ADVANCED DEEP LEARNING ALGORITHMS AND BIOINFORMATICS TO IDENTIFY UNIQUE TYPES OF BRAIN TUMOURS

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Abstract: Integrative bioinformatics may be used to study the many different routes of nitroglycerine action in a range of malignancies to better understand how it effects tumours. Throughout our inquiry, we relied on public resources. This study's initial stage is to identify the genes that are linked together. The nitroglycerine target genes were discovered by the use of PubChem. The Closeness Coefficient and effect on cancers of 12 direct target genes were examined in a PPI network. The CluePedia App was used to study the activity of biomolecules in particular genes. There was no doubt about the connection between certain types of cancer and certain types of gene alterations. The PPI network was used to discover the types of tumours that were impacted by 12 target genes. Even in a developed country like the United States, where haematologists and oncologists are plentiful, there is a doctor-to-patient ratio of 1:20,366. Think about what it would entail if it were implemented worldwide. Recent years have seen tremendous advancements in the medical industry, and visual and image recognition technology is now widely used across various fields for a number of purposes. Artificial intelligence researchers have increasingly focused their attention on neural networks (NNs) and related concepts (AI). Data augmentation and image processing methods were used to build a convolutional neural network (CNN) for this investigation. Using the VGG-16 pre-existing architecture, the CNN model was compared to determine whether the CNN model was more suited for identifying these types of errors. It was shown that our model beat the VGG-16 in this detection test, even though we only used a little amount of training data. The VGG-16 model, on the other hand, consumes more memory and computational resources. This study also has the side benefit of reducing the amount of data derived from unidentified sources. Study shows how we can use permission from users to collect and preserve information for future educational and medical researchers and how we can retrain models to produce better results.

Keywords: Nitroglycerine, Neural Networks, data augmentation, image processing approaches

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I. Introduction

The brain's importance as the body's most vital and sensitive organ cannot be overstated. According to the National Brain Tumor Society (NBTS), around 700,000 people in the United States have a primary brain tumour, and an additional 84,170 people are predicted to be diagnosed in 2021 [1]. Brain tumours are classified as benign or malignant. The brain is home to benign tumours, which are noncancerous and develop slowly, while malignant tumours, which are cancerous and swiftly spread throughout the body, pose a major health concern. Malignant tumours, such as gliomas, are more frequent in adults than in children, accounting for 78% of all gliomas [2]. The images below show MRI scans of a benign and a malignant tumour [3]. CT, EEG, and MRI scans are used to identify any kind of brain tumour, but MRI scans give the most extensive and feature-based information. Images of a certain body part are generated using magnetic fields and radio frequency radiation.

Even with computers and technology, identifying a disease used to take a long time and be boring. Thanks to the latest technology advancements, the medical business has risen significantly during the last few years. Even though AI and machine learning have revolutionised many aspects of cancer therapy, a shortage of oncologists in the United States, as shown in the ASCO 2020 snapshot, continues to claim the lives of far too many patients (State of Cancer Care in America). Despite the fact that this list only includes oncologists that focus only on cancer, the total number of cancer patients is substantially higher. Patient's need for a second opinion may be due to the urgency of the issue, which may lead to lengthy treatments and even death for the patient fighting a tumour. Because the stakes are so high, more precision and cutting-edge technology are required. This study's purpose is to develop a better CNN model that will assist us in achieving that goal.

Motivation: It is estimated that there are only 12,490 oncologists practising in the United States. Given this figure, the ratio of patients that may be treated by a single oncologist is around 1:26,000. The patient's overall health and well-being will suffer as a direct result of getting a second opinion, which will also cause the treatment to be delayed. This line of thinking is what has inspired me to carry out this inquiry. By the year 2020, it is anticipated that brain tumours will be responsible for the deaths of around 18,600 people in the United States alone.

On the market today, you may choose from a few different CNN models. These models are pretrained with a predetermined value set so that they can carry out a certain task. We are unable to determine whether or whether CNNs that are tailor-made to solve a particular problem perform better than commercially available generic models.

If it is successful in its goal of providing patients with additional time for treatment and allowing them to cross-check their preliminary diagnosis from the comfort of their own home without having to wait for a visit from another doctor, then it will be a huge success. The patients will be able to cross-check their preliminary diagnosis without having to wait for a visit from another doctor.

When the user gives their permission to use their tumor-related information, which is not required; they are still able to use the software even if they do not give it, we use their information to further enhance the software and collect the true dataset for the purposes of educational or medical research, as well as to better understand how the software works.

Instead of using a CNN model that already exists, we may postulate that utilising a CNN model that was developed from scratch and customised it for a particular model, as opposed to a generic one, may produce better results. This would be done in place of utilising a pre-existing CNN model. In more technical language, this is our alternative theory. To put it another way, the null hypothesis may be stated as follows: "There is a possibility that developing a model from scratch would not provide better results in comparison to making use of a network that already exists."

II. Literature Review

The number of individuals who pass away each year as a direct consequence of brain tumours continues to stay the same, despite the fact that research into these tumours has become more popular. At this very moment, there is a dizzying array of classification schemes being devised and put through their paces in the realm of practise. According to Zahra Sobhaninia's findings in their research, they came up with an innovative method for CNN to automatically differentiate between the various types of brain tumours. Although Cires [8] and Bosch [9] both wrote articles on the subject of breast cancer, the study conducted by Sobhaninia illustrates that the accuracy of segmentation may be improved by viewing images from different angles. In addition, she said in her report that the technique that she utilised does not need any previous

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processing to be carried out. It is said that this tactic was utilised in order to get a dice score of 0.79. The score improved significantly once the tumours in the photographs were divided apart using the Sagittal View. Sagittal pictures make tumours simpler to see due to the fact that other organs are obscured from view, making them stand out more clearly. They discovered that images of the skull taken from an axial angle had the lowest Dice score (0.71), and these were the photographs that they utilised in their investigation. In comparison to other views, the axial perspective shows fewer individual characteristics. It is anticipated that the improvement in the classification of tumor-related pixels that would result from pre-processing these images will lead to an increase in the Dice score. [10] It is possible for physicians to apply the technique that has been suggested in order to swiftly and effectively segment brain tumours on MRI images.

Since there are many different kinds of pictures, the research article that Tonmoy Hossain and Summers conducted shown that image segmentation is an essential component of the whole process of image processing. This is especially true in the area of medicine. However, one of the most remarkable aspects is that they do this via the use of CT scans [11]. Image segmentation is essential in the processing of medical photographs because to the wide variety of medical images. In tandem with one another, MRI and CT scans are the diagnostic tools of choice for dividing up brain tumours. On the other hand, MRI scans are utilised to classify brain tumours in a more exhaustive way. According to Hossain, they make use of FUZZY C. An example of this would be the use of clustering as a tool to assist in the subdivision of tumours. Once the segmentation process is complete, the data is next classified using a combination of conventional classification methods and convolutional neural networks. A classical classifier makes use of several classifiers, such as your nearest neighbour logistic regression and multilayer preceptor random forest. With an accuracy rate of 79.42 percent, SVM has the lowest percentage of accuracy out of all of the classifiers that were tested. In addition, the accuracy rate increased to 97.87 percent when combined with CNN. [13] The ratio of training pictures to test images was 80:20, meaning that out of 217 shots, 80 percent were used for training and 20 percent were used for testing. The research conducted by Javed [14] and titled "MRI Brain Categorization Using Texture Characteristics, Fuzzy Weighting, and Support Vector Machine" addresses fuzzy weights and vector machines as well.

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An article written by Ming Li and his co-authors describes a method for identifying brain tumours using three-dimensional MRI that combines multi-modal information fusion with convolution neural networks. This method is referred to as the "three-dimensional MRI with multi-modal information fusion" technique. The starting point: 3-D CNNs are meant to gather 3D photos of brain tumours from a distinct modality in order to discover independent information from the many various moods. The characteristics of brain tumours have been standardised in order to address the issue of conversion times on networks becoming too slow [15]. A weight-loss function has been developed in order to lessen the impact that the discovery of non-focal tumours has. This capacity may be honed to lower the chance of detecting brain tumours in certain regions of the head. This study employed 3-D analysis to investigate a conventional method of brain tumour identification [16], with the goal of improving the accuracy with which brain tumours may be identified.

The use of VGG-16, Inception-v 3, and ResNet 50 for the detection of brain cancer was revealed in an article [17], which was authored by Hassan Ali Khan and his colleagues. It seems that problems associated with binary classification might be resolved using CNN's architecture. On the other hand, papers written by Chen H. and Jiang detail the classification of lung nodules using 2-D and 3-D photographs, respectively. These images were used. [15] [19] [20].

The book published by Springer [21] contains essential information about the use of MRI scans to the diagnosis of brain tumours. When it comes to X-ray imaging, the authors of this study state that they are able to assist in the categorization of the organs that can be seen in the pictures, in addition to the locations of the organs in relation to one another [22]. In addition to this, he was a co-author on another study that investigated the use of deep learning to diagnose chest pathology. [23]. Because Cheng J has written three publications on the subjects of augmentation of areas, structural segmentation, and spatial pooling, it is possible to create a CNN model using the information presented in those articles. Through their research, Maki, Bengio, Cameiro, and Yang were able to educate us on a wide range of deep learning methodologies as well as many forms of neural network technology.

Several fascinating uses of neural networks were shown in the papers that Weston, Joffe, John, and Karpathy wrote for the conference proceedings as well as the papers that they published. These studies supplied me with useful knowledge that I was able to employ in my own research to get a deeper comprehension of the atomic-level processes underlying the operation of neural networks. Reading Hinton G.'s books, speeches, and even conference papers, which deal with learning algorithms and self-operating devices and systems, was extremely beneficial. These materials may be found on his website. Deep neural networks, the processes involved in machine learning, and various algorithms were all topics that he covered in great depth in his work.

II. Materials And Methods

There are three primary elements that make up a CNN model: the filter layers, the padding layers, and the pooling layers. After these levels comes a totally connected layer, which studies the patterns that were present in the layers that came before it.

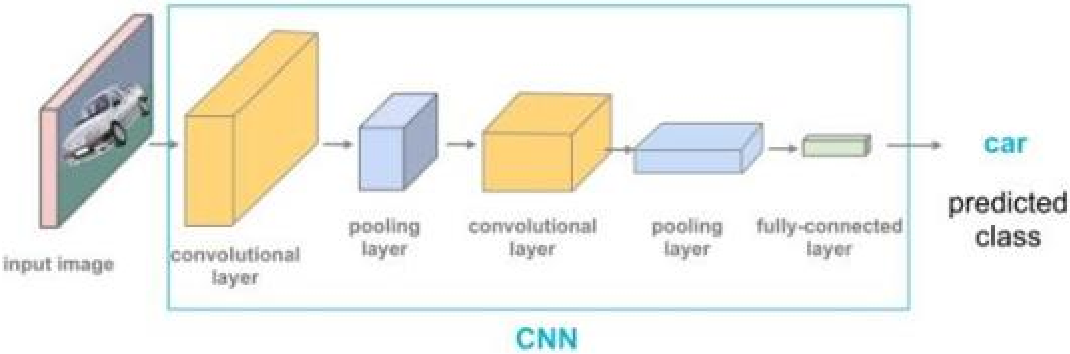

Figure 1: General CNN Architecture.

The open-source neural network architecture known as VGG-16 was used in the prior testing and experimentation, and it was successful enough to win the ImageNet Challenge in 2014. It was published in 2015 by the Visual Geometry Group (VGG), which is based out of the University of Oxford [6]. The structure of the VGG-16 architecture may be seen in Figure 2 [7]. It has come to our attention that the architecture is composed of a total of four floors. We make use of pre-trained CNN models.

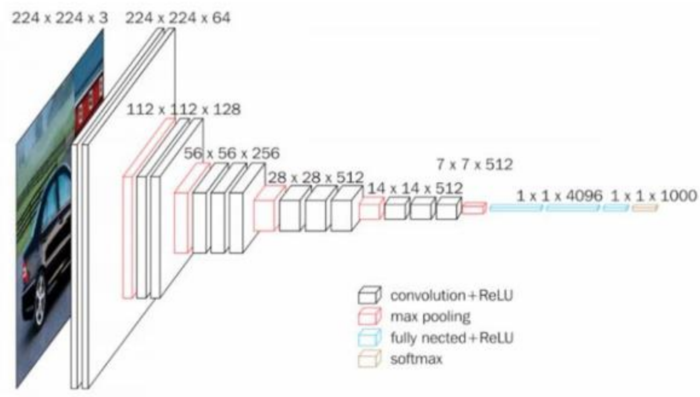

Figure 2: VGG-16 Model Architecture

An architecture for a CNN has been provided, and it is based on a dataset that contains four different types of tumour images. These images have been divided into two groups: one for training, and the other for testing. The information came from a source that was available to the general public. This collection has a total of 962, 937, 901 and 500 photographs. These correspond, respectively, to the dataset's glioma, meningioma, pituitary, and no tumour. As can be seen in Table 1, both training and testing may be further broken down into their respective training and testing categories.

Table 1: Data for the model

Type of images	Training	Testing	Total
Glioma	826	100	926
Meningioma	822	115	937
Pituitary	827	74	901

The CNN model, which is built from the ground up, has a total of 19 layers. As seen in figure 3, there are five convolutional layers, five pooling layers, five dropouts, one flattening, and three thick layers. One flattening level and three dense levels are illustrated in figure 3, with a total of 19 levels presented in total in figure 3. To save space, the original image was reduced to 128 × 128 pixels. There are two kernel sizes used in the model: five by five and three by three. A single padding type and the activation algorithm ReLU were used for all convolutional layers.

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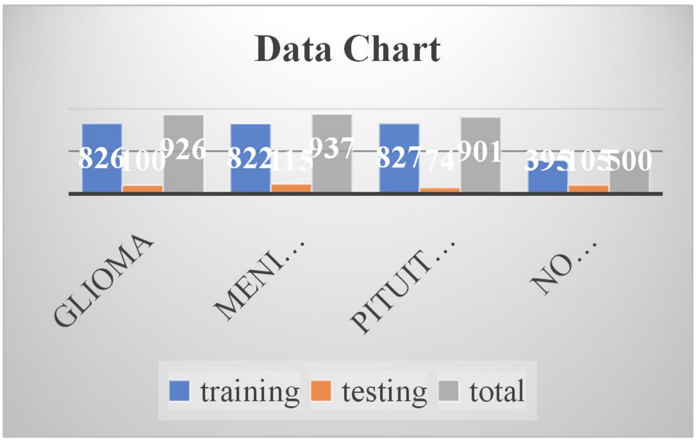

Figure 3: Data chart Analysis

An activation function is used to normalize the output of each neuron such that it falls within the range of 0 and 1 or -1 and 1. Linear and non-linear activation functions may be subdivided into a number of different subcategories. The Rectified Linear Unit, more often known as ReLU, is a regression-based activation function that we used in our model. It is not centered on zero and has a very effective computationalism. In the case when x exceeds 0 but is less than 1, the derivate is 1; otherwise, it is 0. Mathematically, the ReLU function can be expressed as f(x) = max (0, x). When the activation function is invoked, each neuron in the model is initialized as well. The padding function used in this model is "the same" as the padding function used in the preceding example. The input x is padded with zeros all the way around it such that it matches the f in this padding function of type "0." (x). It makes use of a technique known as Max-pooling in the pooling layer.

This model relies on the categorical cross entropy loss function to help us sort through the various types of cancer. Using equations 1 and 2, we can characterize the category cross entropy, and the Adam optimizer is used to optimize the loss functions, which are provided in equation 3.

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

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

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

when epsilon (ϵ) the rate at which a wide variety of unique values may be learnt is represented by the minuscule number that precludes the zero-division error. Figure 4

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shows CNN's approach used in this analysis, which can be accessed here. To begin, information is fed into the model as an input. Next, it goes through image processing, or more specifically, reshaping, before moving on to the next step. Data augmentation and feature extraction are the next steps, and the CNN and Adam optimizer are utilised at this stage in the process. Classification is the next stage, and here is where neural networks make their debut. In this stage, the patterns are really learned. Finally, the data is organised into groups. According to the results, which can be shown in figure 4, they may be divided into four groups: glioma tumour, meningioma tumour, no tumour, and pituitary tumour.

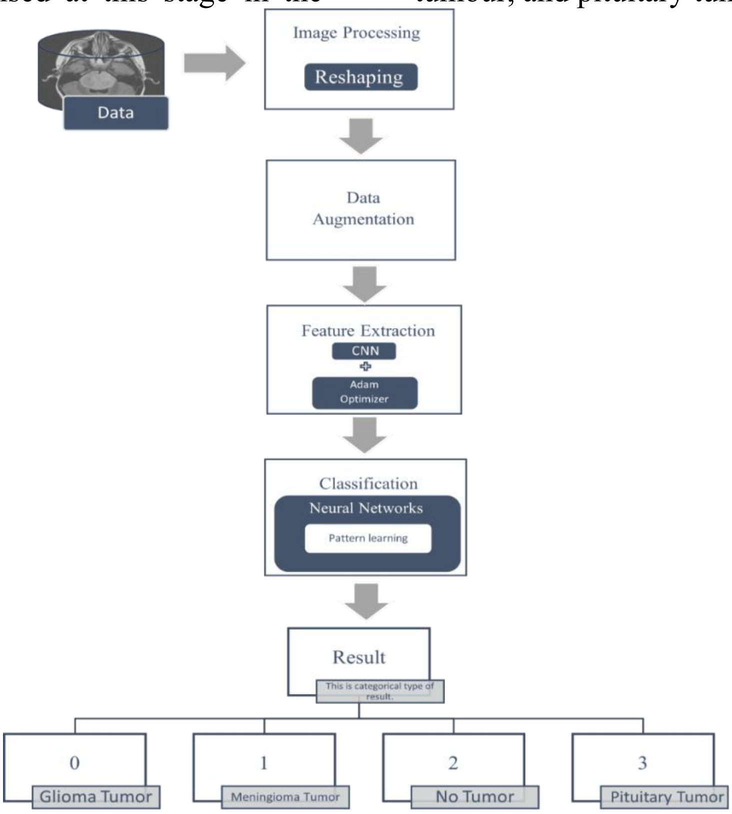

Figure 4: Methodology for CNN model

T is a certification exam. We compare the scratched CNN model to the VGG-16 model, which was pre-trained on the same dataset as the recommended CNN model. During the ImageNet Challenge in 2014, a team from University of Oxford's Visual Geometry Group (VGG) presented VGG-16, which includes sixteen layers, as seen in figure 4. The VGG-16 was called by the number of layers it had. – There are close to 138 million parameters in the network. It requires a 224x224x3-pixel image as an input source. A scratched CNN model is being used as a benchmark for this particular issue. As a consequence, we've tweaked the pre-defined VGG-16 a little to get better outcomes. We're comparing it against a model that was developed for general-purpose picture recognition.

Figure 4 shows how the model was changed to include 24 layers instead of 16 in order to produce more accurate outcomes. We increased the number of thick layers in the VGG-16 architecture to help in categorization and pattern recognition. It doesn't matter if we tweak the VGG-16 model slightly to make it more suited to the job at hand; the model's performance will ultimately be determined by how well the pre-designed convolutional layers identify features. Although we've made many changes, we still need to ensure that the model isn't overfitting or underfitting the data. This is due to the fact that the dataset is also used.

III. Results and Discussions

This model was built from scratch to identify different brain tumours, therefore it was reviewed and analysed for several characteristics like CPU power, memory power, error rate, and loss. Our team also drew a matrix of bewilderment. The CNN model, which was detailed above, was built with a total of 19 layers. As can be seen in Figure 5, there are a total of 19 layers, including 5 convolutional layers as well as 5 pooling layers, 5 dropout layers, 1 flattening layer, and 3 denser layers, all of which are carried out in order. The CNN model was modelled to have 19 layers.

This research included the use of the confusion matrix as one of its evaluation methods. A confusion matrix is used to measure a classification method's accuracy by measuring both the rate of accurate classification and the rate of wrong classification. Classification rate refers to the percentage of correct predictions made by a model, while misclassification rate refers to the percentage of incorrect predictions made by that model. The scratched CNN model's confusion matrix is plotted using Python's learn and matplotlib library methods. The scratched CNN model is used to produce this matrix. Figure 5 illustrates this point nicely. It is possible to determine other qualities such as accuracy and precision, recall and f-1 score with the use of the confusion matrix. Equations for each of these are provided below for your convenience.

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,

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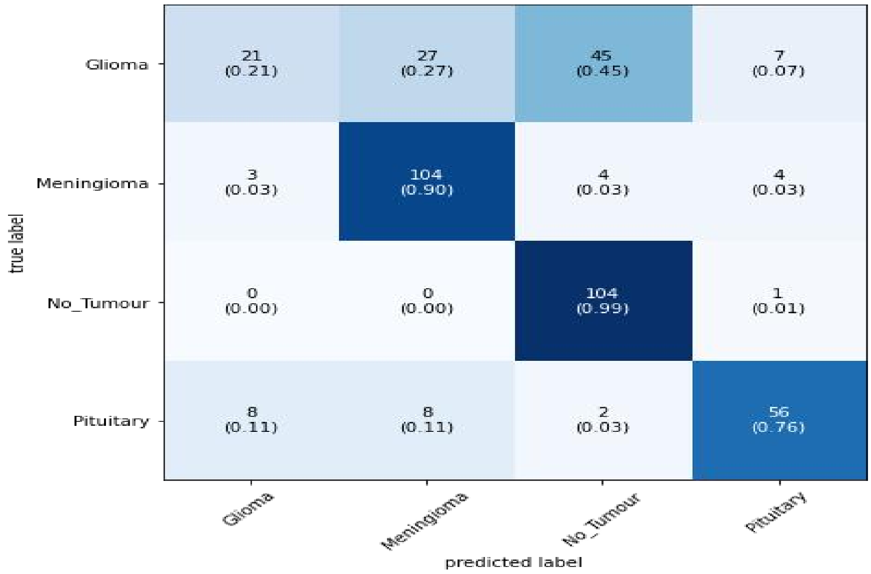

Figure 5: CNN Model Confusion Matrix

TP= TruePositive, FP = FalsePositive, TN =TrueNegative and FN= FalseNegative

When it comes to plotting the loss function as well as the accuracy, we make use of the matplotlib Python module. The accuracy value graph of the CNN Model is given in figure 6, while the loss value graph of the CNN Model can be seen below in figure 21.

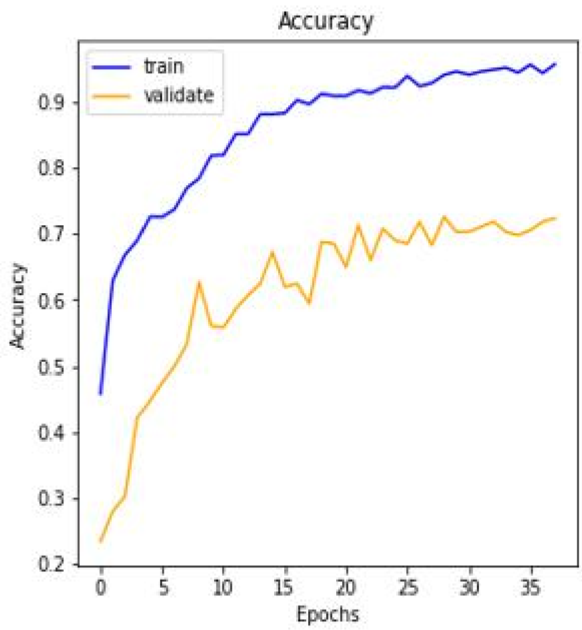

Figure 6: Accuracy of the CNN Model

Using the VGG-16 model, we can observe that the system is running at 2.03 GHz and making use of every available CPU resource. The CNN model, on the other hand, is only using 41% of its computational power and running at a

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speed of 3.33 GHz. It is therefore possible to claim that the CNN model takes less computing power. The figures show how much memory is required for each model. Even though the VGG-16 model makes use of 9.8 GB of RAM, there is only 1.9 GB of free space left for other applications to run in. When compared to a VGG-16 model, the CNN model uses 9.2 GB of RAM, yet there is still 2.5 GB of spare space to execute other applications. It is clear that the two models vary significantly.

Table 2: Accuracy and Loss Table

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

The VGG-16 model only provides an accuracy of 87.21 percent, but the CNN model provides an accuracy of 96.22 percent. This is something that we can see. The corresponding losses in the table allow us to make the observation that the scratched CNN did well in both of the aspects. This is something that we can witness.

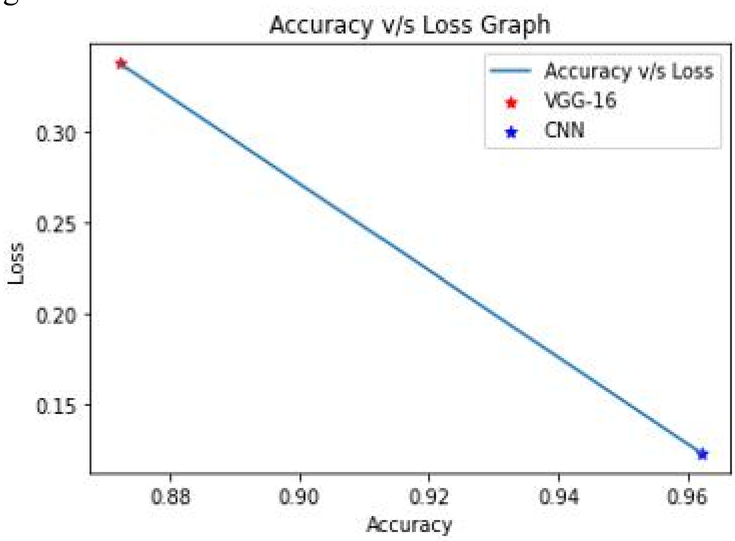

Figure 7: Accuracy v/s Loss Graph

IV. Conclusion And Future Enhancements

To better detect various types of brain tumours, researchers used the study's results to develop a new diagnostic technique. We'll begin by reshaping the supplied image using image processing. If you want to do things like cropping or zooming the image, you may do it through a technique called "data augmentation." This is when the Brain layers and the optimizer come into play (in this case Adam optimizer).

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Classification is the last step before the final result. Neural networks are used in this stage to carry out the pattern learning process. A value between 0 and 3 is used to indicate pituitary cancer, glioma, meningioma, or no tumour in the final step of neural network analysis. While our data is sparse compared to that of the VGG-16 model, the results show that we can still achieve a reasonable accuracy rate. As a result, the model employed in this work has reduced processing and memory needs.

Those with brain tumours may be able to benefit greatly from this finding, which has the potential to make a significant contribution to the field of cancer diagnostics. For categorization concerns, this proposed classification system is capable of identifying glioma and meningitis and pituitary malignancies as well as no tumours. This separates it from other comparable systems. This kind of issue may be tackled more effectively by constructing a model customized to the specific nature of the problem rather than using a system that has been pre-trained for a more general purpose. Even a little increase in detection accuracy may have a big impact on the final result. Individuals may utilize a computer application to verify a preliminary diagnosis made during this research from the comfort of their own homes, and the results will be published online. Furthermore, this study's production of a dataset that can be utilized for future research and development is another crucial reason why this research is so essential. Expanding the input dataset and testing this strategy with additional pretrained models, such as ResNet 50, VGG-19, and so on, might continue this investigation. A smartphone version may also be made available so that people could check their findings. One or both of these choices is a realistic path to progress in the profession.

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