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U-Net Segmentation for CNN Classification to Improve the Accuracy of Automatic Prediction of Brain Tumors Using MRI Images

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Abstract: - Among various cancers, a brain tumor is a serious one that affects the patient's brain and causes sudden death. Several clinical diagnoses of brain tumors help medical experts provide the proper treatment at the right time; earlier identification and detection of brain tumors are much less. With the increase of cancer patients, managing and diagnosing efficiently with massive data collected is complex. Diagnosing patients with a brain tumor in the earlier stages is also tricky. Medical image processing methods and computer-aided diagnosis methods proposed in earlier works have not provided a high level of accuracy in classification, but the segmentation accuracy was good. Some recent research works have focused on implementing machine learning algorithms for predicting brain tumors for a massive amount of data, where the accuracy still needs to be improved. Machine learning and deep learning algorithms are used to predict brain tumors and their types earlier. With a large amount of data available, the ML and DL models are trained efficiently to make accurate prediction models. The DL models provide better accuracy in processing and predicting medical images than ML models. Some pre-trained deep learning algorithms like VGG16, VGG19, InceptionV3, and ImageNet provide improved accuracy and less computation power to achieve the required results. This paper proposes a CNN algorithm with a VGG16 pre-trained model for detecting brain tumors with MRI images. The input images are segmented using a U-Net model, improving the prediction process's accuracy, and are classified using a CNN model with VGG16, which helps in the efficient and faster prediction of brain tumors from the MRI images. The results show that the proposed model provides better accuracy than the existing ones.

Keywords: Brain MRI Images, Brain Tumor Detection and Classification, Pre-Trained Models, U-Net Segmentation, CNN Classification.

I. INTRODUCTION

Growth of abnormal cells within the brain area called brain tumors. Benign and malignant are the two types of tumors. The malignant tumors are further classified into primary and secondary stages tumors that can spread to other portions of the brain and create metastasis tumors. All tumors show symptoms, whereas the symptoms vary depending on the parts of the human brain. It includes vision problems, severe headaches, mental changes, vomiting, and seizures. Based on the symptoms, the patient needs a medical diagnosis. MRI diagnosis involves medical image processing methods in earlier days. A sample MRI brain tumor is shown in Fig. 1. Brain tumor causes sudden death in all aged people. The medical industry focuses on developing efficient methods to avoid death due to brain tumors. Thus, it is essential to accurately predict brain tumors for better cancer diagnosis and treatment planning. The manual brain tumor segmentation process is tedious and provides less accuracy [1]. Hence, various automatic and semi-automatic brain tumor segmentation and classification methods are proposed.

The existing classification methods concentrate on the gliomas of the brain tumor images, whereas they are not concentrated on other parts of the brain tumors. These brain tumors are mainly seen in adults and can be easily detected through Magnetic Resonance Imaging (MRI). It consists of T1-weighted, T2-weighted, fluid-attenuated, and contrast-enhanced MRI images [2]. It helps in analyzing the structural details of the brain. Though various imaging technologies like Computed Tomography and Positron Emission Tomography are used for brain tumor analysis, MRI images are cost-effective and provide an accurate solution for the brain tumor prediction process. By quantitatively analyzing brain MRI images, various diseases like Alzheimer's, epilepsy, cancer, Schizophrenia, and other infectious and degenerative diseases are found [3].

One critical parameter in detecting such diseases is tissue atrophy, which needs to be found in the image. It must adequately segment and analyze brain tissues to detect tissue atrophy accurately. The change in the size of the brain tissues needs to be explored, which can be obtained by the segmentation of MRI images. The images from various time points need to be compared to detect changes in the brain structure and tissues. The accurate

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detection and localization of the affected tissues from the healthy tissues is also a crucial aspect of MRI segmentation. It helps in the accurate planning of surgeries and the post-operative analysis of the tissues. In the clinical diagnosis of diseases, it can be usually seen that both the quantitative and qualitative aspects play an essential role in the detection of normal and pathological structures of the tissues. It helps in differentiating the regular patients from the affected.

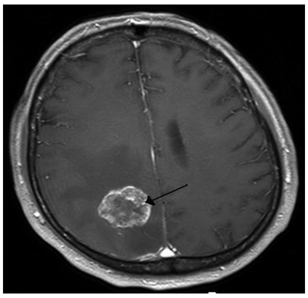


Fig. 1 Brain Tumor

MRI image analysis of the quantitative aspects is common in most neurological disease diagnosis processes. The segmentation of the images and their labeling process is very critical for quantitative analysis. In the traditional diagnosis methods, this segmentation and analysis were carried out manually with 2D and 3D slices of brain MRI, which is both expensive and tedious. It can also lead to human error, resulting in false and inaccurate predictions. Hence, these manual works need to be automated, and accurate result prediction needs to be done. With the increase in data, it is difficult for the healthcare sector to manage them. In the search for a tool to handle such data efficiently, various machine learning and deep learning algorithms are proposed. These algorithms make predictions based on the data. It can be trained to make predictions and provides efficient prediction of various diseases with better accuracy. Various research works are made in image analysis through machine learning algorithms that identify the abnormal tissues in the images [4]. However, proper segmentation and engineering are needed to create these image features with more expertise. In addition, the traditional machine learning algorithms do not provide efficient and accurate results in that prediction. It is also challenging to build automated systems with machine learning algorithms that do not consider the 3-dimensional features like morphology, tissue variation, and imperfections in the image acquisition process [10]. In order to overcome such difficulties, deep learning algorithms are proposed. It takes advantage of the 3-dimensional features and can self-learn to extract the necessary features from the images. Various trained models are available in deep learning models that provide the required accuracy without training [5]. It helps boost the accuracy of the training process and does not require that much computational power and time for the prediction. They extract the features themselves and provide the required accuracy in the prediction process. The computation of the deep learning algorithms can also be accelerated through GPUs, leading to faster and more efficient results prediction. It can be trained with millions of images, which helps in achieving maximum accuracy.

The authors H. Dong et al. (2017) [6] and A.Z. Atiyah and K H (2021) [7] define the efficiency of the U-Net model in segmenting the MRI image for tumor detection. The performance of the U-net model is evaluated using various performance metrics such as fi score, precision, recall, specificity, and accuracy. The simulation result of this research states that the U-Net-based model segmented the input medical image with 99% accuracy. P. Tiwari et al. (2022) [8] proposed a deep learning approach to the convolutional neural network (CNN) for medical image classification. This research mainly aims to classify benign and malignant tumors from the MRI image. The result shows that the proposed CNN model classifies the tumor with 99% accuracy. A. Chattopadhyay and M. Maitra (2022) [1] proposed a CNN model to detect the brain tumor image from the input MRI medical image datasets. The result of the proposed work is compared with the existing approaches. The final comparison result of the model indicates that the CNN model is more beneficial to the doctor in detecting the brain tumor from MRI images with 99.74% accuracy. W. Ayadi et al. (2021) [9] stated that in recent years, CNN-based image classification techniques have been widely used in many healthcare sectors to classify diseases accurately. So, in this work, CNN is used to classify the tumor from the input MRI brain image. The simulation result of the CNN model shows that it outperforms the others.

A. Contributions of the Paper

This paper provides a hybrid deep learning model for achieving maximum accuracy and providing the necessary efficiency for the automatic segmentation of brain tumors from MRI images. For this, the paper contributes the following,

1. Efficient segmentation of the MRI images through the U-Net model.
2. Intelligent extraction of features from the MRI images through the CNN algorithms.
3. Efficient prediction of Brain tumors through the VGG16 model.

The paper's novelty is that the input images are segmented using the U-Net model, in which 2 x 2 up-convolutions are used to recover the bottleneck in the dimensions of input images based on the up-sampling feature maps. All the stages of the U-Net model have regular 3 x 3 convolution and 2 x 2 up-convolution with ReLU functions for activation. For all the up-sampling, the number of channels in the same path is reduced to half whenever the up-convolution size increases in width and height.

B. Limitation and Motivation

From the literature survey, it is clear that various deep learning algorithm provides better prediction results. Clinical brain tumor diagnosis uses imaging modalities like MRI, CT, ultrasonic, and X-ray. Among them, MRI images are widely considered one of the most effective ways to diagnose a brain tumor. MRI images are used in most of the works as they are easy to process and extract features through the algorithms. The MRI images can be directly processed through deep learning algorithms like CNN. However, the efficiency of the model and the number of features extracted from them are significantly less. It is due to the poor quality of images and the dormant features in the images. Hence, preprocessing of images becomes mandatory. Various preprocessing models like thresholding, edge, region, clustering, watershed, and graph are proposed. Among these models, semantic segmentation is the segmentation of medical images. In that case, U-net is a widely used semantic segmentation model that provides better segmentation accuracy. Concentrating on the extraction and prediction of brain tumors is also essential as it helps improve the model's accuracy. CNN algorithms are capable of efficient extraction of features and processing of the data. However, it is time-consuming and needs more computational power to make the prediction. The computational power can be reduced using pre-trained models that provide better accuracy and reduce the time required for feature extraction and classification.

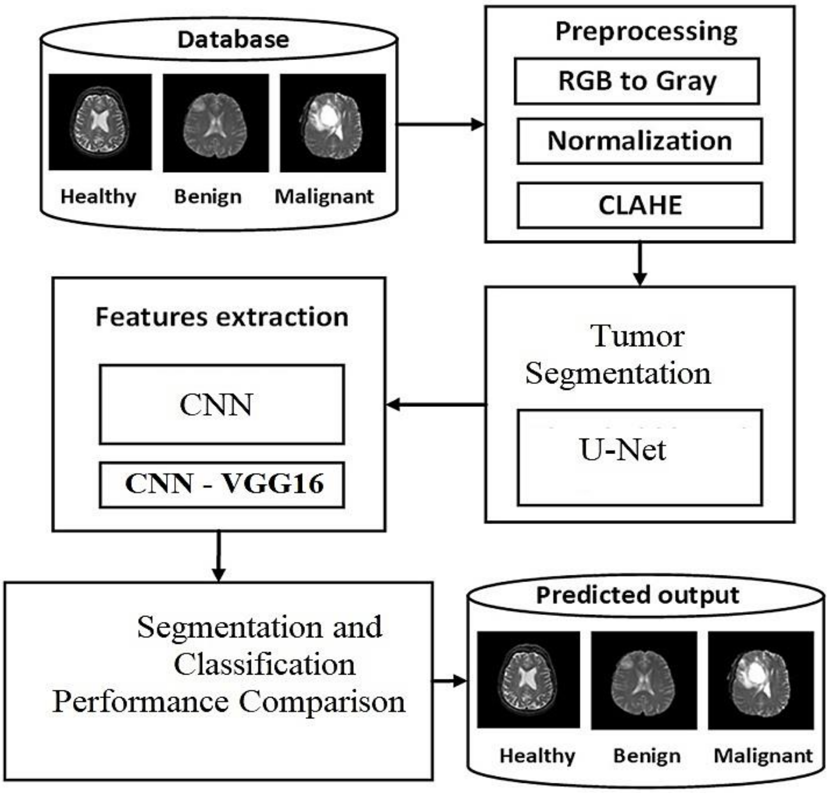


Fig. 2 Proposed Hybrid Model

II. PROPOSED HYRBID DEEP LEARNING MODEL

The proposed model preprocessed and segmented the input MRI brain image using the U-Net model before classification. U-Net is also a convolutional network model mainly used for image segmentation processes. This model segments the image and accurately detects the area of infected tissues in the human body [11]. Then, using CNNs and VGG-16 models, the features are extracted from the segmented brain images. This paper uses deep learning algorithms because deep learning is the subset of machine learning algorithms that mimic the human brain in classification. The DL algorithm can easily classify unlabelled data from large datasets. It reduces the complexity during the computation. DL-based classification systems are used in various applications such as healthcare, education, image recognition, speech recognition, text classification, finance, social media, and gaming. The DL algorithm includes classification techniques such as ANN, CNN, LSTM, RNN, and DNN. CNN and VGG-16 are the most common classification techniques in many real-time applications.

In this proposed work, the input datasets comprise three types of reports gathered from the patients. In order to accurately predict the severity level of the tumor, the input MRI images are preprocessed using the preprocessing technique to convert the color image into a grayscale image which normalizes the input image. Then they are segmented using the U-Net model and classified using the CNN and VGG-16, shown in Fig. 2. The performance of each classified image is evaluated to predict the final result. From the comparison result, three different outputs, such as normal, benign, and malignant brain images, are accurately detected from the input datasets.

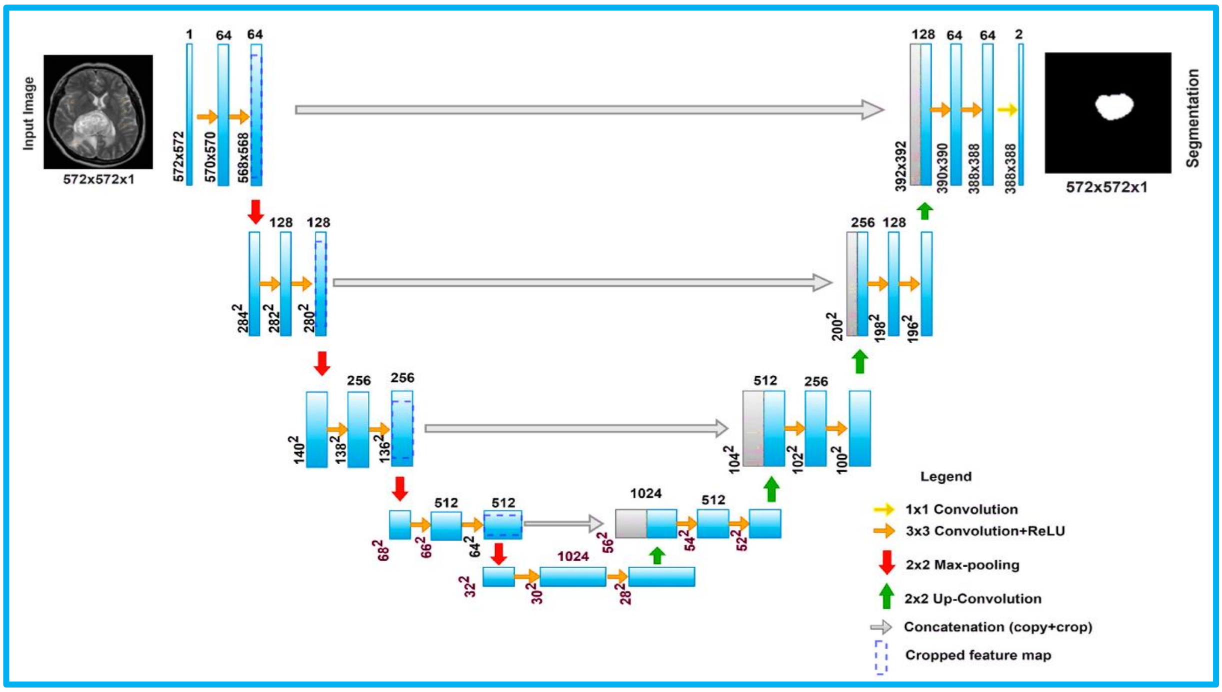


Fig. 3 U-Net Model for MRI Brain Image Segmentation

A. MRI Segmentation Using U-Net Model

U-Net is also one of the convolutional neural networks invented to perform medical image segmentation. Image segmentation assigns labels to each pixel to get detailed information from the input image. The segmentation process is classified into two types such as semantic and instance segmentation. Semantic segmentation is used to classify the pixels of the input image with labels. The general U-Net architecture contains encoder and decoder parts. The encoder part is used to minimize the spatial resolution of the input image, and the decoder path is used to maximize the resolution of the image and provides the final output. The features of the input images are mapped and segmented using the encoder and decoder parts, respectively. The use of skip-connection in the U-Net enhances the features of the input image to produce high-resolution details. The obtained input image value produces the final segmentation result with high accuracy. The state-of-art of U-Net model is highly efficient in performing image segmentation tasks.

$$H(p,q) = -\sum p(x) log q(x)$$

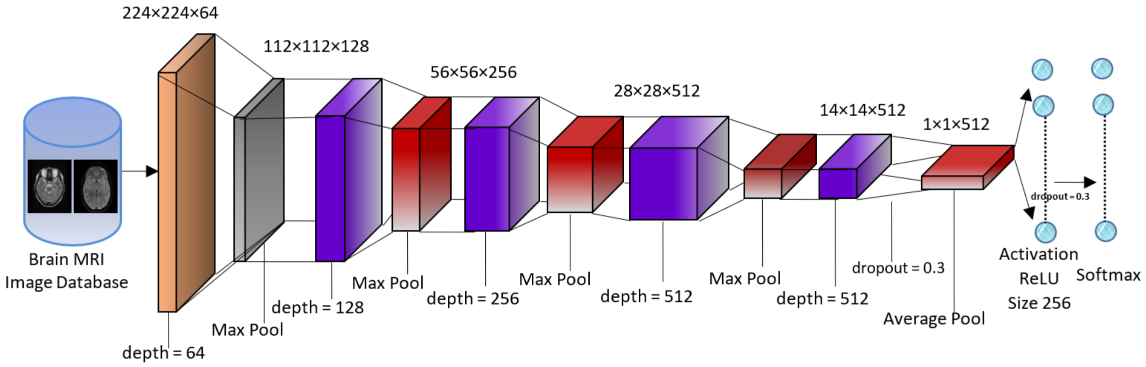


Fig. 4 CNN Model

B. MRI Tumor Classification Using Convolutional Neural Network

CNN is the most popular type of deep learning classifier. It is mainly developed to perform the classification process on image data. The CNN architecture comprises three layers: convolutional, pooling, and fully connected layer. The convolutional layer is the building block of the CNN model, in which the features of the input data are mapped using the filters (kernel). The final resultant value is observed from multiple iterations. After each iteration, the final result value is observed using the dot (·) product. Then using the activation function (ReLu), the computational speed and accuracy value of the mapped input image are improved.

$$Z^l = h^{l-1} * W^l$$

The pooling layer is applied to reduce the spatial size and over-fitting issues in the input image received from the convolutional layer. The pooling layer is classified into three types maximum, average, and sum. The max-pooling layer is mainly used in wide applications to reduce the size of the input image.

$$h_{xy}^l = maz_{i=0,j=0} h_{(x+i)(y+J)}^{l-1}$$

The final layer of the CNN model is fully connected. In this layer, each neuron is connected with the previous and upcoming neurons in the network. The dense layer is more important in a fully connected layer to produce the final classification result.

$$Z_l = W_l * h_{l-1}$$

C. Model Implementation

In this paper, the input dataset is collected from various healthcare sectors. It contains the details of the tumor-affected and regular patients. The input data are classified into two phases: training and testing to evaluate the performance of the proposed approach. For the training phase, 80% of the data is classified, and 20% is classified in the testing phase. In order to improve the quality of the input MRI image, the input image is initially preprocessed. Then the preprocessed images are segmented using the U-Net model. Now the deep learning classifier CNN is applied to extract the features from the segmented input MRI brain image, and finally, the CNN model classifies the input datasets into three categories such as normal, benign, and malignant.

D. Image Preprocessing

Image preprocessing removes unwanted artifacts from the input image, such as noise, features, and clarity. Generally, the image preprocessing technique is applied to reduce or crop the input image, normalize the intensity of the image pixels, remove unwanted data, reduce the noise, adjust the edges of the image, image filtering, and enhance the contrast or quality of the input image. These steps are performed to make the model process the following function in the model without any overfitting problems. A Bias field correction of images reduces the non-uniformity of the details that are affected due to the variation in the signal intensity while capturing the images. It helps to normalize the intensity of the non-uniformities.

$$I_{corrected} = I * (M/M_{smoothed})^p$$

The MRI images to be processed are represented as I, and the mask of the images representing the brain region is represented as M, while the same is smoothed and obtained as $M_{smoothed}$. The bias field correction is represented as p, and the corrected image obtained is $I_{corrected}$. The skull stripping then follows it. It is done through various methods like morphological and thresholding methods. It combines both methods to remove the skull from the images.

$$I_{stripped} = I * (M_{opened})$$

$I_{stripped}$ represent the stripped image obtained from the MRI images. The M_{opened} represent the masks opened. Based on the information obtained from the image, they are compared with similar images to identify the similarity. It can be done in the following manner,

$$T = \text{argmax MI (I1, I2)}$$

The transformation matrix is represented as T, the reference image is represented as I1, the moving image is represented as I2, and the information measure is represented as MI. Finally, the images are denoised through the Gaussian filter. The following equation shows the denoising,

$$I_{filtered} = G * I$$

Where the $I_{filtered}$represents the denoised image. In this proposed approach, the U-Net model contains two paths: up-sampling and down-sampling. The encoder path contains 5 convolutional blocks, each comprising 2 conv layers with a 3×3 filter and 1 stride. The maximum pooling layer with a 2×2 stride is applied to each block in the encoder path except the last block. It reduces the size of the input image from 24×24 to 15×15. The convolutional layer is applied in the decoder path with 3×3 kernel and 2×2strides. It again increases the size of the input image from 15×15 To 24×24. In each decoder block, the feature map number is reduced by two. In order to maintain the dimension of the output image in both the decoder and encoder path, the zero-padding function is applied. Finally, the 1×1 Conv layer is applied to minimize the number of future maps in both parts and produce the final segmentation result. The binary cross entropy (BCE) function evaluates the proposed model's loss function value. The following formula is used to compute the loss function:

$$LF_{bce} = \frac{-1}{N}\sum_{i=1}^{N}\left(log(p_i)\right)$$

Where p_i, denotes the probabilities of negative classes.

E. MRI Brain Tumor Classification Using CNN

The input brain MRI image features are extracted using the VGG16 and CNN models, and CNN classifies the final tumor. The proposed CNN model comprises 4 conv layers, 1 max-pooling, 1 fully connected, 1 classification layer, 6 batch normalization layers, 3 dropouts, and 1 flatten layer. The activation function (ReLu) is applied to perform the computational processes to produce the final output. The proposed model generates three different outputs to define the three different tumor classes in the input MRI image. In the first conv layer, the input image is fed with the resolution of $224 \times 224 \times 3$, then convolving with the 3×3 kernel (64) and generates output as $224 \times 224 \times 64$. The output of the convolutional proceeding layer is transferred to the next conv layer. The 64 kernels with the size of 3×3 are utilized to convolve the data size using the Conv layer. It produces the resultant volume of $224 \times 224 \times 64$. Then using the max-pooling layer 2×2 filter size with 2 strides, the output volume of the input MRI image is reduced to $111 \times 111 \times 64$. Again, the process is repeated from the first process and produces the output with $54 \times 54 \times 64$ volume. The flatten, drop out, and FC produces the result value of 186624, 0.3, and 512, respectively. Finally, the activation and BN layer are performed to produce the final extraction result of the input MRI image. The output of the proposed model is executed with 3 layers.

And the proposed VGG16 model consists of 1,1,1 flatten, drop out, and dense layer. The first layer in the VGG 16 model is trained with a volume of $7 \times 7 \times 512$. The transfer learning technique (VGG-16) extracts the features from the input MRI image to compute the task effectively and reduce the computational time. At first, the set of the trained input image is passed to the VGG16 model, where the layers of the VGG-16 model extract all the features from the input image. The size of the extracted image is reduced using a flattened layer to reduce the dimensionality. Then using the dense and dropout layer, the extracted image is classified and produces the final output value. The dropout layer with 25088 volumes converts and produces the input image's volume. Then the final output of the VGG16 model is produced by the dense layer with 1 extraction result.

After completing the feature extraction process, the overall result is evaluated by comparing the segmentation and feature-extracted results produced by the U-Net, CNN, and VGG16 models. The comparison result shows that the input datasets are classified into three classes: normal, benign, and malignant, with high accuracy.

F. Dataset

The dataset consists of both malignant and benign Brain MRI images. In total, there are 98 normal images and 155 malignant images. It covers all types of Brain Tumour images. The images are obtained from patients of different age groups and are verified. It is widely used in various deep learning models in the Kaggle environment and is the most sorted out dataset for brain tumor detection in terms of processed datasets to make efficient predictions of the dataset.

III. Experimental Results And Discussion

The proposed model is simulated in an open-source environment Kaggle, and the specification of the environment is 4 cores and 30 gigabytes of RAM; on the GPU side, P100 GPU, 2 CPU cores, and 13 gigabytes of RAM are available. Nvidia Tesla T4 GPUs and 13 gigabytes of RAM are for the tensor processing unit. The proposed model is simulated in the Kaggle environment, the results obtained are demonstrated in detail and compared with similar other models, and the performance evaluation. The training process with the training dataset initially creates the proposed model, and the structure of VGG-16 is given in Table-1. The VGG-19 model uses 9 convolutions, 1 flattened, 4 max-pooling, 1 dropout, and 1 dense layer at each operation round. The number of epochs is changed from 250 to 450 to improve the accuracy.

Table. 1 Architecture of VGG-16

Layer (type)	**Output Shape**	**Param #**
vgg16 (Model)	(None, 7, 7,512)	14714688
flatten_1 (Flatten)	(None, 25088)	0
dropout_1 (Dropout)	(None, 25088)	0
dense_1 (Dense)	(None, 1)	25089
Total params: 14, 739, 777 Trainable params: 25, 089 Non-trainable params: 14, 714, 688		

The main function of the proposed approach is to develop the CNN-based tumor detection model to produce accurate results. The input medical image is obtained from the MRI scan report. The input MRI brain Images are segmented using the U-Net model and transferred to the CNN model. The features of the input images are extracted using the CNN and VGG16 models. In order to evaluate the performance of the proposed model, the input images are classified into three phases: training, testing, and validation. From the entire input data, 70% of the data is used for testing, 20% for validation, and the remaining 10% for testing. It can be seen in Fig. 5. The input datasets contain the repost of three sets of patients. that is, normal, benign, and malignant types of patients' brain images. The training, validation, and testing samples are classified based on these MRI images.

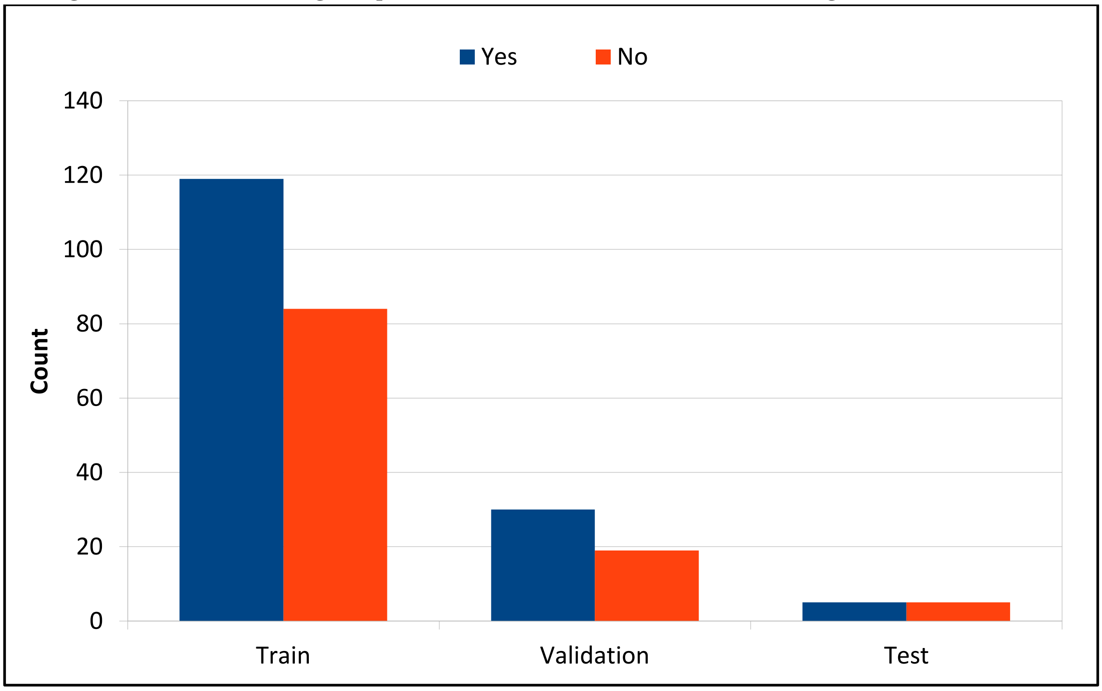


Fig. 5 Classification of Dataset for Training, Testing and Validation

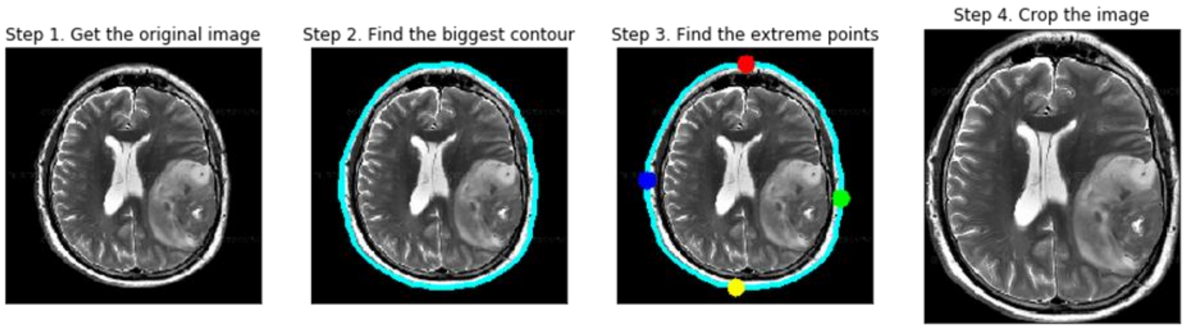


Fig. 6 Cropping Procedure Carried Out in The Image

Fig. 6 shows the cropping procedure carried out to crop the images through the cv2 module. From this, it can be clear that the proposed model provides the cropped image to avoid processing the unwanted areas in the images and only the parts of the brain. This helps reduce the proposed model's time consumption and processing power.

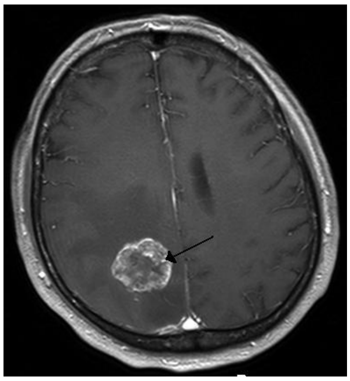
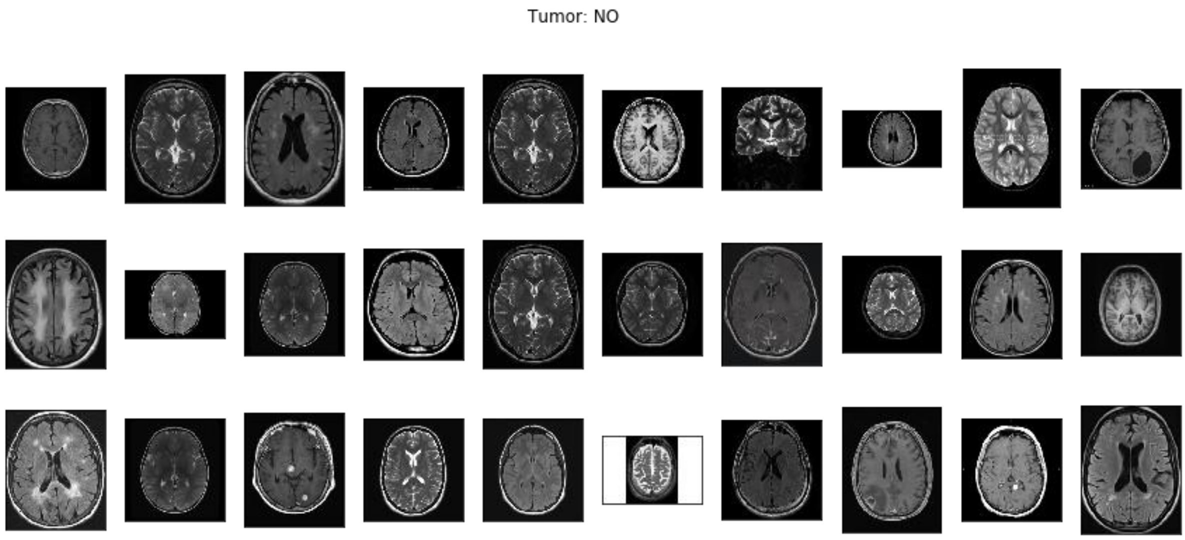


Fig. 7 Sample Image with Tumour

After classifying the image for the training and validation process, the normalization technique is implemented to reduce the size of the input brain image to perform further tasks. As mentioned in the proposed work, the image normalization process improves the quality of the input image to make it easier for the system to predict the tumor from the original image. Fig. 7 shows a sample tumor image from the dataset. Fig. 8 illustrates the distributed input brain image ratio. In order to crop the unwanted region, the size of the input image is distributed to the different ratio values. After detecting the external contour, the input image is cropped using the preprocessed technique.



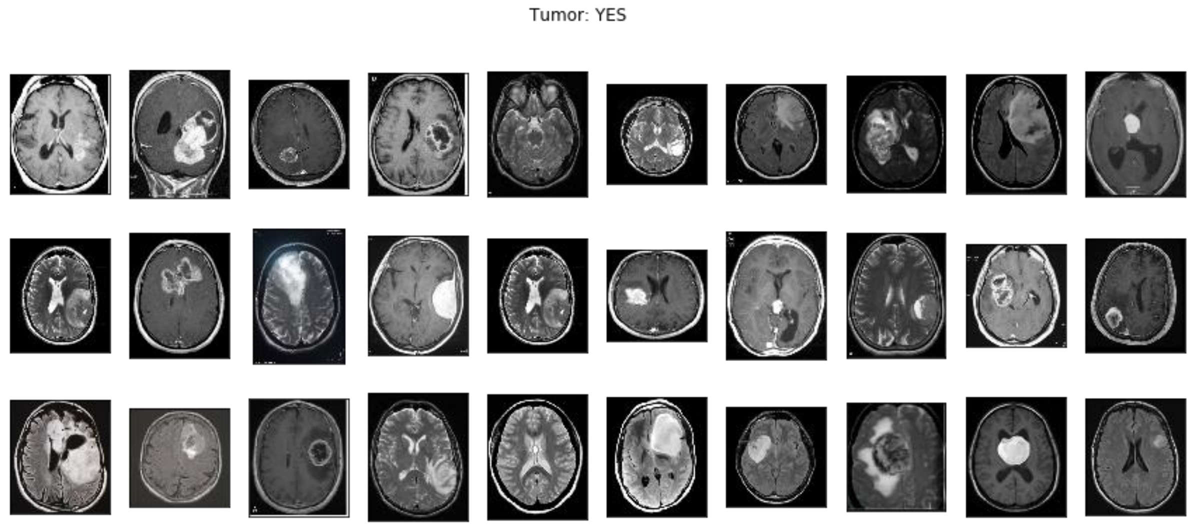


Fig. 8 Cropped images from the dataset

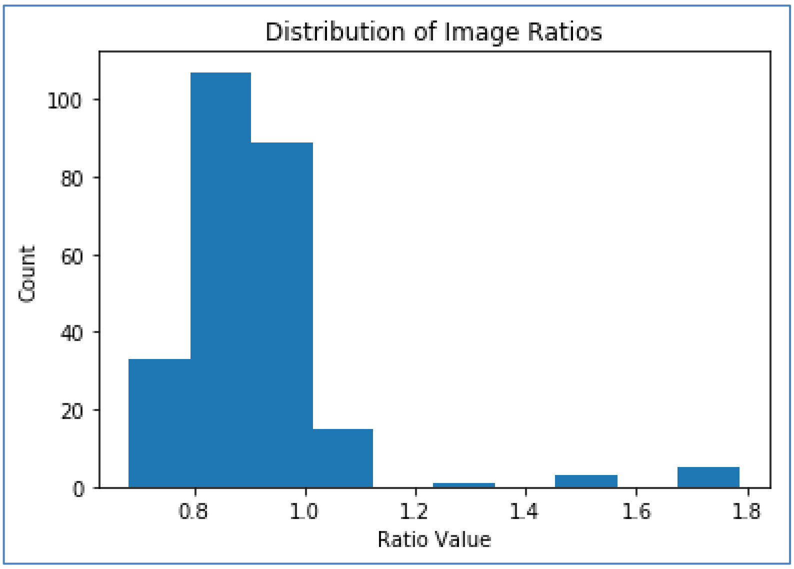


Fig. 9 Ratio of distribution of images

Fig. 9 shows the ratio of distribution of images in the model. It also shows the count of distribution in the graph. From this figure, it can be said that more images are concentrated towards 0.8 to 0.1, where most of the images are seen. The images are preprocessed after cropping and are used to train the VGG16 model for predicting brain tumors. The preprocessed images are shown in the following Fig. 10.

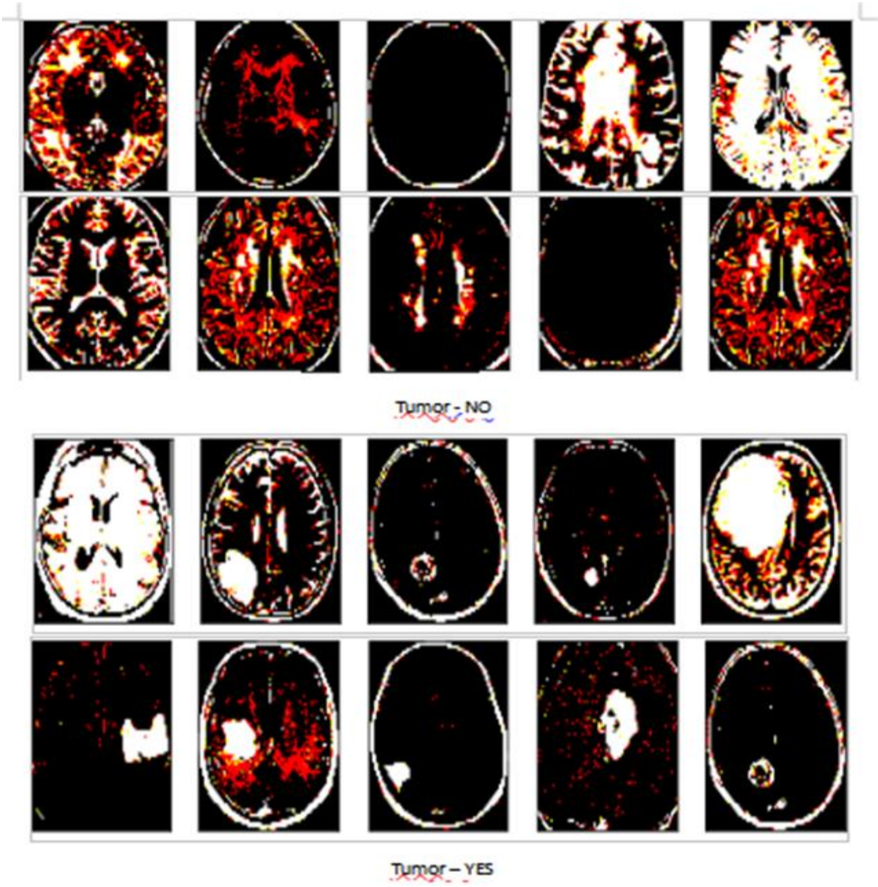


Fig. 10 Preprocessed normal and brain tumour image

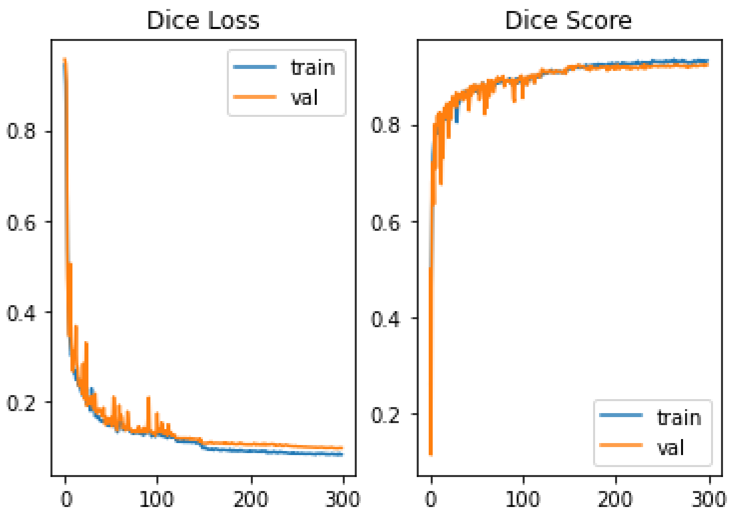


Fig. 11 Dice score and Dice loss for the images in U-Net

Fig. 11 illustrates the dice score and dice loss produced by the U-net model on segmenting the input MRI image. The graphical result of the U-Net model indicates that when a number of epochs increases, the dice score of both training and validation increases. From this value, the finale segmentation result of the U-Net model on brain MRI image is accurately predicted.

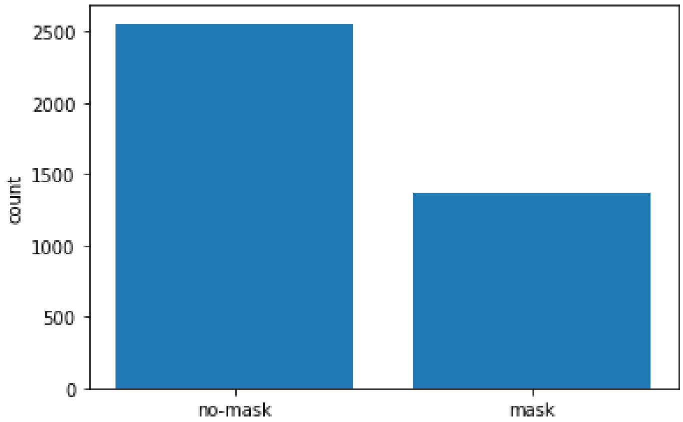


Fig. 12 Mask and no-masked images in the dataset

Fig. 12 shows the number of masked and unmasked images that can be seen in the dataset. Now, CNN and VGG16 model is implemented to extract the features from the segmented brain MRI image. Fig. 13 illustrates the overall accuracy result obtained from the training and validation set on applying CNN and VGG16 models. The result of the proposed approaches shows that both the models accurately extracted the futures from the input segmented MRI brain image.

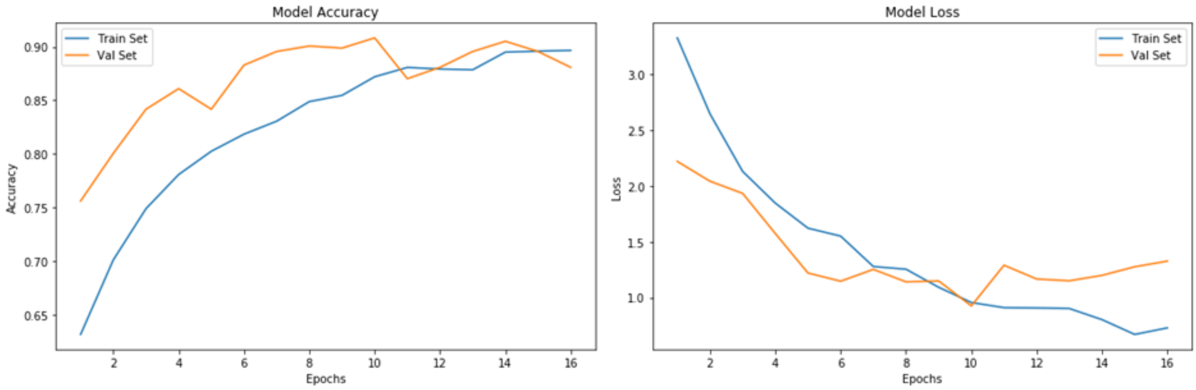


Fig. 13 Accuracy and loss of the proposed hybrid model

Table 2 shows the existing algorithms and their accuracy compared with the proposed model. It can be seen in all the models for both segmentation and classification of the features. Various filters and autoencoders are used to segment the images, and for the classification of the features, different classifiers like SVM, CNN, and other deep learning models are considered.

Table. 2 Comparison of the Proposed Model with Other Similar Models

Segmentation	**Classifier**	**Dataset**	**Accuracy**
SWE [15]	KSVM	Harvard	0.98
Fractional Sobel Filter, Statistical features [16]	SVM	Brats 2013	0.98
Stacked sparse autoencoder (SSAE) [17]	Softmax	2012-15 BRATS	0.95
CNN [18]	SVM	Local data	1.00
U-Net	CNN-VGG16	Brain MRI dataset (Kaggle [19])	1.00

IV. Conclusion and Future Work

Various machine learning and deep learning models are used to predict brain tumour through MRI images. Brain tumour detection through this paper's proposed hybrid deep learning model provides better results than the existing models for the following reasons. The initial preprocessing and segmentation of the images through the U-Net model make it easy for the deep-learning models to extract the necessary features. Along with that, it also removes unwanted areas from the images. This helps to concentrate on the tumour portions only. The proposed

CNN-VGG16 model provides better prediction accuracy as a pre-trained model is used for prediction. The overall hybrid architecture provides the necessary classification of the Brain tumour images and provides better prediction of the brain tumour images. This type of hybrid learning is made possible through the transfer learning process of the deep learning algorithms, which helps in transferring the prediction accuracy of one model to another, which helps improve the accuracy further. Hence, the proposed model provides better performance metrics than other deep learning models like InceptionV3, ResNet50, and VGG19. Thus, the new hybrid deep learning model provides the necessary segmentation of brain tumour images. The accuracy of the proposed model is nearly 99% percent in detecting the brain tumour of different types and with better efficiency.

In future prediction models, models can be trained with diverse datasets to improve the model's accuracy. It helps reduce the computational complexity and improve the model's performance. With numerous deep learning models built using transfer learning, efficient prediction can be made out.

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