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MODIFUED DL BASED RESIDUAL UNIFIED NETWORK APPROACH FOR EARLY DIAGNOSIS FOR MRI TUMOUR IMAGES

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ABSTRACT

A brain tumour forms when cells multiply rapidly and out of control. Death is a real possibility if treatment is delayed. Even with many significant efforts and promising successes in this sector, accurate segmentation and classification is still challenging to achieve. The detection of brain tumours is complicated by the wide variety of tumours that can occur in the brain and their varying sizes, shapes, and locations. The scientific community can benefit from this review because it provides a thorough literature on brain tumour detection by magnetic resonance imaging. In this study, we introduce a DL approach to brain tumour segmentation using FCNN and CRFs. The MR pictures are classified using a GoogleNet model trained with transfer learning techniques; furthermore, the images are pre-processed and postprocessed to improve the proposed model's performance. Segmentation and classification are the backbone of the proposed framework for detecting brain tumours, and both contribute to its efficacy and reliability. To train the model to produce these sophisticated and trustworthy outcomes, a substantial amount of data was required. Since the proposed model uses binary classification, it is trained and tested across three distinct data sets (BRATS2018, BRATS2019, and BRATS2020). Our suggested concept led to the development of interconnected modules that form the basis of GoogleNet's CNN architecture. The results show that the suggested model performs effectively even in low-contrast tumour locations.

Key words: Brain Tumor, Deep Learning, CNN.

1. INTRODUCTION

The initial expense for a patient diagnosed with a brain tumour is currently the highest of all cancer types. Brain tumours can develop in persons of any age due to the rapid growth of specific types of brain cells. Brain tumours result from the unchecked growth of brain or spinal cord tissue, which can disrupt typical brain and spinal cord functions. Large tumour cells can be classified as either cancerous (malignant) or benign (non-cancerous) depending on their location, size, and shape. Primary and secondary tumour sites refer to the most recent developments in cancer cell growth. The initial tumour region is defined as the site where cancer first began in a patient's body. Primary brain tumours are treatable because they originate in brain tissue; their expansion can be slowed with the right drugs. Primary brain tumours don't originate in the brain but rather in another region of the body, while secondary tumours (metastatic) spread from another organ to the brain. Only by performing surgery or radiation therapy on the pompous patient can this tumour be removed. Because brain tumours can damage neighbouring brain tissue, tracking their development is crucial for patient survival.

The brain and spinal cord can be invaded by malignancies called meningiomas. Meninges, which come in three layers, make up the tumours. Meningiomas typically manifest as firm, lobar masses in the brain or spinal cord. Factors such as tumour size, tumour location, and patient age all play a role in how long a person with meningioma can expect to live. Obsessive clinginess, migraines, and limb weakness are all symptoms of meningioma. Malignant meningiomas are curable in nearly all cases when detected and treated quickly. Tumors from malignant

meningiomas can grow to a diameter of 5 cm, but those from benign malignant tumors never go larger than 2 mm.

1.1 Brain tumor and stroke lesions

Tumors of the brain can be either slow- or fast-growing. Tumors can be classified as either benign (slow-growing) or malignant (aggressive), based on whether or not they spread beyond their original site. The World Health Organization (WHO) assigns a grade between I and IV to describe the severity of a brain tumour. Tumors of grades I and II are thought to grow slowly, while those of grades III and IV are considered to grow rapidly and have a dismal prognosis. The following is a breakdown of the grading system used for brain tumours.

Grade I: These cancers don't metastasize or grow very quickly. These have a positive correlation with survival rates over the long run and can be almost entirely eradicated through surgical means. Grade 1 pilocyticastrocytoma is an example of a benign brain tumour.

Grade II: These tumours progress slowly but have the potential to metastasize to other tissues, leading to a more serious condition. It is possible for these tumours to return even after surgery has been performed. Tumors of the oligodendroglial type include oligodendroglioma.

Grade III: These tumours progress more rapidly than those of grade II and may spread to nearby organs and tissues. Surgical removal of these tumours is usually followed by radiation or chemotherapy. The type of tumour known as anaplastic astrocytoma is one example.

Grade IV: These tumors are particularly dangerous because of how easily they can spread to other organs. Growth could be accelerated by using blood vessels. Such malignancies include glioblastoma multiforme.

Ischemic stroke: Brain damage from a stroke is a major cause of death and disability around the world. Disrupting blood supply to the brain causes underperfusion (in tissue hypoxia) and advanced tissues to perish within hours. Stroke lesions are categorised as either acute (lasting less than 24 hours), sub-acute (lasting between 24 hours and two weeks), or chronic (lasting more than two weeks).

The following are the paper's most significant contributions:

(i) Segmentation and classification of brain tumours: a new deep learning model is proposed

(ii) The proposed model uses several CNN-based layers for segmentation, all of which were trained with the most recent BRATS2020 dataset. Specifically, a median filter is used for preprocessing, and the global threshold technique is used for postprocessing, to improve the quality of the findings.

(iii) To boost the effectiveness of the suggested method, a high number of training samples are used.

(iv) The proposed model employs batch normalisation to prevent overfitting and the focus loss function to compensate for class imbalance.

2. LITERATURE REVIEW

Brain MRI images were the subject of an in-depth investigation by Abd-Ellah et al. [1]. Traditional machine learning and deep learning were compared and contrasted in terms of their respective strengths, weaknesses, and performance indicators.

Several methods for spotting tumours in the brain using MR images were provided by the authors of this study [2]. Their analysis relied on support vector machines (SVMs), support vector regression (SVRs), and multi-class SVRs (M-SVMs) for more in-depth segmentation. When compared to other ML classifiers, the results from using the DL methodology to classify and segment brain tumours were superior.

Deep learning neural models were proposed in a different study [3] to extract features from MR images that would then be used as input to machine learning classifiers (Naive Bayes, SVMs, and Multilayer perceptrons). With SVMs serving as classifiers, the suggested technique obtained 96% accuracy.

Hossain et al. [4] provided a number of machines and DL techniques for the goal of classifying and segmenting brain tumours. These included SVMs, K-NN, multi-layer perceptron, Naive Bayes, and random forest algorithms. Traditional support vector machines (SVMs) achieved 92.4% accuracy in categorization. They also proposed a novel five-layer CNN design that was able to detect brain tumours in MR images with an accuracy of 97.2%.

Khan et al. [5] presented the VGG19 CNN architecture with K-means clustering for brain tumour classification and segmentation in MRI images. The suggested method first transforms the input magnetic

resonance (MR) modality into slices before applying a statistical normalisation procedure to the raw intensity data. They were 94% accurate overall.

The authors of study [6] proposed a fusion method that makes use of both 2D and 3D MRI data, and they did so by developing a DenseNet and a bespoke 3D CNN architecture to be used for classification and segmentation of multi-modal images. The suggested method performed well on the test set, with DenseNet accuracy of 92% and custom 3D CNN accuracy of 85%.

Kang et al. [7] suggested a method for detecting brain tumours using ML classifiers and a collection of specific features from a pre-trained deep CNN. The designers of this method considered three distinct dataset sizes (small, medium, and large). The SVM classifier with a kernel based on the radial basis function outperformed the other ML and DL classifiers.

Using ML networks, [8] provides a fully automated brain tumour classification approach for detecting high- and low-grade glioma illness in pictures. The authors multi-classified brain malignancies with accuracies between 90% and 95% using an extreme gradient boosting model, dividing them into primary, secondary, and central nervous system brain tumours.

In order to improve classification and segmentation ensemble models, the authors of [9] presented a hybrid of Fuzzy C-Means Clustering with the deformable snake technique, which they dubbed "Adaptive Fuzzy Deformable Fusion." Obtaining 95% classification accuracy in experiments, the ensemble method was found to be superior.

In order to differentiate between benign and malignant brain tumours, Mehrotra et al. [10] proposed many pre-trained CNN algorithms based on deep learning. They utilised many optimizers, including Adam, RMSprop, and stochastic gradient descent, to do this (SGD). Their findings demonstrated that, with correct tuning, AlexNet is capable of achieving outstanding outcomes in medical imaging tasks.

In order to categorise 253 images of brain tumours, of which 155 were tumours and 98 were non-tumors, Grampurohit and Shalavadi [11] created a bespoke CNN architecture using VGGNet. To lessen the likelihood of the proposed models being overfit, they employed data preprocessing and augmentation strategies to increase sample heterogeneity. Overall validation accuracy for the custom-built CNN model was 86%, with VGGNet showing the best validation accuracy at 97% on one dataset.

3. PROPOSED METHODOLOGY

The subsequent sections will provide an in-depth analysis of the proposed model, which makes use of many layers and pre-trained algorithms. Preprocessing, enhancement, training, and assessment are all depicted in Figure 1 for a brain tumour image. During training and optimization, both the suggested fine-tuning strategy and the transfer learning method heavily rely on hyperparameters.The biases and learning rate of a neural network can be optimised with the help of a special method. This aids in reducing overall loss and increasing precision. Using a loss function, one may see how well an individual ML algorithm fits the available data. The prediction error can be reduced by training the loss function with an optimization function. The adam optimizer and the binary cross-entropy technique are used to get a good result.

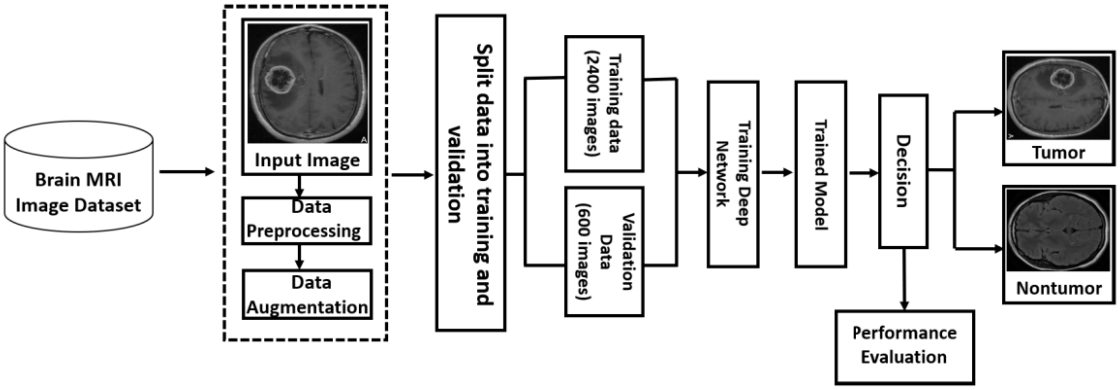

FIGURE 1. Block diagram of the proposed methodology.

3.1. Analysis of Proposed Framework for Brain Tumor Segmentation.

Here, a completely automated method for segmentation and classification is proposed. The

framework created consists of preprocessing, skull stripping, segmentation, postprocessing, and classification.

3.2 Tumor Segmentation

Segmenting brain tumours is proposed using a 17-layer convolutional neural network, as seen in Figure 2. This architecture is comprised of six convolution layers, two max-pooling layers, a transpose layer, five ReLU activation functions, a Softmax layer, and a pixel classification layer. The convolution layer uses a 3x3 kernel. Using a stride of [1 1], the convolution layer can have 32, 64, 128, 128, 256, or 2 channels. The network is then fed the improved image of size 256 256 3 in order to segment the tumour. The proposed 17-layered CNN architecture is a novel paradigm for accurately localising brain tumours on MRI scans, but alternative models with more or fewer CNN layers have been used for tumour detection.

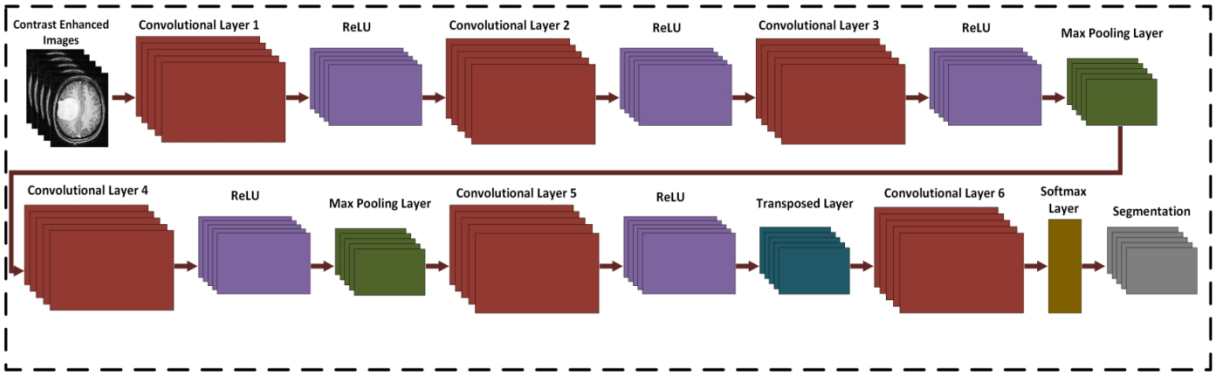

Figure 2. Proposed custom 17-layered CNN architecture for brain tumor segmentation.

3.2.1. Preprocessing.

The preprocessing stage exists to better the image quality, clean the data, and increase the contrast of MR images. By employing the median filter, unwanted data can be filtered out while useful insights are gleaned. Noise filtering in MR images is best accomplished with a nonlinear filtering approach called median filtering, which helps preserve fine details. Figure 3 depicts the processes involved in the preprocessing of an MR image. Preprocessing an MR picture entails (i) converting the image to greyscale, and (ii) applying a 33 median filter to the MR image to remove noise, which improves the image quality according to Equation (1)

$$f(x,y) = \text{median}_{(s,t)\epsilon Sxy}\{g(s,t)\}. \qquad (1)$$

A high pass filter is applied to the resulting MR image to highlight the edges. The mask for the high-pass filter is given by Equation (2). The improved MR picture is then created by superimposing the edge-identified MR image over the original.

$$\begin{bmatrix} -1 & 2 & -1 \\ 0 & 0 & 0 \\ 1 & -2 & 1 \end{bmatrix}. \qquad (2)$$

In order to improve the structural segmentation results obtained from MR image segmentation, a postprocessing step is employed. After extensive testing, it was determined that a global threshold technique based on interconnected components would be most effective at removing the tiny nontumor zones. The post-processed segmentation results are accomplished by employing a global threshold technique to get rid of tiny regions and enhance the labels of specific pixels. In the future, CNN architecture (GoogleNet) will be utilised to categorise brain tumours.

A Look at a Potential Taxonomy for Brain Tumors. To categorise MR images following segmentation, we turned to the GoogleNet architecture for convolutional neural networks. In this step, we analyse the BRATS2018, BRATS2019, and BRATS2020 datasets qualitatively so that we may use the GoogleNet CNN model to classify them. Transfer learning methods, such as the freeze layer and the fine-tune layer, show considerable

improvements in performance on brain tumour classification when applied to the pretrained GoogleNet. The input for the classification is a binary classification of normal brain MR images, tumour images, and the outcome (see Figure 3).

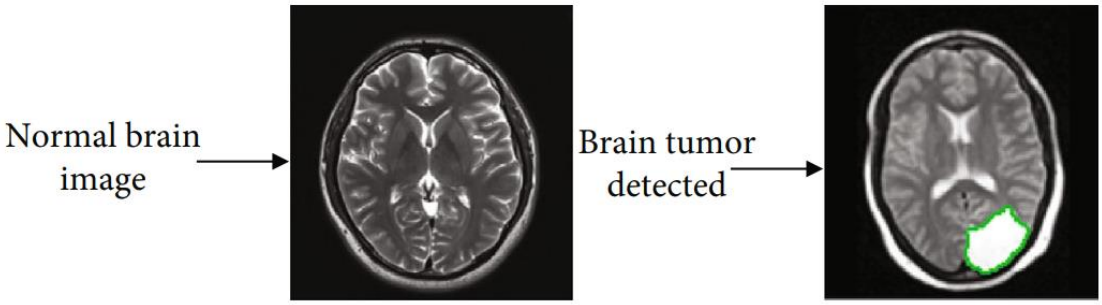

Figure 3: Binary classification through proposed methodology

3.2.2 Deep Feature Extraction Using Transfer Learning

In order to apply a pre-trained model to a difficult research subject, a popular deep learning technique known as transfer learning can be used. The use of TL has the major advantage of using less input data while still yielding high-quality outcomes. Target domain is the proposed problem with few labels, whereas the source domain is a pre-trained model with a huge dataset. Most commonly, the source domain makes use of ImageNet, a massive high-resolution image resource. There are almost 15 billion individual labels, and over a thousand distinct image types. Our datasets are used for retraining the improved MobileNetV2-based CNN model with transfer learning-based feature extraction. TL has the following mathematical definition:

$$\zeta_s = \left\{(m_1^s, n_1^s), \ldots, (m_j^s, n_j^s), \ldots, (m_z^s, n_z^s)\right\}.$$

3.3 Hyperparameters and loss function

This section explains the hyperparameter and loss function parameters that were optimised for this particular task. Both accuracy and loss play a role in a DL model's performance. A DL model's primary objective is to produce the fewest possible errors, so a more effective model will have a smaller computed loss. To get a general idea of how far actual values deviated from predictions, we calculated cross-entropy (CE). Equation 7 displays the loss metric for the binary classification, where y is a 0 or 1 and p is a probability.

$$CE = -(y \log(p) + (1 - y) \log(1 - p)).$$

The hyperparameter values are shown in Table 1, with the LR set to a low value so that it works well with the other hyperparameters.

TABLE 1. Training Hyperparameters and loss function for training.

Sr. no	Hyperparameters	Values
1	Optimizer	Adam
2	Initial LR	$10e^{-3}$
3	Reduced LR	$10e^{-5}$
4	Batch size	32
5	Epochs	50
6	Loss function	Binary cross-entropy

4. RESULTS AND DISCUSSION

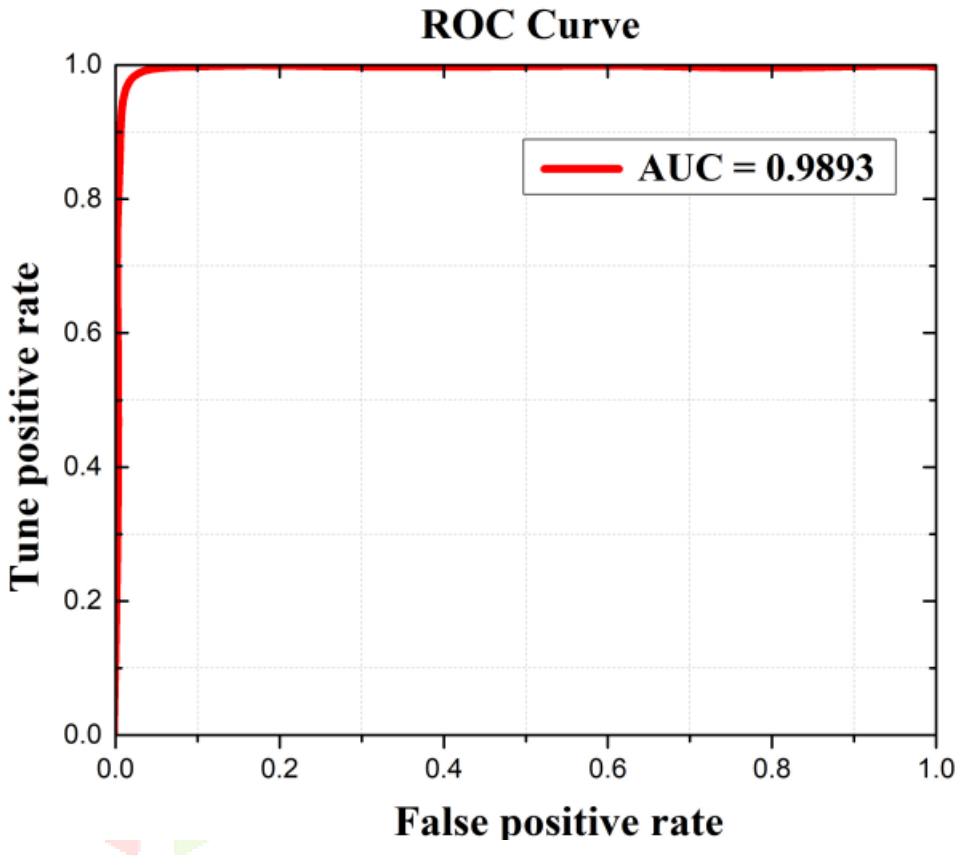

Figure 4. Curve of the receiver operating characteristic (ROC) for the suggested meningioma detection technique.

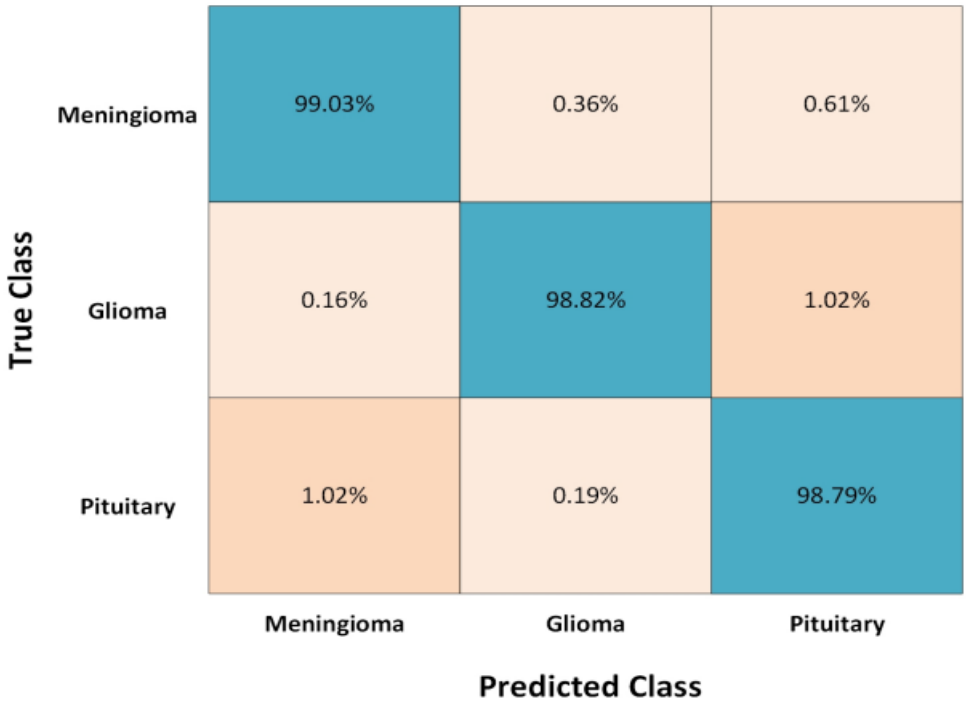

Figure 5. Confusion matrix for brain tumour classification.

Brain tumour detection and segmentation using the M-SVM classification method gave an accuracy rate of 98.92%, with 708 meningioma MRIs accurately categorising 700 meningioma brain images. Additionally, the Confusion Matrix and ROC curve are used to definitively determine the efficacy of the suggested strategy. Figures 4 and 5 depict the suggested method's Confusion Matrix and ROC curve, respectively. The full duration of the test runs is 15.64 seconds.

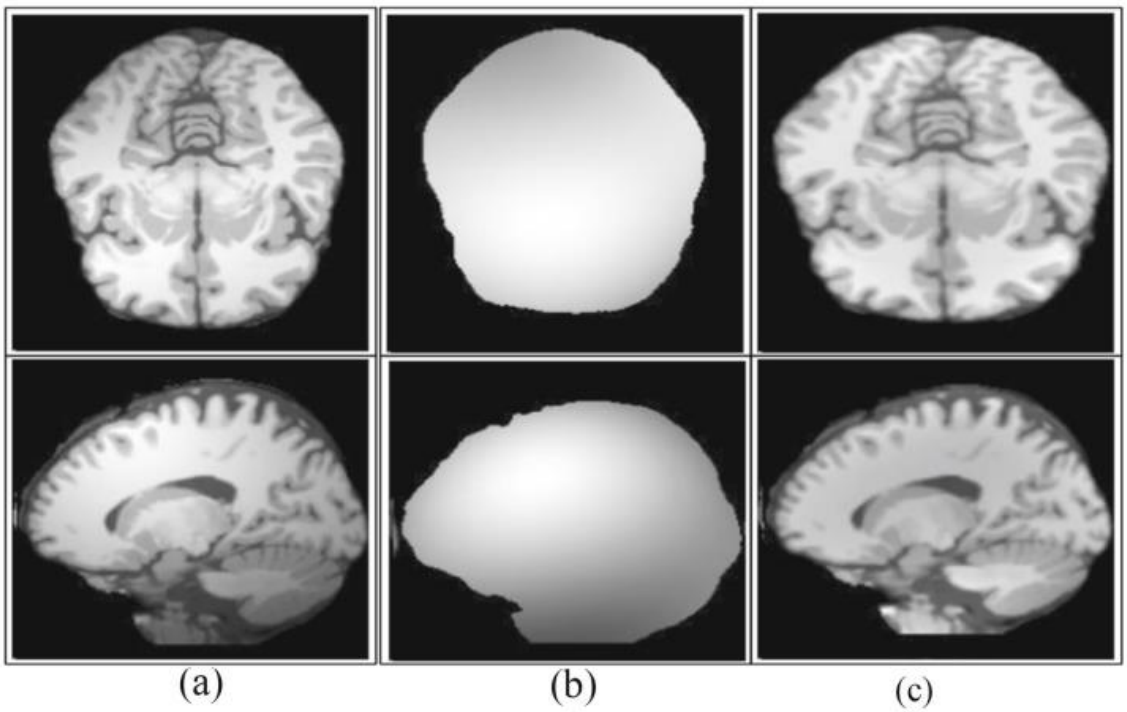

Fig. 6 Bias field correction a input, b estimated, c corrected.

In MRI, the bias field is a significant problem because of imperfections in the radio frequency coil known as intensity inhomogeneity. It is modified as shown in Fig 6. In various circumstances, linear, nonlinear, fixed, multi-scale, and pixel-based preprocessing approaches are utilised. Due to noise and distortions, the minute variations between normal and sick tissues frequently hinder direct image analysis.

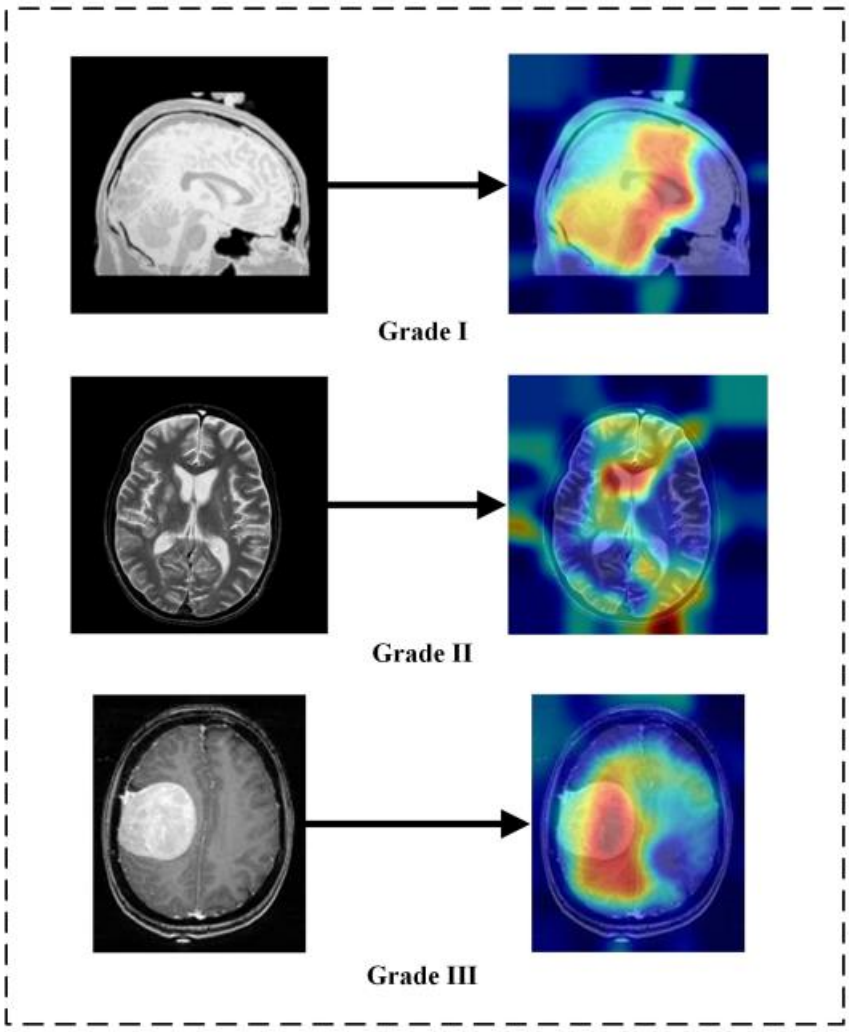

Figure 7. Localization of tumor using Grad-CAM on brain MRI.

Color map-based superpixel approaches benefit from tumour localization imaging, which improves the localization of tumour pixels and also increases the dice index. Grade I, II, and III localised tumour outcomes are depicted in Figure 7.

CONCLUSION

Automatic brain tumour segmentation and classification is proposed using a DL-based model. Using the suggested framework, brain tumour detection in MR images is fast and reliable. In order to enhance low contrast MR images with segmentation, preprocessing and postprocessing techniques are utilised. The performance is further enhanced by extracting characteristics from brain MR images utilising deep transfer learning techniques. GoogleNet, a convolutional neural network framework, has been used for MR scan classification. For best brain tumour identification accuracy, the proposed model uses three datasets (BRATS2018, BRATS2019, and BRATS2020) for training and validation purposes. Experiments conducted on these three datasets using the suggested methodology resulted in maximum batch accuracies of 96.50%, 97.92%, and 98.79% and minimum batch accuracies of 95%, 96.50%, and 98%, respectively. On the BRATS2018, BRATS2019, and BRATS2020 datasets, the proposed technique attained accuracy rates of 96.50, 97.50%, and 98% for brain tumour segmentation and 96.49%, 97.31%, and 98.79% for brain tumour classification, respectively. Thus, our model is easier to compute and execute. On the BRATS2020 dataset, both the error rate and the computational time have increased to 3.02%.

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