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Use of Cutting-Edge Deep Learning Algorithms in Combination with Bioinformatics to Detect Rare Brain Tumors

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Abstract: Integrative bioinformatics can research nitro-glycerine's several pathways of action in various cancers to better understand its effects. 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. AI researchers are actively studying neural networks (NNs) and related ideas. This study employed data augmentation and image processing to develop a CNN. The CNN model was compared to the VGG-16 architecture to see whether it could detect these flaws better. Our model outperformed the VGG-16 in this detection test despite using minimal training data. However, the VGG-16 model uses more memory and compute. Reducing unidentifiable data is another advantage of this research. Study highlights how we may leverage user consent to gather and retain data for future educational and medical researchers and retrain algorithms for better outcomes.

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

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 photos below depict benign and malignant tumour MRI scans [3]. CT, EEG, and MRI scans may detect any brain cancer, but MRI scans provide the most detailed information. Magnetic fields and radio frequency radiation create body part images.

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 work aims to improve CNN models to help us achieve that objective.

Motivation: Only 12,490 US oncologists are estimated. This suggests that one oncologist can treat 1:26,000 people. 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

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perform better than commercially available generic models.

If it gives patients more time for therapy and lets them cross-check their preliminary diagnosis at home without waiting for another doctor, it will be a big success. Patients may verify their preliminary diagnosis without seeing another doctor.

If the user gives us permission to use their tumor-related information, which is optional; they can still use the software, we use it to improve the software, collect the true dataset for educational or medical research, and better understand how the software works.

A CNN model that was designed from scratch and adapted for a specific model may provide better results than a generic one. This replaces using a CNN model. Technically, this is our alternate hypothesis. 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 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] Doctors may use the recommended method to quickly and accurately segment brain tumours on MRI scans.

Tonmoy Hossain and summers' study piece showed that image segmentation is vital to image processing since there are various types of photos. This is particularly true in medicine. The fact that they employ CT scans is extraordinary [11]. Medical pictures are diverse, hence image segmentation is necessary. For brain tumour division, MRI and CT images are used together. However, MRI scans categorise brain malignancies more thoroughly. Hossain claims they utilise FUZZY C. Clustering helps subdivide tumours. The data is categorised using convolutional neural networks and standard classification techniques after segmentation. Classical classifiers employ closest neighbour logistic regression and multilayer preceptor random forest. SVM has the lowest accuracy of all classifiers examined at 79.42%. When paired with CNN, accuracy rose to 97.87 percent. [13] Out of 217 shots, 80 percent were utilised for training and 20 percent for testing. Javed [14]'s "MRI Brain Categorization Using Texture Characteristics, Fuzzy Weighting, and Support Vector Machine" discusses fuzzy weights and vector machines.

Ming Li and colleagues used multi-modal information fusion and convolution neural networks to diagnose brain tumours using three-dimensional MRI. This approach is called "three-dimensional MRI with multi-modal information fusion". Starting point: 3-D CNNs collect 3D brain tumour photographs from different modalities to get independent information from different moods. Standardising brain tumour features addresses sluggish network conversion times [15]. A weight-loss function was created to mitigate the effects of non-focal tumours.

. 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.

In [17], Hassan Ali Khan and colleagues disclosed the application of VGG-16, Inception-v 3, and ResNet 50 for brain cancer identification. CNN's design may overcome binary classification issues. Chen and Jiang's works classify lung nodules using 2-D and 3-D images, respectively.

The Springer book [21] provides crucial information on brain tumour diagnosis using MRI images. This research claims that X-ray imaging may help categorise and locate organs [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.

In their conference proceedings and published publications, Weston, Joffe, John, and Karpathy demonstrated many intriguing neural network applications. These findings helped me understand neural network atomic-level mechanisms in my own study. Hinton G.'s publications, talks, and conference papers on learning algorithms and self-operating systems were very helpful.

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.

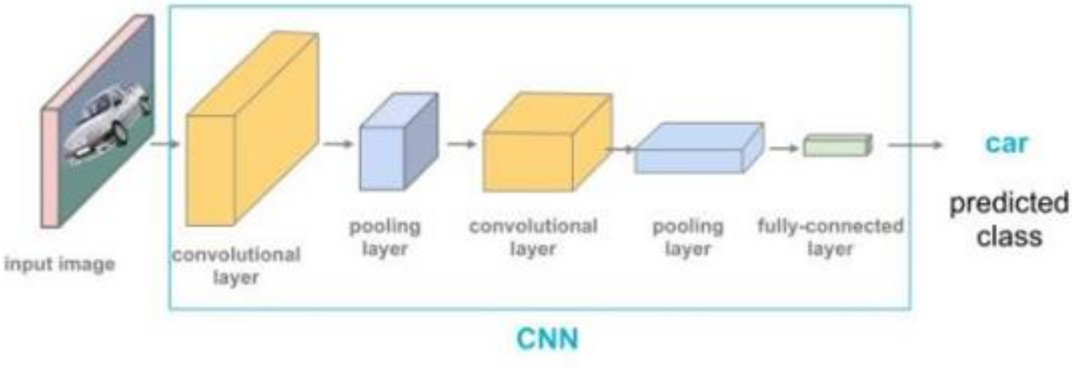

Figure 1: General CNN Architecture.

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.

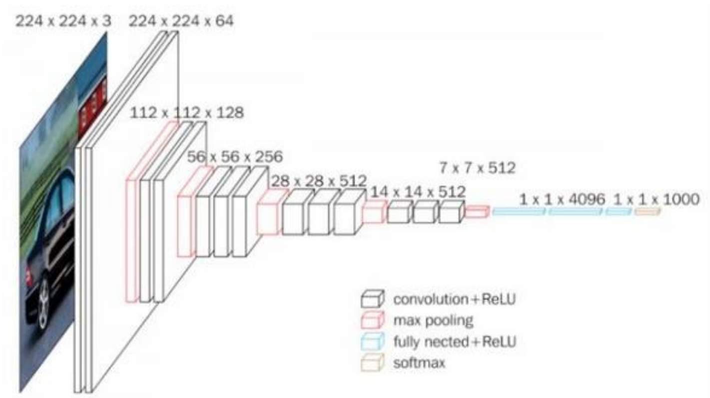

Figure 2: VGG-16 Model Architecture

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 has 19 layers and is constructed from scratch. Figure 3 shows five convolutional, five pooling, five dropout, one flattening, and three thick layers. Figure 3 shows one flattening and three dense levels, totalling 19 levels.

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.

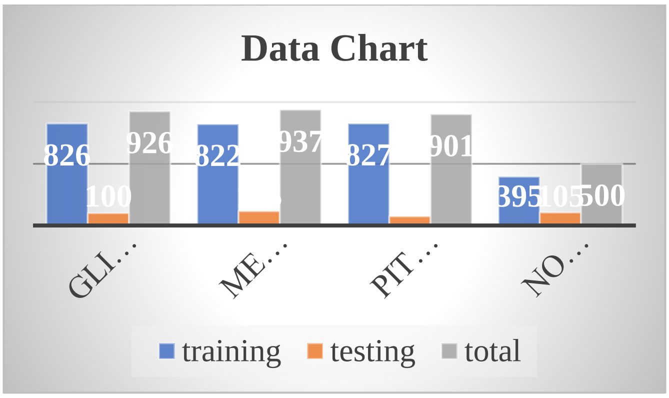

Figure 3: Data chart Analysis

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.

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

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

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

With epsilon (ϵ), the pace of learning unique values is represented by a small integer that prevents zero-division errors. Figure 4 demonstrates CNN's analytical method, available 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. Next, CNN and Adam optimizer are used for data augmentation and feature extraction. Next comes classification, when neural networks debut. This is when patterns are learnt. Finally, data is grouped. According to figure 4, they may be separated into four groups: glioma, meningioma, no tumour, and pituitary tumour.

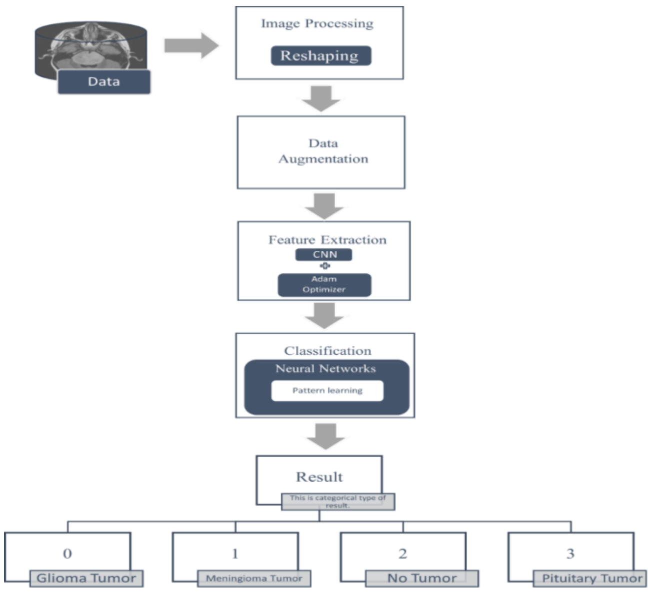

Figure 4: Methodology for CNN model

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 19-layer CNN model was described above. Figure 5 shows the 19 layers, which are ordered: 5 convolutional, 5 pooling, 5 dropout, 1 flattening, and 3 denser. CNN was modelled using 19 layers.

The confusion matrix was used to evaluate this study. A confusion matrix measures a classification method's accuracy by measuring correct and incorrect classifications. Classification rate is a model's proportion of right predictions, whereas misclassification rate is its percentage of wrong predictions. Python learn and matplotlib plot the scratched CNN model's confusion matrix. The scratched CNN model creates this matrix. Figure 5 shows this well. The confusion matrix may also measure accuracy, precision, recall, and f-1 score. Individual equations are 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,

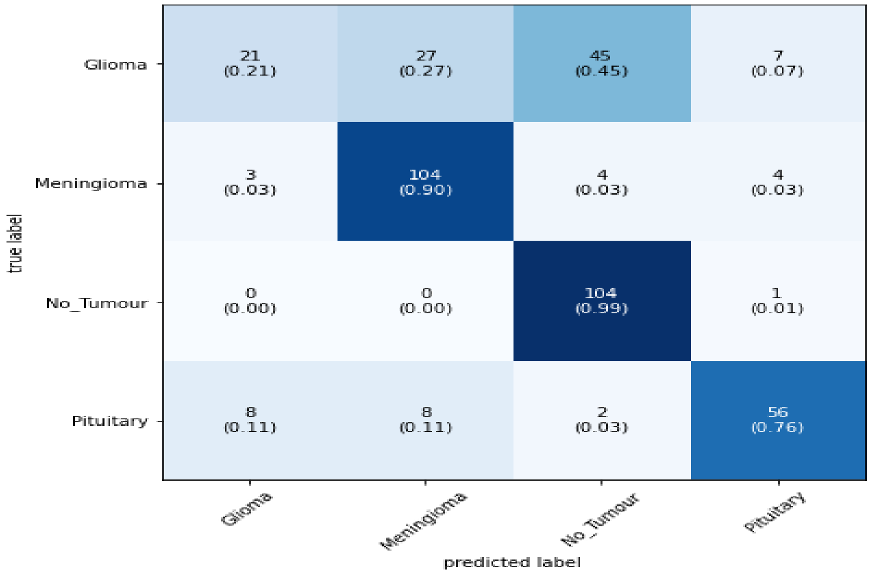

Figure 5: CNN Model Confusion Matrix

True Positive, False Positive, True Negative, and False Negative.

We visualise the loss function and accuracy using matplotlib Python. Figure 6 shows the CNN Model's accuracy value graph, whereas figure 21 shows its loss value graph.

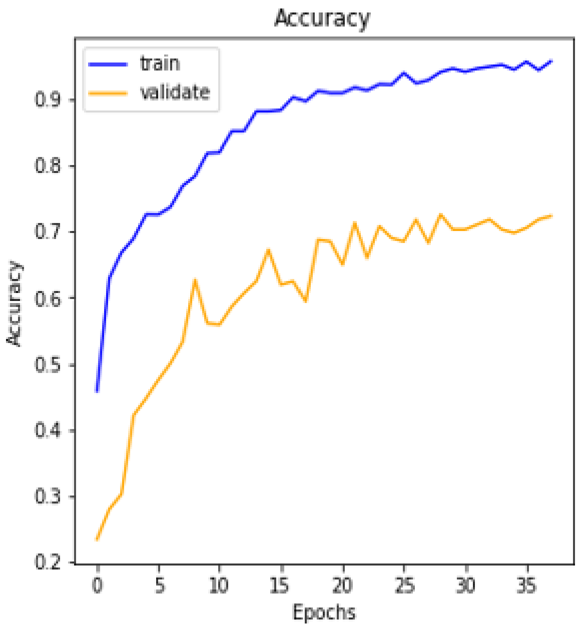

Figure 6: Accuracy of the CNN Model

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 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

CNN has 96.22 percent accuracy, whereas VGG-16 has 87.21 percent. We can see this. The table's losses show that the scratched CNN fared well in both areas.

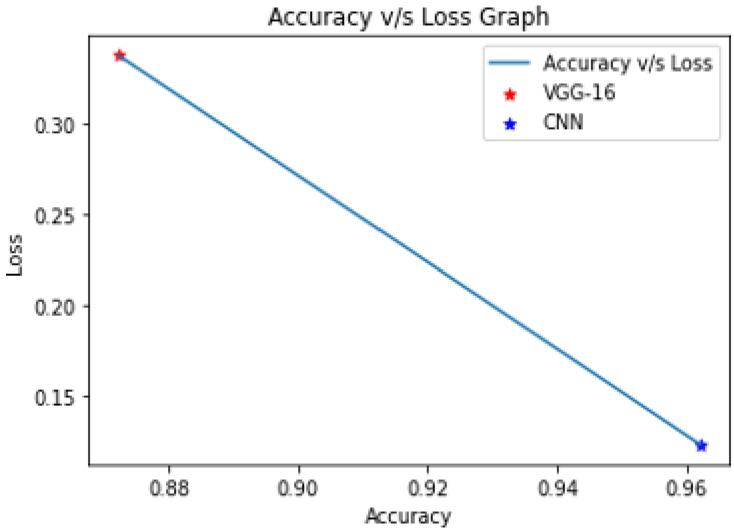

Figure 7: Accuracy v/s Loss Graph

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).

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 tumors 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 method with pre-trained models like ResNet 50, VGG-19, etc. might continue this research. 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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