Glioma Tumor Detection Through Faster Region-Based Convolutional Neural Networks Using Transfer Learning.

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Abstract: - Glioma Tumor is generally found in the brain and spinal cord. This tumor begins in glial cells that cover the nerve cells and control the function of that. The Glioma tumor is classified based on glial cells involved in the Glioma tumor formation. The tumor affects the normal activity of the patients such as loss of memory, difficulties in speech, confuse the identification of objects, and also causes difficulties to maintain the balance of the body. The early detection of Glioma tumor helps healthcare practitioners to suggest a suitable treatment for the disease. The detection of a Glioma tumor is a challenging task. Many types of approaches had been proposed by the researchers and academicians for accurately detecting the Glioma tumor. Accurately detecting the brain tumor is still a big challenge. Because of recent advances in image processing and computer vision, healthcare professionals are using sophisticated disease diagnostic tools for disorders/disease prediction. The Neurosurgeons and Neuro-Physicians use the magnetic resonance imaging technique to identify multiple brain tumors. The approaches to computer vision play a significant role in the automated identification of different Brain tumors. This research paper explores the Convolutional neural network-based Faster R-CNN approach for the Glioma tumor detection using four pre-trained deep networks such as Alexnet, Resnet18, Resnet50, and Googlenet. The proposed approach of object detection as compared to other R-CNN approaches is more efficient and accurate having higher precision. The proposed model detects the Glioma tumor with 99.9% accuracy. The pre-trained networks used to train the tumor detection model are Alexnet, Resnet18, and Resnet50, and Googlenet. As compare to Alexnet, resnet18, and Googlenet deep networks, the Resnet50 Pre-trained network performed well with higher accuracy of detection.

Keywords: Glioma Tumor, Magnetic Resonance Imaging, Computer vision, Convolutional Neural networks, Pre-trained networks, Deep learning.

1. Introduction

Since the dawn of human civilization human beings have been battling against different diseases. Many forms of health-care programs have been created and evolved from time to time according to individual needs. Healthcare experts have discovered and examined different forms of brain-related diseases. Glioma tumor is one form of neurodegenerative brain disease which affects normal brain functioning[3]. A glioma may affect functions of the brain and can become life-threatening depending on its location and growth rate. Gliomas are among the most prevalent forms of primary brain tumors[32]. Symptoms of Glioma tumors are strongly dependent on the tumor type and its tumor size, growth rate, and location in the brain [32]. The Glioma tumor sign and symptoms typically evolved because of damage to healthy brain tissues. Swelling is created around the tumor surrounding area inside the brain. Due to this brain disorder patient's normal activities are affected. The common sign and symptoms of tumors are headaches, seizures, vomiting, nausea, discomfort, and memory loss [33]. according to the brain tumor statistics report(2019), 23890 people including men and women have been diagnosed with a primary brain tumor and spinal cord tumor In the United States only. In 2019, 3540, children under the age of 15 are also diagnosed with a brain tumor [34].

Magnetic resonance imaging (MRIs) has been the primary diagnostic source of disease. The healthcare practitioners use various MRI modalities, such as axial, coronal, and Segital, for referring. Medical experts can diagnose brain abnormalities with MRI images, and monitor disease progression via proper care. Magnetic resonance images display the progression of the disease and active lesions. The neurologists compare the scanned images based on the distribution of white and dark areas to find out about the damaged and healthy tissues[12]. Imaging techniques are very useful in the identification of numerous brain cancers, traumatic brain injury, Alzheimer's disease, Parkinson's disease, brain strokes, dementia, brain infections, and different brain disorders [12]. T1-weighted, T2-weighted, and Fluid Attenuated Inversion Recovery (Flair) are the widely used sequences for MRI imaging. The contrast and brightness of the images are regulated through Echo Time (TE) and Repeating Time (TR). The neurological experts use both the T1-weighted and the T2-weighted MRI images for disease diagnosis[12]. In this research paper, The T1-weighted contrast-enhanced MRI images of Glioma Tumor are downloaded for the practical implementation of the Tumor detection model [33].

Recent advances in the field of artificial intelligence and machine learning have opened the door for the healthcare professional to use the tools and systems for automated disease diagnosis to find out the nature and effects of different diseases on humans. The deep learning method, which is the sub-field of machine learning, plays an important role in the medical image analytics domain [21]. Using the deep learning approaches, a large volume of medical imaging data records can be explored and analyzed for the prediction of various abnormalities. The higher computing power as such Graphics Processing Units (GPUs) manufactured by different leading companies also plays a dramatic role in the field of machine learning. Graphics Processing Units with intensive computing power are used to trained deep networks having several Convolutional layers with additional computing layers such as ReLU, Maxpooling layer, Batch-Normalization layer, softmax layer, fully connected layer, and a classification layer[22].

The object detection capability of the deep networks is highly influencing the application area of automatic disease classification, infected brain tissue detection. For feature extraction from the large volume of image datasets, the Convolutional neural networks are used. Through the convolution operation, different sizes of filters/kernels are used to learn weights as a part of training the deep network [13]. The Convolutional Neural Network architecture is composed of different layers for automatic extraction and classification of features. Pre-trained Neural Networks are often used as a Deep Learning Directed Acyclic Graph Networks[21]. The DAG networks are one kind of deep network designed and implemented by the researchers for object detection and classification [16]. All these deep networks were trained on large image datasets. Based on learnable weights, these networks are used by the academicians and researchers as the pre-trained networks for the classification and object detection. [14]. Deep networks such as Alexnet, VGG16, VGG19, Googlenet, Resnet18, Resnet50, resnet101, etc are widely used by the research community for image classification and object detection in the various domain of computer vision [15]. All these Large Deep networks are trained by the designers with a large volume of images collected from different sources. These networks can be trained for the classification and detection of objects. The Faster RCNN (Region with Convolutional Neural Network) object detection method dramatically improved in the state-of-the-art in object recognition and object detection. Faster R-CNN (Region with Convolutional Neural Networks) approach with pre-trained Deep networks is widely used for object detection in many areas. This approach of object detection is more powerful, efficient, and accurate [14].

The object detection network such as Faster R-CNN is designed for feature extraction using the pre-trained networks such as Resnet18, Resnet50, and inception v3, etc. The features extracted through the training process of deep networks using ground truth labeled images are fed into the region proposal network (RPNs) based on object detection methods such as Faster R-CNN. [15]. A region proposal network is trained to produce the proposals for an object where there is an object of interest exists. The next subnetwork is architecture and trained using the features extracted by the deep network to predict the object of interest.

In this research paper Glioma, the tumor detection model is proposed and implemented in the Matlab environment using the object detection approach such as a Faster R-CNN. The Faster RCNN network model takes as input an entire image and set object proposals [19]. The Faster RCNN network is trained with the help of ground truth values of images through Pre-Trained Deep networks such as AlexNet, Resnet18, and resnet50. The proposed model is implemented in the Matlab R2020a version using deep learning and computer vision approaches.

The rest of the paper is divided into four parts, such as section 2 focusing on related work done by researchers and academics to identify and recognize brain tumors by Fast R-CNN and Faster R-CNN. Section 3 discusses the object detection methods and methodologies, for the proposed model implementation using the online gathered magnetic resonance images of the Glioma tumor dataset. Section 4 describes the implementation strategy of transfer learning with the Faster R-CNN technique, using pre-trained networks. The last section relates to the conclusion of the results obtained through the experiments and suggesting the study's future scope.

2. Related Work

Through the literature review, it is found that various research papers and research articles are published in international journals and conferences. It is also found that deep learning approaches are playing a major role in medical image classification and object detection. The transfer learning approaches are used for the classification and object detection in various application areas. The pre-trained network was trained on a large size of image data by the original developers. For the trained of these networks, high-speed computing power and huge image datasets are required. It becomes quite difficult for the researchers and academicians to train such kind of a deep network; therefore pre-trained networks are used for classification and object detection for small datasets.

Shaoqing Ren et al. Published a paper based on real-time object detection through region proposal networks. Researchers proposed an approach based on Region Proposal Networks used for real-time object detection. The features are extracted through Convolutional Neural Networks and fed into the region proposal networks. Authors found that object detection through Region Proposal Networks detects the objects with higher accuracy [16].

Ross Girshick contributed a research paper based on the Faster R-CNN approach used for object detection [16]. The author found that the object detection process is quite a typical task as compared to the object classification task. The object detection task requires the image dataset labeled with ground truth labels. Obtaining the ground truth label data requires an additional image process approach to draw the anchor boxes around the desired object. The author's proposed algorithm was based on a single-stage training process that jointly learns to classify object proposals by updating the corresponding spatial locations. The author also found that the faster R-CNN approach trains the VGG16 deep network 9 times faster at training time and 213 times faster at a testing time as compared to the simple R-CNN approach [17].

Krishna N. et al. proposed a methodology based on the segmentation and detection of Glioma using the deep learning approach. The authors used the U-Net model based on a deep learning approach for the detection of Glioma with BrtaTS dataset2018. The authors implemented a model-based on a Convolutional neural network for the segmentation of Glioma regions from the raw Magnetic Resonance Images. A series of convolutions and de-convolutions were used to achieve higher segmentation results as compared to other approaches. The ReLU and softmax activation factions were used to maintain the non-linearity throughout the training process by finally calculating the output probabilistic value for deciding the class of the output pixel respectively [2].

R. Ezhilarasi, P. Varalakshmi, using the Faster R-CNN method, suggested a model for the identification of brain tumors. Using the Faster R-CNN method, the Alexnet Deep Neural Architecture was used along with the Region Proposal Network to identify different tumors as a basic model. During the network design and implementation, the approaches to transfer learning were employed. The Faster R-CNN was used for brain tumor detection. [23].

The approach for classifying and detecting brain tumors from MRI images was proposed by Ercan AVSAR and Kerem SALCIN via Faster R-CNN. To identify and locate the tumor region, the authors applied the Faster R-CNN approach to brain MRI images. Compared to simple R-CNN and Fast R-CNN approaches, the authors said the methodology used for detection and classification is more effective and accurate with 91.66% detection accuracy[24].

3. Materials and Method

This section of the research study illustrates the methodologies and image datasets used to diagnose Glioma tumors. Different techniques to the identification of Glioma tumor are carried out systematically from data collection to pre-processing the image datasets and subsequently, the proposed method is implemented. The research's most critical step is the selection of an appropriate dataset to apply the model. Model output depends mainly on image dataset consistency and quality. Following the selection of appropriate datasets and pre-processing of MRI images, Convolutional Neural Network architecture selection is a very necessary and important phase. The research methodology adopted for the proposed study is focused on the labeling of ground truth-values of Glioma datasets and the selection of the pre-trained deep network.

A very important part of the research methodology is the labeling phase for the datasets. MRI image Dataset for four pre-trained DAGNetworks is labeled with the help of the image labeler approach available in the Matlab version R2020a. After labeling the Glioma tumor images, the deep network is trained through the Faster R-CNN approach to extract the features from labeled ground truth Glioma image datasets. The Region Proposal Network is trained using the extracted features obtained from the training process of the deep network. To train the proposed model different training parameters are chosen.

3.1 *The Dataset Collection*

The T1-weighted contrast-enhanced Glioma tumor MRI images are collected online from [38], the dataset contains 1426 MRI images of 233 patients, the MRI images originally download in the .mat image file formats. Three MRI images modalities such as axial, coronal, and segital are included in the dataset. The contrast of all the MRI images is enhanced through a Matlab program with the help of an image process toolbox.

3.2 *Pre-processing of MRI images*

Downloaded Glioma MRI images are converted into.PNG image file format and the contrast of all the images is enhanced using the image processing toolbox of Matlab versionR2020a. After enhancing the quality of images, an image datastore is created using the Matlab Software. All the images are labeled and ground truth labels are generated for each image through the image labeling approach available in the Matlab image processing toolbox. A Ground Truth datastore is created with a Label "Glioma_Tumor". Few sample images are shown in figure 1.

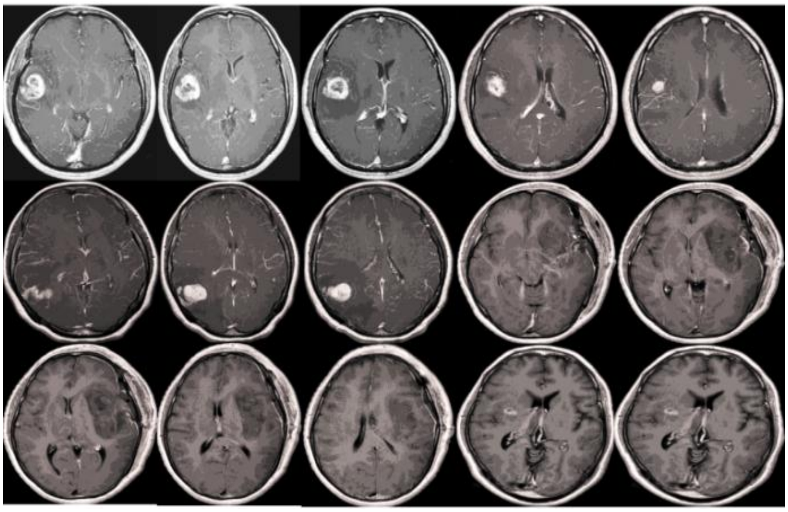

Figure 1. Glioma Tumor sample images [38].

3.3 *Pretrained Deep Networks for Glioma Tumor*

Pre-trained deep networks are the type of Convolutional neural networks widely used for object detection and classification in the application area of computer vision. The deep networks automatically extract the features with the approach of learnable parameters such as weights from the large volume of MRI image datasets.[13]. Faster Region-based Convolutional neural networks approach proposed and implemented by Ren et al. , have been used by computer scientists in the area of computer vision for object detection purposes. The desired features are extracted from the MRI images Through the deep networks, all the extorted features are fed into the Region Proposal Network [14]. In this research paper, deep networks such as Alexnet, Resnet18, Googlenet, and Resnet50 are selected and trained with the Faster R-CNN object detection approach. The labeled ground truth dataset of the original MRI image dataset is generated through the use of an image labeler app available in the Matlab version R2020a, and after that stored in a ground, truth labeled image datastore.

The Alextnet was designed and implemented by Alexander Krizhevsky with his team and was trained on large datasets such as imageNet. It was the first Deep network designed for computer vision applications in the year 2012. The network was designed with five Convolutional layers and three fully connected layers with additional layers such as the Batchnormalization layer, the ReLU layer, the softmax layer, and the classification layer [21]. In the proposed method, the Resnet18 deep network is used as the second deep network to extract the necessary features through the Convolutional process. Resnet18 pre-trained network designed with 18 layers known as the residual deep network was trained on a large volume of images is capable to classify the 1000 image categories. It was trained on the images of size 224 into 224. Through the long training process network has been learning a wide range of futures using learnable hyper-parameters. The last layer of the resnet18 deep network is named as "ClassificationLayer_predictions" as an output layer [13].

The Resnet50 pre-trained Convolutional neural network is selected in the purposed research works based on image classification and object detection performance obtained in the ILSVRC 2015 classification challenge. This deep network has been built with 50 layers to extract the valuable features through various Convolutional operations with different size of filters/kernels [35].

The Googlenet is the fourth deep network chosen in the proposed research study for Glioma tumor detection. Googlenet deep network was designed with 22 layers for feature extraction and the 27 layers for downsampling including additional layers such as fully connoted layers and a classification layer[36]. The deep network Googlenet was designed and implemented by the researchers at Google having collaboration with various universities. The researchers were participated with designed architecture in the ILSVRC 2014 image classification challenge and secured the first position. The classification error rate of the proposed model was very less as compared to the other contemporary models. The concept of 1x1 convolution operation in the middle of the designed architecture with global average pooling for down-sampling was introduced the first time in the deep network [36].

In this research study, selected four deep networks as described above are trained through the Faster Region-based convolutional neural network object detection approach using the ground truth labeled images to extract the features of original MRI images. After extracting the region of interest including valuable features from the labeled image files, the two sub-networks are used for object detection based on the outcomes of the pre-trained deep networks by the Faster R-CNN method. After the completion of the feature extraction process through pre-trained deep networks, the extracted features are used as input for Region Proposal Networks to get the object proposals [13]. The object of interest exists inside the object proposals that are found inside the labeled images. The desired class of the object is predicted based on outputs produced through the RPNs[13]. Regions proposal network introduced with the Faster R-CNN approach is a very important convolutional neural network used by many researchers for object detection within a scene.

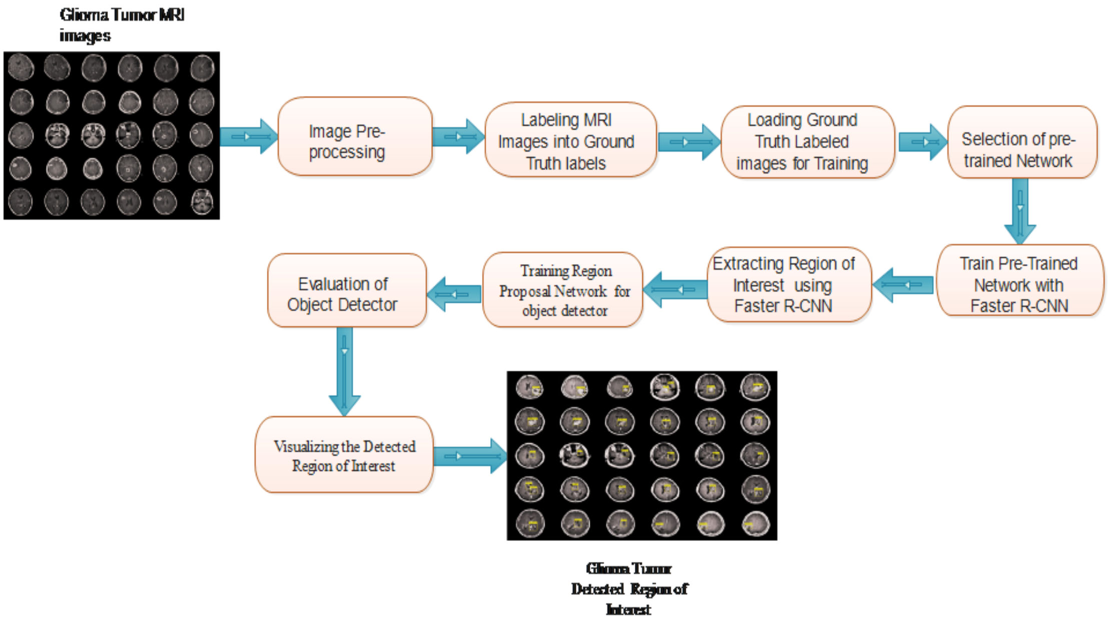

Figure 2. Proposed Glioma Tumor Detection process.

The bounding boxes with the probability of detection are drawn within the image showing the region of interest (ROI) by evaluating an object detector trained using the Region Proposal Network. The performance of the proposed models for glioma tumor detection is measured based on infected area detection with higher accuracy and precision. The performance matrices such as precision, recall, Mini-batch accuracy concerning Mini-batch loss, and Region Proposal Network accuracy are used to evaluate the object detection models implemented through the four deep networks.

After each convolution process, the Rectified Linear Unit (ReLU) activation function is used to take positive values. In deep learning algorithms it's the most widely used action function.

$$f(x) = max\,(0, wx + bias) \tag{1}$$

Where w is the hyper-parameter consists of learnable weights and the x is the value of the input in the form of a matrix. The performance of the models is measured through training as well as the testing period. The performance evaluation matrix such as precision indicates the accuracy of tumor detection based on the actual infected area and the infected area detected by the object detection model. The predicted values with positive results are divide by the overall sum of positive values and the values detected with false-positive results. It can be written in the following formula

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive}+\text{False Positive})} \tag{2}$$

The recall is one of another performance measurement parameters generally used in the machine learning field to evaluate the performance of the implemented model. This is the ration of positively predicted outcomes concerning the sum of positively predicted outcomes and false negatively predicted outcomes. the recall is calculated using formula 3 as shown below.

$$Recall = \frac{TruePositive}{(True\ Positive+False\ Negative)} \tag{3}$$

4. Experimental Setup and Results

The proposed models for the tumor detection are implemented on the computer system of HP Z6 Workstation with Windows 10 pro 64 bit for Workstation. The computing system is equipped with two Intel Xeon Silver 4110 central processor units having 2.1 GHz. Computing frequencies and 32GB main memory [37]. The System is also equipped with the Quadro P5000 GPU (Graphics Processing Unit) of NVIDIA having the 16GB GDDR5X GPU main memory. The GPU consists of 2560 CUDA Cores and 8.9 Teraflops Computing power for floating-point operations [38].

All the pre-trained deep networks are implemented using the Matlab programming environment with available toolboxes such as deep learning and computer vision in Matlab version R2020a [14]. The optimizer Stochastic Gradient Descent Momentum (SGDM) is used as one of the training choices. SGDM is one of the very popular optimization algorithm used to train the object detection and classification model based on convolutional neural networks.

There are 1426 MRI images of Glioma tumors in the Dataset. All the images are labeled with label name as "Glioma Tumor" in the form of a rectangular region of interest using the image labeler method in Matlab version R2020a with ground truth labels. The ground truth labels obtained after labeling the MRI images are stored in the .mat file format for further processing.

In the Matlab programming environment, the ground-truth labels are loaded. The gTruth value is created with three data values such as data source, Label Description table, and ground truth Label data stored in a table form after loading the ground truth labels. Ground truth labeled image dataset is further divided into two sets such as training dataset and testing dataset. The training dataset is used to train the deep network and the testing dataset is used to detect the object of interest.

First of all four pre-trained deep networks are trained through the transfer learning approach considering the various learnable parameters. In the next step of tumor detection, the Region Proposal Network is trained with extracted features gathered from the first step of training. Through the training process, RPN produces the region of interest with two possible outcomes such as tumor or background. The last step of the tumor detection approach detects the tumor to draw the bounding box around the tumor affected area.

4.1. Tumor Detection Through Deep Networks

All of the steps mentioned in section 4 are repeated to train the deep network AlexNet, Resenet18, Googlenet, and Resnet50.

4.1.1. Tumor Detection Through Alextnet Pre-trained Network

The pre-trained Alexnet network is trained on the aforementioned hardware. During the training cycle Negative overlap Range and positive overlap, range values are determined so that the testing samples closely align with the real rectangular ground truth area of interest. The pre-trained network such as Alexnet is trained through the Faster R-CNN object detection function with considering other training options e.g. learning rate, learning rate drop factor, maximum epochs, and mini-batch size.

The network is trained in 5 hours, 39 minutes, and 19 seconds. A training table consisting of Training Epochs, Iteration required for training, Time Elapsed, Mini-batch loss, Mini-batch accuracy, Mini-batch Root Mean Squared Error, Region Proposal Network Mini-batch accuracy, Region Proposal Mini-batch Root Mean Square Error and Base Learning Rate is generated after the completion of the training process with 80 epochs. The numerical values of precision and recall are calculated at every epoch during the training time of the pre-trained deep network. A graph plotted between precision and recall is shown below in figure 3. The values of precision are varying with respect to recall.

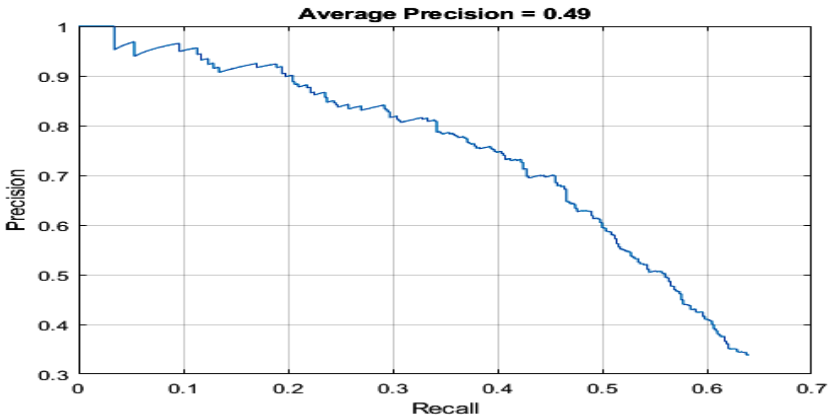

Figure 3. precision versus recall graph (Alexnet).

Figure 4 as shown below is plotted between mini-batch accuracy and mini-batch loss. It can be seen that the mini-batch accuracy during the training time is increasing with respect to the decline of the values of mini-batch loss.

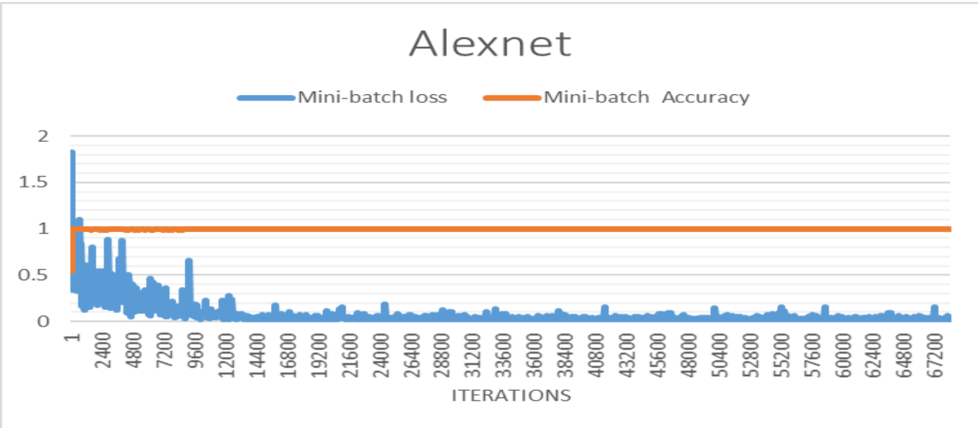

Figure 4. Mini-batch loss versus the Mini-batch Accuracy graph (Alexnet).

Mini-batch Root Mean Squared Error and Region Proposal Squared Errors are generated through the training process of the Alexnet network concerning each epoch. The graph between these two values is plotted as shown in Figure 5. Both values are decreasing during the training period.

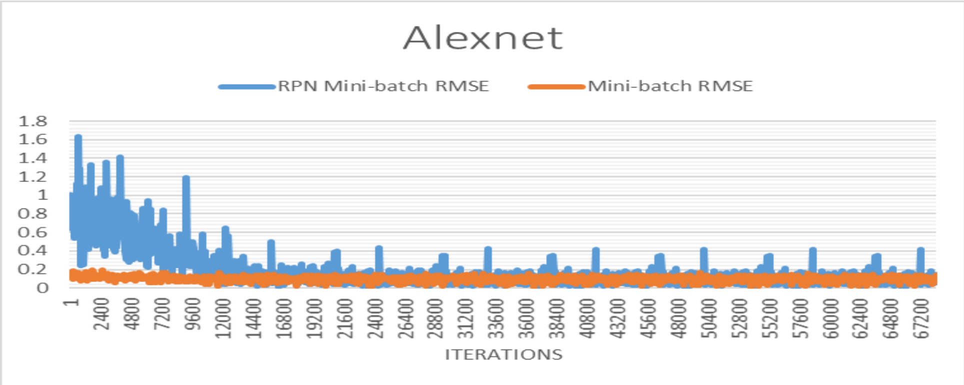

Figure 5. RPN Mini-batch RMSE versus Mini-batch RMSE graph (Alexnet).

It can be seen in figure 6 that the RPN Mini-batch accuracy and the Mini-batch accuracy of the pre-trained network are almost equal with a very little variation, during the training period.

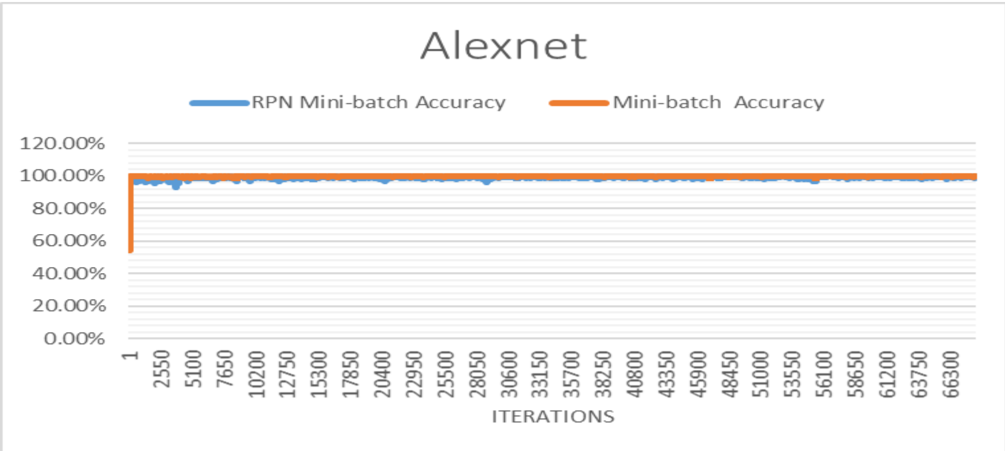

Figure 6. RPN Mini-batch Accuracy versus Mini-batch accuracy graph (Alexnet).

After the completion of the entire training process using a pre-trained network and Region Proposal Network an object detector model is built. This model is again tested on 48 MRI images of Glioma tumors. The Glioma tumor is detected with bounding boxes and detection probability, written inside each image.

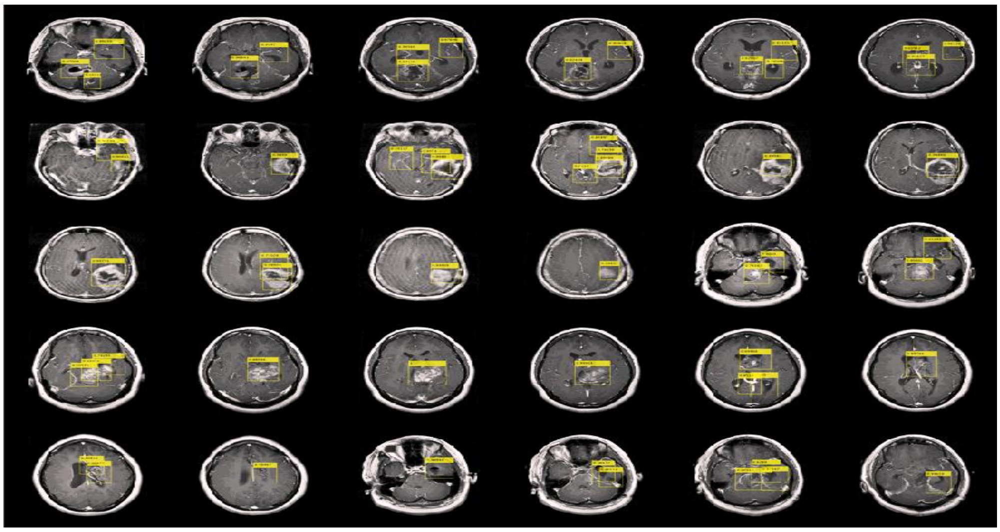

Figure 7. MRI Images with detected Glioma Tumor (Alexnet).

4.1.2. Tumor Detection Through Resnet18 Pre-trained Network.

The Resnet18 is a residual pre-trained deep network previously trained on RGB images is retrained with a Faster region-based Convolutional neural network on grayscale MRI images of Glioma tumor. The training process of Resnet18 deep network is finished in 25 hours, 42 minutes, and 02 seconds on the hardware platform as described above in section After the completion of the entire training process with 80 epochs, a table is created with attributes showing the accuracies and errors, as mentioned in the result section of Alexnet.

Again the values of precision and recall are generated through the entire training process. A graph is plotted between the precision and recall as shown in figure 8. The values of precision and recall are based on the detection of truly infected regions versus the background region with false-negative detected values. Mathematically the precision and recall are calculated using the formula (2) and (3). Resnet18 network is bigger than Alexnet pre-trained CNN.

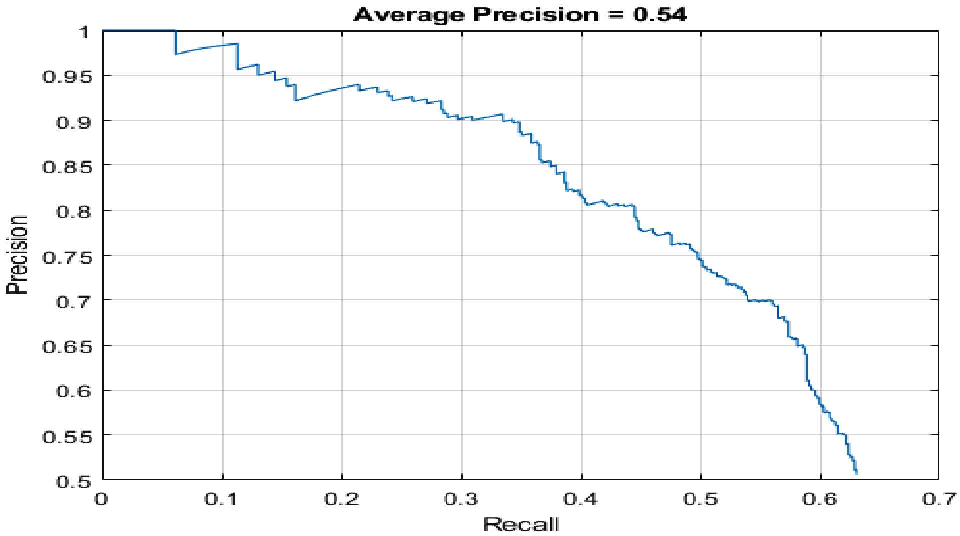

Figure 8. Precision versus recall graph (Resnet18).

Through the training process of this deep network, a training table is created after the completion of the training process with 80 epochs. The graph shown in figure 9 is plotted between the Mini-batch accuracy of the resnet18 network and corresponding mini-batch loss.

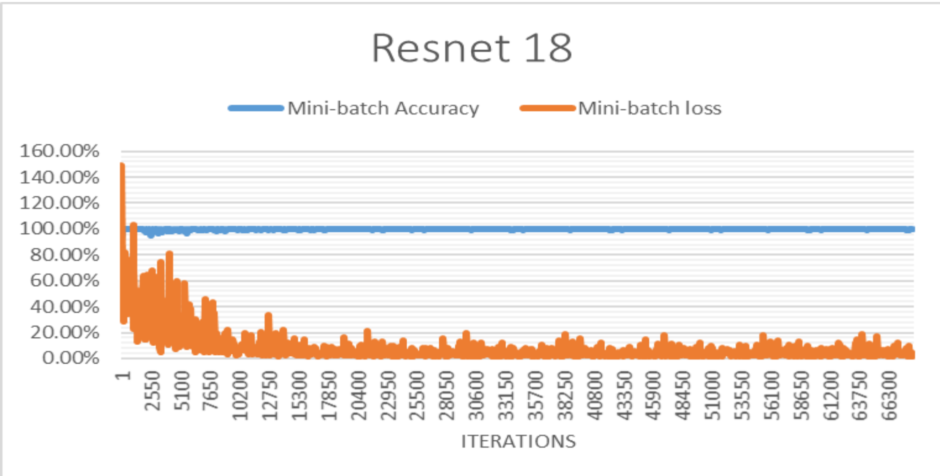

Figure 9. Mini-batch Accuracy versus Mini-batch loss (Resnet18).

The values of mini-batch Root Mean Squared errors are generated through the training process of the deep network and Region Proposal Network. İt can be seen that both the values are decreasing during the training period. A graph is plotted between both types of errors as shown in figure 10.

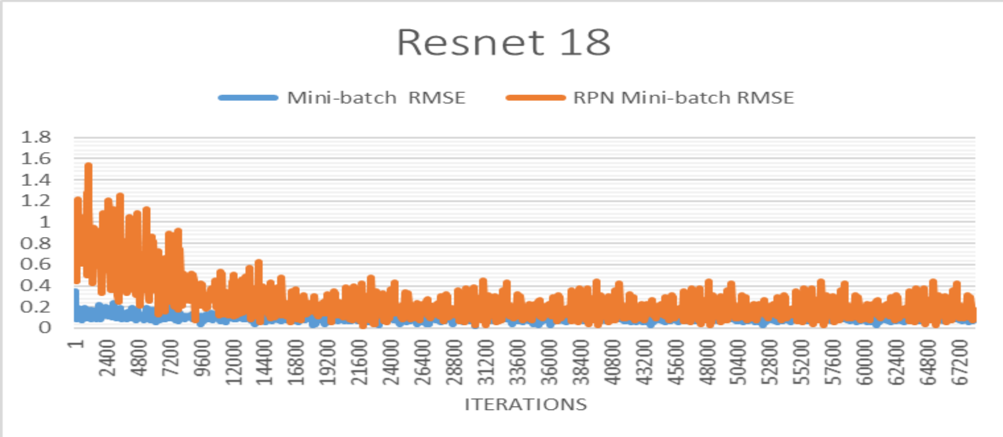

Figure 10. Mini-batch RMSE and RPN Mini-batch RMSE (Resnet18).

It can be seen through the graph as shown in figure 11, plotted between pre-trained residual deep network's mini-batch accuracy and the mini-batch accuracy of the RPN Convolutional neural network that the accuracies of both networks are varying with a very small change. Both curves are overlapping with each other.

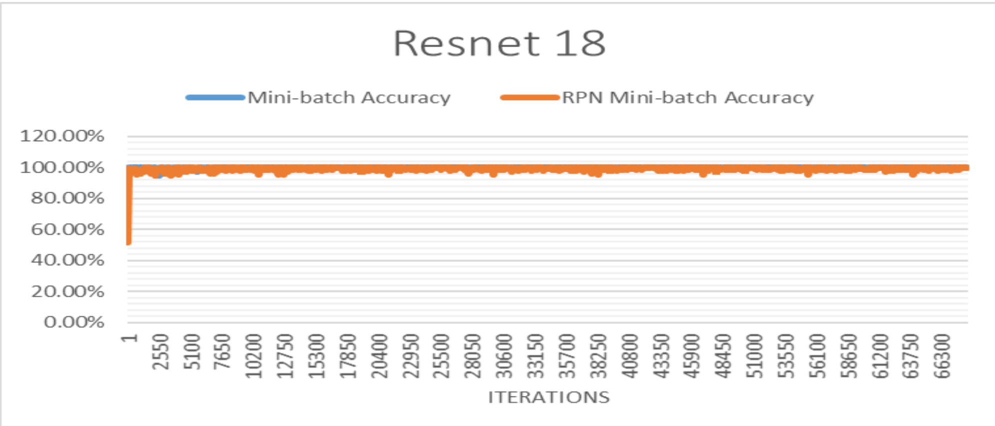

Figure 11. Mini-batch Accuracy versus RPN Mini-batch accuracy (Resnet18).

The Glioma tumor detection model built through the training process of Resnet18 deep network, Region Proposal Network, with the Faster R-CNN approach is tested on 48 MRI images of Glioma tumor. The testing process finished with creating the bounding boxes around a tumor infected area inside each MRI image with tumor detection probability.

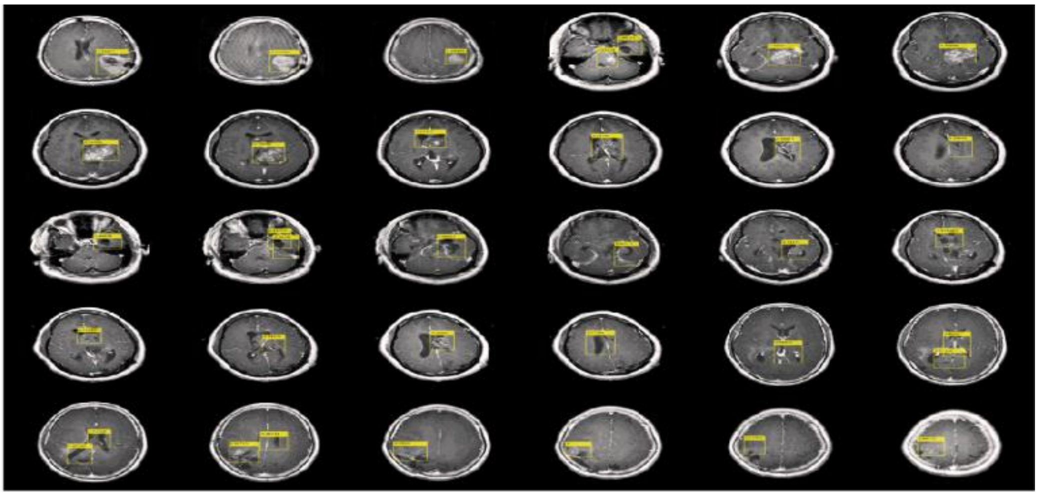

Figure 12. Glioma Tumor was detected through the detection model (Resnet18).

4.1.3. Tumor Detection Model through Resnet50 Pre-trained Deep Network

The third deep network selected for feature extraction from Glioma tumor MRI images is the Resnet50 Convolutional neural network. The deep network having 50 Convolutional layers is trained on the same hardware as used to train the Alexnet and Resnet18 networks. The DAGNetwork[14], in this proposed study, is retrained on the grayscale MRI images of Glioma tumor. A training table is developed by the training process which consists of the same fields as the table produced by the Resnet18 Training process[14]. Figure 13 below shows the graph plotted between Precision and Recall.

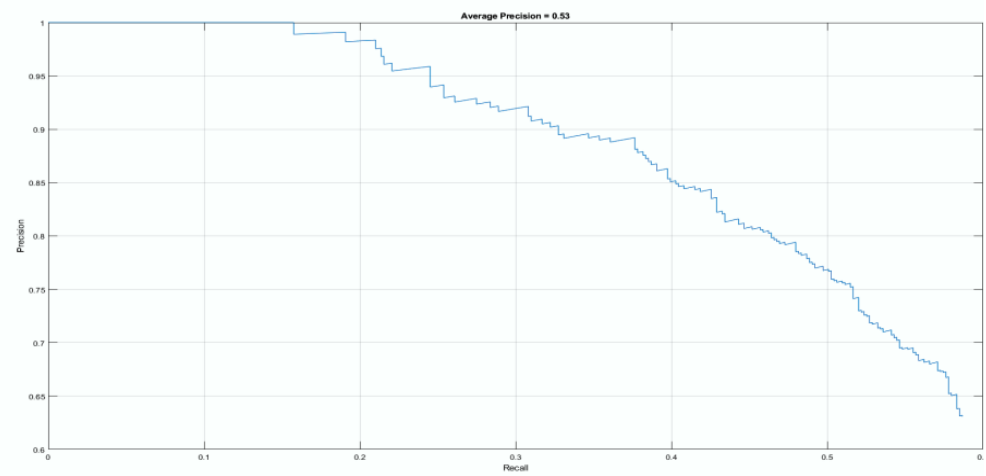

Figure 13. The graph between precision and recall (Resnet50).

Figure 14 below demonstrates the pre-trained deep network's Mini-batch accuracy and Mini-batch loss. The mini-batch accuracy of the model during the training period is not equal to 100 at every epoch, but the values are varying between 99 and 100. 100% training accuracy is obtained at the 80th epoch of the training process.

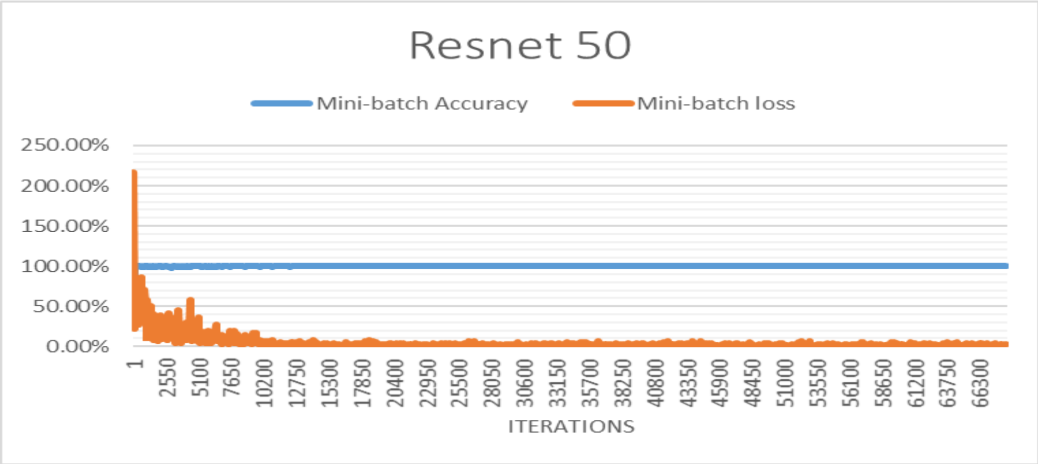

Figure 14. Mini-batch accuracy versus Mini-batch loss.

The graph shown in figure 15 is plotted between the Root Mean Squared Error generated during the training time for the pre-trained deep network as well as RPN convolutional neural network.

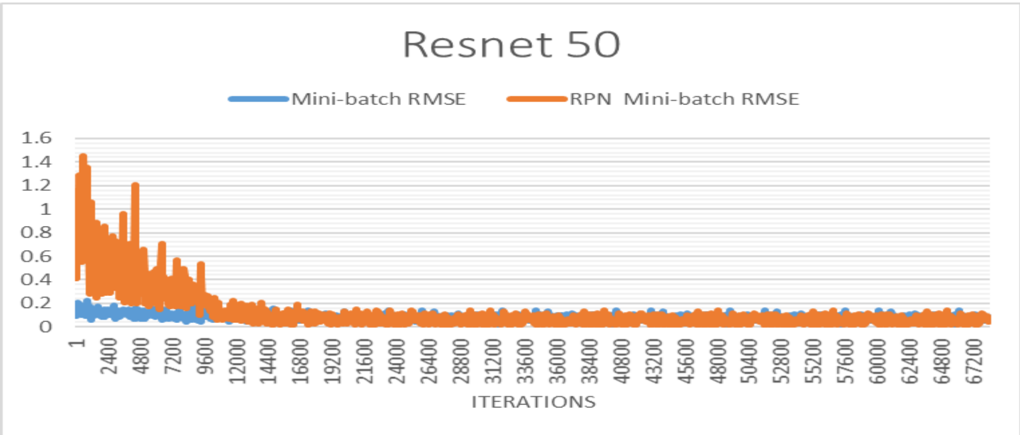

Figure 15. Mini-batches RMSE versus RPN Mini-batch RMSE.

Mini-batch accuracy and RPN Mini-batch accuracy values differ only slightly, as can be seen from figure 16.

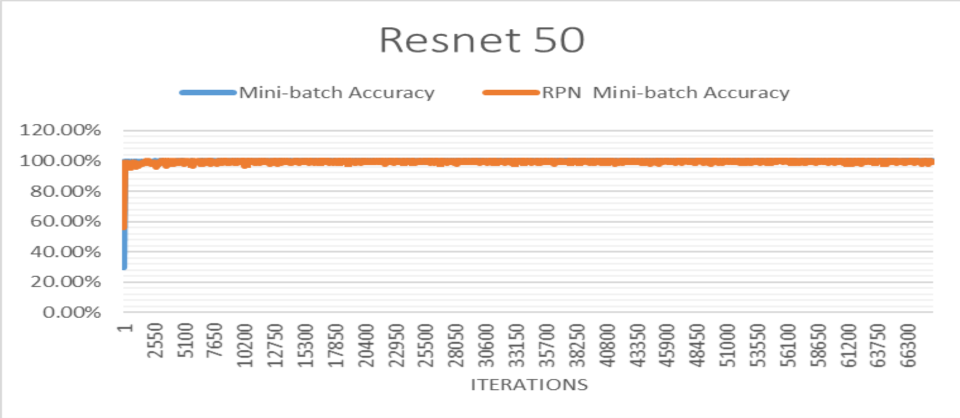

Figure. 16. Mini-batch Accuracy versus RPN Mini-batch Accuracy.

Glioma tumor detection accuracy of the tumor detection model built through the Faster R-CNN approach with Resnet50 pre-trained deep network is higher than the models developed with Alexnet and Resnet18 pre-trained networks. The built model is tested on 48 MRI images of Glioma tumors. The bounding boxes are created around the tumor infected area inside each MRI image with tumor detection probability. 30 MRI images with tumor detected areas are shown below in figure 17.

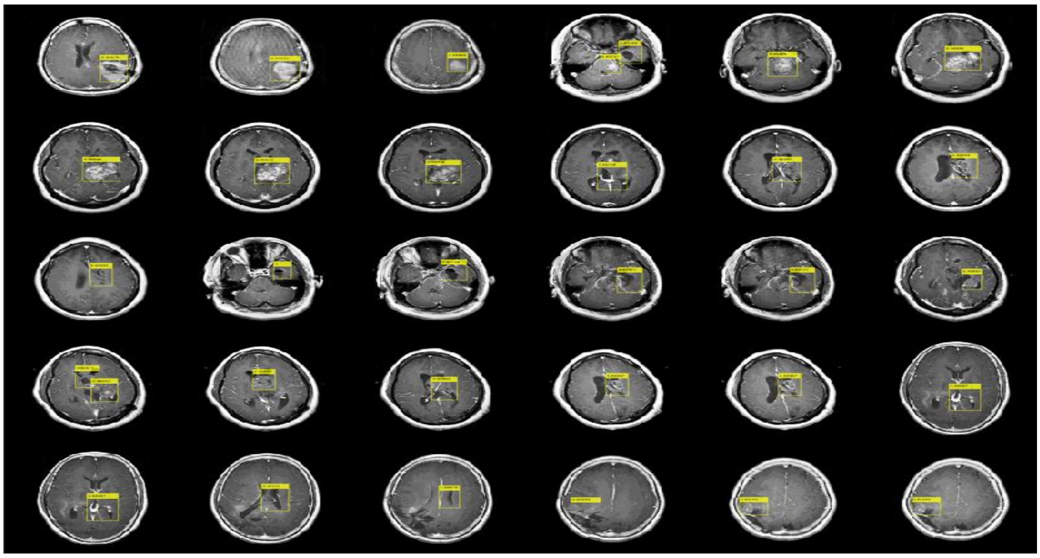

Figure 17. Glioma tumor infected regions with Resnet50.

4.1.4. Tumor Detection Model Through Googlenet Deep Network

The GoogleNet convolutional neural network is designed with 22 convolutional layers at the Google research lab. The network designers with this architecture participated in the 2014

ImageNet Large scale Visual Recognition Challenge, which was based on the classification of 1000 leaf-node categories.1.2 million RGB images were selected for the training, 50,000 images were selected for validation and 100, 000 images were selected for testing [37]. Through this deep architecture, researchers obtained a top-5 error of 6.67% during the validation stage and testing stage, placing first among others [36]. In this research study, Googlenet deep network is selected as a fourth pre-trained deep based on the classification and object detection performance in the 2014 ILVRS image classification challenge.

The convolutional neural network is retrained through the use of the Faster R-CNN object detection approach [15], on the ground labeled Glioma tumor grayscale MRI images. The labeled ground truth image dataset is split into an 855 training dataset and 571 test dataset. The training process is completed in 56 Hours, 41 Minutes, and 33 Seconds on the NVIDIA Quadro p5000 Graphics Processing Unit(GPU) with 16GB GDDR5X GPU memory and 2650 CUDA computing. The training process finished with resulting in an object detector. A table is generated after the completion of training resulting in many outputs as mention above in section 4.1.1, 4.1.2, and 4.1.3. The graph as shown below is plotted between precision and recall.

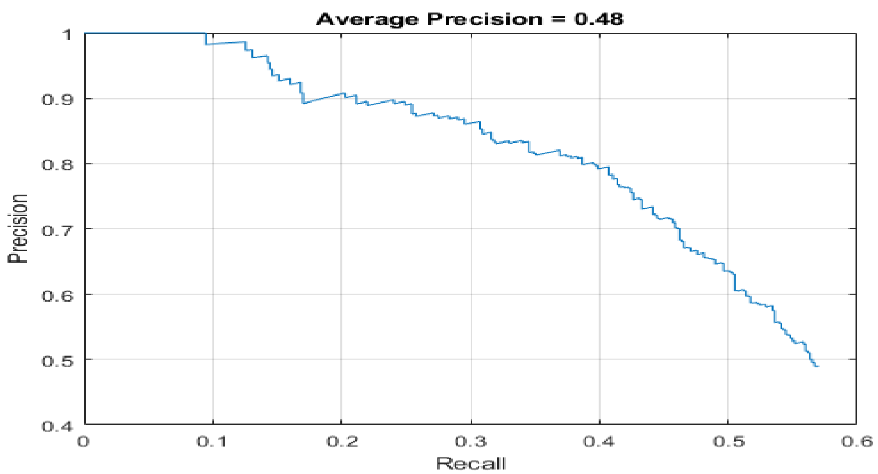

Figure 18. Average precision concerning the recall

Figure 19 as shown below indicates the pre-trained deep network's Mini-batch accuracy and Mini-batch loss, during the training phase of the deep network. The graph plotted in figure 19, shows that Mini-batch loss decreases in terms of increment in mini-batch accuracy.

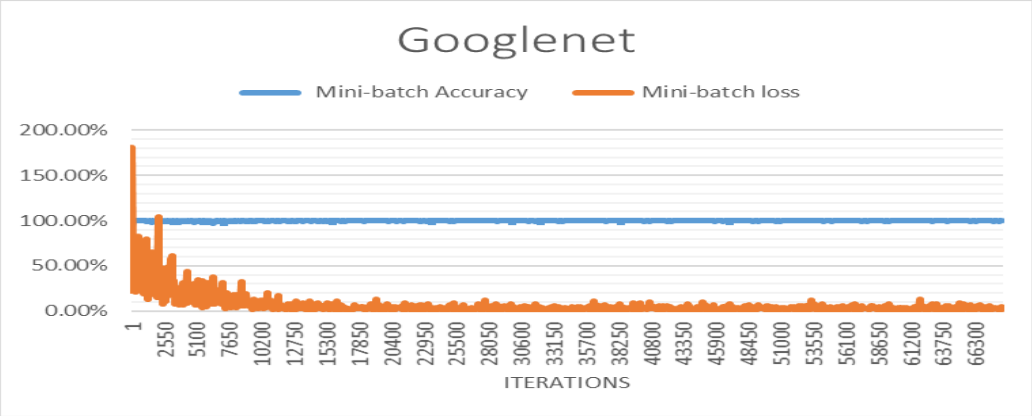

Figure 19. Mini-batch Accuracy versus Mini-batch loss.

Figure 20 is a graph plotted between the mini-batch Root Mean Squared Errors generated during the training time for Googlenet deep network and Region Proposal Network.

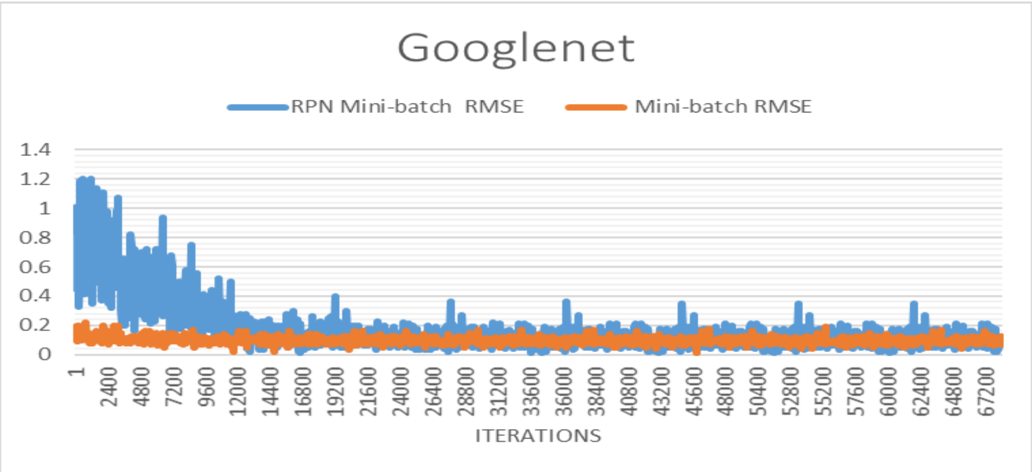

Figure 20. RPN Mini-batch RMSE versus Mini-batch RMSE

RPN Root Mean Squared Error is higher at the very start of the training phase but decreases with increasing iterations. Figure 21 shows the mini-batch accuracies for the Googlenet deep network and RPN convolutional neural network during the training period, as shown below.

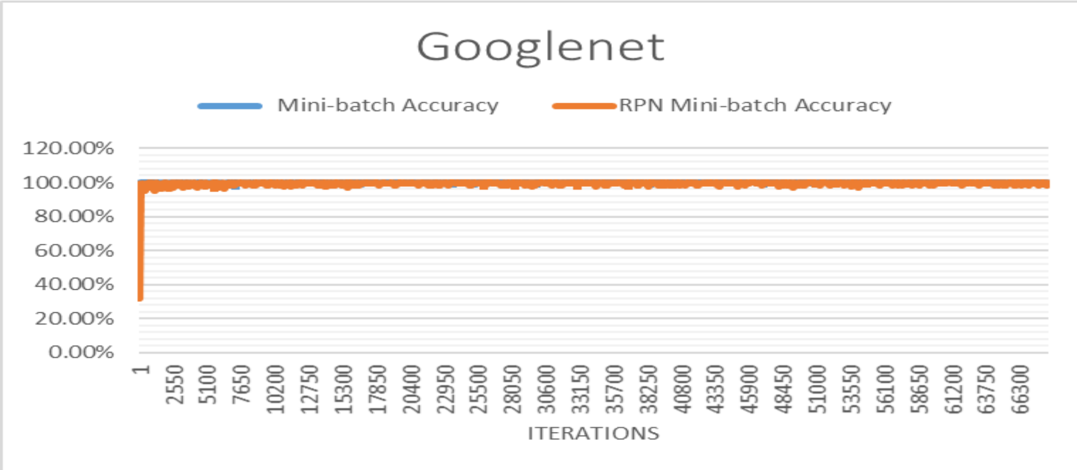

Figure 21. Mini-batch Accuracy versus RPN Mini-batch accuracy

On 48 Glioma tumor MRI images, the trained model is tested. The bounding boxes inside each MRI image are generated around the region infected by the tumor with the probability of tumor detection. 30 MRI images with tumor detected areas are shown below.

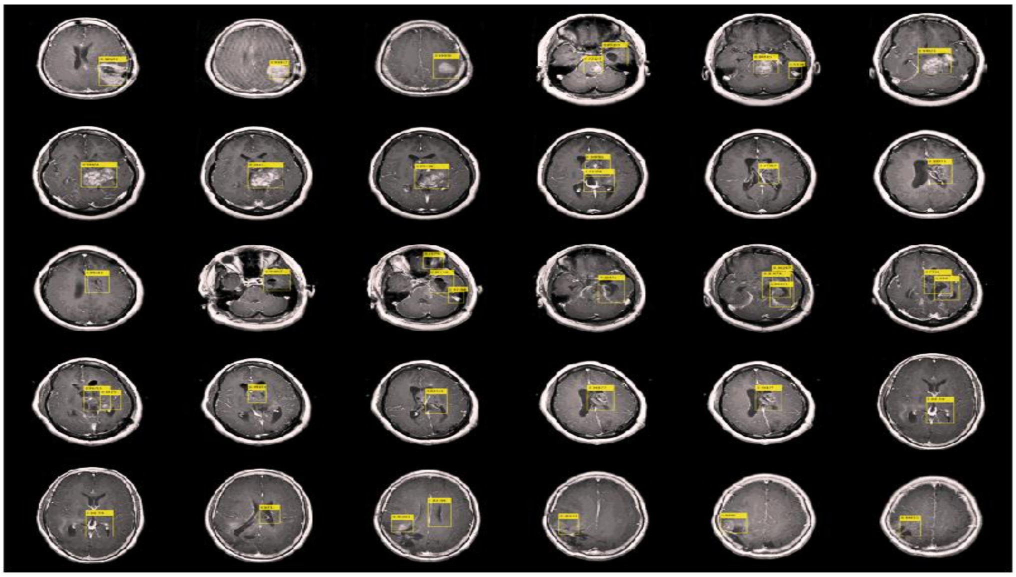

Figure 22. Glioma Tumor detected regions (Googlenet).

Table 1 Performance Comparisons

	Alexnet	Resnet18	Resnet50	Googlenet
Average Precision	0.599435	0.752767	0.817308	0.742977
Average Recall	0.459828	0.421836	0.366376	0.378445

The Glioma detection accuracy, precision, and recall values of all four pre-trained deep networks are created during the pre-trained network training process. Precision and recall values are produced through each period, and all values are determined on average. During the training phase of each pre-trained network, a table is created for precision and recall with other useful values also.

5. Conclusion

The object detection and classification both approaches are similar as explained by many researchers and academicians. İmages are categorized by the classification process based on features, but the detection of the infected area inside each image is related to object localization. The object detection task is a very complex process as compared to classification. Finding the object of interest within the image dataset is a challenging task. This research paper focused on transferring learning methods to offer more comprehensive brain disease recognition results.By comparing the object detection efficiency of four pre-trained deep networks, trained on grayscale images, it is found that the Alexnet convolutional neural network's tumor detection accuracy is lower than the other three deep networks.

The performance of all four pre-trained networks is compared using bounding boxes based on precision, recall, and detection accuracy. As compared with Alexnet, Resnet18, and Googlenet deep networks, the Resnet50 Deep network has a higher mean precision value. Through the testing of the Glioma tumor detection model, built with the Resnet50 deep network, it is found that more accurately bounding boxes are drawn on the infected area inside each image. The higher accuracy of object detection is achieved through the glioma tumor detection model that has been developed through the object detection approach of Faster R-CNN with the use of pre-trained deep networks. The tumor detection model can be used to identify damaged tissues for the real-life glioma tumor images. The proposed research study is more beneficial In the domain of medical image processing and disease diagnosis through automated systems. the future scope of the research study is not limited to the medical imaging area.

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