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Voting Based VGG-16 for Feature Selection and Classification of The Brain Tumor Types



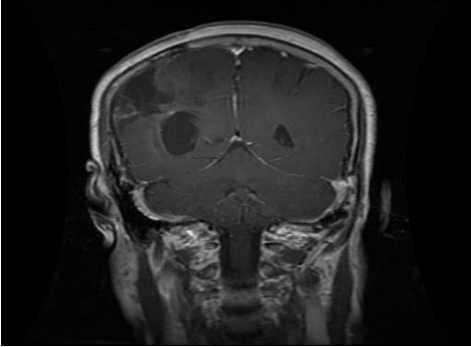
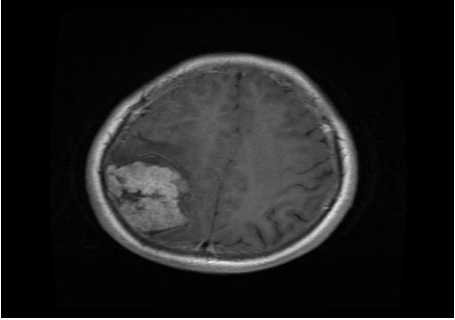
Abstract: - Brain tumors, especially malignant ones, can be life-threatening if not detected and treated early. Identifying benign tumors, such as Meningiomas or Pituitary tumors, enables preventive measures and long-term monitoring to detect any changes in tumor size or behavior. This ensures timely intervention if needed. ML related methods for analyzing types of brain tumors have made significant advancements but brain tumour records often have a mismatch of classes, which means that some kinds of tumours are much less common than others. This may result in models that are biased and work well for the majority of the class but not so well for the minority class. Latest research techniques have focused on deep learning approaches. Identifying brain tumor types using neural networks is a complex but promising approach in medical image analysis. Combining NN with ML techniques is what the suggested model does to get to the exact type of brain tumour. In this regard, the proposed model has extracted the features from the tuned model of VGG-16 and after extracting the features from the network to further classify the stage, the model has applied ensemble voting mechanism.

Keywords: Majority Voting Classifier, Tuned VGG-16, Feature Selection, Data Bias, Image Analysis

I. INTRODUCTION

Brain tumors are growths of cells that don't work right in the brain's cortex or the vertebral column. They can be categorized into various types based on their origin, behavior, and characteristics. These are discussed in table 1.

Table 1: Popular Categories of Tumor Cells Identified in Proposed Model

Type	Description	Sample Image
Gliomas	Gliomas are brain tumours that arise from brain-supporting glial cells.	
Meningiomas	Meningiomas are neoplasms that arise from the meninges, the membranous coverings that envelop the brain & spinal cord.	

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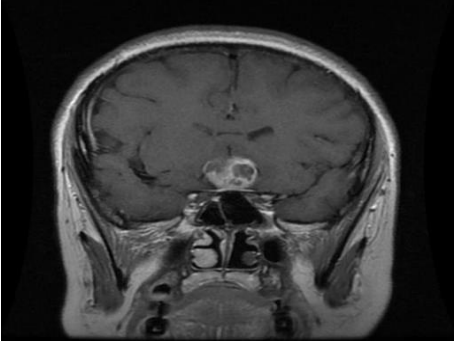
<p>Pituitary Tumors</p>	<p>The formation of these neoplasms occurs inside the pituitary gland, which is a diminutive organ located at the cranial base responsible for the regulation of hormonal activity.</p>	
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Image processing plays a pivotal role in the identification of brain tumours from medical images. Medical images can contain noise that affects the quality of tumor detection. Techniques like Gaussian smoothing or median filtering are used to reduce noise. The proposed model initially cleans the noisy data using the median filter using the below pseudocode.

```

for i in len(image):
    for j in len(image[i]):
        pixel_list ← []
        if(pixel[i][j] > pixel[i-1][j-1]):
            filter_pixel.append(pixel[i][j])
        median_pixel ← Σ filter_pixel / n
    return median_pixel
    
```

Image processing relies on the information present in the pixel values of an image. If important details are not captured in the image or if the image is of low quality, it can hinder the effectiveness of image processing techniques. The use of pre-trained models facilitates the application of transfer learning, a technique that involves the fine-tuning of models previously trained on extensive datasets, using a smaller dataset that is unique to brain tumour stages. This significantly reduces the data requirements. Using the VGG architecture for brain tumor detection involves adapting and fine-tuning the VGG model to work effectively on medical image data. Different types of VGG are presented in the figure 1.

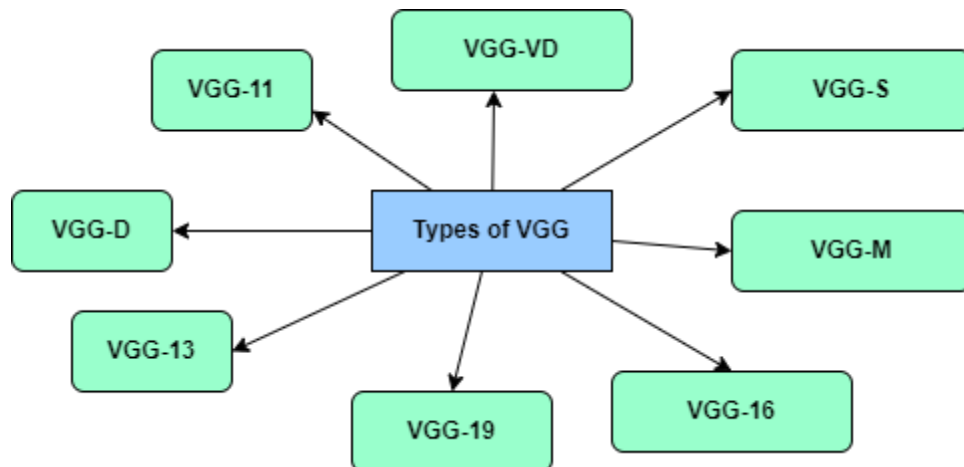


Figure 1: Classification of VGG

VGG-16 is a deep neural network with 16 weight layers, which makes it computationally expensive, both during training and inference. The initialization of the model often involves the use of pre-trained weights obtained from the data set provided by ImageNet. This TL approach helps the model generalize well to various image

classification tasks. Max-pooling layers are often used subsequent to every group of convolutional layers. The process involves decreasing the spatial size of the map of features while preserving the crucial information.

1.1. Working of VGG-16: Among convolutional neural network architectures, VGG-16 is distinguished by its deep and simple design. Thirteen convolutional layers and three fully connected layers make up the model's total of sixteen layers. A series of 3x3 convolutional filters with a stride of 1 are found within the convolutional layers, and a max-pooling layer with a 2x2 window and a stride of 2 follows each convolutional block. Low-level features are obtained by combining the initial two convolutional blocks, while higher-level data is gradually combined by the remaining blocks. The fully connected layers act as a classifier at the end of the network, combining the learned characteristics to provide final predictions. In the fields of visual recognition and computer vision, the VGG-16 architecture's consistent design and stack of convolutional layers have made it easier to use and understand.

Visual Geometry Group-16, or VGG-16, offers a lot of advantages for computer vision applications. Its main benefit is that it has a simple, uniform design with 16 layers that have max-pooling layers and moderate receptive fields (3x3 convolutional filters). This simplicity makes the approach easier to understand, use, and adjust to different tasks and datasets. VGG-16's deep design allows it to extract hierarchical traits from input photos that include both high-level semantic information and low-level details. Because of this feature, it works well for tasks like object identification and picture categorization. The model also performs exceptionally well in terms of generalization over a range of datasets, making it a solid choice for a wide range of visual recognition applications. Even if more modern architectures are more efficient than VGG-16, VGG-16 is still relevant to the area of computer vision because of its versatility and robustness in a variety of situations.

The VGG-16 (Visual Geometry Group-16) architecture's high resource needs and computational inefficiency are two of its main drawbacks. With a total of 16 layers—many of which are fully linked and convolutional—VGG-16 has a significant processing cost during training and inference. The model's enormous number of parameters makes it memory-intensive, which can make it challenging to implement in real-time applications or on devices with limited resources. Furthermore, VGG-16's deep design may lead to overfitting, particularly with smaller databases, as the high number of features may mistakenly identify noise in the data for real patterns. Some of these problems have been solved by more contemporary architectures, notably those that utilize residual networks (ResNet) or efficient topologies like MobileNet, which offer greater performance with fewer variables, making them more appropriate for real-world applications.

II. LITERATURE REVIEW:

J. N. Stember et al [1] has introduced a Deep reinforcement learning & Deep Q learning for the identification of brain tumour. 2D picture slices from the 2014 BraTS public brain tumour were used in the investigation. combining Deep Q learning (DQN) with ordinary TD(0) Q-learning. 90 episodes total, chosen at random from the 30 instructional photos, were used in the training. The action selection process balanced exploration and exploitation using the off-policy epsilon-greedy algorithm. The state-action values were estimated using a CNN known as the Deep Q network (DQN). An output layer consisting of three nodes was reached via fully connected layers that were preceded by four convolutional layers using elu activation in the DQN architecture. The difference between the target Q value (Q_{target}), as determined by the Bellman equation, and the Q values obtained from a forward pass (QDQN) served as the loss functions for DQN training. The replay memory buffer was used to randomly choose batches of transitions for the DQN's backpropagation. The DQN was trained using the Adam optimizer.

Ayesha Younis et al [2] has implemented a CNN, VGG-16, and Ensemble methodologies for the detection of BT. The brain tumour detection dataset that was used was called "Brain MRI Images." The main input for the suggested framework was brain MRI pictures, which was the first of several steps in the process. To improve the accuracy of classification and differentiate between the presence and absence of tumours, the pre-trained convolution layer VGG 16 was used. For automatic brain tumour identification and classification, the Faster CNN algorithm—which makes use of the VGG 16 architecture—was put into practise. MR image irregular black edges were addressed using amplitude normalisation during pre-processing, and bias field distortion was corrected with the N4ITK system. Prior to extracting the brain region, black borders from the pictures were removed using convolution. The real MRI brain's edges were found using multi-phase edge detection, and the only part of the image that remained was the brain. An MRI scan input shape was used to build a CNN. The final fully-connected

layer of the ensemble model, VGG 16, was used to extract features. A thorough examination of several metrics was used to evaluate the outcomes, giving rise to a thorough grasp of the efficacy of the suggested framework. The CNN model's structure and the ensemble classification method were visualised.

Narayanan Ganesh et al [3] has developed a RDO-GDRL methodology for the quick identification of BT. The MRI dataset for brain tumours was pre-processed using AGBF and skull stripping. For precise tumour identification, non-brain tissue removal, and increased computing efficiency, skull stripping is essential. AGBF performed better than conventional BLF when used for noise reduction and sharpening. During segmentation, grayscale images were converted to binary images using a threshold approach. Fourier transformations and two-dimensional Gabor functions were used to extract features. The BWO approach was used in the feature selection process. In GDRL, incentives were determined by the Q-function values and decisions were made with an ϵ -greedy method. Using RDO, the optimal number of DRNN layers for classification was found. The GDRL model was trained using a linear feature vector combination, then tested using unseen data. Selecting the finest was made simpler by the RDO approach. Selecting the optimal placements and ratings for the DRNN layers was made simpler by the RDO method. The recommended approach's accuracy served as a performance criteria to evaluate its effectiveness.

Akmalbek Bobmirzaevich Abdusalomov et al [4] has suggested using YOLOv7 to quickly identify BT. The researchers make use of an MRI dataset from Kaggle that is available to the general public and contains meningioma, pituitary, glioma, and no tumor categories. Preprocessing includes converting RGB images to grayscale, reducing size for resolution, eliminating noise, applying Gaussian blur, sharpening, and morphological techniques. The core modules of YOLOv7 are convolution, batch regularization, SiLU, and E-ELAN modules. In order to capture both channel and spatial dimensions, we introduce the CBAM attention approach. A suggested enhancement to SPPF is called SPPF+, which combines Convolutional Spatial Pyramid Convolutional with SPPF feature reuse. In order to solve the scarcity of original data for training, BiFPN is used to provide two-way data flow with connections at various sizes. By allowing each job to function separately and using additional convolutional layers for classification, regression, and prediction, YOLOX's decoupled head design increases detection accuracy. In order to accommodate the new class size, fine-tuning entails adjusting the class configuration and quantity of convolutional filters of the model.

Aya M. Al-Zoghby et al [5] has introduced a Dual CNN approach for early detection of BT. The study's dataset included 3064 T1-weighted and contrast-enhanced MRI pictures from 233 individuals who had brain tumours identified as pituitary, glioma, or meningioma. VGG-16, pre-trained on ImageNet, uses transfer learning to extract features and categorise the pictures. Every CNN in the DCTN model has two branches, after which GlobalMaxPooling2D extracts important characteristics. A SoftMax outcome layer for classification, three FC layers neurons, and a dropout layer to avoid overfitting make up the DCTN model. There are 12 layers in the custom CNN and 13 layers in the VGG-16. The input layer of the DCTN model makes adjustments for the original picture resolution. Important low- and high-level characteristics for picture categorization are extracted by the convolution layer. In order to shorten the training period and downsample the output, max pooling is used after the convolution layer. Features gleaned from many photos are combined in the fully linked layer. Multiclass classification is handled by the SoftMax layer, while the DCTN model is trained using the sparse category loss function.

Ming kang et al [6] has implemented a RCS-YOLO methodology for the identification of BT. The ShuffleNet-inspired RCS module uses channel shuffle to divide an input tensor into two, which are trained in distinct convolution layers. Effective feature communication between channel groups is achieved by enhancing information fusion between two tensors using the channel shuffle operator. RCS uses channel split and shuffle to minimise computational complexity, resulting in a 2x reduction during inference while preserving inter-channel information transmission. RCS-OSA modules lower memory access costs by keeping the lowest number of output channels and the same quantity of input channels. RCS-OSA modules extract semantic information at various backbone and neck network phases using varying numbers of stacked RCS. As measures of computing efficiency, FLOP and MAC procedures are used. When compared to ELAN, RCS-OSA shows a 50% decrease in FLOPs and a smaller MAC.

Francesco Mercaldo et al [7] has developed a YOLO method for the detection of BT. Brain MRIs are used for the automatic identification & localization of brain malignancy. It is emphasised how important a trustworthy, well annotated dataset is to building a strong object detection model. To prepare images for analysis, they are

preprocessed to a standard dimension. Bounding boxes are used to annotate images when recognised objects—in this example, tumors—are seen. The online application Labelbox is used for annotation. Techniques for image augmentation are used to increase the dataset without collecting fresh samples. The YOLO model is chosen because to its effectiveness in object identification, which combines precise object location with picture categorization in a single step. YOLO's self-contained process breaks images up into a grid of cells and guesses the edges and chances of each cell being a certain class. A backbone is used to gather features, a neck is used to combine features, and a head is used to predict box sizes and classes. The thorough feature extraction & fusion made possible by this integrated structure enhances the model's object identification capabilities.

Shweta Suryawanshi et al [8] has proposed a YoloV5, and Fast RCNN methodology for the early detection of BT. The dataset "BR35H" is used. During the training phase, the Faster R-CNN and YOLOv5 models are trained separately on the annotated dataset. While Faster R-CNN is a two-stage approach that involves region proposal generation and object identification, YOLOv5 is an advanced version of the YOLO architecture. In order to improve their capacity to identify observed objects as tumours and forecast the precise coordinates of tumour borders, both models repeatedly modify internal parameters during training. The reserved dataset is used to rigorously test the learned models. The models produce bounding boxes around tumours they identify based on their autonomous analysis of MRI scans. Performance measures provide quantitative information on how well the models detect brain tumours. The independent evaluation of YOLOv5 & Faster R-CNN enables a more nuanced comprehension of the advantages and disadvantages of each model for the identification of brain tumours.

Loveleena Gaur et al [9] has introduced a CNN methodology through LIME & SHAP for identify tumour in brain via MRI Scans. The dataset was collected from publicly accessible MRI images from Bhuvaji, categorized in four tumours. The dataset contained a total of 2k images, with 2k images used for training and the rest for testing. In data pre-processing the image rearrangement was performed to improve convergence and stop the CNN framework from figuring out the training sequence. Gaussian noise was introduced for better classification results, that has a mean value of 0 & a variety of 100.5. Comprising including frameworks for explanation the extraction process, a CNN framework, quantitative performance measurements, and feature extraction. The CNN model receives two copies of the dataset to enhance accuracy, comprising six layers that are hidden & a result layer that is 1 * 4 in size. ReLU and softmax are used as ac with Adam optimizer. The For the statistical precision evaluation, LIME, & SHAP clarifications, CNN model is employed. Disturbance is used in LIME explanations whereas a gradient explainer is used in SHAP.

Omar Kouli et al [10] has focused on survey on ML and DL techniques for identify tumour in brain via MRI Scans. The search was conducted in databases like PubMed, Web of Science, and Scopus within a specific timeframe. Including those developing or validating aged brain tumour identification or segmentation methods utilizing MRI. In exlcusion phase encompassed tumour classification studies, pediatric tumours, studies using only MRI spectroscopy, abstracts, and studies without performance metrics. Quality was evaluated using CLAIM, while Bias and relevance risks were assessed with the QUADAS-2 guideline, incorporating some CLAIM items. DL or TML based on the algorithms used. A meta-analysis compared DL and TML methods for automated detection.

Table 1: Analytical Approach on Existing Models

Author	Algorithm	Merits	Demerits	Accuracy
J. N. Stember et al	Deep reinforcement learning and Deep Q learning	Triple actions are performed parallely where less time is consumed.	The validation was not properly derived.	92%
Ayesha Younis et al	CNN, VGG-16	The combination has huge performances.	The images should contain high resolution.	98.5%
Narayanan Ganesh et al	RDO-GDRL	Hybrid model has a great efficiency.	For less images count the accuracy was also less.	98%
AkmalbekB obmirzaevic	YOLOv7	Implementation was quite easy.	Working with Different brain	99.5%

hAbdusalomov et al			images like MRI, PET, & CT SCAN is time taking process	
Aya M. Al-Zoghby et al	Dual CNN	The training accuracy was high.	The automation prediction was not processed.	99%
Ming Kang et al	RCS-YOLO	The combination of approach has achieved good efficiency.	Comparison results are not shown accurately.	94%
Francesco Mercaldo et al	YOLO	The process is efficient.	Slicing the image was little tuff.	94.3%
Shweta Suryawanshi et al	YoloV5, Fast RCNN	The model is very simple and efficient.	The comparison approaches doesn't have much differences.	98.3%
Loveleen Gaur et al	CNN, SHAP, LIME	The explanation was done by using LIME, and SHAP	The accuracy should be increased.	94.6%
Omar Kouli et al	DL, TML	Multiple methods are analyzed.	The transparent validation was not accurate.	90.14%

Novelty: The proposed research initially processes the images using different manipulation techniques. In this paper, the values are adjusted according to the specifications of the dataset. This augmentation helps in testing the images with real time data. The major goal of this paper is to perform feature extraction for this purpose the model tunes the metrics like optimizer, learning rate and loss function of VGG-16 and performs feature extraction. Once the features are extracted once again these are reduced further by computing the rank of each features using the voting on ensemble mechanisms.

III. PROPOSED METHODOLOGY

Deep architectures like VGG-16 are susceptible to vanishing gradients during training, which can slow down or hinder convergence. The proposed model hyper tunes the VGG-16 for performing the feature extraction. The proposed model integrates image processing with neural networks. Image processing can be used to augment the training dataset by applying transformations like rotation, scaling, cropping, and flipping to generate additional training examples. This data augmentation helps improve the robustness and generalization of neural network models. The following parameters are adjusted to perform the augmentation and are presented in table 2.

Table 2: Adjusted Parameters in Augmentation Approach

Parameter Name	Description	Formula	Best Possible Values	Value Adjusted
Rotation	By applying rotations, model can generate more samples for underrepresented classes, helping to balance the dataset and prevent bias in the model.	$X_{New} = X_{Old} * \cos \phi - Y_{Old} * \sin \phi$ $Y_{New} = X_{Old} * \sin \phi + Y_{Old} * \cos \phi$	-30 to +30	15

Brightness	Gamma correction is employed in the proposed model to alter picture brightness and contrast by applying the power-law conversion to pixel values.	$Pixel[X_{New}, Y_{New}] = e^{\frac{Pixel[X_{old}, Y_{old}] * \gamma}{255}}$	0.5 to 2.5	0.7
Shift	1. Augmenting the training data with width shifts can reduce overfitting. 2. Height shift helps the model learn to recognize objects regardless of their vertical placement, which can be important in real-world scenarios.	$Pixel[X_{New}, Y_{New}] = Pixel[X_{Old} + Shift_Value, Y_{Old} + Shift_Value]$ if it is shift of 2 then X_Old=[1,2,3,4,5] X_New=[4,5,1,2,3]	1-100	50%
Validation Split	It serves as a proxy for how well the model will generalize to unseen data	$Val_split = split_ratio * num_samples$	0.10% to 0.30%	0.15%
preprocessing_function	It ensures that the input image is properly preprocessed according to the requirements of the VGG16 model	It takes care of normalization, mean subtraction, ensuring that the inputted data matches what the pre-trained model thought it would see.		

Now the model trained using the VGG-16 on ImageNet, uses a hierarchical structure called "synsets" (short for synonym sets) to organize categories. Each synset represents a group of synonymous terms or closely related objects. Computer vision projects have started with models that had already been trained on ImageNet. This lets both students and professionals gain from transfer learning. This has significantly reduced the size of labeled info required the training new models. Then the methodology adds few 4 more layers for extraction and 1 layer for classification. In the next part, we'll talk about the levels in more depth.

A. Flatten Layer primary function is to convert multi-dimensional input data into a one-dimensional (flat) vector or array. The Flatten layer is often used as an intermediate step in a neural network architecture, especially when transitioning from convolutional layers to fully connected layers in CNNs.

B. Dense Layer, the model uses 3 dense layers. Dense layers consist of multiple neurons, each connected to every neuron in the previous layer, thus forming dense connections. 2 layers are designed using the ReLu activation function. It is customized as shown in equation (1)

$$Pixel[X_{New}, Y_{New}] = \begin{cases} \max(0, e^{-\frac{1+Pixel[X_{old}, Y_{old}]}{2}}) & \text{if } fine_tune > 2 \\ \max(0, Pixel[X_{old}, Y_{old}]) & \text{else} \end{cases} \quad (1)$$

The working methodology is presented in figure-2.

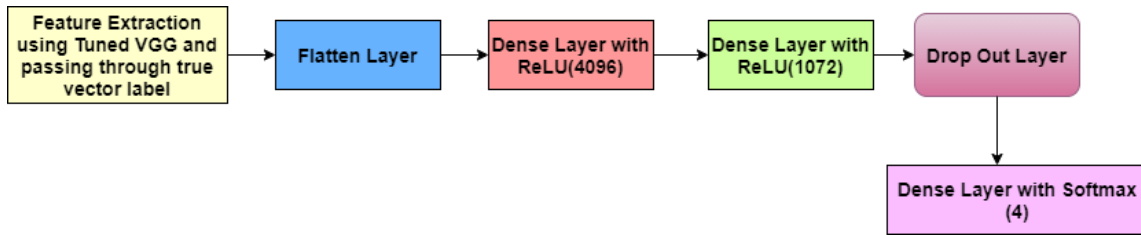


Figure 2: Layered Architecture of Customized VGG-16

The model has fine-tuned the three popular metrics of VGG-16 for improving the efficiency of feature extraction approach. Table 3 presents the considerable parameters.

Table 3: Considerable Parameters of Neural Networks

Parameter	Description	Remarks
Optimizer	RMSprop is particularly effective in mitigating the vanishing or exploding gradient problem and helps to accelerate convergence.	$v_i = \beta * v_{i-1} + (1 - \beta) * gradient^2$ $X_{new} = X_{Old} - \left(\frac{l_rate}{\sqrt{V_i + \epsilon}}\right) * gradients$
l_rate	It is a small positive scalar value that scales the change in the loss function as a function of the model factors.	$L_{new} = l_rate - \alpha * \frac{d(Loss)}{d\theta}$
Loss Function	The proposed model has utilized “Categorical Cross Entropy” that checks how different expected class probabilities are from real one-hot encoded names of classes	$Categorical_Loss = - \sum_{i=1}^c Encoded_i \log (Predicted_i)$

When working with critical applications like medical diagnosis, it's essential to minimize false positives and false negatives. Ensembling helps in achieving this by making predictions based on consensus among multiple models. Features extracted using deep learning methods on one dataset may not transfer well to a different dataset or domain, making them less versatile in some cases. Feature selection helps in eliminating irrelevant or redundant features, which can lead to better model performance. Voting classifiers allow you to consider multiple feature selection algorithms, potentially capturing different aspects of the data, and combining their outputs can lead to improved accuracy.

RF gives you an idea of how important a trait is, and these can be useful when interpreting the results of the voting classifier. Knowing which features are most influential in making predictions can help in understanding the underlying patterns in the data. AdaBoost is used to boost the performance of weak classifiers. It emphasises the samples that were wrongly labelled by the earlier models and gives them more weight. This helps in improving the overall model performance. SVMs perform well in high-dimensional feature spaces, which is often the case in machine learning applications. They are good at identifying a hyperplane that divides data into different groups, which makes them useful for many tasks, such as classifying images. Figure 3 shows how the voting algorithm is used to rank things.

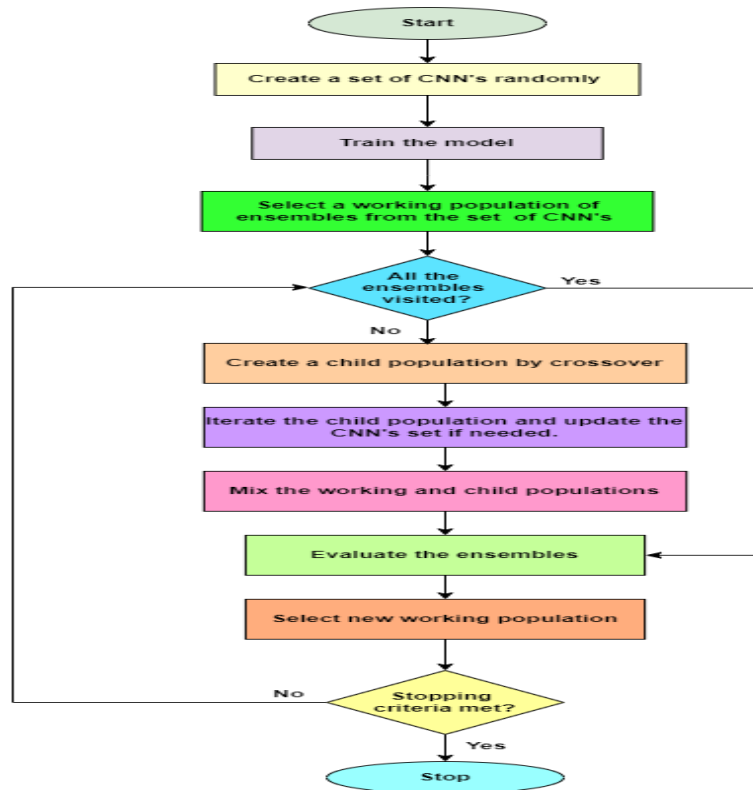


Figure 3: Feature Selection using Voting Classifier

IV. RESULTS & DISCUSSION

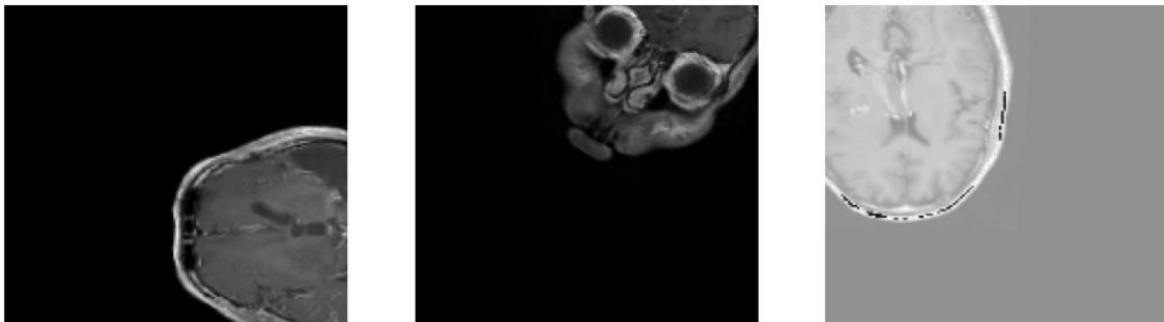


Figure 4: Augmented Images Created using Tuned Notations

Figure 4 presents the augmentation techniques like random cropping and resizing help teach the model to be invariant to translations (shifts) in the input data. The proposed model has applied 5 important manipulation techniques on the images to create real time scenario and to remove the noise from the images.

```

[[1.41805085e-05 6.28428673e-03 9.93701577e-01 1.04309175e-08]
 [4.56385136e-01 5.38490832e-01 3.99133749e-03 1.13269826e-03]
 [2.92409174e-02 6.15208387e-01 4.39631380e-02 3.11587602e-01]
 ...
 [7.26525206e-03 5.81470616e-02 9.33802545e-01 7.85163720e-04]
 [6.32372859e-04 9.23862085e-02 3.87219450e-04 9.06594157e-01]
 [6.68080866e-01 3.29307109e-01 1.56149827e-03 1.05049205e-03]]
    
```

Figure 5: Features Extracted using Voting Classifier

Different feature extraction methods capture different aspects of the data. By using multiple feature extraction techniques and combining their outputs, you can leverage the diversity of information. This can lead to improved model performance because you're considering different perspectives of the data. Figure 5 presents the features extracted after applying voting on three popular machine learning approaches namely Random Forest, SVM and AdaBoost

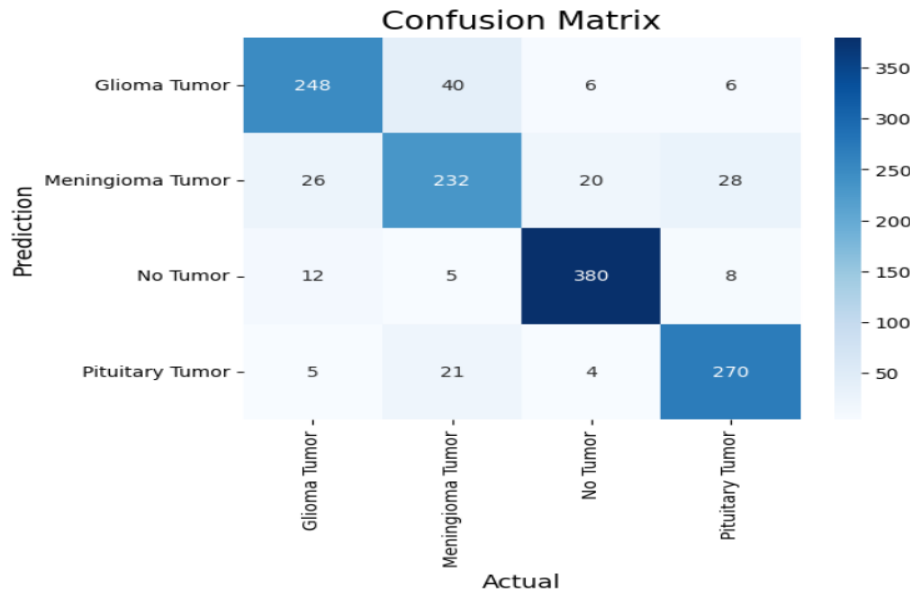


Figure 6: Confusion Matrix of Proposed Model

Figure 6 presents the confusion matrix for multi classification of brain tumour detection. By examining the elements of this confusion matrix, model can assess how well the model performs for each class and identify any patterns of misclassification. It helps in understanding which classes the model is confusing, and whether it is biased towards certain classes.

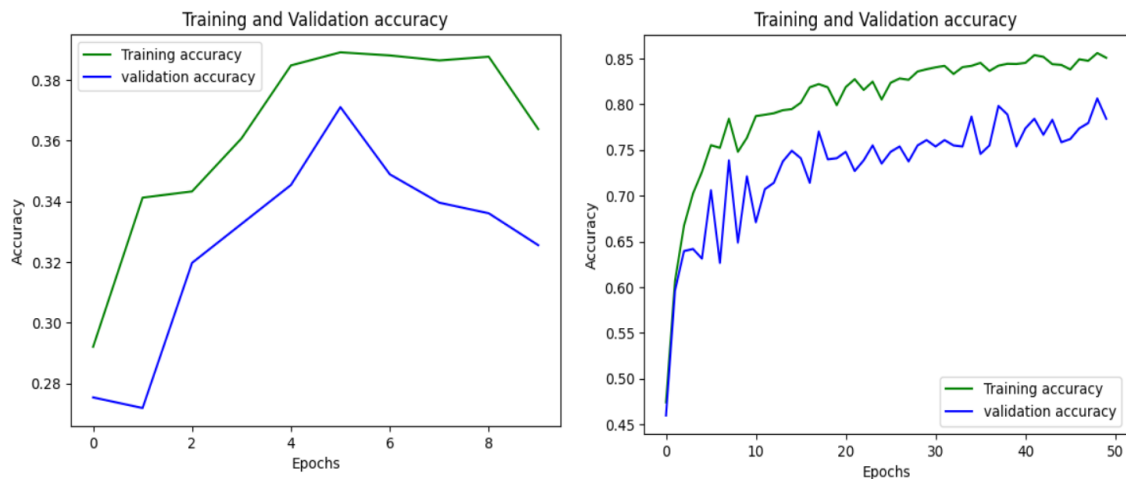


Figure 7: Accuracy Analysis on Tumour Detection using CNN & Proposed Model

Figure 7 presents the training and validation accuracy. Training accuracy represents how accurately your model predicts the labels or classes of the data it was trained on. It is determined by dividing the sum of all training dataset samples by the fraction of those samples that were properly predicted. Training accuracy can provide insights into how well your model is fitting the training data.

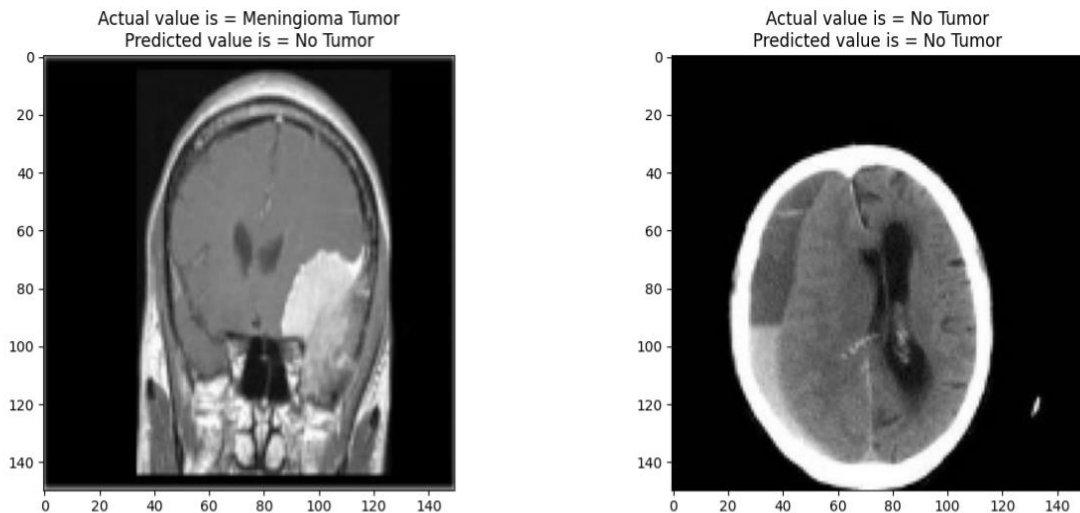


Figure 8: Prediction of Test Images

Figure 8 presents the prediction values of the test images along with the actual labels. Once a model has been properly trained, this can be used to guess what will happen with brand-new pictures. When the user feed an image into the model, it processes the image's features through its layers and produces an output.

5. CONCLUSION: Detecting brain tumor types using neural networks is a challenging but crucial task in medical image analysis. Detecting brain tumors using pre-trained models is a common and effective approach in medical image analysis. While pre-trained models are excellent at generalizing from large datasets, they may not perform well on highly specific or novel tasks. The proposed model instead of using the traditional pre-trained model it implements tuned VGG-16 and extracts the features. After extracting the features, to reduce them it implements the voting classifier designed with one bagging, one boosting and one traditional machine learning approach. Voting classifiers are a form of ensemble learning where multiple models (classifiers) are combined to make predictions. This can lead to more robust and accurate results by reducing the impact of individual model biases. In future work, model develops automated tumor segmentation methods that can accurately delineate tumor boundaries in MRI images. This is crucial for treatment planning and monitoring.

V. CONCLUSION

Detecting brain tumor types using neural networks is a challenging but crucial task in medical image analysis. Detecting brain tumors using pre-trained models is a common and effective approach in medical image analysis. While pre-trained models are excellent at generalizing from large datasets, they may not perform well on highly specific or novel tasks. The proposed model instead of using the traditional pre-trained model it implements tuned VGG-16 and extracts the features. After extracting the features, to reduce them it implements the voting classifier designed with one bagging, one boosting and one traditional machine learning approach. Voting classifiers are a form of ensemble learning where multiple models (classifiers) are combined to make predictions. This can lead to more robust and accurate results by reducing the impact of individual model biases. In future work, model develops automated tumor segmentation methods that can accurately delineate tumor boundaries in MRI images. This is crucial for treatment planning and monitoring..

REFERENCES

- [1] Stember, J. N., & Shalu, H. (2022). Reinforcement learning using Deep Q networks and Q learning accurately localizes brain tumors on MRI with very small training sets. *BMC Medical Imaging*, 22(1). <https://doi.org/10.1186/s12880-022-00919-x>
- [2] Younis, A., Qiang, L., Nyatega, C. O., Adamu, M. J., & Kawuwa, H. B. (2022). Brain Tumor Analysis Using Deep Learning and VGG-16 Ensembling Learning Approaches. *Applied Sciences (Switzerland)*, 12(14). <https://doi.org/10.3390/app12147282>
- [3] Ganesh, N., Jayalakshmi, S., Narayanan, R. C., Mahdal, M., Zawbaa, H. M., & Mohamed, A. W. (2023). Gated Deep Reinforcement Learning With Red Deer Optimization for Medical Image Classification. *IEEE Access*, 11, 58982–58993. <https://doi.org/10.1109/ACCESS.2023.3281546>

- [4] Abdusalomov, A. B., Mukhiddinov, M., & Whangbo, T. K. (2023). Brain Tumor Detection Based on Deep Learning Approaches and Magnetic Resonance Imaging. *Cancers*, 15(16). <https://doi.org/10.3390/cancers15164172>
- [5] Al-Zoghby, A. M., Mohamed Al-Awadly, E. K., Moawad, A., Yehia, N., & Ismail Ebada, A. (2023). Dual Deep CNN for Tumor Brain Classification. 13, 2050. <https://doi.org/10.3390/diagnostics>
- [6] Kang, M., Ting, C.-M., Ting, F. F., & Phan, R. C.-W. (2023). RCS-YOLO: A Fast and High-Accuracy Object Detector for Brain Tumor Detection (pp. 600–610). https://doi.org/10.1007/978-3-031-43901-8_57
- [7] Mercaldo, F., Brunese, L., Martinelli, F., Santone, A., & Cesarelli, M. (2023). Object Detection for Brain Cancer Detection and Localization. *Applied Sciences (Switzerland)*, 13(16). <https://doi.org/10.3390/app13169158>
- [8] Kesana, A., Nallola, J., Bootapally, R. T., Amaraneni, S., & Reddy, G. S. (2023, May). Brain Tumor Detection Using YOLOv5 and Faster R-CNN. In *2023 2nd International Conference on Vision Towards Emerging Trends in Communication and Networking Technologies (ViTECoN)* (pp. 1-6). IEEE.
- [9] Gaur, L., Bhandari, M., Razdan, T., Mallik, S., & Zhao, Z. (2022). Explanation-driven deep learning model for prediction of brain tumour status using MRI image data. *Frontiers in genetics*, 13, 448.
- [10] Kouli, O., Hassane, A., Badran, D., Kouli, T., Hossain-Ibrahim, K., & Steele, J. D. (2022). Automated brain tumor identification using magnetic resonance imaging: A systematic review and meta-analysis. *Neuro-Oncology Advances*, 4(1). <https://doi.org/10.1093/naajnl/vdac081>
- [11] Asif, S., Yi, W., Ain, Q. U., Hou, J., Yi, T., & Si, J. (2022). Improving Effectiveness of Different Deep Transfer Learning-Based Models for Detecting Brain Tumors From MR Images. *IEEE Access*, 10, 34716–34730. <https://doi.org/10.1109/ACCESS.2022.3153306>
- [12] Ullah, N., Khan, J. A., Khan, M. S., Khan, W., Hassan, I., Obayya, M., Negm, N., & Salama, A. S. (2022). An Effective Approach to Detect and Identify Brain Tumors Using Transfer Learning. *Applied Sciences (Switzerland)*, 12(11). <https://doi.org/10.3390/app12115645>
- [13] Ali, Z. H., Al-Ali, A. K., & Al-Moosawi, N. M. (n.d.). International Journal of INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING Deep Learning and Feature Extraction of Brain Tumour Detection. In *Original Research Paper International Journal of Intelligent Systems and Applications in Engineering IJISAE (Vol. 2023, Issue 6s)*. www.ijisae.org
- [14] A. Mallikarjuna Reddy, V. Venkata Krishna, L. Sumalatha, “Efficient Face Recognition by Compact Symmetric Elliptical Texture Matrix (CSETM)”, *Jour of Adv Research in Dynamical & Control Systems*, Vol. 10, 4-Regular Issue, 2018.
- [15] Mallikarjuna Reddy, A., Rupa Kinnera, G., Chandrasekhara Reddy, T., Vishnu Murthy, G., et al., (2019), “Generating cancelable fingerprint template using triangular structures”, *Journal of Computational and Theoretical Nanoscience*, Volume 16, Numbers 5-6, pp. 1951-1955(5), doi: <https://doi.org/10.1166/jctn.2019.7830>
- [16] Mallikarjuna Reddy, A., Venkata Krishna, V. and Sumalatha, L.” Face recognition approaches: A survey” *International Journal of Engineering and Technology (UAE)*, 4.6 Special Issue 6, volume number 7 , 117-121,2018.
- [17] Swarajya Lakshmi V Papineni, Snigdha Yarlagaadda, Harita Akkineni, A. Mallikarjuna Reddy. Big Data Analytics Applying the Fusion Approach of Multicriteria Decision Making with Deep Learning Algorithms *International Journal of Engineering Trends and Technology*, 69(1), 24-28, doi: 10.14445/22315381/IJETT-V69I1P204.
- [18] Sudeepthi Govathoti, A Mallikarjuna Reddy, Deepthi Kamidi, G BalaKrishna, Sri Silpa Padmanabhuni and Pradeepini Gera, “Data Augmentation Techniques on Chilly Plants to Classify Healthy and Bacterial Blight Disease Leaves” *International Journal of Advanced Computer Science and Applications(ijacs)*, 13(6), 2022. <http://dx.doi.org/10.14569/IJACSA.2022.0130618>.
- [19] Mallikarjuna A. Reddy, Sudheer K. Reddy, Santhosh C.N. Kumar, Srinivasa K. Reddy, “Leveraging bio-maximum inverse rank method for iris and palm recognition”, *International Journal of Biometrics*, 2022 Vol.14 No.3/4, pp.421 - 438, DOI: 10.1504/IJBM.2022.10048978.
- [20] Reddy, K.S., Naga Santhosh Kumar, C.H., Effective data analytics on opinion mining, *International Journal of Innovative Technology and Exploring Engineering* 8(10), pp. 2073-2078, 2019..
- [21] A. M. Reddy, K. SubbaReddy and V. V. Krishna, "Classification of child and adulthood using GLCM based on diagonal LBP," 2015 International Conference on Applied and Theoretical Computing and Communication Technology (iCATccT), Davangere, 2015, pp. 857-861, doi: 10.1109/ICATccT.2015.7457003.
- [22] Shah, H. A., Saeed, F., Yun, S., Park, J. H., Paul, A., & Kang, J. M. (2022). A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet. *IEEE Access*, 10, 65426–65438. <https://doi.org/10.1109/ACCESS.2022.3184113>.
- [23] Mamidiseti, Suresh and A. Mallikarjuna Reddy. “Enhancing Depression Prediction Accuracy Using Filter and Wrapper-Based Visual Feature Extraction.” *Journal of Advances in Information Technology* (2023),14(6), pp. 1425–1435.

- [24] Naik, S., Kamidi, D., Govathoti, S., Cheruku, R., & Mallikarjuna Reddy, A. (2023). Efficient diabetic retinopathy detection using convolutional neural network and data augmentation. *Soft Computing*, 1-12.
- [25] V. NavyaSree, Y. Surarchitha, A. M. Reddy, B. Devi Sree, A. Anuhya and H. Jabeen, "Predicting the Risk Factor of Kidney Disease using Meta Classifiers," 2022 IEEE 2nd Mysore Sub Section International Conference (MysuruCon), 2022, pp. 1-6, doi: 10.1109/MysuruCon55714.2022.9972392.
- [26] S. Mamidiseti and A. M. Reddy, "A stacking-based ensemble framework for automatic depression detection using audio signals," *International Journal of Advanced Computer Science and Applications*, vol. 14, no. 7, pp. 603–612, 2023.
- [27] P. S. Silpa *et al.*, "Designing of Augmented Breast Cancer Data using Enhanced Firefly Algorithm," 2022 *3rd International Conference on Smart Electronics and Communication (ICOSEC)*, 2022, pp. 759-767, doi: 10.1109/ICOSEC54921.2022.9951883
- [28] Zeineldin, R. A., Karar, M. E., Elshaer, Z., Coburger, J., Wirtz, C. R., Burgert, O., & Mathis-Ullrich, F. (2022). Explainability of deep neural networks for MRI analysis of brain tumors. *International Journal of Computer Assisted Radiology and Surgery*. <https://doi.org/10.1007/s11548-022-02619-x>