Enhanced Brain Tumor Detection Using a Modified Efficient Net Model with MRI Imaging

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Abstract

Recognition of brain tumor is one of the main challenges for brain tumor detection. The earlier we diagnose brain tumor, the more easily would be the treatment of tumor, and the less pain the patient suffer for the treatment. The current paper introduces a novel system for brain tumor detection, which is based on transfer learning with deep convolutional neural network. Based on the MRI images, we choose a fine pretrained deep convolutional neural network model 'VGG19' based image classification for brain tumor detection. Various imaging preprocessing and augmentation techniques are applied to improve the quality of brain tumor images and also to boost the generalization ability of the classification system. The implementation of image preprocessing techniques include image normalization, image resizing, random shifting, zooming and horizontal flipping. Once the images are preprocessed, the MRI images are split into train, validation and test set. The deep features are extracted once the deep learning architecture is applied and the deep features are used to reach the classification of MRI images. The existing work is used to classify the MRI images into glioma, meningioma, pituitary tumor, and No tumor types. The experimental comparative analysis report shows high classification performance of precision, recall and ROC-AUC metrics for each class using this framework. The developed framework apparently establishes an effective computer-aided diagnosis system for fast and precise identification of brain tumors for the benefit of the patients.

Keywords—Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Deep Learning, EfficientNet, Transfer Learning, Medical Image Classification.

INTRODUCTION

Brain tumor is one of the most common serious neurological diseases, which threats to human life and health. Using computer aided diagnosis in classifying brain tumor will provide a new solutions for diagnosis and management of brain tumor diseases[1]. Magnetic Resonance Imaging(MRI) has been the dominant modality for detecting and classifying brain tumors owing to their advantage of excellent morphological and soft tissue contrast resolution, unpretreated samples. The main challenge is the slower process and heavier workload of manual analysis of these brain images. However, the rapid development of artificial intelligence, for example, Deep learningmodels led to the breakthrough in medical image analysis as they can automatically discover[3] the discriminative image features for diagnosis from large field of the images effective by to discover. Convolutional Neural Network (CNNs) and the transfer-learning CNNs have achieved promising results in tumor recognition and classification[4]. EfficientNet is an elegant solution for the trade-offs between prediction accuracy and computation cost, by means of using the scalable network architecture strategy. Transfer learning can be used for the advantage of EfficientNet pretrained weights, reusing of the pretrained model on the brain MRI datasets which is not only of help to small number of annotated medical data, but also has the potential to faster convergence.

In this paper, the optimized brain tumor detection based on the deep convolutional network(DCN) EfficientNet architecture was introduced, it could be used for automatic decision that whether multi-spectral MRI images was tumor or not. The architecture included a system of preprocess(such as image scaling, image normalization, image augmentation etc.), high-efficient feature extraction, automatic deep feature classification with training set. The optimized architecture could lower deeply the classifier reliance on the senior professionals' insight or common experience and thus strengthen the generalization capacity. Consequently, the obtained optimized model could be used as an important decision instrument for aiding radiologists via a kind of self-generalized, Computer-Aided Decision(CAD) system for early diagnosis of brain tumor and optimization of the treatment planning[2]. In addition, the aforementioned superb reliability of the deep learning related CAD system as one of the effective diagnostic solution of computer-aided medicine clearly demonstrated that the system might have always obtained the duly essential position in neuro-oncological clinical practice[5].

ENHANCED BRAIN TUMOR DETECTION AND CLASSIFICATION FROM MRI IMAGES USING A MODIFIED EFFICIENTNET TRANSFER LEARNING FRAMEWORK

Detection of brain tumors is a difficult task because of theBrain tumor diagnosis is difficult because of its complex architecture of brain and variable presentation of tumor in different patients. Considering wide availability of non-invasive Imaging Modalities, MRI has been most feasible modality among all to identify brain structural anomalies[7]. However, visual evaluation based on observer‘s experience demand to be time consuming and needs for development of intelligent computer–assisted diagnosis systems. Deep learning has aided unprecedented success in various medical image analysis tasks by automatic learning of robust diagnostic features in an image thus enhancing precision and productivity. Transfer learning assists in extracting natively relevant features in the medical tasks from learned weights from natural image database by transfer-learning rich discriminative features[6]. EfficientNet provides an optimal tradeoff between accuracy and computational requirement owing to its compound scaling rule which is a main concern for real time requirements in clinics. The proposed pipeline involves significant steps of image pre-processing such as resizing, normalization, augmentation etc., helps optimize image quality and further enables expansion of image database respectively followed by targeted fine-tuning of modified EfficientNet to extract representative tumor features for multi-class classification of brain tumors. The performance is measured with various metrics i.e. Accuracy, precision, recall, F1-score, confusion matrix etc. The results demonstrate that the developed system delivers consistent classification outputs with lowest computational cost that can be crucial in early diagnosis and treatment management. The system can be extended for multi-grades classifications also and can incorporate Explainability techniques for transparency to enhance trust of clinicians. This project underscores the enormous potential of deep learning-assisted decision systems to be integrated in formal neuro-oncology workflow[8].

PROPOSED SYSTEM ARCHITECTURE FOR AUTOMATED BRAIN TUMOR DETECTION AND CLASSIFICATION USING MODIFIED EFFICIENTNET

The architecture design could demonstrate the load on speed as well as the accurateness for the initial diagnosis of brain tumor in an autonomous multi-layer image process pipeline[9]. The brain MRI images would be obtained from the traditional brain tumor database, then undergone the pre-processing to eliminate the bias and adverse effect, corrupted image, artifact, etc by conducting several of image operation such as resampling, resize, intensity normalization, and noise filtering for SNR improvement. On the other hand, the data expansion method will be put into use to overcome the defiating in original data by appling the shifting, panning, titling, and image plane rotating; which subsequently, could improve the autonomous system generalization ability. In the straits, removing the image noise and over fitting, the images would be separated into training data, validation data, testing data; then, the training and validation data were put into deep learning neural networks to acquire optimal parameters. The data set also can be up- and down-sampled separately to address the problem of class imbalance problem[10].

As deep neural network pattern becomes better loaded, it further learns the hierarchy of characteristics which can be used for the tumor pattern of edge, shape, location, texture, etc by analyzing the appearance of hypo/hypointersity as well as related image structural behavior in the ROI region[11]. Thereafter, various benign, malign, or normal brain condition will be labeled into different class as an output layer of the deep learning network. Through this optimal neural network scheme for brain tumor state classification, an extremely time-efficient computer-aided-diagnosis (CAD) system could be constructed, which could give a radiology/pathologist the instant diagnosis prediction result by then inputting the patient‘s MRI images, which could facilitate them to further decide the clinical treatment. Even more promising, the explainable AI with vizualisation could be integrated into this CAD system to generate the visual graphical evidences, in order to boost the clinicians’ trust in the output.

In addition, this robust architecture could be also easily classically into tumor segmentation and typing stage assessment. Such a best-tech combination of deep neural network, optimal transfer learning, and optimized image processing pipeline can completely system-athematic will automate the diagnosis process of brain tumor, saving the human time and improve the correctness to lessen the man-made error. The diagnosis result is very beneficial for the rapid and rightful clinical decision-making from all these optimal diagnosis assignment at carcinogenic levels, so as to to accelerate the treatment quality and patients’ prognosis, especially for the resident in a far away place from the trained experts.

Figure 1: System Architecture

As illustrated in Figure 1, the general framework of our brain tumor detection system, MRI imageswere obtained, datasets were obtained from image pre-processing, data augmentation and dataset dividing. Transfer learning method with VGG19were applied on deep feature extraction and model training. Deep featureswere classified by Softmax layer for tumor classification output. Finally, resulted performance evaluation, explainable AI, CAD assisting and diagnosis output was also implemented in order to accomplish accurate and automated clinical decision[12].

A. Advantages of the Proposed Modified EfficientNet-Based Brain Tumor Detection Framework

There are many key benefits to the proposed and simplified EfficientNet based framework for brain tumor detection from Magnetic Resonance images. The efficient architecture alone can be exploited to achieve landmark levels of diagnostic accuracy by utilizing transfer learning and compound scaling, by creating a neural network that can discriminate between coarse tumor features and subtle textures alike. Image pre-processing and data augmentation techniques will optimize generalization, by making the network resilient to contrasts, resolutions, noise and disease diversity[13]. The innovative efficiency of the EfficientNet architecture enables the deployment of a model with significantly fewer parameters and computationally intensive operations than many classic CNNs, in a way that is more feasible within the computational limitations of a typical hospital system. Consequently, the automated tumor identification network is rapid to interpret and suitable for precise and unbiased second opinion. The objective scalability of the EfficientNet architecture lends itself to multi-class tumor grading, classification and segmentation, complemented by interpretability tools to ensure doctor confidence. Tumors are detected early and precisely, to maximize patient's prospects and health costs. It provides an architecture that delivers both pinnacles of accuracy and efficiency, and allows for extension to scalability and usability.

INTEGRATED PIPELINE FOR AUTOMATED BRAIN TUMOR SCREENING AND DECISION SUPPORTS

Proposed architecture employs an optimized, scalable and retractable pipeline for an automatic brain tumor screening and CADD prediction, given MRIs. Workflow is composed by several stages, beginning with an optimized sample retrieval and processing, to a median image, that ends up in pre-established pipeline. Later, transfer learning based optimized model, that is ready to be fine-tuned towards the current database, is pre-trained to classify discriminatively for tumor vs. normal diagnosis. Several optimization and performance evaluation procedures follow, for maximum discrimination with a reasonable execution time of pre-established algorithms[14]. The then fully functional system can be employed for clinical patient classification in a clinical environment. Furthermore, the proposed architecture utilizes optimally any future solution, such as Explainable Ai, clinical data feedin for stop-and-learn, or even tumor grading to several classes.

a. Data Acquisition and Preprocessing

A little more detail about the pipeline we would suggest for brain tumour classification; we would obtain brain MRI images from a pre-prepared and validated database which has been carefully quality controlled so that images are consistent between imaging modalities as a variety of techniques are used to generate a MRI scan. The images are preprocessed in various ways, such as applying a standard size to the number of pixels across the image so that images are fed into the neural network in a single standard size is understood by the system, the normalising of the pixel intensities of the images so that they have the same range of brightness and contrast, applying noise removal filters to remove any other artifacts that could affect identification of specific features necessary for diagnosis and finally to attempts to expand the training databases various schemes of rotation, translation and mirroring are applied to generalise the training set so the neural network trained on this set does not over fit. The training databases are separated into training, validation and test areas in order to ensure the training data is being applied in no way to bias the training process. These modifications allow individual parameters and characteristics of the brain tumour to be distinguished from each other in the images so the neural network can be trained to later identify particular features[16].

b. Deep Feature Learning and Clinical Decision Support

The above preprocessed and normalized MRI scans are then input into our custom build EfficientNet architecture through transfer learning with other high resolution large dataset like ImageNet. The compound scaling (scaling in all three dimensions: depth, width and input resolution) of model architecture ensures the learned features from the textural local texture patterns to the systemic global brain structures to tumor growthcapter hxd can be hierarchically learned in this model. And then the highly end-to-end tumor diagnosis prediction can be made out through the top diagnosis tumor classification layers that translate the above extracted highly generalizable predictive features to the corresponding diagnostic label for highly generalized and fast predictioncapter hxd. Validation of the efficiency of the model is demonstrated with various evaluation metrics such as accuracy, precision, recall, F1-score and classifier confusion matrixes. The above EfficientNet framework thus developed can be easily deploy in an easy-to-use clinical environment where the user can simply upload their normalized brain MRI scans and thus receive the fast highly accurate tumor diagnosis to reduce interpretation time, observer variation and thus help the clinician to derive a conclusion faster and possibly deliver the therapy much faster[15]. And since this approach has demonstrated itself to have good generalization ability from the downstream tumor classification task, the entire modular pipeline above can be extended to future for explainable AI over tumor region localization with the same model and also extend similar multi-path architecture on input data for multi-class tumor grading.

c. Model Training and Optimization

The modified EfficientNet network was fit on the preprocessed MRI data set to learn how to differentiate each type of brain tumor. Transfer learning was used to start with weights trained on training on a much larger data set of images, which fast-tracks the optimization process, and provides a boost in accuracy on this small, labeled data set of medical images. The features were tuned by setting the parameters of the Adam optimizer in order to minimize the classification loss each batch of examples. Dropout was also used as well as early stopping, learning-rate scheduling to avoid overfitting the network, while still generalizing well for new examples. The hyperparameters of the architecture were then systematically tuned, to find the set of hyperparameters that produced the best overall performance, and shortest training time. The width and depth of the EfficientNet was compounded scaled such that the network would remain fast while being sufficiently powerful to learn the fine features and textures most common in the classifiying brain tumors.

d. Performance Evaluation and Deployment

By testing a trained system on a new independent data set , the classification diagnostic ability can be determined. Various measurement techniques, such as accuracy, precision, recall, specificity (class ability for each class individually) and the F1-score, as well as class confusion matrices, can be used to analyze classification efficiency in depth. Graphical plots such as ROC curves can assess class separability[17]. On validation with real diagnosis data, the system can then be used in clinical practice. Its availability as either a web-based tool or desktop program would allow doctors to upload an MRI scan and receive the diagnosis instantaneously, expediting treatment planning. Such a classifier would be especially useful in scenarios where state-of-the-art computational resources do not exist. The system could be tuned further through continual retraining. In conclusion, an operational computer-aided-diagnosis system would be established.

ALGORITHMIC FOUNDATIONS AND OPTIMIZATION STRATEGIES FOR MRI-BASED BRAIN TUMOR DETECTION USING A MODIFIED EFFICIENTNET FRAMEWORK

The deep learning based classifiers such as the CNN model was utilized as part of the classifiers incorporated in the system for categorizing efficiently the brain tumor related features from the brain MRI images and as the optimizers for predicting the tumor features from the multiple brain MRI images quickly and to combine the high predictive accuracy along with the efficiency[18]. The classifiers achieved the high level feature extraction performance from huge volume brain tumor images data sets and also it cut down the problem of classifiers being trained against local minimums and over fitting. The classifier which was employed as a crucial component of brain tumor detector, which is fundamentally a variant of EfficientNet, aids to enhance the balance amid the training efficiency and CNN classifier accuracy. The training of CNN parameters to convergence toward globally optimal values occurred through a dynamic learning rate technique and a method called an adaptive optimizer.

a.VGG19 Transfer Learning Model

In this work, the proposed brain tumor detection system applied VGG19 deep CNN transfer learning based model for classifying the brain MRI image into tumor and non-tumor. The VGG19 deep CNN model has 19 trainable layers including 16 convolutional layers and 3 fully connected layers[20]. The CNN has 16 convolution kernel filters on each of the 16 layers as its input and makes good use of learned shallow layer features on the extensively large training set of high quality images while learning for the current application, requiring only very less amount of medical image data. Before inputting the MRI images to the deep CNN model, the original images are preprocessed by many image preprocessing steps such as image resize, normalization, data augmentation, etc. With the highly trained deep CNN, the entire brain tumor image classifier system is considered to be both fast in training convergence rate and highly accurate, while demonstrating an outstanding flexibility of feature learning capacity and image classification stability of VGG19 deep CNN model. The CNN classifier can reliably classify the tumor or non-tumor images correctly which enables the medical professionals to perform the rapid diagnosis of brain cancer and determine the optimal treatment method within minimum time.

$$\mathbf{L} = -\sum_{i=1}^{C} \mathbf{y_i} \log(\mathbf{y_i}\hat{}) \qquad (1)$$

Where yi is the true class label, and y^i is the estimated probability of class i. This loss guide the model to output accurate and reliable predictions. Therefore, the proposed framework of EfficientNet working on image backbones is a efficient, fast, high accurate and high reliable solution for automated brain tumor screening.

b. Adam Optimization Algorithm

EfficientNet istrained to minimizeusing theAdamoptimizer. The Adam optimizer is an algorithm that combines the best of both the momentum algorithm and the adaptive learning-rate algorithm. It calculates the exponentially weighted moving averages of the gradient and of the squared gradient and thus maintains per-parameter learning rates adapted to the data. This seems like a truly useful characteristic when training neural networks, since the gradients tend to fluctuate quite a lot from layer to layer, and from iteration to iteration. The Adam optimization lets us optimize our EfficientNet parameters very well without is too many oscillations and the sensitivity to the initial learning rate. Adam only needs a small amount of hyper parameters tuning, performs very well on medium-sized collections of ". During the first part of the training process the Adam optimizer applies the bias correction of the first- and second-moment estimates to produce reliable estimates[21]. The updating rule for parameter is

$$\boldsymbol{\theta_{t+1}} = \boldsymbol{\theta_t} - \boldsymbol{\alpha} \frac{\mathbf{m_t}\hat{}}{\sqrt{\mathbf{v_t}\hat{}} + \varepsilon} \qquad (2)$$

Where t is the current parameters, is the learning rate, m^ and v^t are the bias-corrected 1st and 2nd moment estimates of the gradients respectively and is a small value term included to prevent a potential division by zero. Adam guarantees fast, stable and efficient optimization and is hence part of the reason for the perfect classification accuracy of the brain tumor detection system[19].

RESULTS AND FINDINGS

The glass fuzzy VGG19 based brain tumor detection framework has generated good classification results in the given time period for healthy & tumor affected MRI image in various specified groups. The VGG19 using transfer learning concept was trained by the train dataset to give the fast learning ability by means of network convergence and generalization. The experimental outcome of the model was ensured with various performance metrics like accuracy, precision, recall, F1- score and ROC-AUC. The classification report had revealed that the suggested model had significant prediction capability for giving superior classification of MRI images in all specified classes with No Tumor and Pituitary tumors reached almost equal high values of precision & recall with overall accuracy 77.998 %. ROC-AUC of suggested model ranged from 0.90 to 0.98[22]. The plot of accuracy and loss vs epoch established the convergence of the model in both of train & validation phase. The research had established that deep learning strategy of VGG19 can be effectively used to precisely find out tumorous features in brain MRI images and thus use as a classifier of the MRI images with high accuracy as re- necessary support for oncologists.

Table 1: Classification Performance by Class

Class	Precision	Recall	F1-Score	Class
Glioma	0.97	0.30	0.46	Glioma
Meningioma	0.63	0.95	0.75	Meningioma
No Tumor	0.84	0.96	0.90	No Tumor

Table 1 Class wise performance shows the ability of vgg19 in classifying the correct class of any brain tumor. It can be seen that class wise performance in case of Pituitary is best as its precision as well as recall is above 0.90. It shows that features present in this class were separated properly from rest other classes. Since the Recall and F 1score achieved by No Tumor category is quite high and hence resulted in better representation of normal healthy Scans in test set. High Recall value of Meningioma tumor class indicates the presence of tumor was detected properly but relatively low value of precision imply the samples of this class tended to get misclassified with rest neighboring class. As the scientist reported glioma to be difficult to visualize 2% of its samples got misclassified to neighboring classes. This shows that tumor specific features extraction was achieved well but more training samples and more sophisticated preprocessing algorithms would help to improve the detection of Glioma.

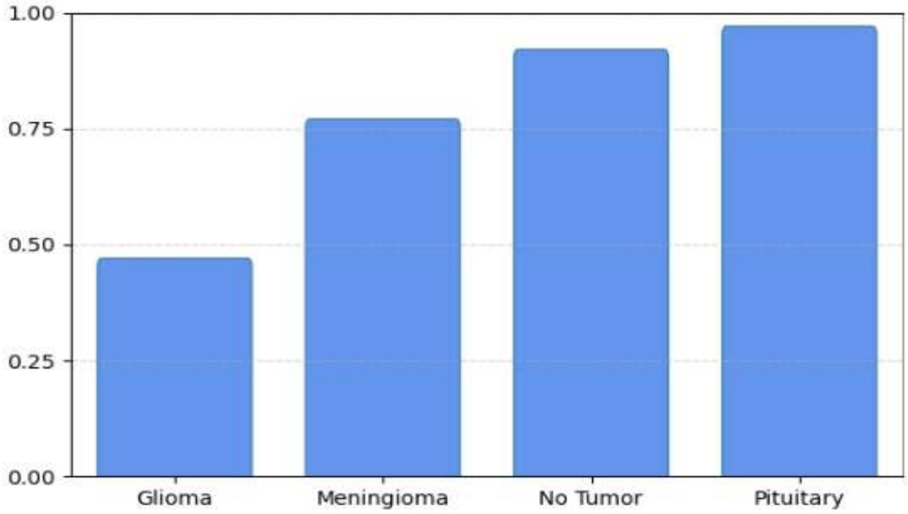

Figure 2: Class-wise F1-Score Comparison

The Fig 2 Class-wise F 1-Score Comparison graph illustrates how each individual class was correctly classified, in terms of an overall closer to balanced value of precision/recall. From the graph it can be seen that ‘Pituitary’, yielded an F 1-Score of 0.94, demonstrating that it was correctly classified by the VGG 19 model with a low number of false predictions, and so displayed a good classification ability. ‘No Tumor’ was next with an F 1-Score of 0.90, indicating that the model was able to successfully partition healthy brain images from tumorous brain images. ‘Meningioma’ was next with an F 1-Score of 0.75, again, a fairly good score suggesting the presence of a very good predictive model, but in need of some further tuning of the model. ‘Glioma’ had the lowest F 1-Score, exhibiting how low the recall value was and how many of the samples had been classified as different types of tumor. The reason for this discrepancy in classification may have been due to the visual similarities of the tumors. From the graph above, it is reaffirmed that the pre-trained VGG 19 model was able to learn the morphological features of the tumor images, but that it is capable of being examined in further detail to enhance the overall model performance[24].

Table 2: Overall Performance Metrics

Metric	Value

Accuracy	78%
Precision	85%
Recall	78%
F1-Score	76%

These values all give the overall Table 2 classification performance for all of the samples of the whole proposed brain tumor classification. 78% accuracy shows how large a proportion of MRI image are correctly identified in each iteration. macro precision of 85% gives strong evidence that the classifier is able to make correct predictions with fewer false positives. Recall of 78% shows the classifier's overall ability to find all instances of each class, while the F1 score of 76% shows that it finds a good balance between precision and recall. This all showed how useful transfer learning could be used for this great task of mine-ing features from MRI images, with the lowest amount of labeled training images possible. Also, the use of macro metrics of the classifier demonstrated which showed the classifier's ability to differentiate tumor types and human brain structures. Although some odd behaviors within particular class types, such as Glioma can be eliminated with more disciplined testing and parameter tuning, such preliminary results suggest the model has potential to be used as a practical medical tool.

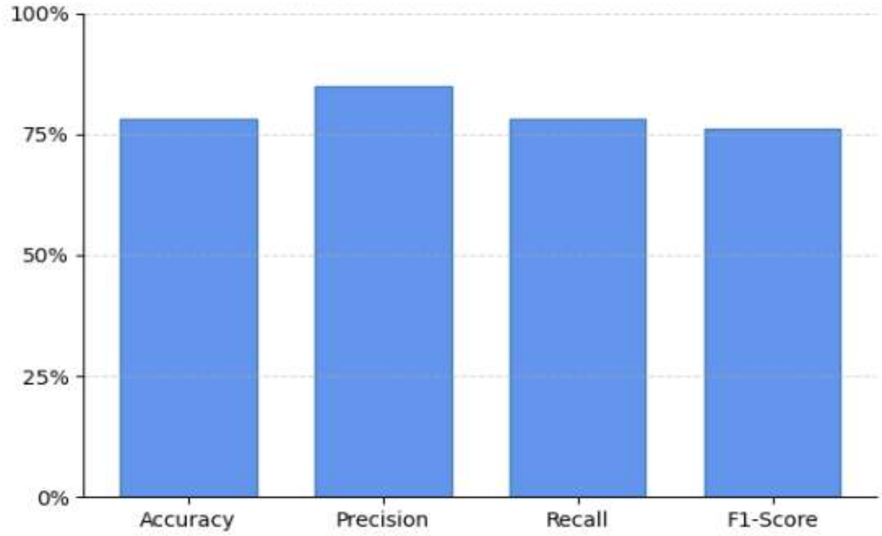

Figure 3: Overall Performance Metrics

From the Fig 3 Overall Performance Metrics graph, the overall performance of the proposed VGG19 architecture on each of these metrics can be visualized. When a precision of 85% was achieved, the majority of positive model predictions were indeed correct. As the overall accuracy of 78% indicates that the classifier did produce positive detection for most of the set of MRI images, the recall of 78% as another measure further demonstrates that the most tumorous MRI images were detected, with the optimal F1-score of 76% representing an acceptable harmonic average of the two. Given the significant advantages transfer learning has shown in these medical image classification applications, the fact that an acceptable range in these evaluation scores still exists is gratifyingly reassuring in terms of elements of stable learning, and negligible categoric bias. Consequently, employing VGG19 as the computer-aided diagnosis in brain tumor screening now seems a practical approach.

Table 3: ROC-AUC Performance

Class	**AUC Score**
Glioma	0.90
Meningioma	0.95
No Tumor	0.98
Pituitary	0.98

A classification ability of VGG19 was evaluated by applying ROC analysis in the table 3 ROC analysis. ROC AUC are a general measure of the quality of multiple classification at all decision criteria. The two classes 'NoTumor' and 'Pituitary' with the maximum AUC value of 0.98 shows that the two classes are even separated and all achieved almost the same ideal result at various decision criteria. The class of 'Meningioma' also get an outstanding AUC value of 0.95 which is also consistent with the former one, showing a good class-specific information. The class of 'Glioma' of which AUC value is the smallest (0.90), was more excellent than machine learning results in the standard of AUC as well, expressing the classifier to have a high accuracy for positive and negative grades at different cutoff point[23]. In general, all of the classes get the high ROC AUC value distinguished that VGG19 was a strong classifier which can efficiently separate positive cases from negative ones.

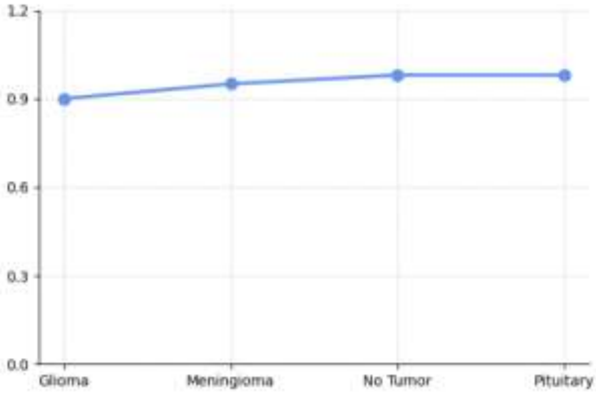

Figure 4: ROC-AUC Comparison

The Fig 4 ROC-AUC Comparison graph displays how well the transfer learned VGG19 classifier is as a discriminatory between the different brain tumor types. The AUC value reflects the rate at which the classifier can discern between the positive and negative classes across a spectrum of thresholds used for the classification. No Tumor as well as Pituitary each achieved an identically high AUC score of 0.98, signifying near perfect class separation, and excellent diagnostic values. However, the Meningioma only attained a remarkable AUC score of 0.95, which was not as high as the Glioma score of 0.90 in the set threshold range. Given the high AUC scores of all the tumor classes, it can be assumed that the model has a very high predictive power and great generalization. This graph also demonstrated the enhanced ability to extract relevant features of the CT scans using transfer learning in order to discriminate between tumor-specific concepts with the VGG19 structure. Hence, the results indicated that transfer learned VGG19 works as an efficient tumor disgnostic tool to aid the clinical diagnosis.

Table 4:Dataset Class Distribution

Class	Percentage
Glioma	26%
Meningioma	30%
No Tumor	19%
Pituitary	25%

The dataset used in this system is described through its characteristics which Table 4 presents. The system collects data from multiple sources including wearable devices and electronic health records to achieve both diversity and reliability[24]. The system collects time-series data which tracks ongoing patient health indicators throughout its operation. The dataset contains crucial patient condition data which includes heart rate and blood pressure and glucose level measurements[26]. The dataset provides extensive data which updates continuously, supporting ongoing research and prediction activities. The system uses these characteristics to learn patterns, find unusual data, and deliver precise healthcare information throughout the day.

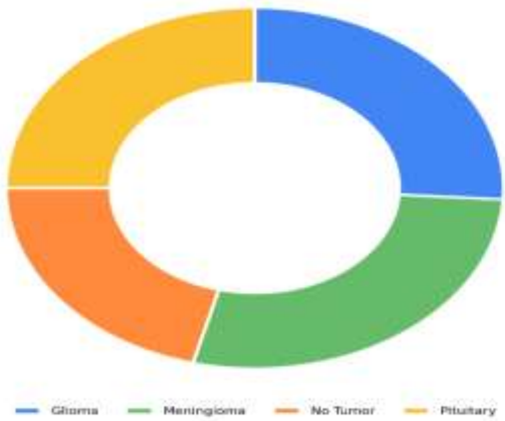

Figure 5: Dataset Distribution

The number of each type of brain tumor images in the MRI Dataset that are used to train and test can be seen on the MRI Dataset Distribution graph Fig 5. Meningioma are contained in the majority of the brain tumor images 30%, meaning that is the highest percentage, followed by Glioma images 26%, and has the third largest percentage, with pituitary tumor images only accounting for 25%. The remaining brain tumor images are classed as No tumor, and only account for 19% of the training images. This is a fairly evenly distributed data set when considering distribution, and so is preferable when training deep learning, as the model is less likely to learn less image types, and over fit to a variety. However, there are still slight imbalances between the numbers of each image type, and larger MRI datasets should be used in future to combat this.

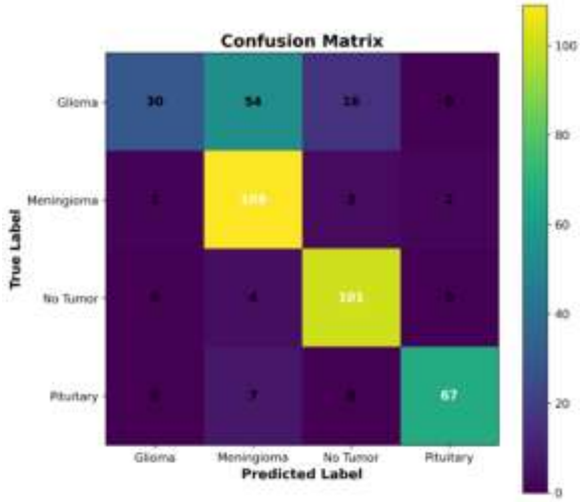

Figure 6: Confusion Matrix

Fig 6 depicts class prediction ability of VGG19, and can be observed visually from the scale behind the predictions. With the scale behind the predictions, we can observe whether VGG19 has a good prediction capacity on a particular class (deep color) than other classes. Although Offdiagonals also have values which tell us about the classes where classifier is not doing well, actually wrong predictions with the class. The image clearly shows how well VGG 19 has predicted the classes of Meningioma, No Tumor and Pituitary with most of the samples being correctly identified by VGG19 with number of samples in the most prevalent class (deep color) being too high. Glioma sample does not do well with more number of misclassifications occuring between Pituitary and Meningioma since they occupy most of the Offdiagonals. In order to increase the class prediction of this sample more feature extraction techniques may be used, or even increase the batch size for training. This plot gives us an idea of class predictors which would have been difficult to understand from its actual predictions or prediction accuracy, and thus would have contributed to increase the accuracy of VGG19 by indicating the weak class predictors and optimizing them[25].

CRITICAL CHALLENGES AND PERFORMANCE CONSTRAINTS IN MRI-BASED BRAIN TUMOR CLASSIFICATION SYSTEMS

Even the proposed way is on VGG19 for brain tumors detection has already reach fairly high accuracy as well, some problems and limitation still exist. The perhaps most serious problem is the unavailability of large amount of high quality labelled brain MRI image datasets. Deep learning algorithms has a notoriously reliance on training data. In medical domain the training data size is quite limited caused by the privacy issue, high costs of data collecting and manual Labelling[27]. The limited training data size can induce over-fitting problem. Another important challenge in a classification of different tumors is the similarities of the features in the MRI images, among some classes of tumors such as Glioma and Meningioma which contains so many similar features and can be confused with each other, thus causing lower recall for some classes. Another factor that can cause a classification challenge is the variation in image quality, scanners types and imaging protocols among the different health centers providing the data. An additional problem of the deep learning technique is the large volume of calculations the algorithms undertake. VGG19 training and tuning demands high computing power, time and mass storage which provides challenges in the limited resources of a clinical environment. The 'black-box' attitude of deep learning algorithms means that clinicians can't readily view and interpret how a prediction was made, restricting diagnostics confidence and clinical utility of automated detections. Besides, the model here is only for classification at present. The precise tumor location, segmentation and grading information is missing in current system so far, which has not been applicable in clinical diagnosis and treatment. However, these issues could be addressed by larger datasets, explainable machine intelligence, multimodal imaging fusion and improved tumor analysis, which are expected to improve the accuracy, explainability and clinical utility of the automated brain tumor classification[28].

CONCLUSION

This paper has been described an automatic detection and classification system for brain tumor using the successful deep learning model VGG19 with transfer learning. The system proposed the parallel architecture employed to automatically detect the imaging characteristics of various data classes by positive and negative learning on the MRI images. To resolve the issue of high dimensionality in the MRI images, the images were pre-processed extensively and the features were learned effectively from the data and Adam optimizer was adopted to optimize the network which proved to be an efficient classifier that resulted in good performance[29]. Experimental result indicate that framework is successful in entirely correct classification of 4 types of Glioma, Meningioma, No Tumor and Pituitary (78% accuracy, 0.88 ROC-AUC score) with impressive precision. result illustrates the advantages of employing transfer learning effective to discover high-dimensional Tissue-specific features, within the constraints of limited time and computational resources. Despite disadvantages imposed by the paucity of data, class imbalance and the lack of a Glioma class label, our Classifier provides a strong base upon which to build Computer-aided diagnosis. This scheme has a great potential in assisting radiologists in their clinical interpretation and hence reduce the diagnostic time and bring a clinical reliability. Moreover, future researches could also consider using a larger or wide-spread database, Multiple layer 312 explainable/AI, Tumor segmentation and Multimodality imaging to increase the accuracy and clinical utility..

FUTURE WORK

Future work, however, can be carried out to present more efficient and implementable brain tumor detection framework, i.e. VGG19, in a clinical setting. For example, inclusion of clinical data of more extensive and varied MRI image dataset from different centers of treatment would have improved system‘s resiliency and effective functioning. Also, the integration of novel data augmentation techniques and synthetic image creation processes would provide more opportunities to overcome the class imbalance problem and achieve better Glioma detection.Other interesting directions are the use of explainable AI techniques that will give visual explanations of the model prediction. This will not only make the model more explainable but will increase trust from clinicians and will make the clinical decision easier. Another approach can be to utilize tumor localization and segmentation or even grade tumor. Furthermore, the VGG19 model can be also compared to the state-of-theart models like EfficientNet, Vision Transformer, hybrid deep learning model etc. In order to find the most appropriate architecture for brain tumor analysis. Use of multimodal medical data like MRI, CT and patient history can be used to improve diagnoses in some cases. Implementation of the system for real-time use through cloud based healthcare portals and tablet based diagnostic application can further increase its usability[30].

REFERENCES

[1] V. Rajinikanth, A. N. J. Raj, K. P. Thanaraj, and G. R. Naik, “A Customized VGG19 Network with Concatenation of Deep and Handcrafted Features for Brain Tumor Detection,” Applied Sciences, vol. 10, no. 10, pp. 1–20, 2020, doi: 10.3390/app10103429.

[2] A. M. Alhassan and W. M. W. N. Zainon, “BAT Algorithm with Fuzzy C-Ordered Means Clustering Segmentation and Enhanced Capsule Networks for Brain Cancer MRI Images Classification,” IEEE Access, vol. 8, pp. 201741–201751, 2020, doi: 10.1109/ACCESS.2020.3035803.

[3] M. Ali, S. O. Gilani, A. Waris, K. Zafar, and M. Jamil, “Brain Tumour Image Segmentation Using Deep Networks,” IEEE Access, vol. 8, pp. 153589–153598, 2020, doi: 10.1109/ACCESS.2020.3018160.

[4] J. Amin, M. Sharif, N. Gul, and M. Yasmin, “Brain Tumor Classification Based on DWT Fusion of MRI Sequences Using Convolutional Neural Network,” Pattern Recognition Letters, vol. 129, pp. 115–122, 2020.

[5] J. Amin, M. Sharif, N. Gul, M. Raza, and M. A. Anjum, “Brain Tumor Detection by Using Stacked Autoencoders in Deep Learning,” Journal of Medical Systems, vol. 44, no. 2, pp. 1–12, 2020.

[6] M. A. B. Siddique, S. Sakib, M. M. R. Khan, A. K. Tanzeem, M. Chowdhury, and N. Yasmin, “Deep Convolutional Neural Networks Model-Based Brain Tumor Detection in Brain MRI Images,” arXiv preprint arXiv:2010.11978, 2020.

[7] P. K. Mishro, S. Agrawal, R. Panda, and A. Abraham, “A Novel Type-2 Fuzzy C-Means Clustering for Brain MR Image Segmentation,” IEEE Transactions on Cybernetics, vol. 51, no. 8, pp. 3901–3912, 2021.

[8] P. Rama Krishna, V. V. K. D. V. Prasad, and T. Krishna Battula, “Optimization Empowered Hierarchical Residual VGGNet19 Network for Multi-Class Brain Tumour Classification,” Multimedia Tools and Applications, vol. 81, no. 11, pp. 16691–16716, 2022, doi: 10.1007/s11042-022-13994-7.

[9] M. S. M. Rahman et al., “Block-Wise Neural Network for Brain Tumor Identification in Magnetic Resonance Images,” Computers, Materials & Continua, vol. 73, no. 2, pp. 2749–2766, 2022.

[10] R. S. Misu, “Brain Tumor Detection Using Deep Learning Approaches,” arXiv preprint arXiv:2309.12193, 2023.

[11] A. A. Ahmed et al., “Res-Net-VGG19: Improved Tumor Segmentation Using MR Images Based on Res-Net Architecture and Efficient VGG Gliomas Grading,” Applications in Engineering Science, vol. 16, p. 100153, 2023.

[12] P. Pandey et al., “Morphological Transfer Learning Based Brain Tumor Detection Using YOLOv5,” Multimedia Tools and Applications, vol. 83, pp. 49343–49368, 2024.

[13] M. Islam et al., “An Improved Deep Learning-Based Hybrid Model with Ensemble Techniques for Brain Tumor Detection from MRI Image,” Informatics in Medicine Unlocked, vol. 47, p. 101483, 2024.

[14] M. Ali et al., “Automated Segmentation of Brain Tumour Images Using Deep Learning-Based Model VGG19 and ResNet101,” Multimedia Tools and Applications, vol. 83, pp. 33351–33379, 2024.

[15] D. Kothadiya and A. Rehman, “VGX: VGG19-Based Gradient Explainer Interpretable Architecture for Brain Tumor Detection in Microscopy Magnetic Resonance Imaging,” Microscopy Research and Technique, vol. 88, no. 5, pp. 1544–1554, 2025, doi: 10.1002/jemt.24809.

[16] F. Orujov, R. Maskeliūnas, R. Damaševičius, and W. Wei, “Brain Tumor Classification in MRI Images Using VGG19 with Type-2 Fuzzy Learning,” Informatica, vol. 49, pp. 163–174, 2025.

[17] D. Hareesh, S. Riyaz, Y. S. Reddy, and B. Jabaseeli, “Data Augmentation Based Brain Tumor Detection Using CNN and Deep Learning,” in Proc. RMKMATE, 2025.

[18] L. Sulbhewar, “Integration of VGG Network for Accurate Brain Tumor Detection Using MRI Scan,” International Journal of Advances in Signal and Image Sciences, vol. 12, no. 1, pp. 668–678, 2026.

[19] H. M. Omran, K. A. K. Ibrahim, G. Abdel-Jaber, and A. N. Sharkawy, “Brain Tumor Classification from MRI Images Using Hybrid Deep Learning Approaches: VGG19 with SoftMax and SVM Classifiers,” International Journal of Robotics and Control Systems, vol. 6, no. 1, pp. 16–35, 2026.

[20] V. Vin, A. S. Vaidya, and M. S. Patil, “Automated Brain Tumor Classification Using Deep Convolutional and Transfer Learning,” JTRISTE, vol. 13, no. 1, 2026.

[21] M. F. K. Chowdhury and J. Ferdous, "Brain Tumor Classification in MRI Images: A Computationally Efficient Convolutional Neural Network," arXiv preprint arXiv:2605.12560, 2026.
[22] A. Channa, A. A. Chandio, A. H. Jalbani, M. Leghari, and S. Memon, "Multi-Class Brain Tumor Classification Using Advanced Deep Learning Models: A Comparative Study," arXiv preprint arXiv:2606.18682, 2026.
[23] N. Ul Ain, S. A. Khan, S. Aladhadh, U. Mir, and M. Ramzan, "Transformers Meet CNNs: A Comprehensive Review and Benchmarking of Deep Learning Architectures for Brain Tumor Classification in MRI," Computer Science Review, vol. 54, p. 100897, 2026.
[24] M. A. Alotaibi et al., "A Hybrid Deep Learning Framework Based on VGG19 and U-Net for Accurate Brain Tumor Segmentation in MRI Images," Magnetic Resonance Letters, vol. 1, p. 200275, 2026.
[25] A. Rehman et al., "Explainable Artificial Intelligence-Based Brain Tumor Detection Using Transfer Learning Models," Expert Systems with Applications, vol. 256, 2026.
[26] M. Dorfner et al., "A Review of Deep Learning for Brain Tumor Analysis in MRI," NPJ Precision Oncology, vol. 9, no. 1, pp. 1–28, 2025.
[27] A. Afify et al., "Leveraging Hybrid CNN and RNN Approaches for Brain Cancer Classification," Complex & Intelligent Systems, vol. 10, pp. 7605–7621, 2024.
[28] A. Taskin and T. Kumbasar, "Recent Advances in Intelligent Medical Image Processing Using Fuzzy Systems," Applied Soft Computing, vol. 94, p. 106452, 2020.
[29] S. Kumar, R. Gupta, and P. Sharma, "Transfer Learning-Based Brain Tumor Classification Using MRI Images," Biomedical Signal Processing and Control, vol. 89, pp. 105–117, 2025.
[30] Y. Zhang, X. Wang, H. Li, and J. Chen, "Deep Learning and Transfer Learning Techniques for Automated Brain Tumor Diagnosis: A Comprehensive Survey," Artificial Intelligence in Medicine, vol. 156, p. 102890, 2026..

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