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Types of Brain Tumor Detection Using Novel Deep Learning

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Abstract: Even in a developed country like America the ratio of the number of hematologist and oncologist together to the number of people per doctor is 1:20,366. Then imagine how much it would be in the entire world? Medical industry has progressed tremendously over the past years and, specifically, the visual and image recognition is being used for many purposes, in many fields very actively. The general Artificial Intelligence (AI) topics, such as, Neural Networks (NN) and related concepts have also gained a lot of popularity lately. For this research, we have proposed a convolutional neural networks (CNN) architecture from scratch with data augmentation, image processing approaches, and neural network pattern recognition. We have compared the pre-existing architecture VGG-16 to our CNN model to determine if the CNN model was more suitable for these types of detection problems. Although, the data that we have used to train the model in our research is comparably small to any industrial application database, the proposed model displayed better accuracy and results than the VGG-16 for this kind of detection problem. Moreover, the proposed model uses less computational and memory power than the VGG-16 model. The secondary purpose of this research is to reduce the use of datasets that are from unrecognized sources. In this paper, we show how we can take the consent of the user and store the data to build a true data set for future educational and medical researchers and to retrain the models for better results.

Keywords: Neural Networks, data augmentation, image processing approaches

I. Introduction

In a human body, the brain is the most vital and sensitive organ. According to the National Brain Tumor Society (NBTS), it is estimated that 700,000 people in the United States alone are living with a primary brain tumor and around 84,170 more will be diagnosed in 2021 and 18,600 people are estimated to have died due to a tumor in 2021 [1]. Brain tumors are classified as two types namely, benign, and malignant. The tumors that are mostly found only in the brain and are non-cancerous and grow slowly are benign whereas malignant tumors are cancerous and spread across other parts of the body growing rapidly, it is fatal and dangerous. Meningiomas and Pituitary are benign kind of tumors that mostly do not spread across the body whereas Gliomas are malignant kind that accumulate as 78% of these kinds of tumors, they are most prevalent in adults [2]. In the figure below you can see the MRI scan of both benign and malignant tumor [3].

Any kind of brain tumor are diagnosed using several methods like Computerized tomography (CT) scans, Electroencephalograms (EEG) and Magnetic resonance imaging (MRI) scans, out of which MRI scans provide most detailed and feature based information. They use magnetic fields and radio frequency waves to generate the images of a particular part of the body.

Earlier even with computers and technology, it was tedious and time taking to diagnose a disease. In recent years, medical field as evolved rapidly with the help of latest technical advancements. Artificial Intelligence and Machine Learning has changed the take on many approaches, But, even with so much technology, many patients are dying and suffering; this is due to the number of oncologists according to the 2020 snapshot of ASCO (State of Cancer Care in America) being so low; figuratively around 12,940 [4]. These 12,940 oncologists are those who practice oncology as primary specialty and the number of patients with cancer are way more than that. It will take very long to get the appointment of one doctor and because of the criticality of the situation the patient will be eager to seek a second opinion all of this while suffering from tumor, which could lead to serious delay in treatment and may lead to fatality. Hence, we need much more precision and cutting-edge technology because it is a matter of lives. This research aims to come one step closer in reaching that by providing a CNN model that yields better results.

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Motivation: According to a study there are only around 12,490 oncologists in the US [4], that makes the ratio of the number of oncologists to the number of patients per oncologist to treat around 1:26,000. Apart from which getting second opinions will cause delays in treatment and overall effect will cost the patient heavily. This idea is what has driven me to do this research. Approximately around 18,600 deaths were estimated to occur due to brain tumors in the year 2020 in the United States alone.
There are a lot of CNN models available in the market. These models are pretrained and have a set of predetermined values that they use to do a task. We do not know if these general models that are available in the market give better results that a CNN model that is designed fully from scratch to fit a particular problem.
It is envisioned to ensure that patients have more time for the treatment, and they can cross-check their preliminary diagnose from the safety of their homes or any time that is feasible to them with their own eyes without any waiting or appointment from a different doctor.
In this research, we also take the consent of the user (it is not required for every user to give consent; they can use the software without it as well) and take their tumor related information and use it to further enhance the software and collect the true dataset for educational and medical research purposes.
We can hypothesize that instead of using a pre-existing CNN model, if a CNN model developed from scratch and designed it to accommodate for a particular model and not in general way, it may yield better results. In formal terms, this is our alternative hypothesis. Therefore, the null hypothesis can be stated as "Instead of using a pre- existing CNN model, if a CNN model developed from scratch and designed it to accommodate for a particular model and not in a general way, it may not yield better results."

II. Literature Review

Brain tumor is a very popular research topic but even though the intense research is being done on it, the death caused by tumors every year are consistent. So many classifications models are being proposed and experimented on in the field. Zahra Sobhaninia mentioned in their paper that they introduced a new method for CNN to automatically segment the types of brain tumors. Similar subject about breast cancer was discussed in a paper written by Cires [8] and one on classifying breast tissue density by Bosch [9], but Sobhaninia's paper shows that the separation of images based on an angle improves segmentation accuracy. She also mentioned in her paper that the technique used does not require any pre-processing. This method is said to have obtained 0.79 dice score. The relatively high score was achieved through the segmentation of tumors using Sagittal View images. Sagittal images don't contain information about other organs, and also, tumours are more noticeable in comparison to other pictures. The most minimal Dice score they measured in their studies was 0.71 which was associated with images from the axial perspective of the skull. In comparison to other images the axial view has smaller details. It is predicted that through pre-processing these images, a better classification of tumour-related pixels can be achieved in addition to this will result in a Dice score will rise. The method they propose could be utilized as a quick and efficient instrument for doctors to segment brain tumours on MRI images [1010.
Tonmoy Hossain showed in their research paper that segmentation of images plays an important part in image processing particularly in the medical field since there are different types of images and two other papers with similar findings are written by Summers who wrote focused on medical imaging and on lung diseases, however, an intriguing aspect is that they employ CT scans to accomplish this [111212. Image segmentation plays an important part in medical image processing since medical images are diverse in their diversity. MRI, as well as CT scans, are employed to segment brain tumours whereas MRI scans are utilized to more extensively classify brain tumours. According to Hossain that they employ FUZZY C Means clustering to aid in tumour segmentation that can identify the presence of tumours with precision. After the segmentation has been completed, it is then followed by a traditional classification as well as convolutional neural networks to serve as purposes of classification. In the classifier that is traditional, they employ various classifiers, including your nearest neighbour logistic regression, multilayer preceptor random forest, and the support machine. The classifiers listed above SVM provided the best accuracy of 92.42%And when coupled in conjunction with CNN the accuracy raised to 97.87 percent. The split ratio was of 80:20, with

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217 images, which is 80percent of the pictures used for training and 20 percent of test images. [13]. One other paper that talks about fuzzy weights and vector machine is “MRI brain classification using texture features, fuzzy weighting and support vector machine.” by Javed [14].
The paper orchestrated by Ming Li and the co-authors describes a method for three-dimensional MRI for the detection of brain tumours that are coupled with multi-modal information fusion, which makes use of convolution neural networks. The initial point to be covered in this paper is that the goal for 3-D CNN is to get three-dimensional images of brain tumours in an alternative modality and to discover the distinct information from the various moods. To address the issue of network conversions becoming slow, the information of characteristics of brain tumours is normalized [15]. A weight-loss function has been developed to lessen the impact of the detection of tumours in non-focal regions. This function is able to be developed to lessen the risk of the detection of brain tumours in these regions. The 3-D analysis of the routine brain tumour detection method in this study resulted in significant improvements in the overall better detection of brain tumours [16].
In a paper written by Hassan Ali Khan and team, they have mentioned the use ofVGG-16, Inception-v 3 and ResNet 50 to experiment with the detection of brain tumors [17]. It mentions that their CNN architecture is fit for problems of binary classification problem. One such other paper is written by Chung Where he describes the classificationof pulmonary nodules in a 2-D views [18] and some papers that emphasizes on a similar matter and works on 3-D images are written by Chen H., Jiang. [15] [19] [20].
In the book published by springer [21], it gives critical information about how to use the MRI scans for brain tumor detection. Similarly, Mr. Greenspan and his co- authors, have written about X-rays in their paper and who they can help categorize the organs and their location in the scans [22]. He also co-authored for another paper that addresses chest pathology identification using the deep learning [23]. Cheng J addressed in his 3 papers about region augmentation, structural segmentation, and spatial pooling which were helpful in the designing of the CNN model. We learned about various deep learning methods and neural networks technology and who they work when combined with other technologies from the papers written by Maki, Bengio, Cameiro, and Yang.
Some other applications of neural networks were showed in the conference proceedings and papers written by Weston, Joffe, John, Karpathy and Hinton G. These papers helped me during our research to gain insight about thefiner and detailed working of neural networks. Especially Hinton G.s writings, lectures, and even conference articles proved very useful; his research is mostly about learning algorithms and self-acting machines and systems. He even went deep about procedures that are used to improve machine learning, the algorithms that are used and provided information about the fine use of deep neural networks in his work

III. Materials And Methods

A CNN model basically consists of 3 major parts, namely, filter layers, padding layers and pooling layers. These layers are followed by a fully connected layer is where it learns the patterns that are extracted by the previous layers.

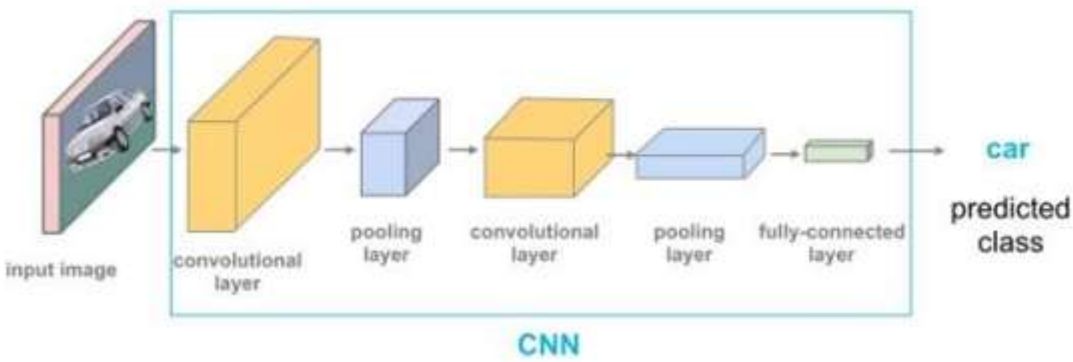

Figure 1: General CNN Architecture.

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VGG-16 is an open-source neural network architecture which was tested and experimented with previously, which won the ImageNet Challenge in 2014. It was published in the year 2015 by the Visual Geometry Group (VGG), University of Oxford [6]. The structure of a VGG-16 architecture is shown in the figure 2 below [7]. We can see that the architecture consists of 4 different types of layers. It is a pretrained CNN model.

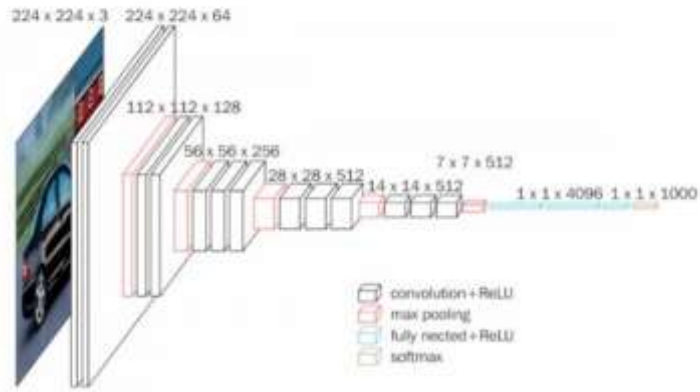

Figure 2: VGG-16 Model Architecture

In this paper, we have proposed a CNN architecture on a dataset that has 4 different types of tumor images, which are divided into 2 groups training and testing. The data was sourced from an open source available on the internet. This dataset contains a total of 3264 images accounting 962, 937, 901 and 500 images that respectively belong to glioma, meningioma, pituitary and no tumour datasets. These are further divided training and testing as mentioned in the table 1 and graphically represented in the figure below

Table 1: Data for the model

Type of images	**training**	**testing**	**total**
Glioma	826	100	**926**
Meningioma	822	115	**937**
Pituitary	**827**	**74**	**901**
No tumour present	**395**	**105**	**500**

Coming to the CNN Model itself, it is built from scratch and trained through 19 sequential layers in total. These layers are shown in figure 3, as we can observe there are 5 convolutional layers, 5 pooling layers, 5 dropout layers, 1 flattening layer and 3 dense layers accounting to a total of 19 layers as mentioned earlier which are performed in a sequential manner. These layers are shown in figure 3, as we can observe there are 5 convolutional layers, 5 pooling layers, 5 dropout layers, 1 flattening layer and 3 dense layers accounting to a total of 19 layers.

The size of the input image used is 224 × 224 which is reduced to 128 × 128. There are 2 kernel sizes that have been used in the entire model 5 × 5 and 3 × 3. A padding type same has been applied to each of the convolutional layers and the activation function ReLU was used.

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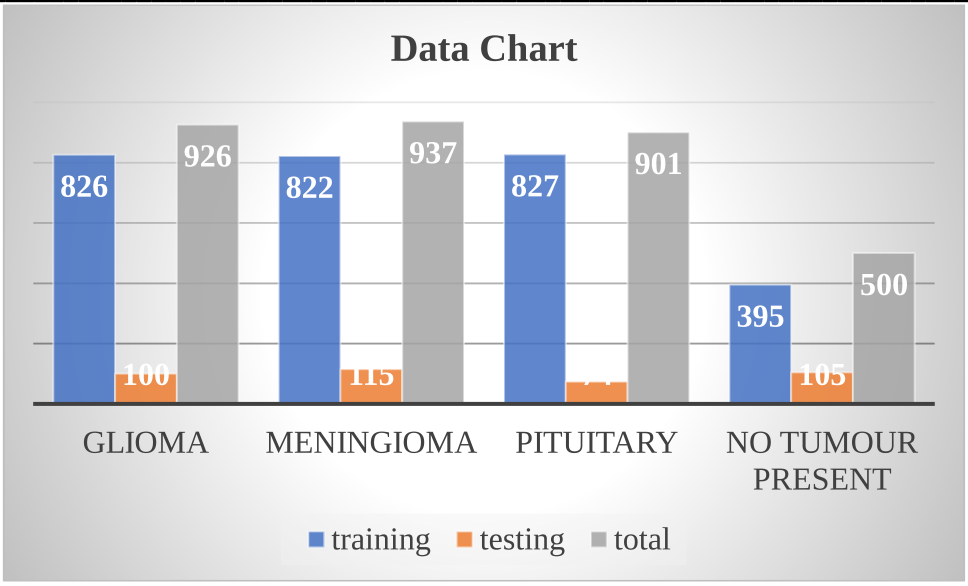

Figure 3: Data chart Analysis

An activation function is used to normalize the output of each neuron to a range of 1 and 0 or between -1 and 1. They are 2 types of activation functions, namely, linear, and non-linear which are further categorized. For this model, we used a non-linear, regression type of activation function Rectified Linear Unit, popularly used as ReLU. It has very efficient computationalism and it is not zero centered. It has a range of [0, ∞] and derivate :1, if x > 0 else 0. The ReLU function is derived as: f(x) = max (0, x). The activation function also initializes each neuron in the model. The padding function used in this model is "same" as mentioned above. This padding function is the "0" type padding function which means the input x is padded with zeros around it to match with the f(x). It uses the Max-pooling method in the pooling layer.

In this model, we use the categorical cross entropy for the loss function, as we are identifying multiple types of tumors. We can represent the categorical cross entropy in equation 1 & 2 and the Adam optimizer is used to optimizing the loss functions, represented in equation 3.

$$f(s)_i = \frac{e^{s_i}}{\sum_j^c e^{s_j}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

$$CE = -\sum_i^C t_i \log(f(s)_i) \ldots\ldots\ldots\ldots\ldots\ldots (2)$$

$$\theta_{t+1} = \theta - \frac{y}{\sqrt{\hat{v}}+g}\hat{m}_t \ldots\ldots\ldots\ldots\ldots\ldots (3)$$

where epsilon (ϵ) is a minute number that prevents the zero-division error and the η is the rate of learning of the range of different values. The methodology of CNN is shown in the figure 4, is followed in this research. First, the data is given as input to the model. It then undergoes image processing, specifically, reshaping and continues to the next step. The next step is data augmentation followed by feature extraction, here is where the CNN with the Adam optimizer is used. Next is classification, in this step neural networks are introduced, where the pattern learning takes place. Finally, the results are classified, as you can see in figure 4, they are classified into 4 0,1,2 and 3 which represent Glioma tumor, Meningioma tumor, No tumor and Pituitary tumor, respectively.

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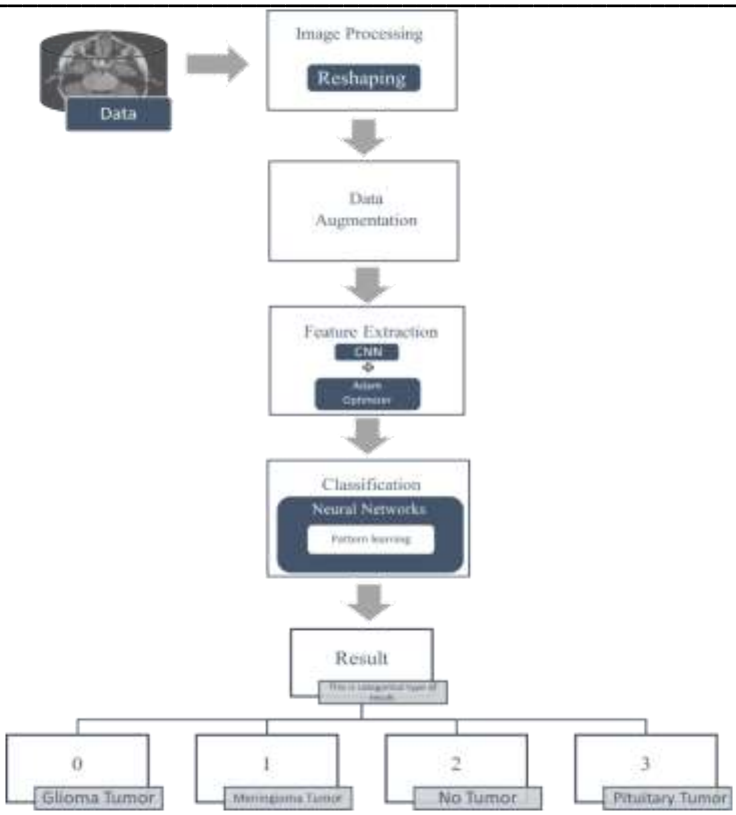

Figure 4: Methodology for CNN model

T test Scratched CNN model, we compare it with the pre-trained VGG-16 model on the same dataset that we gave as input to the proposed CNN model. VGG-16 was proposed in the year 2014 in the ImageNet Challenge by the Visual Geometry Group from University of Oxford, and it consists of 16 layers, hence, its name "VGG-16" as shown in figure 4 [43]. It is a large network with approximately 138 million parameters. It takes a 224 × 224 × 3 dimensions image as an input. It is designed for general purposes in image recognition, and we are comparing it to a scratched CNN model that has been designed particularly for this problem, so, we have made some changes to the pre-defined VGG-16 for producing better results.
As you can see in Figure 4, the model has been finetuned to have 24 layers instead of 16 for it to yield better results. We added dense layers to the VGG-16 architecture for better categorization, pattern recognition. Although we finetune the VGG-16 model to suit the problem, its function will be based on how well the feature recognition done by the convolutional layers that were pre-designed. We need to make sure that the model is not over or under fitting despite all the changes because it depends on the dataset as well

IV. Results and Discussions

After the CNN model was built from scratch, to fit the detection of types of brain tumors, we measured the parameters such as CPU power, memory power, the accuracy and the loss. We also plotted the confusion matrix. As mentioned in the section 3.2, the CNN model was model to have 19 layers, these layers are shown in figure 5, as we can observe there are 5 convolutional layers, 5 pooling layers, 5 dropout layers, 1 flattening layer and 3 dense layers accounting to a total of 19 layers as mentioned earlier which are performed in a sequential manner.
The evaluation methods that were used in this research are confusion matrix. A confusion matrix is used to evaluative a classification algorithm, it measures the classification rate and mis-classification rate. Classification rate, in simple words can be stated as the correct predictions that a model made whereas the mis-classification rate is the number of incorrect predictions. The confusion matrix for the scratched CNN model is plotted using the sklearn and matplotlib library functions in python. It is shown is the figure 5 below. We can calculate other parameters using the confusion matrix such as accuracy, precision, recall, f-1 score, TPR and FPR. These can be represented as equation that are given below Respectively.

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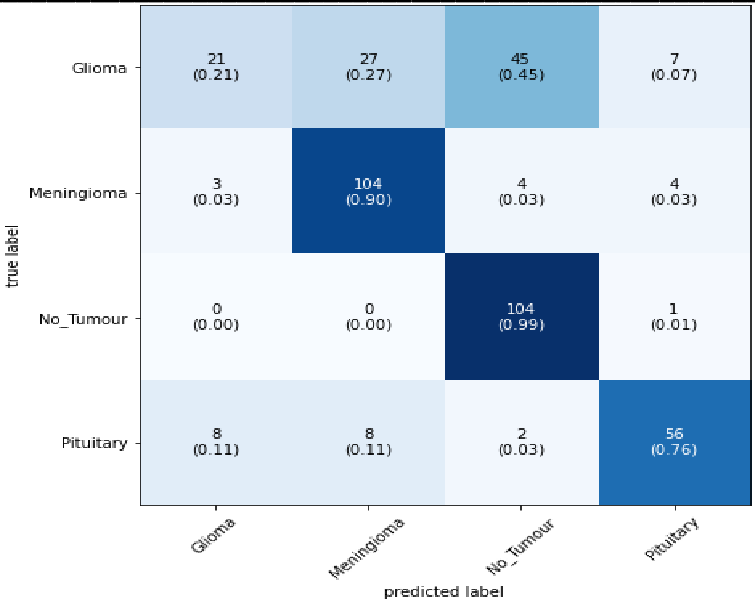

Figure 5: CNN Model Confusion Matrix

Accuracy= TP + TN/total No. of samples. Precision = TP/(TP+FP)
Recall = TP/ (TP + FN)
F1- Score = 2 × (Precision × Recall)/ (Precision + Recall) TruePositiveRate (TPR) = TP/ (TP+FP)
FalsePositiveRate (FPR) = FP/ (FP + TN) Were,
TP= TruePositive, FP = FalsePositive, TN =TrueNegative and FN= FalseNegative

We use the matplotlib python library to plot the loss function and accuracy as well. The figure 21 below shows the loss value graph of the CNN Model whereas the accuracy value graph is shown in figure 6.

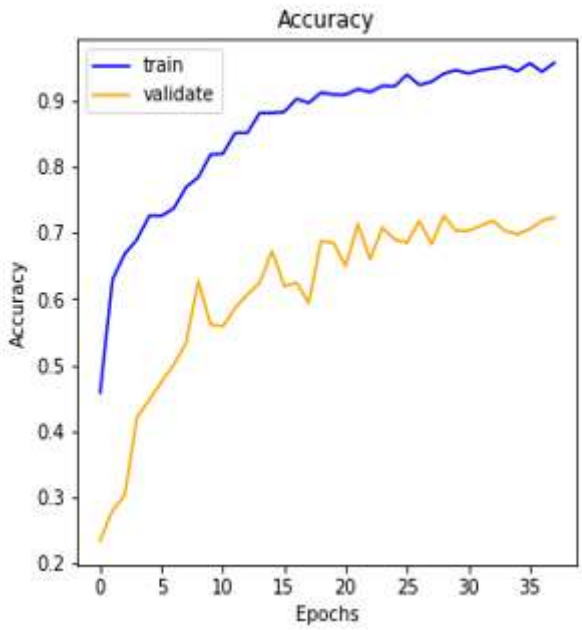

Figure 6: Accuracy of the CNN Model

We can notice that the VGG-16 model has 100% CPU utilization, and the speed of the system is 2.03 GHz, whereas the utilization of the CNN model is just 41% with the computational speed of 3.33 GHz. Hence, we can say that the CNN model uses less computational speed. The memory requirements of both models are shown in figures. We can notice that the VGG-16 model uses 9.8 GB of the RAM and the available space to run other programs is only 1.9 GB, whereas the utilization of the CNN model is 9.2 GB which is close to VGG-16 but the available space to run other programs is 2.5 GB.

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Table 2: Accuracy and Loss Table

Model	Accuracy	Loss
VGG-16	0.8721	0.3376
Scratched CNN	0.9622	0.1230

We can notice that the VGG-16 model gives 87.21% accuracy whereas the CNN model gives an accuracy of 96.22%. As we can notice, the corresponding losses in the table, we can observe that the scratched CNN performed well in both the aspects.

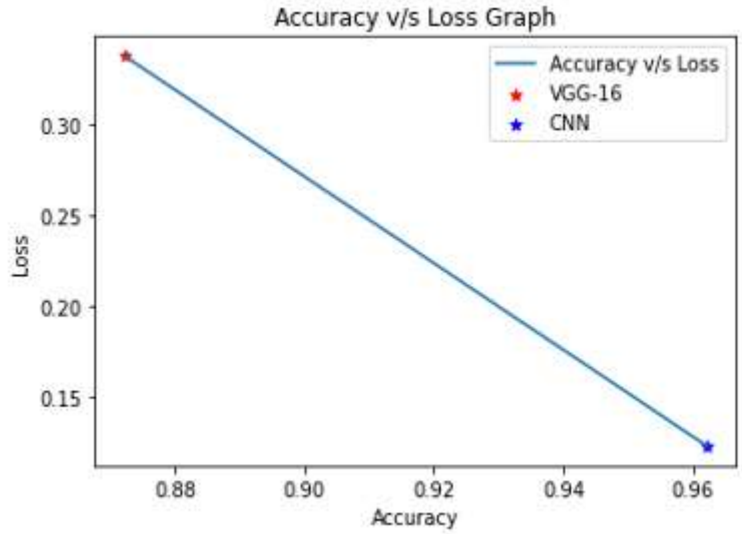

Figure 7: Accuracy v/s Loss Graph

V. Conclusion And Future Enhancements

In this research, a new method of approach was proposed to detect the types of brain tumors. First, we perform the image processing, where we reshape the input image. Second, using data augmentation technique to perform various actions like zooming the image, cropping it etc. The next step that follows is the feature extraction, this is the step where the CNN layers and the optimizer (in this case Adam optimizer). Before the result, there is one last step, classification step, in this step the neural networks are used to perform the pattern learning. The last step is the result itself; the neural networks give the result as 0,1,2 and 3 which are glioma, meningioma, no tumor and pituitary, respectively. Despite of having comparatively less data, the experimental results shows that we can attain good accuracy rate compared to VGG-16 model. So, the model in this research needs less computational and memory requirements.

This research can help play an important role in the detection of types of tumors in brain tumor patients. Also, this proposed system is for categorical classification problems, it detects 4 kinds for categories which include 3 types of tumors glioma, meningioma and pituitary, and no tumor which makes it unique. These kinds of problems can be solved in a more efficient manner if a model is built accommodating this kind of problem; a pretrained system might not be suitable as it is trained for a general purpose. Even the slightest increase in the accuracy can change the detection process where lives are at stake. The approach that has been built in this research can be accessible to use via web application from the safety of their homes, where the preliminary diagnosis can be validated by using this method. One more main importance of this research is to create a true dataset to use in the future, to use for R&D purposes in the medical and the educational field. We can prolong this research by further increasing the input dataset as well as testing this approach with other pretrained models like ResNet 50, VGG-19 etc., It can also be made accessible to use on the mobile devices, where people can check their results.

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