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# Optimized Brain Tumour Segmentation and Classification Using VGG UNET and VGG-19 withABC-WOA Algorithm

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***Abstract*—Accurate brain tumour classification is essential for treatment planning and patient care in medical image analysis. In this study, we used sophisticated deep learning algorithms to improve brain tumour categorization. We used VGG-UNET for segmentation to precisely delineate tumour locations in MRI scans and VGG-19 for classification, a popular convolutional neural network architecture for image classification. We used a hybrid ABC-WOA hyperparameter tweaking technique to increase the accuracy and resilience of our VGG-19 model. We compared our model against ResNet-50 and AlexNet, two popular convolutional neural network designs, on accuracy, precision, recall, and F1-scores. Hyperparameter-tuned VGG-19 model had excellent discrimination, with accuracy metrics topping 99.1% and a remarkable AUC value of 0.99. ResNet-50 and AlexNet performed well, however they were not as accurate and precise as VGG-19. These data show that our technique could revolutionize brain tumour classification, providing doctors with a trustworthy tool for precise diagnosis and treatment planning. Future study might examine the scalability and generalizability of our findings in larger datasets and clinical contexts, improving patient outcomes and neuro-oncology research. VGG-UNET segmentation, VGG-19 classification, and a hybrid ABC-WOA hyperparameter tuning approach improve brain tumour classification accuracy. The hyperparameter-tuned VGG-19 model's proven performance makes it a promising choice for clinical brain tumour classification tasks, providing physicians with accurate diagnosis and prognosis.**

***Keywords*— VGG-UNET, VGG-19, ResNet-50, Alexnet, Brain-Tumour, ABC-WOA, Segmentation, MRI Images.Introduction**

A brain tumour is an atypical growth of cells in the human brain. Various types of brain tumours are seen in different regions of the world. There are two types of brain tumours: benign, which are non-cancerous, and malignant, which are cancerous. Tumours may originate in the brain or develop from tumours in other regions of the body and then metastasize to the brain. The primary manifestations of brain tumours are severe headaches, impaired vision, impaired coordination, cognitive disorientation, and convulsions [1]. Common treatment options for human brain tumours are surgical intervention, radiation therapy, and chemotherapy. The human brain has billions of active cells and is very intricate to analyse. Brain tumours are becoming a major cause of higher death rates in both children and adults. Approximately 250,000 people worldwide are diagnosed with primary brain tumours each year, which represent less than 2 percent of all cancer cases. This abnormality often suggests the presence of a brain tumour. The location of these tumours is established by magnetic resonance imaging (MRI). An important issue in the categorization of the images is the arrangement of prominent vectors that are similar. Consequently, the extraction of sufficient key features is a necessary need for efficiently segmenting the images. Extracting the important components from images is a challenging task due to the intricate patterns of the many tissues in the brain.

When it comes to medical research, brain tumours are among the most terrifying disorders. That was the leading cause of cancer-related deaths among children 0–14 years old in the US in 2016 [2]. The three most common types of brain tumours are meningioma, glioma, and pituitary. Levels of malignancy in these tumours vary. Gliomas are the most common kind of malignant brain tumours that may develop in glial and spinal cord tissues. A meningioma, on the other hand, is a benign tumour that grows slowly and originates on the membrane that surrounds and protects the brain and spinal cord.[3]The area around the pituitary gland is where the pituitary emerges. Even though it is a benign tumour, it may cause further medical complications, unlike meningioma. Particularly, brain MRI images are utilized to identify tumours and their progression. Compared to CT or ultrasound images, MRI images provide more specific information on the anatomy of the brain. When radiologists examine different MRI slices, they may detect brain malignancies. For many patients, early tumour diagnosis improves their chances of life and aids in the treatment of their condition. Nonetheless, radiologists often deal with several complicated malignancies and enormous volumes of MRI data. This results in a lengthy treatment procedure and a significant chance of mistake, particularly when little slices are impacted. Therefore, distinguishing between different forms of brain tumours and diagnosing brain tumours are challenging undertakings.

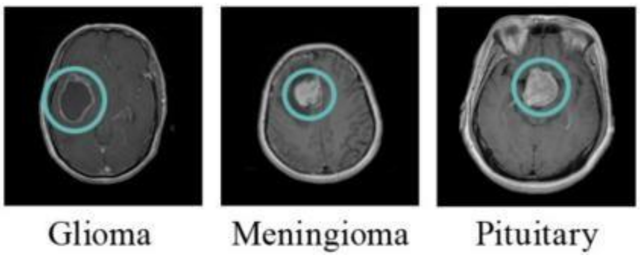


*Figure 1 Types of Brain Tumors*

Brain tumours may be of two types. The first kind of tumour is called a primary tumour because it originates in the brain; it is the most frequent type of tumour. The other type of tumour is called a secondary tumour because it spreads from another area of the body to the brain[4]. Gliomas are the most common kind of brain cancer, accounting for more than 35% of all brain malignancies, while there are other varieties as well. Glial cells, which are in charge of maintaining the health of neural nerves, are the source of gliomas. On the basis of the particular targeted cell, gliomas are further classified into other categories. The most dangerous kind of glioma among them is a glioblastoma [5].

MRI is an imaging method that uses radio waves and a magnet to let physicians view inside the human body. Compared to CT, X-ray, and ultrasound modalities, MRI offers superior resolution in the brain imaging because the brain is the most prevalent soft tissue. Certain MRI modalities are used to provide better results for the targeted locations; the most used modalities are T1, T2, T2*, and FLAIR weighted mages. Repetition Time (TR) and Time to Echo (TE) are used sparingly to create TI weighted pictures, while T2 weighted images are created with larger TR and TE than T2. In a similar vein, FLAIR weighted pictures are a variation of T2 that are created by using higher TR and TE than T2. Every tissue has a distinct picture that is produced by the contrast between several modalities. The total survival rate of the patient is significantly influenced by the accuracy of the brain tumour diagnosis. Image segmentation divides an image into distinct sections with comparable properties, assigning each resolution to a certain category [6]. Brain tumour segmentation is the separation of tumorous and non-tumorous regions[7]. There are two forms of brain tumour segmentation. Manual breakdown is time-consuming and difficult. However, automated segmentation is straightforward and accurate because to advancements in artificial intelligence. Artificial intelligence (AI) is increasingly being used in medical imaging owing to improved machine learning algorithms and frameworks [8].

### *A. The Role of Medical Imaging in Brain Tumour Diagnosis*

The primary objective of computerized brain tumor diagnosis is to gather crucial clinical data on tumor existence, location, and type. The information gathered by clinical imaging may guide subsequent actions, leading to accurate tumor identification and therapy. Automated brain tumor diagnostic approaches combine many methodologies into a pyramid. Various strategies are required for data preparation, selection, labeling, and description at each level of the pyramid. Early tumor identification improves therapy. Brain imaging methods, including PET, SPECT, CT, MRI, and MRS, aid in diagnosing brain tumors by revealing their location, size, shape, and type. Due to its ubiquitous availability and soft tissue contrast, MRI is a typical tool for obtaining detailed information about human tissues. MRI produces pictures of human tissues using radio frequency signals and a strong magnetic field[9].

Brain tumor diagnosis involves tumor detection, segmentation, and classification methods. Brain tumor identification relies on identifying MRI pictures from a database, a straightforward operation. Brain tumor segmentation methods are utilized to identify and isolate specific tumor tissues within MRI images. Brain tumor categorization algorithms identify aberrant pictures as either malignant or benign. These three hybrid methodologies and strategies help radiologists comprehend and interpret MRI material for diagnosis. Numerous scholars have undertaken substantial study in the area of brain tumor diagnostics during the last few decades. Various approaches have been suggested for both tumor segmentation and classification. The clinical adoption of diagnostic procedures has relied on the level of user supervision and the ease of calculation. Nevertheless, the practical uses of this technology are now restricted, despite the considerable quantity of research conducted. doctors continue to rely on manually projecting the tumor, perhaps due to the absence of a strong collaboration between doctors and researchers.

Magnetic resonance imaging is the most widely used technique for tumor type differential diagnosis (MRI). It is subject to human subjectivity, however, and it is difficult for humans to observe a big quantity of data. Radiologist expertise is mostly responsible for early brain tumor identification [10]. Before determining whether the tumor is benign or malignant, the diagnostic process could not be finished. Typically, a biopsy is done to determine if the tissue is benign or cancerous. The biopsy of a brain tumor is often not performed prior to final brain surgery, in contrast to cancers located elsewhere in the body[11]. It is crucial to provide an efficient diagnostics tool for tumor segmentation and classification from MRI images in order to get accurate diagnoses, prevent surgery, and eliminate subjectivity [12].The medical sector has been greatly impacted by the development of new technologies, particularly artificial intelligence and machine learning, which have become vital support systems for many medical specialties, including imaging. In order to provide radiologists a second opinion, many machine-learning techniques for picture segmentation and classification are used in MRI image processing.

MRI is a radiation-free imaging technology that is considered safer than CT. It offers superior visualization of the brain, spinal cord, and vascular anatomy owing to its excellent contrast. [13]The axial, sagittal, and coronal planes are fundamental imaging planes used in MRI to examine the anatomical structures of the brain, as seen in Figure 2. The MRI sequences most often used for brain analysis are T1-weighted, T2-weighted, and FLAIR [36]. A Tl-weighted scan offers distinct contrast between gray and white matter. T2-weighted imaging is highly responsive to the presence of water and is hence ideal for detecting illnesses characterized by the accumulation of water inside brain tissues. T1- and T2-weighted images are used for distinguishing cerebrospinal fluid (CSF). The cerebrospinal fluid (CSF) is devoid of color and is located inside the brain and spinal cord. The object appears hypointense in T1-weighted imaging and hyperintense in T2-weighted imaging. The third sequence is fluid attenuated inversion recovery (FLAIR), which is comparable to a T2-weighted picture except for its distinct acquisition methodology. FLAIR is used in pathology to differentiate between cerebrospinal fluid (CSF) and brain abnormalities. FLAIR may identify the presence of an edema area in the cerebrospinal fluid (CSF) by reducing the signals from free water. As a result, periventricular hyperintense lesions can be easily seen in the pictures.

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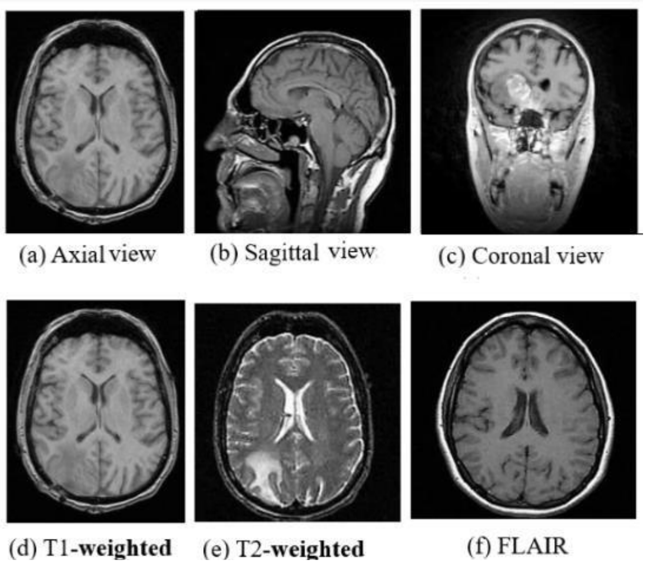


*Figure 2(a) Axial view, (b) Sagittal view, (c) Coronal view and (d) T1-weighted, (e) T2-weighted and (f) FLAIR Images of MRI. (image courtesy: AtheroPointTM).*

Figure 2 depicts a comparison of the three sequences described above. Diffusion-weighted imaging (DWI) [14] is another MRI sequence used to identify the random motions of water particles inside the brain. As water flow becomes limited, a very strong signal is reflected on the DWI, hence the DWI method is mostly employed for acute stroke detection. Perfusion-weighted MRI (PWI) identifies the exact region of the brain where blood flow has changed. Diffusion-tensor MRI (DTMRI) identifies water migration in tissues using a microscopic picture, which aids in the surgical excision of a brain tumor. Functional magnetic resonance imaging (fMRI) is another kind of MRI that measures changes in blood oxygenation in order to understand neurological activity. When a certain area of the brain becomes more active, it consumes more oxygen and blood. As a result, an fMRI monitors the brain's continuing activity by linking mental processes with location. Although MRI is an excellent tool for analyzing brain images, it has certain drawbacks when compared to CT. The motion artifact effect is lower in MRI, which aids in the diagnosis of acute bleeding and brain damage, but it also requires a longer acquisition time than many other imaging modalities.

## II. EASE OF USE

This[15] study proposed a deep learning architecture to automatically identify brain cancers using two-dimensional MRI slices with high accuracy and low error. Square Array Filtering (SAF) removes noise from the input picture and generates a square grid format array to update missing pixel values, creating a noiseless image. The Kernel K-means Clustering (K2C) model segments the wounded region by separating diseased regions and reducing noise using weighted mean augmentation. The Optimization Empowered Hierarchical Residual VGGNet19 (HR-VGGNet19) model uses convolution layers to combine low-level and high-level features to determine the output class. The algorithm is implemented in MATLAB and assessed using accuracy, sensitivity, specificity, PPV, NPV, FPR, FNR, and FDR. These measures show that the suggested technique outperforms state-of-the-art methods.

[16] Examined that Image segmentation as a computer-based diagnostic approach in brain tumour magnetic resonance imaging (MRI) is critical for medical diagnosis. The primary goal of picture segmentation is to see the distinct form of the tumour. Several approaches for deep learning have been developed using the U-Net architecture. The UNet-VGG16 with transfer learning + dropout is a novel architecture that combines the U-Net and VGG-16 with transfer learning + dropout regularization. The dropout scenario is a method of reducing overfitting since VGG-16 has several nonlinear hidden layers and intricate interactions that might lead to overfitting. This innovative design has been shown to be both quick and accurate in segmenting low-grade glioma MRIs using fluid-attenuated inversion recovery sequence. As a result, the purpose of this research is to find the optimum optimizer for UNet-VGG16 with transfer learning + dropout that can handle overfitting. This investigation successfully identified Adamax as the optimal optimizer.

[17] This article described using several VGG-19 architectures as a foundation layer for particular models. The suggested system includes pre-processing, cropping, augmentation, VGG-19 as a base layer, transfer learning-based brain tumor binary classification, and additional layers such as normalization, dense, and activation. The proposed approach achieved Cohen Kappa Score, f1-score, recall, accuracy, precision, and ROC AUC score of.9900,.9949,.9950,.9950, and 1.000 for brain tumor kaggle MRI datasets, respectively. The trials showed that the suggested technique is more efficient and successful than previous research on Kaggle MRI datasets.

[18] proposed two models, ResNext101_32×8d and VGG19, to classify pituitary and glioma brain tumours, respectively. The suggested models are applied to a dataset of 1,800 MRI images with two diagnoses: glioma tumor and pituitary tumor. The suggested models use a single-image super-resolution (SISR) approach to categorize and improve fundamental elements of MRI images. This enhances certain parts of the pictures and helps with model training. The models are built using PyTorch and TensorFlow frameworks, with Hyperparameter tweaking and data augmentation. The suggested model's performance is evaluated experimentally using the receiver operating characteristic curve (ROCC), error matrix, precision, and recall. Results show that VGG19 and ResNext101_32 × 8d have testing accuracies of 99.98% and 100%, with loss rates of 0.0120 and 0.108, respectively. The F1-score, Precision, Recall, and Area under the ROC for VGG19 were 99.89%, 99.90%, 99.89%, and 100%, respectively, whereas ResNext101_32 × 8d had all values of 100%. The suggested models can quickly and accurately discriminate between pituitary and glioma tumours in MRI scans, potentially helping physicians and radiologists check for brain malignancies.

[19] Bio-imaging tools, such as MRI and CT scans, are critical for detecting brain tumours (BT) and assessing patient outcomes. However, manual examination of these photos takes time and needs experience. To address this, we offer an image fusion model that integrates MRI and CT images using Wavelet-based fusion and takes use of the VGG-19 architecture for enhanced accuracy. Image fusion mixes modalities to improve their strengths and mitigate

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limitations. Our solution uses the Wavelet fusion technique to decompose pictures into frequency bands. The low-frequency LL band contains important structural information. The VGG-19 network, including convolutional and pooling layers, merges LL bands and reconstructs fused pictures. We evaluate brain MRI and CT images via pre-processing, feature extraction, and fusion phases. Our technique not only decreases the doctor's burden and analysis time, but it also improves tumour detection accuracy. Automation of image processing and early, precise tumor diagnosis result in improved patient treatment.

[20] Magnetic Resonance Imaging (MRI) scanning is the fastest growing discipline in recent years. Radiologists find it difficult and time-consuming to diagnose and categorize brain tumours based on their size and characteristics. A brain tumor occurs when abnormal cells proliferate in the brain. Each year, around 11,700 people are diagnosed with brain tumours. Approximately 34% of men and 36% of females survive five years after being diagnosed with malignant brain or tumours. This research focuses on several brain cancers, including meningioma, pituitary, glioma, and "no tumours." Using deep learning and machine learning, an autonomous system was developed for brain tumor classification and segmentation, leading to improved early detection. Simple Convolutional Neural Network (CNN) models like VGG-16 and Efficient NetB7 are among the top performers. The research found that utilizing MRI to diagnose brain cancers may lead to faster, more accurate judgments. We utilized 7022 brain magnetic resonance images to train and evaluate our model. Experimental results show that the proposed differential deep CNN model can effectively categorize MRI images of brain tumours, including aberrant and conventional images, with a 98.19% accuracy rate.

[21]A brain tumor is a serious condition that may be deadly and has a substantial influence on quality of life. The conventional way of diagnosing malignancies is based on doctors, which is time-consuming and prone to mistakes, putting the patient's life at risk. The significant anatomical and geographical variety of the brain tumour's surrounding area makes identifying its classes challenging. To successfully treat this severe condition, an automated and exact diagnostic strategy is essential. Deep learning technologies, such as CNN, may be utilized to detect several tumor forms in the early stages of development utilizing brain MRI. This paper introduces a deep transfer learning framework based on VGG-19 to correctly identify three prevalent types of cancers using brain MRI. The proposed framework consists of two main stages. The first step is the frozen VGG-19, followed by the modified neural style classification. Certain updated strategies were used to fix the class imbalance effect inside the MRI dataset as well as the generalization error problem throughout the training phase. The suggested model achieves 94% classification accuracy and 94% F1-score.

## III. METHODOLOGY

In MRI brain tumour categorization, finding a pattern is the most crucial step. MRI images are complicated, which might cause mislearning and lower classification accuracy. We developed a three-step pre-processing strategy.

### *A. Dataset*

We obtained data from the following websites: https://archive.ics.uci.edu/dataset/759/glioma+grading+clinical+and+mutation+features+data set

### *B. Dataset Description*

We segmented brain tumour photographs from this collection. This dataset contains 20 typically mutated genes and three clinical features from TCGA-LGG and TCGA-GBM brain glioma studies. This task involves determining if a patient has LGG or GBM using clinical and molecular/mutation data.

### *C. Pre-Processing*

This study explores the accuracy differences between standard preprocessing strategies for basic convolutional neural networks. We have mentioned some preprocessing techniques below.

*Read Image:*

We first loaded photo groups in arrays by storing the address of the A field holding the image collection, enabling image retrieval.

*Resize Image:*

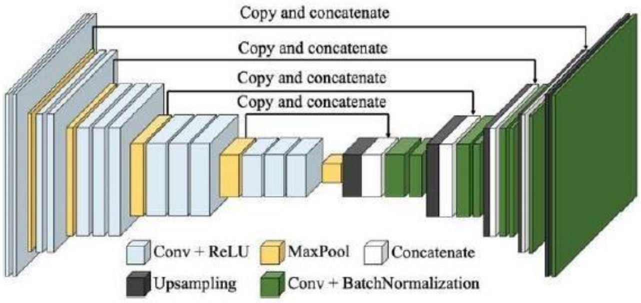
To highlight variations during picture resizing, use two presentation techniques. One approach displays one image, while the other displays two. We developed a processing technique that only takes images as input.

*Remove Noise:*

To quiet the noise Gaussian blurs may be created by applying the Gaussian function to images. To reduce visual noise, this popular graphics effect is often used. Gaussian smoothing is another machine vision pre-processing technology that improves visual structures at different sizes.

### *D. Segmentation*

Segmentation is crucial in medical imaging for tumour diagnosis, organ delineation, and treatment planning, providing valuable information to healthcare practitioners. To segment brain tumour images, the VGG-UNet method combines a VGG19 encoder with a UNet decoder. The dataset consists of brain MRI images and tumour masks, divided into training, validation, and testing stages.



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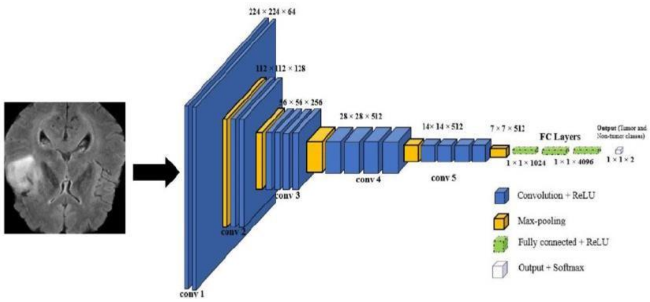
### E. Train_test split

Train-test splits the dataset into training and testing sets. The model learns patterns and characteristics from the training set, which contains most of the data. Check the model's generalization performance using a dataset not used for training. Split testing with fresh data provides a valid measure of model performance and detects overfitting. To balance training and assessment, conventional splits allocate 70-80% of data to training and 20-30% to testing.

### F. Our proposed model

VGG-19 is a deep convolutional neural network with 24 layers. The network has 16 convolutional layers, 5 pooling layers, and 3 fully linked layers, contributing to its complex architecture. It was pre-trained using over one million images from ImageNet. For the VGG-19 network, the input image size is 224 by 224 pixels. There are almost 138 million parameters in VGG-19. The VGG-19 design reduces parameter count by using 3x3 pixel-sized filters in its convolutional layer. This purposeful choice improves network efficiency, maintains capacity, and extracts key data properties.




### G. Hyperparameter tuning

Hyperparameters affect model learning and must be adjusted. Hyperparameters control network design and training and may affect deep-learning model performance. The model may perform better with proper hyperparameter tuning. We utilized the ABC_WOA hyperparameter tuner to considerably increase the model's performance.

### H. Hybrid Optimization Model

A novel hyperparameter tuning strategy for brain tumour segmentation using the VGGUNet model and the hybrid ABC-WOA algorithm is introduced. The Whale Optimization Algorithm (WOA) and Artificial Bee Colony (ABC) work together to explore hyperparameter space via complementary adaptive exploration capabilities. Inspired by bee foraging, ABC's local search method mimics whale hunting and boosts WOA's global exploration. The approach maximizes accuracy and Dice coefficient by repeatedly adjusting hyperparameters like learning rate and dropout rate based on performance evaluation. This comprehensive approach enhances processing efficiency, convergence, and robustness, leading to enhanced MRI image segmentation. An objective function might be the improvement in segmentation metrics achieved by hyperparameter adjustment over several rounds. Hyperparameters x are used to calculate segmentation metrics like accuracy or Dice coefficient. The objective function f(x) may be defined as the overall segmentation measure improvement within iterations.

### I. Train the model

VGG19 was trained on segmented images. The Alex Net and ResNet50 techniques are used to evaluate the suggested model's efficacy.

### J. Model Evaluation

A method's efficacy could be assessed through the utilization of metrics.

### K. Performance Metrics

Performance measurements from the confusion matrix, including Accuracy, Recall, Precision, and F1-score, are used to evaluate model performance.

*Accuracy:*

Accuracy is the proportion of participants who, out of all subjects, had accurate identification.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

*Precision:*

To assess an outlook's accuracy, add up all correctly predicted events. Another name for this concept is forecast value.

$$\Pr ecision = \frac{TP}{TP + FP} \quad (2)$$

*Recall:*

The ratio of correct proportional to the sum of the real and false negatives.

$$\mathrm{Re}\, call = \frac{TP}{TP + FN} \quad (3)$$

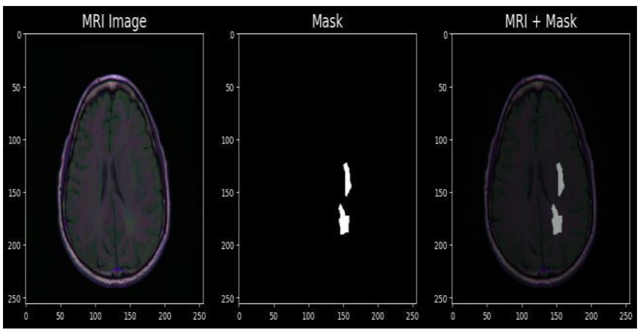
*F1-Score:*

The F1 score is a single score that includes precision and recall.

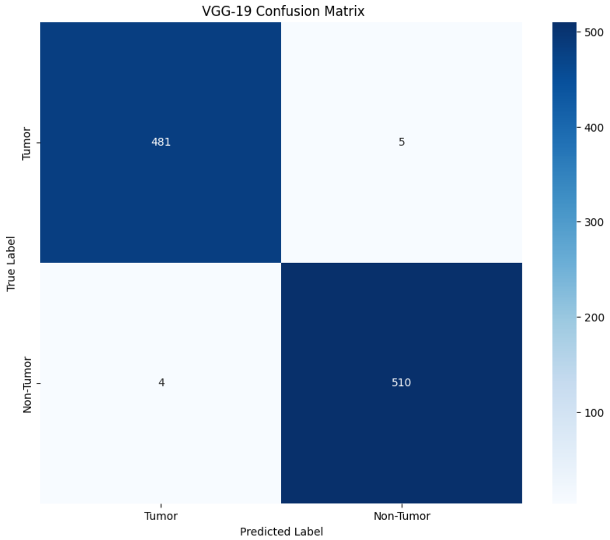
$$F1\text{–}\ Score = 2 * \frac{\Pr ecision * \mathrm{Re}\, call}{\Pr ecision + \mathrm{Re}\, call} \quad (4)$$

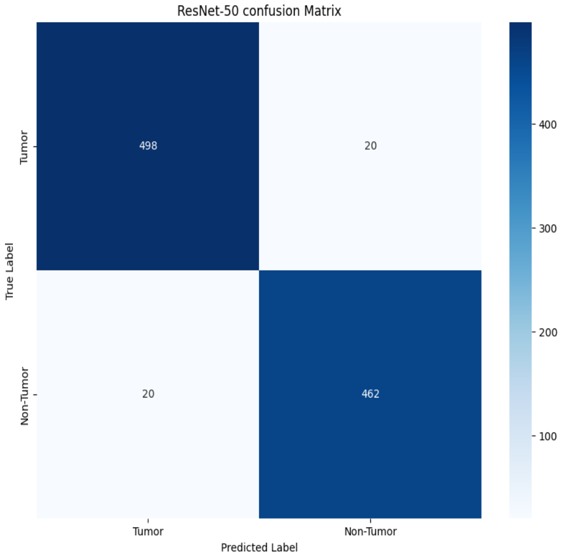
## IV. RESULTS

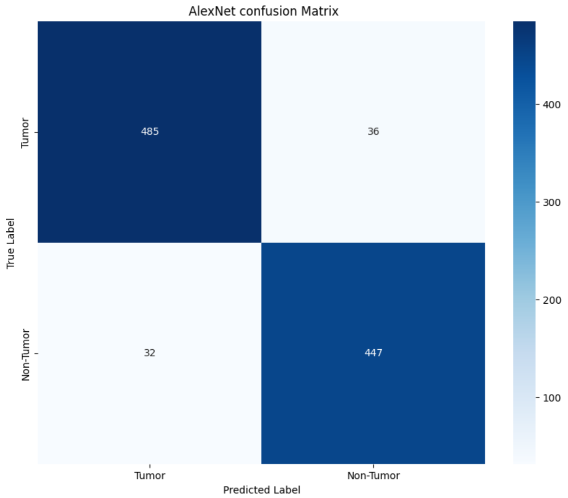
In this part, we use VGG-UNET for segmentation and VGG-19 for classification, and compare their performance to ResNet-50 and AlexNet models. To improve our proposed VGG-19 model, we use a hybrid ABC-WOA hyperparameter tuning method. The purpose of this comparison study is to assess the efficacy of our technique in brain tumour classification tasks vs current models.



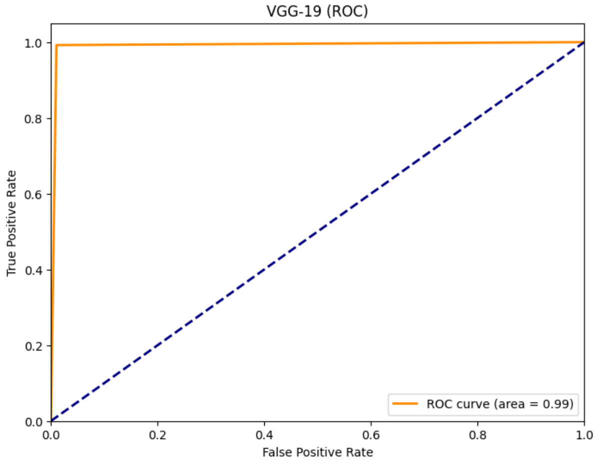
This graphic clearly shows the effectiveness of VGG-UNet in segmenting brain tumours from MRI data. Along with the original MRI image, the VGG-UNet model's segmentation mask is shown. The mask painstakingly emphasizes the tumour region with distinct colours, allowing for obvious and exact identification of its borders and size. This precise segmentation, made possible by VGG-UNet's deep learning capabilities, is critical for accurate tumour diagnosis and the development of effective treatment plans.

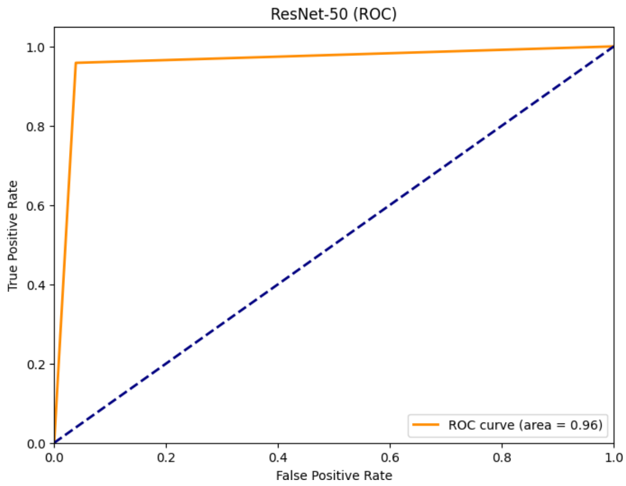


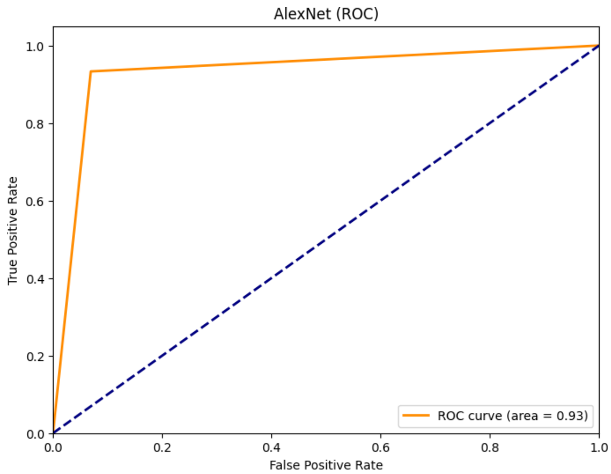




From the above confusion matrices, we can observe that there are two classes Tumour and Non-Tumour so our suggested VGG-19 model performs very well in reliably categorizing cases in both the tumour and non-tumour classes. It successfully classifies 481 tumour patients as true positives (TP), while separating non-tumour cases with 510 true negatives. However, the model experiences few misclassifications, with just 5 occurrences labelled as positives (FP) and 4 instances misclassified as negatives (FN) inside the tumour class. Similarly, in the non-tumour class, it shows accuracy by accurately classifying 510 instances as genuine negatives while experiencing just four erroneous positives and four false negatives. In comparison, the ResNet-50 model achieves a laudable 498 true positives and 462 true negatives for tumours, but has a greater misclassification rate, with 20 false positives and 20 false negatives within both groups. Similarly, the AlexNet model, which has 461 true positives and 471 true negatives for tumours, exhibits increasing misclassification, with 35 false positives and 33 false negatives in the tumour class and 33 false positives and 35 false negatives in the non-tumour class. Overall, the VGG-19 model's low misclassification rate demonstrates its better accuracy and efficacy in discriminating between tumour and non-tumour occurrences, cementing its status as the best option for brain tumour classification tasks..

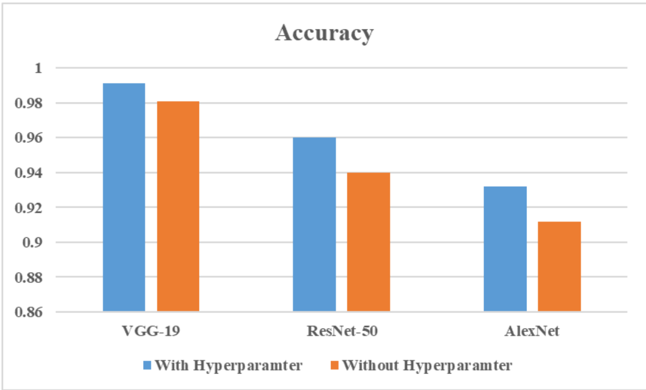


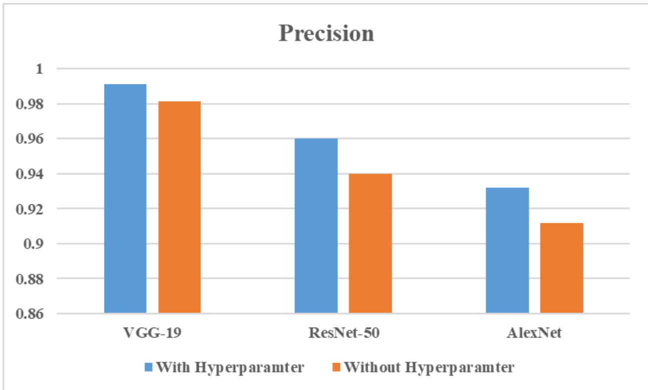


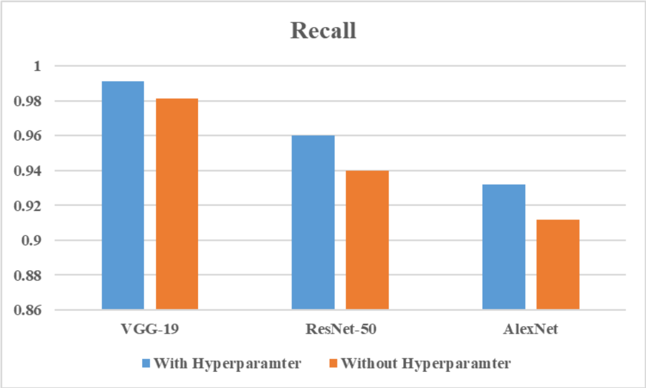



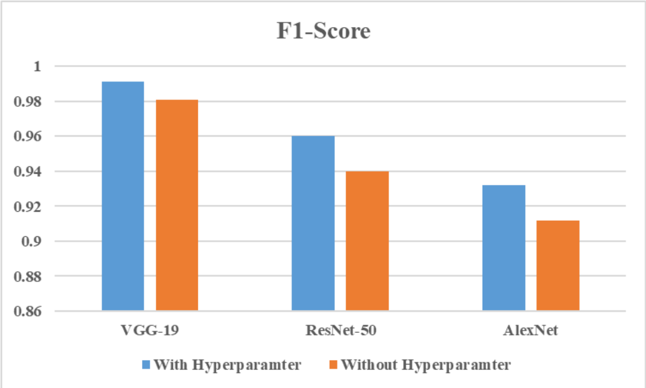

In the assessment of brain tumour classification algorithms, ROC curves offer useful measures for assessing model performance. The ROC curve for our suggested VGG-19 model shows a remarkable area under the curve (AUC) value of 0.99, showing that it can distinguish between tumour and non-tumour cases across multiple thresholds. This high AUC value demonstrates the model's resilience and efficacy in properly categorizing examples, adding to its excellence in brain tumour classification tasks. In comparison, although the ResNet-50 and AlexNet models have reasonable AUC values of 0.96 and 0.93, respectively, they fall short of VGG-19's excellent performance. The greater AUC of VGG-19 demonstrates its improved ability to balance sensitivity and specificity, resulting in more correct predictions and fewer misclassifications. Thus, the ROC curve analysis confirms the suggested VGG-19 model's superiority in reliably discriminating between tumour and non-tumour instances, making it the best option for brain tumour classification applications.

| | Models | Accuracy | Precision | Recall | F1-Score |
|---|---|---|---|---|---|
| With Hyper parameter | VGG-19 | 0.991 | 0.991 | 0.991 | 0.991 |
| | ResNet-50 | 0.96 | 0.96 | 0.96 | 0.96 |
| | AlexNet | 0.932 | 0.932 | 0.932 | 0.932 |
| Without Hyper Parameter | VGG-19 | 0.981 | 0.98123 | 0.9812 | 0.981 |
| | ResNet-50 | 0.94 | 0.94 | 0.94 | 0.94 |
| | AlexNet | 0.912 | 0.912 | 0.912 | 0.912 |






Thus, VGG-19 model is the most recommended for brain tumour classification due to its excellent performance metrics across a variety of criteria. A hyperparameter optimized VGG-19 achieves an accuracy of 99.1%, 99.1% precision, recall and F1-scores indicating its strong and consistent performance. Even without hyperparameter adjustment, VGG-19 remains the leader with an accuracy of 98.1% as well as precision, recall and F1-scores around this value. Conversely, ResNet-50 records lower figures of 96% accuracy while retaining both precision and recall at 96%, and F1-scores with or without hyperparameter adjustments. Although AlexNet is much less accurate; it still remains competitive as it gives an accuracy of 93.2% upon tuning and 91.2% if not tuned for. Nonetheless, these models lag behind in terms of their remarkable accuracy, specificity, sensitivity as depicted by VGG-19 results only. With great performance indicators like this one, VGG-19 thus appears the top choice in brain tumour classification ensuring superior precision that guarantees reliability in making medical decisions.

## V. DISCUSSION

Our findings show that using VGG-UNET for segmentation and VGG-19 for classification outperforms the ResNet-50 and AlexNet models in brain tumour analysis. Using a hybrid ABC-WOA hyperparameter tuning approach, we discovered that the hyperparameter-tuned VGG-19 model achieves remarkable accuracy, precision, recall, and F1-scores of 99.1% or higher, demonstrating its exceptional performance in distinguishing between tumour and non-tumour instances. Even without hyperparameter adjustment, VGG-19 retains its lead with an accuracy of 98.1%, confirming its status as the best-performing model. In comparison, although the ResNet-50 and AlexNet models perform well, they fall short of VGG-19 in terms of accuracy and precision. The ROC curve study supports VGG-19's greater discriminative capacity, with an impressive AUC value of 0.99, compared to lower values for ResNet-50 and AlexNet. Overall, our results show that the suggested VGG-19 model is effective at properly categorizing brain tumour pictures, with greater accuracy and reliability, suggesting that it might be the preferable option for brain tumour classification tasks in clinical settings.

## VI. CONCLUSION

In this extensive study, we dived into the complex landscape of brain tumour classification, utilizing advanced deep learning algorithms for segmentation and classification tasks. Our technique makes use of VGG-UNET for segmentation, allowing for the exact delineation of tumour areas within MRI data. The following classification stage makes use of VGG-19, a well-known convolutional neural network architecture that has been shown to be effective in image categorization. To improve the performance of our proposed VGG-19 model, we used a hybrid ABC-WOA Hyperparameter tuning technique to maximize its accuracy and resilience in discriminating between tumour and non-tumour occurrences. This methodology demonstrates the synergy between cutting-edge deep learning methodologies and novel optimization strategies, paving the path for breakthroughs in medical picture analysis.

We thoroughly tested and analyzed the performance of our proposed VGG-19 model against that of ResNet-50 and AlexNet, two widely used convolutional neural network architectures in the field of image categorization. Our findings show that the hyperparameter-tuned VGG-19 model has greater accuracy and precision, with performance metrics routinely above 99.1% across a variety of criteria. This clear superiority is supported by the ROC curve analysis, which demonstrates VGG-19's excellent discriminative capacity, as indicated by its high area under the curve (AUC) value of 0.99. In comparison, while ResNet-50 and AlexNet perform admirably, they fall short of VGG-19's accuracy and precision. This detailed comparative analysis demonstrates the usefulness of our proposed technique in delivering cutting-edge performance in brain tumour classification tests.

To summarize, our research marks a big step forward in the field of medical image processing, notably in the classification of brain tumours. We have shown that deep learning approaches can improve diagnosis accuracy and treatment planning in neuro-oncology by combining the power of VGG-UNET for segmentation, VGG-19 for classification, and a hybrid ABC-WOA Hyperparameter tuning algorithm. The remarkable performance of our proposed VGG-19 model highlights its potential as the preferred choice for brain tumour classification tasks in clinical settings, providing doctors with a dependable tool for accurate diagnosis and prognosis. Moving forward, further research can investigate the scalability and generalizability of our findings in larger datasets and real-world clinical settings, ultimately leading to better patient outcomes and advances in neuro-oncology research..

## VII. References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