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Deep Learning Model with VGG16 Model for Brain Tumour Detection

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Abstract
A mass or collection of abnormal brain cells is referred to as a brain tumour. The skull, in which the brain is housed, is exceedingly sturdy. There are several phases involved in the detection of brain tumours from biomedical images, including pre-processing, segmentation, feature extraction, and classification. The various schemes for the brain tumor detection are proposed in previous years but those schemes give low accuracy. In this paper, novel scheme is proposed which is based on transfer learning model. In the proposed scheme Parallel Non-Local Mean is used for the filtering and snake segmentation is used for the image segmentation. Transfer learning will be employed for classification in the final stage. The VGG16 and CNN models are combined to create the transfer learning model. Python will be used to implement the suggested model, and accuracy, precision, and recall will be evaluated of the outcomes.

Keywords: Brain Tumour, Snake Segmentation, Parallel Non-Local Mean Filter, VGG16, CNN

1. Introduction

Since computer technology has developed over the past few decades, a significant number of hospitals have implemented artificial intelligence techniques to aid in medical diagnosis, which simultaneously supports reform and the advancement of intelligent medical treatment. The central nervous system of the brain, which is the most complex structure, controls human higher neurological activity like memory, intelligence, and awareness [1]. Whether benign or malignant, the tumor will cause damage to the body's many functions after it has spread to any area of the brain. Brain tumors that are malignant are caused by the unchecked expansion of brain tissue. Malignant brain tumours can cause an increase in encephalic pressure, which can cause normal tissues to be destroyed and result in death. Cancer cells can develop quickly and spread to their surrounding tissues. One of the factors for lowering death is the early recognition of an affected individual with the aid of the initial detection of a malignant region. The use of image processing mechanisms has increased recently, and the technology has suddenly gained support from all sections of the field. Understanding the necessary internal knowledge about it has always been a taxing and time-consuming procedure. The storage and capture of the medical photographs are mostly retained in a digital environment [2].
Brain tumour diagnosis and remediation have advanced significantly in recent years, and imaging methods like computed tomography (CT) and magnetic resonance imaging (MRI) are also frequently employed to find brain tumours. When used to examine individuals with brain tumours, these procedures are incredibly successful and the detection rate is also quite high. MRI has grown to be a crucial component of contemporary imaging medicine. This process is typically automated with the aid of a system run entirely by machines or computers in order to produce quick and accurate results. Relevant clinical studies have

shown that MRI has a 98% accuracy rate in the diagnosis of intracranial brain tumours, outperforming CT. MRI imaging technology has several benefits [3]. On the one hand, radiation concerns are on the rise, yet the human body won't be harmed by this imaging method. In contrast, it is possible to image it using a variety of parameters, and this imaging strategy can offer a plethora of valuable information for diagnostic purposes. It is also easier to use and more efficient for examining human metabolism and function. Also, the anatomy of human soft tissue can be learned a great deal thanks to MRI imaging technologies. A common medical procedure called brain magnetic resonance imaging (MRI) is used to examine and diagnose a variety of neurological conditions such epilepsy, sclerosis, and brain tumours [4]. The pipeline for MRI-based brain tumour detection is shown in Figure 1.

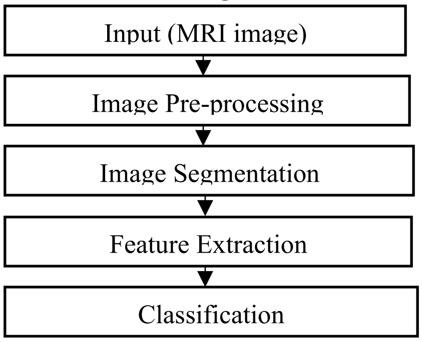

Figure 1: Brain Tumor Detection Pipeline

Accurate imaging is necessary for the clinical field to deliver reliable diagnoses. Although MRI creates high-quality pictures, the images also contain undesired elements like the scalp and skull and may contain noise as a result of operator neglect. The suggested technique requires images that are not only sharp but also noise- and undesired component-free in order to increase accuracy. The data will be transformed into a typical categorised format through pre-processing the photos. To preserve the original visual qualities, pre-processing methods including filtration, intensity correction, and skull stripping are generally applied [5]. In the field of segmentation, the segmentation of brain imaging is a difficult and challenging task. Nonetheless, maintaining accuracy during the segmentation process would greatly aid in the detection of tumours, neurotic tissue, etc. The identification of brain structures using MRI is of utmost relevance in neuroscience and has numerous uses, including the study of brain development and the analysis of neuroanatomical studies of the brain. As a result, MRI pictures are typically employed for study analysis and comprehension in the field of medical image segmentation. For the examination of brain images, MRI segmentation employing learning algorithms and pattern recognition methods has been very effective [6]. Technically, the strategy describes a parametric model that takes into account a subset of attributes depending on density function.

The most important phase in this endeavour is feature extraction. It speaks of the extraction of aspects that can convey an image's properties [7]. Brain MR scan characteristics including shape, structure, wavelet, and Gabor are recovered while extracting features. Often investigated is the Gray-Level Co-occurrence Matrix (GLCM). A well-known statistical feature extraction technique is Principal Component Analysis (PCA). In order to extract the key features of the data in the original space and eliminate correlation between the features, that is, to eliminate redundant information—the sample data in high-dimensional space must be projected into low-dimensional space using a linear transformation under the assumption that the original data will be represented as accurately as possible [8]. The most important phase in this endeavour is classification, which entails identifying the photos that need to be classified. According to this system, brain MRI images are divided into three categories: normal, glioma, and other using

classification techniques. This distinguishes between brain imaging with gliomas and those with other types of brain tumours [9].
Due to the quick advancement of technology and the application of sophisticated mathematical tools that can produce clearly discernible medical images, medical image analysis has undergone a revolution in practicability and novel notions. Effective image analysis can aid clinicians in diagnosing and treating patients based on these medical images. Computer-assisted medicine has considerably benefited from the use of machine learning techniques in medical image processing, such as support vector machines (SVMs) and random forests. SVM is a non-probabilistic linear classification technique that can learn to distinguish between two classes of data. The margin between two known classes is widened as a result of the search for the linear boundary known as the hyperplane [10]. In this instance, the input designates an array x with n properties that identify it as a point in n-dimensional space. Support vector machines are used to divide two clouds of n-dimensional points into the two classes along a linear surface of dimension n-1. In order to reduce a quadratic error function, the hyperplane parameters are optimised for growing the distance between it and the nearest point. The nonlinear kernel trick can be used to do the nonlinear classification process even though SVM is a linear classifier [11]. In addition, by lowering the hard margin restriction in the context of a soft margin, this model can be easily adjusted in the event that the separation of two classes in n-dimensional space is not completed clearly. The Support Vector Machine can be modified in a number of ways to handle multiclass issues, usually by integrating a bank of SVM classifiers.
A large ensemble of decision trees is trained for the random forest regression and classification method, which is based on bagging, with little correlation between them before being averaged later. They have included successive binary splits of the input space in a Fashion that is frequently depicted in their flowchart format [12]. A tree has a root, which represents the first split, branches, which represent the subsequent splits, and leaves, which represent the expected value. Squares with parallel lines to the coordinate axes are used to build a tree that corresponds to the input space. Learning in a decision tree refers to making decisions at each node, dividing the threshold for the nth input characteristic by thorough study, and minimizing an error function by classifying data using two widely used metrics: cross-entropy and the Gini index. As a tree is built to a large enough size, some of its branches are removed as part of the pruning process. A measure of model complexity and the error function are balanced for this. The RF includes the planting of several trees [13]. Every time, the random forest (RF) selects a portion of the input variables. After training the anticipated number of classification trees, a majority vote is used to determine the output classification. Instead of taking into account a single enormous tree, the trees are bagged to reduce the model's total variance while maintaining its bias..

2. Literature Review

D. Rammurthy, et.al (2020) investigated an optimization-driven method called WHHO (Whale Harris Hawks Optimization) in order to detect brain tumor based on MRI (Magnetic Resonance Imaging) images [14]. The cellular automata and rough set theory employed for segmenting the images. Moreover, this method aimed to extract the attributes from the segments such as tumor size, LOOP (Local Optical Oriented Pattern), Mean, Variance, and Kurtosis. Afterward, DeepCNN (Deep Convolutional Neural Network) algorithm was implemented for diagnosing the brain tumor for which the model was trained. The investigated method was a hybrid of WOA (Whale Optimization Algorithm) and HHO (Harris Hawks Optimization) algorithms. The investigated method offered 81.6% accuracy, 79.1% specificity and 97.4% sensitivity as compared to the traditional techniques.

S. Patil, et.al (2023) suggested EDCNN (Ensemble Deep Convolutional Neural Network) framework for detecting the brain tumor [15]. First of all, SCNN (Shallow Convolutional Neural Network) and VGG16 network were built considering T1C modality MRI (Magnetic Resonance Imaging) image. After that, this framework emphasized on computing the loss and accuracy. The efficiency was enhanced by fusing the extracted features from the built models for augmenting the accuracy to classify 3 kinds of tumors. The results demonstrated that the suggested framework assisted in increasing the accuracy of multiclass classification problem after fusing DL model and tackling the overfitting issue for imbalance dataset. Additionally, the suggested framework yielded an accuracy around 97.77% as compared to the existing methods.

G. Raut, et.al (2020) formulated a CNN (Convolutional Neural Network) algorithm to diagnose the brain tumor [16]. Primarily, this algorithm was exploited to augment the brain MRI (Magnetic Resonance Imaging) images for producing the adequate data for DL (deep learning). The next task was to pre-process the images so that the noise was eliminated and the images were enhanced for the next stages. The pre-processed MRI images utilized to train this algorithm for classifying the newly input image as tumorous or normal on the basis of extracted features. The error was mitigated and the precise outcomes were attained using BP (Back Propagation). AEs (Autoencoders) assisted in eliminating the irrelevant features and K-Means algorithm were employed to segment the tumor region. The formulated algorithm attained 0.9555 accuracy to diagnose the brain tumor.

H. A. Shah, et.al (2022) constructed a DCNN (deep convolutional neural network) based EfficientNet-B0 algorithm classifying and detecting the brain tumor images [17]. Different filters were executed for enhancing the quality of images. DA (Data augmentation) techniques helped in maximizing the data samples to train this algorithm. The results depicted the superiority of the constructed algorithm over other methods with regard to accuracy, precision, recall, and AUC (area under curve) and its accuracy was measured 98.87% for classifying and detecting the brain tumor.

U. Hasanah, et.al (2021) intended a system which was useful for physicians to diagnose the brain tumors on the basis of MRI (Magnetic Resonance Imaging) images [18]. The median filters utilized to pre-process the data; the skull was stripped for eliminating the non-cerebral tissues; thresholding was executed to segment the image; the statistical attributes of 1st order helped to extract features from the detected tumor; and 2nd order features were extracted using GLCM (Gray Level Co-occurrence Matrix). SVM (Support Vector Machine) algorithm was suggested and implemented for classifying the brain images. T1-weighted CE-MRI applied to test the intended system. According to results, the intended system offered an accuracy of 95.83%, precision of 94.08%, sensitivity of 93.33%, and specificity of 96.87% for classifying brain tumor as meningioma, glioma, and pituitary.

A. Biswas, et.al (2021) developed an accurate three-class algorithm from MRI (Magnetic Resonance Imaging) images and presented a hybrid approach for eliminating issues [19]. At first, the images were resized, sharpening filter was employed, and the contrast was enhanced to pre-process the images. At second, KMC (K-means clustering) algorithm adopted to pre-process the images. At third, the attributes were extracted using 2D (two dimensional)-DWT (discrete wavelet transform) and PCA (principal component analysis) adopted to reduce the features. At last, ANN (artificial neural network) was put forward to classify the tumor as Glioma, Meningioma and Pituitary. The developed algorithm yielded an accuracy of 95.4%, sensitivity of 94.58% and specificity of 97.83%. Moreover, this algorithm performed more effectively in contrast to other methods.

S. Sangui, et.al (2023) presented a modified U-Net model based on DL (deep-learning) to diagnose and segment the brain tumors from MRI (Magnetic Resonance Imaging) images [20]. The median filtering methods were utilized to pre-process MRI images. BRATS 2020 dataset employed to compute the presented model. The presented model attained 99.4% accuracy and performed well in comparison with the existing methods. The presented model was implemented for segmenting the target region and determining whether the tumor was present or not and allowed clinicians for planning therapy and monitoring the tumors. Furthermore, this model was effective for improving the level of process of segmenting the image and localizing its spatial localization. The presented model performed quickly and consumed lower time.
B. V. Isunuri, et.al (2019) recommended an adaptive threshold selection technique with the intend of diagnosing the brain tumor [21]. An ATSN (Adaptive Threshold Selection Network) technique was deployed which had 2 stages: training and testing. The initial stage was executed for attaining an adaptive threshold using pre-processed train images and real images. Next stage utilized thresholding to extract the tumor segment from the image. A dataset was generated in which 2295 images of meningioma, pituitary and glioma tumors were comprised. Diverse metrics like dice similarity, jaccard coefficient, accuracy, sensitivity, and specificity considered to compute the recommended technique. Based on results, this technique provided higher specificity as compared to the other techniques.
A. Chattopadhyay, et.al (2022) projected an algorithm to segment brain tumors from 2D MRI (Magnetic Resonance Imaging) in which CNN (convolutional neural network) model was deployed [22]. This algorithm was trained on the basis of diverse MRI images having tumor sizes, locations, shapes, and different image intensities. An analysis was conducted using SVM (support vector machine) and other activation algorithms namely Softmax, RMSProp, sigmoid. TensorFlow and Keras were executed in Python to deploy the projected algorithm. The projected algorithm offered 99.74% accuracy in contrast to the traditional methods. Additionally, this algorithm assisted the doctors in diagnosing the brain tumor in precise way for curing the disease on time.
N. Kesav, et.al (2021) designed a new model to classify the brain tumor and its types through RCNN (Region based Convolutional Neural Network) on Figshare and Kaggle datasets [23]. A two channel CNN algorithm was implemented for classifying the Glioma tumor from normal MRI (Magnetic Resonance Imaging) samples at accuracy of 98.21%. This algorithm was adopted as the feature extractor for diagnosing the tumor areas of Glioma MRI sample and the bounding boxes were employed to bound the tumor area. Moreover, this model classified other 2 kinds of tumor namely Meningioma and Pituitary. The designed model consumed lower execution time in contrast to the conventional methods and its average confidence level was found 98.83%.
T. Rahman, et.al (2023) established a new PDCNN (parallel deep convolutional neural network) model to recognize and categorize the brain tumors from MRI (Magnetic Resonance Imaging) images [24]. The dropout regularizer with BN (batch normalization) employed for extracting global and local features from 2 parallel phases. This model concentrated on resizing the input images and performing the grayscale transformation for mitigating the complexity. Thereafter, the data was augmented for increasing the datasets. Two simultaneous DCNNs (deep convolutional neural networks) were integrated with 2 diverse window sizes for learning the local and global information. The established model attained an accuracy of 97.33% on binary dataset-I, 97.60% on Figshare dataset-II, and 98.12% on Multiclass Kaggle dataset-III. The established model worked accurately and efficiently.

A. S. Musallam, et.al (2022) introduced a three-step pre-processing approach for improving the quality of MRI (Magnetic Resonance Imaging) images using a novel DCNN (Deep Convolutional Neural Network) model to diagnose glioma, meningioma, and pituitary [25]. BN (batch normalization) was implemented to train the system quickly at superior learning rate. This model contained least number of convolutional, max-pooling layers and training iterations. A dataset consisted of 3394 MRI images employed to compute the introduced approach. The accuracy of the introduced approach was measured 99% to detect glioma, 99.13% for meningioma, 97.3% for pituitary and 97.14% for healthy images. The experimental outcomes revealed that the introduced approach was robust and offered higher accuracy to detect tumor in least time.

3. Proposed Technique for Brain Tumour Detection

In this research work TL (transfer learning) is integrated with VGG16 and CNN (Convolutional Neural Network). This approach contains diverse stages which are defined as: -

1. Input MRI image and Pre-process: - This approach employs MRI (Magnetic Resonance Imaging) image as input, and the Gaussian filter is implemented to pre-process this image. Thus, the noise is eliminated from the image. This filter removes the blurriness from the images and called a smoothing operator. Moreover, it assists in removing the intrinsically available fine image details. The impulse response of this filter is called GF (Gaussian function) for highlighting the probability distribution of the noise. The Gaussian noise is eliminated effectively. This filter is also considered non-uniform, linear and low pass due to use of GF of a given standard deviation.

2. Segmentation: - This stage deploys SS (snake segmentation) approach for segmenting the brain area portion from the MRI image. This approach is planned on the basis of raster scan, thus, it is effective for covering the extreme edges of the image. SAC (Snake Active Contour) algorithm is utilized to set a parameterized primary CC (contour curve) in the image space, and an EF (energy functional) is introduced for characterizing the shape of the area on the basis of internal and external energy. The attributes of the curve including, definition of curvature, curve length, etc., lead to verify the inner power. On the other hand, the attributes of image help in illustrating the outer one. EF is mitigated to converge the primary CC denoted with $C(s) = (x(s), y(s), s \in [0,1])$ to the boundary of the target area in the presence of restraints of the internal and external powers as:

$$E(C) = \int_0^1 \alpha E_{int}(C(s)) + E_{img}\left(C(s) + \gamma E_{con}(C(s))\right) ds \ldots (1)$$

In this, EF has 3 portions in which E_{int} is used to denote internal energy, and for ensuring that the curve is smooth and regular; the image energy is represented withE_{img}, its assignment is done in accordance with desired target position attributes like edges. E_{con} is utilized for illustrating the constrained energy. In general, a curve is employed for determining the length and curvature. The major emphasis of utilized algorithm is on considering the geometric constraints in detailed way. Instead of quality of the image, this algorithm aimed at extracting the smooth and closed boundaries. However, its efficacy is mitigated due to some limitations, among which the most complex issue is its dependence on the primary contour. The position, shape and number of control points are capable of attaining the wanted impact only after selecting an appropriate primary contour.

3. Filtering: - The Parallel Non-Local Mean filter that a modification of NLM model is implemented for de-noising the MRI images as they are consisted of special kind of noise. This filter offers lower MSE (mean square error) in comparison with the earlier one. The images are comprised of weighted average of all the voxel intensities. This assists in computing the stored intensity value of the voxel. For a discrete

noisy image, u = {u(i)|i∈ I}, the computation of the predictable value denoted with NL[u](i), for a pixel i, is done as a weighted average of all the pixels in the image as:

$$\text{NL[u] i} = \sum_{j\in I} W(i,j)u\,(j) \qquad \dots (2)$$

The similarity amid pixels i and j is the base and the family of weights {w(i, j)}j relied on it. It results in satisfying the conditions 0≤w(i, j)≤ 1 and w(i, j) is equal to 1. u(N_k) is a square neighbourhood of set size and its center is at a pixel k. Whereas on the similarity of the intensity gray level vectors u(N_i) and u(N_j) is considered as the base that is responsible for resemblance of two pixels i and j. The likeness is quantified by computing the descendant function of ED (Euclidean distance) as:

$$\left\|u\,(N_i) - u\,(N_j)\right\|_{2}^{2}, a \qquad \dots (3)$$

In this, 'a' represents the standard deviation of the Gaussian kernel and it is found superior to 0. EF to the noisy neighbours leads to arise given equality as:

$$\text{E}\left\|u\,(N_i) - u\,(N_j)\right\|_{2}^{2}, a = \left\|u\,(N_i) - u\,(N_j)\right\|_{2}^{2}, a + 2a^2 \qquad \dots (4)$$

ED is executed to maintain the order of similarity among pixels and also this similarity is used to illustrate the durability of the algorithm. A huge weight is available in the average of the pixels in which an analogous gray level neighbourhood is comprised. These weights are expressed as:

$$\text{W (i, j)} = \frac{1}{z(i)} e^{-\left\|u\,(N_i) - u\,(N_j)\right\|_{2}^{2}, a \big/ h^2} \qquad \dots (5)$$

At which, Z (i) defines the normalizing constant

$$\text{Z (i)} = \sum e^{-\left\|u\,(N_i) - u\,(N_j)\right\|_{2}^{2}, a \big/ h^2} \qquad \dots (6)$$

In this equation, metric 'h' is employed as a degree of filtering. It is responsible for restricting the regression of the exponential function. This metric helps to control the exponential function regression. Consequently, there is no difference amid the regression of the weights and a function EDs.

4. Classification: - This stage aims to deploy a model called TL (transfer learning) in which VGG16 is integrated with CNN (Convolutional Neural Network). The initial one is exploited as the base and the latter is executed to train the data.

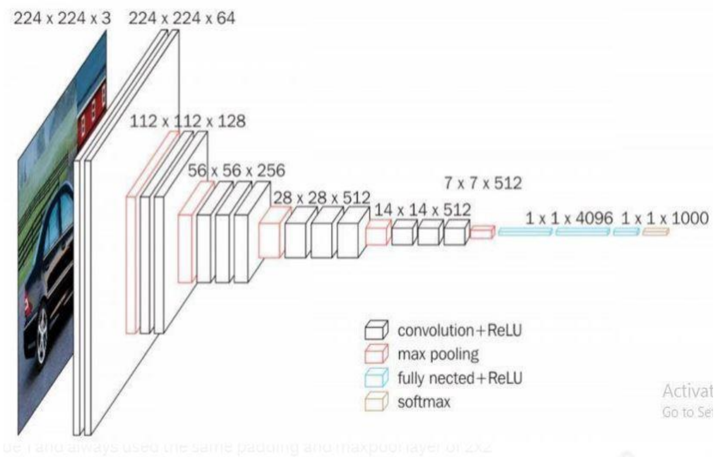

Figure 2: VGG16 Model Architecture

Different specifications of VGG16 are discussed as: -

1. In this model, 16 implies that there are sixteen layers available which are further consisted of weights. Among them, 13 layers are Conv (convolutional), 5 are MP (Max Pooling) and 3 are Dense and they

are summed up to twenty-one layers. However, only 16 weight layers are present such as learnable parameters layer.

2. The tensor size of 224, 244 with 3 RGB channel is employed for input in this model
3. This model emphasizes in comprising Conv layers of filter of 3x3 having stride 1 regardless of a huge amount of hyper-parameters. This model makes the implementation of similar padding and MP layer of 2x2 filter having stride 2.
4. The entire structure aims to arrange the Conv and MP layers in a steady way
5. 64 filters are contained in Conv-1 Layer, 128 in Conv-2, 256 in Conv-3, 512 filters in Conv 4 and Conv 5.
6. A stack of Conv layers is considered in 3 FC (Fully-Connected) layers in which the initial 2 are consisted of 4096 channels each. The 3rd is responsible for executing 1000-way ILSVRC classification. There are 1000 channels (one for every class) in this layer. The last layer is called the soft-max.

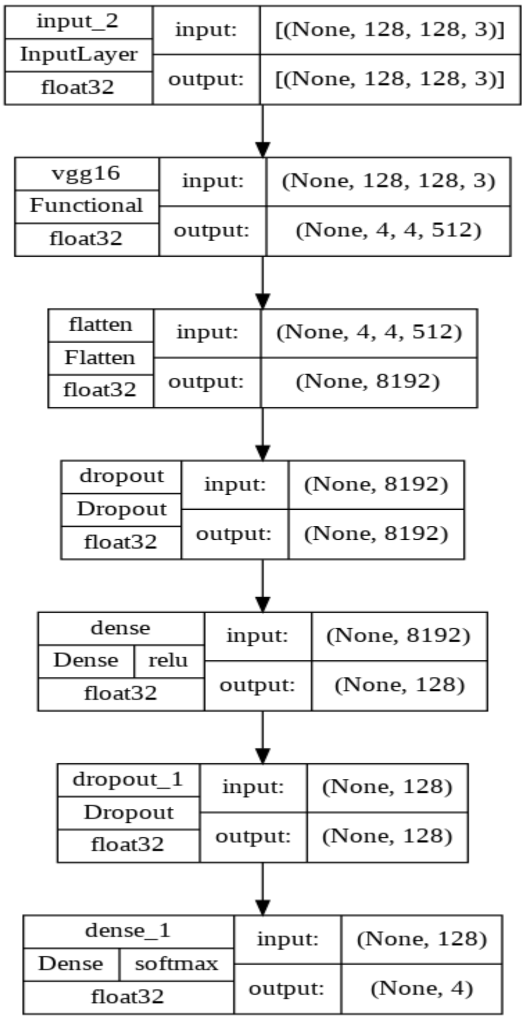

Figure 3: Proposed Transfer Learning Model

4. Result and Discussion

The goal of this study is to identify brain tumours via transfer learning. The Kaggle platform, which includes four classes named Glioma, Meningioma, Pituitary, and no tumour, is where the information about brain tumours is gathered. There are around 5700 photos in the data set, which is utilized for training and testing. Accuracy, precision, and recall are used to gauge the models' effectiveness.

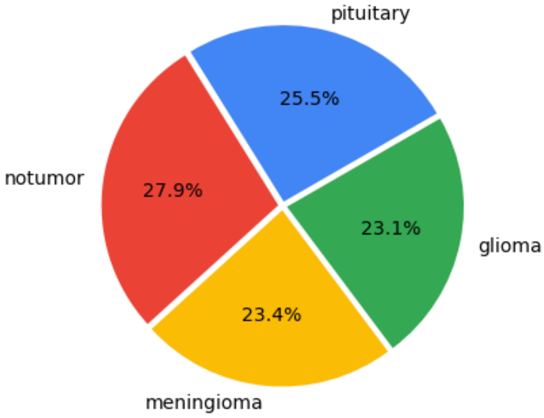

Figure 4: Class Distribution for Dataset

The dataset, which comprises four classes and a distribution of roughly 25 to 30 percent, is depicted in the image.

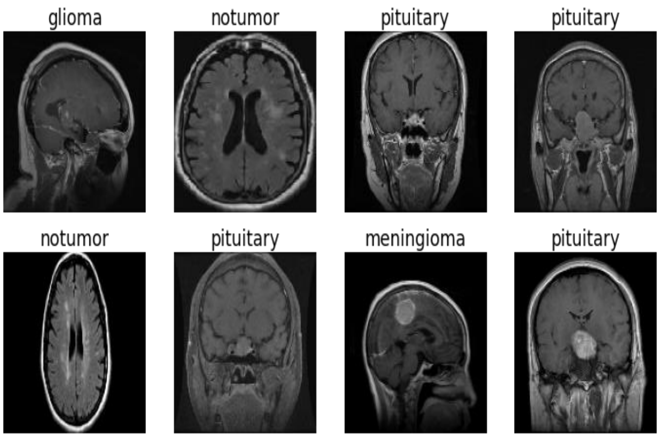

Figure 5: Sample Pictures

The representative photos from the brain tumour dataset are depicted in figure 5. For training purposes, the sample picture for each class is displayed.

Figure 6: Accuracy of the Developed Methodology for Training

As seen in figure 6, the training accuracy of the developed framework is approximately 96 percent, and loss is decreased to 3 to 4%. The new model's effectiveness was demonstrated throughout training.

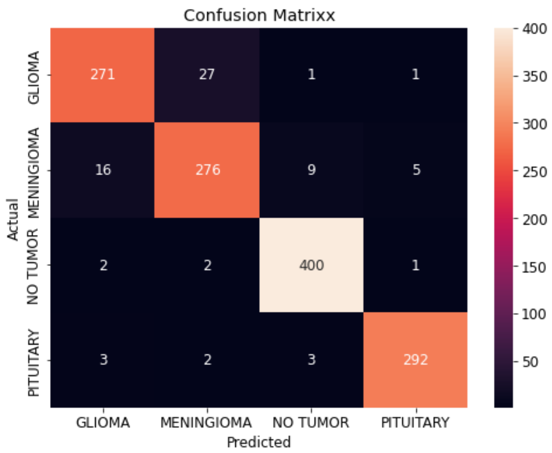

Figure 7: Confusion Matrix

Using the actual value and anticipated value, the confusion matrix of the developed framework is displayed. The classes are quite well distributed, and there were no overfitting issues during prognosis.

Table1: Experimental Results of Various Techniques

Model	Accuracy	Precision	Recall
Random Forest	66%	56%	66%
SVM	77.59%	78%	78%
KNN	69.88%	70%	70%
Proposed Model	95%	94%	95%

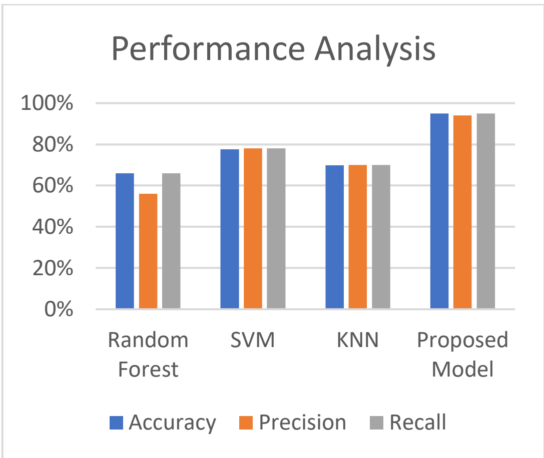

Figure 8: Results Examination of the Developed Framework

Figure 8 illustrates a comparison of the developed framework's output with that of SVM, KNN, and Random Forest. The suggested model has an accuracy of up to 95%; by comparison, the accuracy of the KNN, Random Forest, and SVM models for the detection of brain tumours is 69.88%, 66.6%, and 77.59%, respectively.

5. Conclusion

This article comes to the conclusion that brain tumour identification is a problem that artificial intelligence can help with. The method for detecting brain tumours goes through several stages, including pre-processing, segmentation, and classification. As part of the pre-processing, Rician noise is eliminated from the image using the parallel non-local mean filtering method. The targeted area is chosen using the snake-based segmentation technique. In the most recent classification, a mixture of the VGG19 model and the CNN model is employed, together with transfer learning. The training accuracy of the suggested transfer learning model is 96%. When the suggested model was evaluated, it had 95, 94, and 95 percent accuracy, precision, and recall, respectively. A comparison is made between the suggested model and machine learning models like Random Forest, SVM, and KNN. Comparing the suggested approach to machine learning models, accuracy can increase by up to 15%. For the purpose of detecting brain tumours, a hybrid transfer learning model may be created in the future.

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