who's height and width must be multiples of 32 and have a channel width of 3. For our model, the dimensions of our input images were 128 x 128 x 3. Before entering stage 1, ResNet50's architecture performs max-pooling with a 3 x 3 kernel size and initial convolution with a 7 x 7 kernel size. After these steps, the first stage begins which consists of 3 residual blocks that each contain 3 layers to perform convolution operations. The first two layers of each block have kernel sizes of 64, and the third layer has a kernel size of 127. As input images move from one stage to the next, the input image's height and width is reduced to half, and the channel width is doubled. Lastly, the ResNet50's architecture has an average pooling layer and then a fully connected layer which outputs an ImageNet class [18]. For training purposes, our model used ResNet50's pre-trained weights were obtained from ImageNet, a large image database, which we used to find our baseline training and validation accuracy and loss. Running our model with the pre-trained weights allowed us to ensure that our model was not overfitting and was free of any biases.

3.6.3 Model Weight Optimization

After training a model using ResNet50's pre-trained weights, we then input weights from a model trained to predict brain tumors. Ideally, we would use a model that is trained on images containing brain aneurysms, however the data set that the pre-trained model used also consisted of MRI's, and brain tumors have similar features to aneurysms so we felt that these weights would be suitable during our feature extraction process. After training our model with the new weights, we were pleased to see that both our train and validation accuracy increased.

3.7 Fine Tuning

3.7.1 Overview

To attempt to obtain a better accuracy, we used the method of fine-tuning. Fine tuning is the method of making small adjustments to a previously trained model in hopes of better training the model and therefore obtaining a better accuracy. This is done by adding additional layers to the network and freezing the initial layers of the pre-trained network, only allowing for the last layers of the network to be trained on. The first layers, which are now frozen, hold the universal features learned from the pre-trained weights of the model, while the added layers have the ability to be trained on and learn new, more specific features for our given goal [19]. We started by fine tuning the ResNet50 model however, we were not able to obtain any better accuracy with this method and thus we fine-tuned a different image classification model called VGG16.

3.7.2 VGG16

VGG16 is a convolutional neural network for large-scale image recognition. It is a 16 layer network that takes in each image and passes it through a stack of convolutional layers interspersed with max pooling, to reduce the dimensionality, making assumptions about features contained in each convolutional layer. This is then followed by three fully-connected layers and a softmax output.

Figure 3.7 outlines what our model's architecture looks like. There are 19 layers, plus the input layer, in this model as opposed to the original 16 layers in VGG16 [20]. We added 3 layers on top of the existing layers of the VGG16 model in order to fine tune the network. We added a sequential model to the end of the network which is essentially another stack of three convolutional layers followed by max pooling. A sequential model was used since this type of model is the most appropriate for a plain stack of layers where each one takes in exactly one input and one output. With fine tuning, we only want to make small adjustments to our model in order to hopefully obtain better accuracy. In order to do this, we had to freeze the initial layers, making them un-trainable, and unfreeze the final layers in order for them to be trained on. For our fine-tuning model specifically, we decided to freeze the first 15 layers of the model, leaving only the last 4 layers to be trainable.

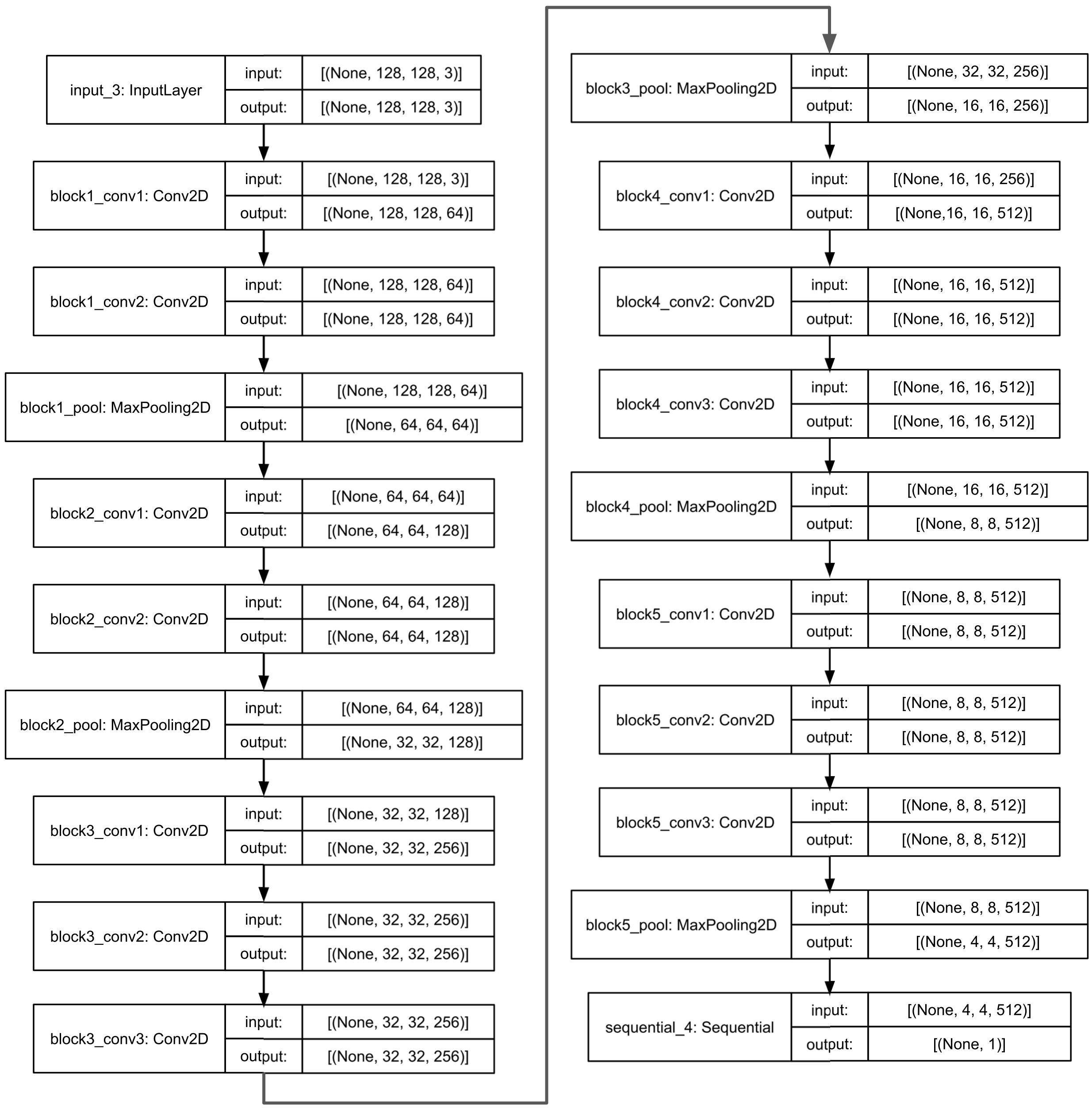

Figure 3.7: Fine tuning architecture

3.8 Results

3.8.1 Feature Extraction

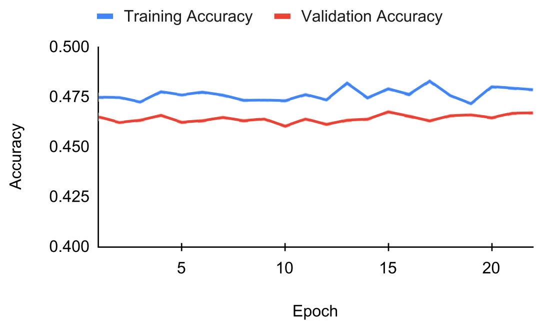

Figure 3.8: Accuracy with ResNet50 weights

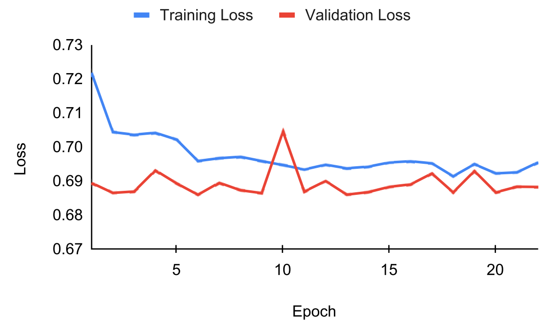

Figure 3.9: Loss with ResNet50 weights

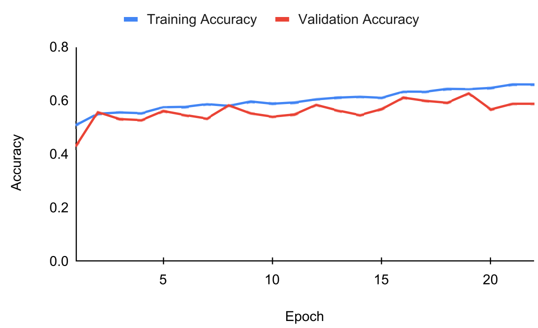

Figure 3.10: Accuracy with brain tumor weights

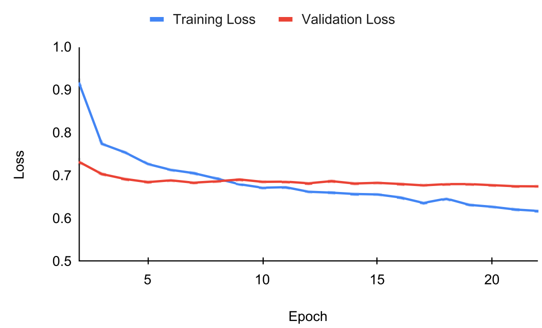

Figure 3.11: Loss with brain tumor weights

Our maximum training accuracy with pre-trained weights was 48.3 percent across 22 epochs, and our maximum validation accuracy was 46.7 percent across 22 epochs as shown in Figure 3.8. We calculated accuracy and loss across each epoch using Keras generated functions. The loss measures the binary cross entropy which calculates the difference between two probability distributions, and the accuracy is calculated using Keras metrics that take the frequency of matches between prediction and training labels into account. Because the ResNet50 weights have nothing to do with brain aneurysms, we did not expect a high accuracy from training or validation, we were looking more at patterns between the loss and accuracy to make sure that our model was training correctly. After training our model with weights generated from the model to predict brain tumors, our maximum training accuracy was 65.2 percent and our maximum validation accuracy was 59.8 percent as shown in Figure 3.10. We attempted to further train our model with output weights that were generated during training with the brain tumor weights which resulted in much higher accuracy's, however our model was over-fitting. Over-fitting happens when a model learns the details and features in the training data too well so that it begins to negatively impacts the performance of the model on new data. thus, we were not able to use those accuracies, but if we were to obtain model weights that are specific to brain aneurysms, we expect that the accuracy's during feature extraction would be much higher.

3.8.2 Fine Tuning

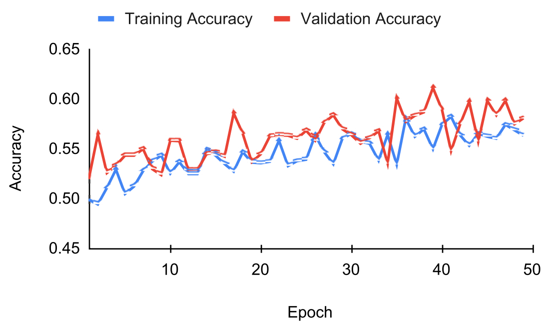

Figure 3.12: Accuracy with VGG16 weights

Figure 3.13: Loss with VGG16 weights

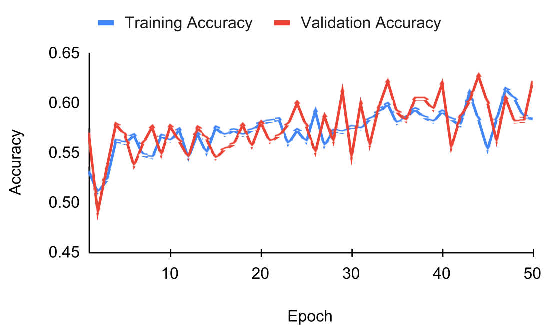

Figure 3.14: Accuracy with brain tumor weights

Figure 3.15: Loss with brain tumor weights

After fine-tuning the VGG16 model with the model's pre-trained weights, we obtained a maximum training accuracy of about 58.1 percent across 50 epochs, and a maximum validation accuracy of about 60.8 percent across 50 epochs as shown in Figure 3.12. We expected this accuracy to be slightly higher since fine-tuning aims to generate a better accuracy from a previously trained model. After feeding the model the brain tumor weights, we obtained a maximum training accuracy of 60.6 percent and a maximum validation accuracy of 63.4 percent as shown in Figure 3.14. We also expected the accuracy to increase when using the brain tumor weights since these weights were obtained from a model trained on brain images as opposed to the ImageNet database.

3.8.3 Result Comparison

Table 3.1: Summary Model Result Comparison

Baseline Network	Approach	Weights	Accuracy
ResNet50	Feature Extraction	Pre-trained	47.2%
ResNet50	Feature Extraction	Brain Tumor	59.8%
VGG16	Fine Tuning	Pre-trained	60.8%
VGG16	Fine Tuning	Brain Tumor	63.4%

Table 3.1 shows the comparison of our accuracies. The results indicate the accuracies increased within each method after feeding the network images specifically trained on brain images. Our accuracies also increased across methods after using the method of fine-tuning. Overall we achieved an accuracy of 63.4 percent. Although this is not an optimal accuracy and our final model is not suitable to be used currently, we know what further steps need to be taken in order to obtain an acceptable accuracy.

Chapter 4

Evaluation

4.1 Experimental Design

We implemented four different approaches of deep learning algorithms to identify brain aneurysms in MRA brain images. The ResNet50 feature extraction network achieved a 47.2% accuracy when trained with ResNet50 pre-trained weights. When trained with brain tumor weights, the ResNet50 feature extraction network achieved a higher accuracy at 59.8%. The VGG16 fine tuning network achieved a 60.8% accuracy when trained with VGG16 pre-trained weights, and when trained with brain tumor weights the accuracy increased to 63.4%. When training the ResNet50 feature extraction network with brain tumor weights, validation accuracy began to decrease. This indicated the model was overfitting. Due to the overfitting, we trained with different epochs to try and mitigate the issue. This was to prevent the model from learning features of the training images too well.

Overall, all of the networks with the exception of the ResNet50 model trained with pre-trained weights detected aneurysms with reasonable accuracy. As a general trend, the networks trained with brain tumor weights showed increases in accuracy as compared to their respective pre-trained weights. The ResNet50 feature extraction model showed a 12.6% increase with brain tumor weights, while the VGG16 fine tuned model showed a 2.6% increase with brain tumor weights. The VGG16 fine tuned networks resulted in higher accuracies than the ResNet50 networks as a whole. The VGG16 fine tuned network with pre-trained weights showed a 13.6% increase when compared to the ResNet50 feature extraction network with pre-trained weights. Similarly, the VGG16 network trained with brain tumor weights showed a 3.4% increase. The best performing network was the VGG16 fine tuned model trained with brain tumor weights with an accuracy of 63.4%, and adjusting the parameters of this model further to achieve a better accuracy remains as future work.

4.1.1 Data Sets

After separating the TOF images from the MIP images, our dataset was 32,545 images with both aneurysm positive and aneurysm negative scans. The images were split into training and validation sets, with the training set being 26,036 images and the validation set being 6,509 images. Though the dataset was large and an ideal size for our training purposes, some of the scans had less than ideal image clarity and contained slight blur. This blur results from possible slight movement of patients during MRA scanning.

4.1.2 Design Challenges

In the design process, there were a few challenges that we had to manage in order to continue work on our project. Firstly, obtaining the correct dataset in a timely manner was an obstacle that we repeatedly encountered in both the pre-processing and the testing phases. In order to first obtain any MRA scan data from SCVMC, our team had to complete training that certified us in being able to handle sensitive patient data. By working with the physicians and residents at SCVMC, we were granted these certifications. However, we did not receive any data until December 2020. We received only 200 positive scans at first, and thus were not able to move forward with testing or developing models until we were given additional scans that included negative samples. Once we obtained those scans in January 2021, we required scans that would have separate files including the coordinates of bounding boxes that would indicate the presence and location of an aneurysm in a positive scan. These scans were necessary if we wished to build a model that could both predict and determine the location of an aneurysm if present. Once we received a labeled dataset from SCVMC, the data was unusable, as the bounding boxes were placed on top of the images themselves instead of separate text files. This remains as future work.

Another challenge we faced was with image formatting. The data set we received from SCVMC was in the form of .jpg images and .avi videos. When we initially attempted to establish a baseline on the DeepMedic model, our images were not compatible, as DeepMedic only processed .nifti image types. We were successful in converting the DeepMedic model to accept .jpg images, however, we were unable to alter the program to read .avi video files. In addition to the image file type obstacles, DeepMedic required very specific pre-processing steps in order to correctly read the scans. We had to create separate pre-processing scripts that traced the contours of the brain in order to strip the skull from the image. We also had to create brain masks that DeepMedic uses in its pre-processing for each image in the entire dataset, which was laborious. Despite making progress on these additional pre-processing steps, DeepMedic was ultimately not compatible with our dataset. These setbacks were significant, as a large portion of our project timeline was used up attempting to establish a baseline with DeepMedic that resulted in our having to switch directions.

Chapter 5

Future Work

As of now, the deep learning neural network can detect the presence of a brain aneurysms. The next steps this project can take is to improve on the sensitivity percentages of aneurysms. It is easier to detect a aneurysms larger than 4mm, so improving that accuracy percentage will be crucial to reach patients who have smaller aneurysms.

Ideally the model will be able to produce outputs with predictions with bounding boxes. It will be important to accurately frame the aneurysms with the boxes but also important to eliminate overlapping bounding boxes by leaving the ones with locally largest probability. Editing the algorithm to sort the bounding boxes into true positives and false negatives will be helpful in adjusting the code to have a better output.

Thus leading to the continuation of this project with building a prediction based model that can give predictions on possible locations and coordinates of where aneurysms might occur or weakened spots in the blood vessels. Labeling individual TOFs that contain aneurysms within the positive data set would be helpful as well, currently the models look at the positive scans in whole.

Chapter 6

Societal Issues

6.1 Ethical

The main ethical concern that we primarily focused on was the issue of patient confidentiality. Because our data set was sourced from real patients and contained sensitive personal information, it was important to protect the confidentiality that is preserved between physicians and their patients when using their data for our model [21]. With MRA scans, the scans and videos generated contain labels with patient information for physician assessment. The DICOM images and AVI files from the MRA scan from Santa Clara Valley Medical Center included headers that described demographic information, name, gender, and date of birth, which had to be removed before we obtained the files. We, along with the physicians at SCVMC, wanted to ensure that patient privacy was not violated in passing along the data or in any of the pre-processing steps. To do so, resident physicians at SCVMC removed patient headers from all of the data we received. This way, patient confidentiality was preserved and we only used images and files in our model that were free of any personal information.

6.2 Social

This project was envisioned as a tool that would ultimately save lives by detecting dormant aneurysms in scans that would otherwise be overlooked. We wanted to create a meaningful technology that could prevent aneurysm ruptures by identifying them sooner, which would have an incredible impact on both patient diagnosis and prognosis. Because aneurysm rupture can escalate quickly and fatality rates after rupture are so high, a predictive model could intervene and make the difference between life and death. Our project, in collaboration with physician assessment, will greatly improve a correct diagnosis outcome.

6.3 Political

Though our project is not political in nature, we still have to consider how it affects society as a whole. Healthcare is a major issue in politics, particularly the cost of healthcare and the use of scans and technology much like ours. While our model could help save lives, the cost of healthcare and insurance that would cover the use of medical technology such as this could be a roadblock in making it accessible to all.

6.4 Economic

Brain MRA scans cost patients thousands of dollars in medical bills and fees. With our design, we hope to alleviate the financial burden for those who need preventative scans and those who require scans after rupture. In future work, these models could lessen the amount of scans necessary to determine aneurysm presence and thus relieve cost for patients and physicians alike. Additionally, our project had no cost to develop, as we received no funding and did not require licensing or cloud storage. Personal laptops and a remote server were used to create and develop our model. While this program is free for everyone to use as it is currently if this program were to be commercialized and implemented in clinical settings, the economic cost for medical imaging programs is typically quite expensive to license.

6.5 Health and Safety

As discussed previously, MRA scans are not radiation-based. Though these types of scans do not subject patients to harmful rays, they can interfere with the function of pacemakers or other implanted electrical devices. MRA scans also use a contrast dye that can be harmful to kidneys and can cause a severe reaction. If patients have a history of kidney disease, they are at a greater risk for a severe reaction. Reactions such as these can affect multiple organs such as the skin, joints, lungs, and liver. Our models use the images from these MRA scans. Because our project can reduce the amount of MRA scans necessary by providing a secondary assessment to physicians, patients would not be exposed to additional scans. Hence, our project could mitigate some potentially harmful effects of MRA scans. Our project has no health and safety concerns from an operating standpoint.

6.6 Manufacturability

While functional as is, our program would be greatly enhanced with a user interface that would make ease of usability and manufacturability. Combining all components into one usable software package would create a simpler and more cohesive product.

6.7 Sustainability

Since our model is computer-based, it is sustainable and environmentally friendly. In regard to the number of MRA images per patient, this is not a sustainable model as that data is spread out and difficult for the radiologists to observe all at one time. Using a machine learning model will help with the sustainability of the radiologist to help them do a better job in catching undetected brain aneurysms. As more data is added to our model, the accuracy and sensitivity will improve. The data will also remain locally, which helps to prevent data sharing and further privacy concerns. Our model can further be enhanced to provide encrypted predictions that can only be decrypted by the doctor or radiologist with the correct password. This creates a sustainable data to machine learning system where there are few privacy issues while also providing a comprehensive treatment plan.

6.8 Environmental Impact

MRI machines require liquid helium as a coolant to allow the magnetic coils to be superconductive, hence allowing for there to be a generation of high-intensity magnetic fields. Liquid helium can cost up to $40,000 per year, per machine [22]. While compared to the cost of an MRI machine about $1-3 million dollars, liquid helium is an incredibly rare element on Earth and it is slowly dissipating [22]. This element is a completely nonrenewable resource and the radioactive decay of uranium and thorium is required but takes thousands of years [23].

It is important to consider the amount of liquid helium that is being used for MRI machines and if it is possible to switch to zero-boil off helium magnets [22]. With the use of our model, a single MRI scan will be more beneficial and accurate in detecting possible brain aneurysms. With the previous system, sometimes more than one scan is required as a patient will go seek a second opinion. But the machine learning algorithm helps in that area as the patients will not have to undergo as many MRI scans hence benefiting the environment as less liquid helium will be used in the long run.

6.9 Usability

MRI scans can be easily misinterpreted due to the difficulty of understanding the scans. This can often lead to misdiagnosis with even unnecessary or harmful treatments that doctors will prescribe if given an incorrect diagnosis. Using a machine learning model will be beneficial not only to the radiologists and doctors but also to the patients as detection of potential aneurysms will be more accurate and more sensitive as it can detect details too subtle for the human eye [24].

Using machine learning algorithms for image detection is becoming increasingly prevalent within the medical imaging field as technology continues to develop. But with this comes issues as radiologists, doctors, and researchers have to adjust their way of diagnosis to accommodate this external source. It will be difficult to get used to as a computer algorithm can process massive amounts of data, but in the end the doctor's opinion will matter more as they have the complete knowledge of the patient's medical history. Further, there are difficulties with image formatting between DICOM, AVI, and JPEG.

6.10 Lifelong Learning

This project has allowed our team to gain real-life experience in software development and employing artificial intelligence to achieve something meaningful. The free-form structure of designing, developing, testing, and troubleshooting our model has provided a depth of complex problem solving not found in traditional college courses that will serve us both in our future careers and our personal relationships. For example, we had to quickly adjust to Terminal programming and learn Python in order to understand how our state of the art baseline functioned, and further employ that knowledge in developing our program to achieve better results.

Having the flexibility and the courage to immerse ourselves in languages we did not necessarily know has given us the capability to apply the same tactics to learn other languages. Though difficulties arose in troubleshooting file formats and running our own data set to establish a baseline, working through those issues has instilled strong communication skills and desire for effective collaboration. This program was also developed with improving medical outcomes and changing lives for the better. This passion will undoubtedly influence our future work, particularly with medical imaging, with the main goal being to create a product that can give hope where there would otherwise be none.

6.11 Compassion

Radiologists, doctors, and nurses work incredibly long hours to serve the needs of our community and help solve complex medical problems. Using our model, some of the pressure and stress may be lifted off their shoulders. The algorithms can be used as a tool to provide radiologists with additional help to identify the size and location of their patient's aneurysm. Our model will not substitute the radiologist's knowledge, but rather be a beneficial element that works behind the scenes. Hence, the radiologists will have more time to spend in direct contact with their patients. They will be able to gather and understand the patient's entire medical history instead of rushing them to an MRI appointment and then rushing to get a diagnosis.

Ideally, with a faster turn-around time from our model, there will be less suffering of the patients as they will receive a diagnosis faster and hopefully catch the brain aneurysm before they have ruptured. Aneurysms may be hereditary. So our model can be used as a potential diagnostic feature to catch very small aneurysms or potential sites where aneurysms might develop. If the model can catch these issues months to years before rupture, the patient can have endovascular repair surgery to get rid of the aneurysm.

Our compassion is evident within this project as we wish to educate and form better strategies to combat patient's history with aneurysms.

Chapter 7

Conclusion

7.1 Lessons Learned

Through this design process, we have experienced software development from start to finish with real-world applications and medical relevancy. Through in-depth research and evaluation of published convolutional neural network models, we explored how deep learning architecture can be modified, trained, and validated to achieve a specific goal using two approaches to transfer learning. As a result of our attempts to build off of the DeepMedic model as a baseline, we developed multiple scripts dealing exclusively with image pre-processing including those that performed skull stripping and mask generation. From building our algorithms from the ground up, we learned about the implementation of convolutional neural networks tailored to our needs.

One main takeaway from this project was the importance of flexibility in the design process. Pivoting from one direction to another was a challenge, however, thorough background research and willingness to start from scratch demonstrated how adaptability in experimental design is invaluable to team success. This was also seen in light of the COVID-19 pandemic, as our project plans required us to be adjustable to an entirely virtual setting. Courtesy of online video conferencing, we successfully navigated group dynamics in rapidly changing environments.

Another key takeaway from this project was a better understanding of how precise the field of deep learning is in practice. The difficulties we encountered while debugging and manipulating our code to suit our needs gave us a stronger appreciation for the successes of predictive models, both in commercial and research settings. Our team experienced first-hand how complex creating these models can be, as well as how much work is involved in simply preparing data to be processed. Developing a model with lower accuracies than we anticipated revealed the variety of variables that can be adjusted to achieve better results in the future.

7.2 Significance

The use of machine learning to analyze, detect, and predict critical health conditions is an extremely beneficial tool in the medical field. Brain aneurysms can be life-threatening if they go untreated, so computerized automation detection systems can potentially save lives by locating aneurysms that go undetected by medical professionals. This field has achieved some of the greatest innovations in recent years out of all STEM professions and will only continue to grow. Studies such as the CNN classifier approach explained in this report show that there are a variety of ways to use combinations of machine learning algorithms to achieve successful results.

Once we can determine a reliable predictive model with great accuracy, accuracy of greater than 95 percent, we can greatly improve and help the medical community in detecting brain aneurysms. These types of methods also work for the detection of all sorts of medical conditions and diseases. By creating these models we will be one, taking some of the stress and load off medical professionals like radiologists, and two, potentially improving the accuracy of these readings by reducing the risk of human error.

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Appendix A

Appendix

A.1 Source Code

Full source code available at: https://github.com/katiebecknell/Machine-Learning-Based-Model-for-the-Detection-of-Brain-Aneurysms-from-MRA-Images