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Brain Tumor Detection from MRI Images using Enhanced Transfer Learning

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ABSTRACT

Brain tumor detection is vital for the diagnosis and treatment of one of the most lethal diseases in both children and adult. Traditional ways of analyzing brain tumour include reviewing Magnetic Resonance Imaging (MRI) images and interpreting results manually by radiologists; this technique has several problems including; complexity of the tumour type, size and location of the tumours may complicate the results of the analysis. Due to this, the above challenges are even more challenging to overcome in areas of scarcity of qualified human resource in healthcare. This study aims at suggesting a novel approach to resolve these challenges together with the utilization of Convolutional Neural Network (CNN) models such as EfficientNet-B2, Xception, Xception with Attention Mechanism. This paper is presented based on how these models can be employed in the classification and detection of the presence of brain tumours; these findings has seen the Xception with Attention Mechanism model register the highest accuracy at 95% among all the employed models. The refinement of the researchers' strategy is as follows, notably Synthetic Minority Over-sampling Technique (SMOTE) which caters for the issues of class imbalance in the set data. In addition to performing better than conventional non-automated techniques, the system provides a reliable solution for the detection of brain tumors that can be applied globally, benefiting physicians, particularly those to from developing countries, determine the patient's condition and choose the right treatment plan. Automated medical testing also means that the results are delivered quickly and with greater accuracy also resulting to positive outcomes for the patients.

Keywords: Brain Tumor Detection, Magnetic Resonance Imaging (MRI), Deep Learning, Convolutional Neural Networks (CNN), EfficientNet-B2.

INTRODUCTION

Brain tumor detection is a significant subject in medical science and the use of diagnostic imaging in the discovery of tumor in the brain [1]. These tumors are known to be benign, invasive and sometimes malignant tumors that can cause a lot of health complications by virtue of their proximity to critical neurological structures and functions. It's possible to prevent the disease from progressing by providing timely diagnosis, assessment of its severity or types, and correct treatment approach – which results in patients' improved outcomes. Typically, brain tumors have been diagnosed clinically, and by imaging such as magnetic resonance imaging (MRI) and computed tomography CT [2] and occasionally histological examination following a biopsy. Nevertheless, these traditional procedures are frequently slow, dependent on professional analysis, and characterized by cases of qualitative fluctuations. Over the years, the techniques in Imaging, Artificial intelligence and machine learning have brought significant improvements in the diagnosis of brain tumors by offering faster, accurate and automated analysis of image data sets. Methods such as improved transfer learning, CNN, and attention mechanism are being applied more frequently in extracting important features from MRI images [3] for highly effective classification of the tumors. They also assist in tumor classification identifying gliomas, meningiomas and pituitary adenomas to mention but a few thus assisting in giving the patient a specific treatment plan.

Moreover, such innovations are decreasing false negatives and raising the level of sensitivity, which is one of the major problems of the conventional approaches to diagnostics. The utilization of AI solutions in the identification and diagnosis of brain tumours not only can supplement the expert decisions of radiologists [4] but also could be equally useful in the circumstance where availability of specialists and interventional treatments are limited. However, there is still much to improve, like the critical requirement of large annotated datasets, inability to

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understand algorithms sometimes, and the general requirement for increased model robustness across the wide range of clinical conditions. Future developments in this area are expected to create a convergence between the diagnostic world of radiologists and oncologists, the engineering world of computer scientists and engineers, and provide the unions between the two. The final objective is to design effective, robust and friendly systems to assist the HL protagonists in the identification of early-stage brain tumors with a high predictive power towards improved prognoses.

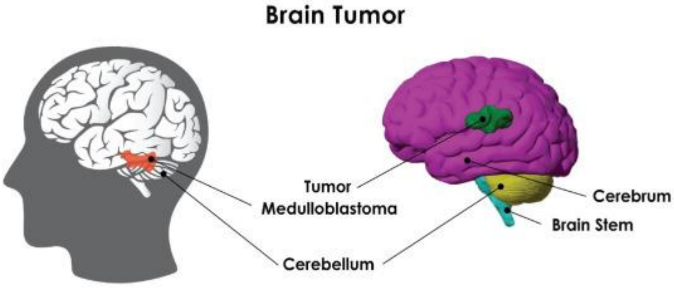

Figure 1: Anatomical representation of brain tumor (medulloblastoma) location by [5]

Figure 1 is an anatomical illustration showing a brain tumor diagram with two complementary views - a grayscale side profile and a colored 3D representation of the brain. The diagram specifically highlights medulloblastoma, a type of brain tumor, and its location in relation to key brain structures.

RELATED WORK

There are some previous works which will show work which is done in different brain tuimor detection field.

The first study which is been provided by [6] where the author presents an overview of segmentation techniques in DPIP which is an important step in diverse applications such as object detection and recognition, medical imaging and video surveillance. The work discusses and classifies segmentation techniques based on the following: thresholding, edge-based segmentation, region-based segmentation, clustering, deep neural network segmentation, and hybrid segmentation. Methods of thresholding include global, local and dynamic while the edge based includes gradient based and histogram based. Region based includes region growing, merging and splitting while clustering has fuzzy and hard clustering. Some of the modern approaches like CNNs, RNNs, encoder-decoder models are also covered; other mixed methods include fuzzy logic and swarm intelligence. To this end, the review of the segmentation techniques presented in this study aims at pointing at the respective strengths and weaknesses of the techniques. Though, challenges including computational complexity, noise sensitivity, and flexibility towards image types are still a problem. The insights highlight the promise of hybrid and deep learning for outcomebased segmentation while stressing the ongoing need to optimise the practice to enhance scalability and generalisation dilemmas in practice.

The study [7] fills the gap in the related literature by aiming at extracting text from the images with complex background, which is a weak point in many OCR systems especially in the cases of sharp contours, the touching and the skewed words and the intricate background. To address this, the study adopted an adaptive thresholding advanced with Tesseract OCR for text extraction. The algorithm it used was a partly user defined adaptive algorithm derived from the Gaussian thresholding method used in area-wise pixel processing to segment the characters from multiple and complicated backgrounds. Original images in JPG, PNG, WEBP formats and with different resolution were taken for testing. Finally, the system using Python 3.6 gave a word level accuracy of 69.7% while character level accuracy of 81.9% which is much higher than the preexisting methods in character level text extraction accuracy. That said, they showed some weaknesses also; specifically, word-level accuracy is only moderate, and the method is designed to work only with English character-based text and can be improved to work at higher accuracy with different languages as well as with more complex backgrounds.

In the above study [8], the author has discussed the development of Microorganism counting methods using digital image analysis which has drawbacks of most conventional methods such as plate counting, hemocytometry and turbidimetry which are exhaust time consuming, qualitative subjective and not fit for large scale applications. The study examines over 144 papers and groups microorganisms into bacteria and other classifications and, in detail, evaluates image analysis of counting approaches as well as segmentation and classification approaches. To give conclusive and systematic advice on the technological trends of microorganism counting and the establishment of integrated systems, commonly used image processing methods are cataloged. The paper emphasizes the advantages of image analysis techniques in comparison with the manual methods with regard to their efficiency and ability to handle large datasets. Among the remaining issues, we distinguish accuracy of the methods for different kinds of microorganisms, how to separate overlapping or clustered organisms, and real time application of the technique. The results are useful for researchers in all domains, but there is a clear indication that further fine-tuning is needed for maximum utility at scale and higher levels of accuracy.

The study [9] deals with multilevel threshold image segmentation using metaheuristic optimization methods to enhance the problems of image processing where segmentation quality is a determinant of analysis outcome. For new researchers, the paper offers general background knowledge about the definitions, procedures, and standard fitness functions used in solving the segmentation problem. A review of related works in this area of study organizes algorithms used in multi-level threshold segmentation and then compares optimisation methods, including the Whale Optimization Algorithm (WOA) and Aquila Optimizer (AO) and others. Eight standard images for quality assessment are utilized, and regression measures, and fitness functions are used alongside PSNR and SSIM. As findings show, the use of metaheuristic algorithms leads to satisfactory segmentation improvements compared to the optimized k-means algorithm, although it is observed that segmentation quality differs depending on the image. Some drawbacks have been identified; it is sensitive to the setting of its parameters and it involves high computational tasks implying the necessity for the development of its mixed or adaptive approaches in the future. The work highlights the areas that require further research and the study provides future research implications that are critical in the development of multilevel threshold segmentation techniques.

This section is going to explain the use of convolutional neural networks (CNN) in brain tumor detection and classification as well. There are some studies which have been showed the performance of CNNs in improving the accuracy and precision of tumor diagnosis.

[10] put forward a novel convolutional neural network (CNN) architecture to classify three kinds of brain tumors based on T1-weighted contrast-enhanced magnetic resonance images. The goal of the study was to help the radiologists with non-invasive tumor identification using a simpler CNN architecture than the pre-existing networks for enhanced predictions in the least amount of time and with accurate generality. For the assessment of the proposed approach two different 10-fold cross-validation strategies (record-wise, and subject-wise) and two databases along with data augmentation were used. A level-wise cross-validation on the provided augmented dataset of images resulted in the highest accuracy of 96.56%. In practice, good execution speed and, to a lesser extent, generalization capabilities are shown, but the specificity of the network to certain imaging modalities and the limited coverage of the datasets might limit its usage in broader medical imaging tasks.

A recent work by [11] suggested for using a CNN to identify and categorize brain tumors from MRI data. In the study, the focus was made on strengths of constructing deep learning model which include high accuracy, low error rates and ability to quickly and accurately predict in order to aid in the decision making process for the right treatment to be prescribed to patients. The proposed CNN-based approach was trained and tested on MRI datasets with results that show a of test subject precision of 96% and classification accuracy of 96%. This highlights that CNN is good in detecting the abnormality in tissue growth and afford precise tumor detection. Still, one of the main weaknesses of the work is the use of certain dataset that might not capture various or realistic medical imaging scenarios.

Another study who presented a new automated system for detection of brain tumors for classification purpose which is also very useful for segmentation of MRI images medical image processing is a big challenge in terms of accurate tumor classification given by [12]. The study's approach involves several steps: Some of the techniques used for the proposed framework include Mr I image preprocessing, noise removal through adaptive filters, segmentation through improved K-means clustering (IKMC), feature extraction using gray level co-occurrence matrix (GLCM) and classification by recurrent convolutional neural network (RCNN). The system divides the tumors in to gliomas, meningiomas, non-tumors, and pituitary tumors. The method was tested on Kaggle dataset with 394 test and 2870 training MRI images and it was found that the proposed RCNN classifier yields accuracy of 95.17% is much higher than present methods such as BP and U-Net. However, as the method is built based on specific datasets the robustness of the approach can remain questionable for different imaging conditions, and the realization of the RCNN can become a challenging task in terms of computational demands in real-world applications. Still, the method proposed in the paper shows the ability to maximize the accuracy of diagnosing brain tumors.

[13] put forward a classification model based on AlexNet to accurately diagnose Alzheimer's disease in the Mild Cognitive Impairment (MCI) phase through MRI medical images. The model seeks to solve the problem of early detection a critical factor when diagnosing Alzheimer's. It is normally used to test networks on the OASIS Brain dataset and included all forms of brain image orientation; axial, sagittal and frontal views. The model proposed for

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this work attained a robust 98.35% accuracy using more than 100 000 MRI images. However, these results indicate that the use of such a model may be useful when learned from a specific dataset and can address issues related to generalization in other populations or imaging conditions.

[14] presented an enhanced deep learning model to detect the brain tumor using MRI images known as Enhanced AlexNet (EAN), in order overcome the limitations of Manual diagnosis. To further enhance the classification of tumor infused portions in the brain the model employs the convolutional neural networks with additional layers. To increase accuracy, some methods of data augmentation were used, which contributed to the development of the model. The evaluation of the proposed model EAN showed that the proposed model is better and had higher accuracy of 99.32%, higher F1 score, recall and precision as compared to the traditional models. However, data augmentation is used by this model and the weaknesses of the evaluated metrics might be potential future directions on how to enhance the model.

METHODOLOGY

This section will provide data preprocessing and feature selection section of this study.

A. Dataset Description

This study's dataset is obtained from Kaggle and deals with Brain Tumor detection based on MRI- Magnetic Resonance Imaging. Brain tumors are one of the continually high-profile diseases in children and adults; 85-90% of all primary tumours in the Central Nervous System are brain tumours. About 11 700 new cases of brain tumour are identified every year, and the 5-year survival of those diagnosed with malignant brain or central nervous system cancer is 34 per cent for men and 36 per cent for women. There are various types of tumors in the brain Such included Benign Tumors, Malignant Tumors and Pituitary Tumors among others. Diagnosis and the design of effective treatment are important aspects of improving the clients' conditions and life span. Magnetic resonance imaging is the most accurate technique to diagnose brain tumors and produces vast amounts of image data. However, there exist errors when these images are interpreted by the radiologist as the brain tumors are complex and possess a variety of properties. This is a particularly big problem in the developing world because expert neurosurgeons in tumor diagnosis and analysis are hard to come by, which prolongs the diagnosis process and makes it less accurate. Due to this, automated tree based classification methods that use ML and AI have been found to be more accurate than other manual classification methods. So, the proposed system has the following objectives: With the help of latest and efficient deep learning methods like Convolutional Neural Network, Artificial Neural Network, and the aim of the proposed system is to detect and classify brain tumor in an efficient manner. This automatically implemented tool has applicability for developments in cloud platforms worldwide, helpful in quickly diagnosing and assisting doctors in regions where there are no many professionals in the field. The dataset includes a large variety of MRI scans with labels for classification, which forms the basis for the current and potential development of deep learning approaches to solve this crucial medical issue.

B. Data Preprocessing

Data Preprocessing is the process by which the desirable data from the given dataset is prepared for learning a model. The underlying data set includes MRI images that belong to different classes like benign and malignant tumours and is available from Kaggle. The first requires the use of label, this converts the categorical values into numerical labels using the LabelBinarizer. These images are converted and then managed by the use of OpenCV. All images are resized to some standard size so as to maintain the consistent input size for the deep learning models. A user-defined function is also defined to take care of the image loading and resizing known as image_array. This scans an image, ascertains its validity and flattens the image into an array. The function also implements exception handling, so that, for example, not readable image does not interfere with the pipeline.

The paths of the dataset are followed to load images from class folders of the data set directory structure. The script then loops through these folders and as it loops it read and recognizes any of the different image file formats that we have but we are going to only allow images that have .jpg and .png formats. It must be noted here that files like the .DS_Store are disregarded here during this process. Each valid image is resized and transformed into an array after which it has been added to the image_list. Similarly, corresponding to the subject which the folder name represents, the label name is added to the label_list. This is done so that each of them is accompanied by the right tags of its category for the supervised learning process.

C. Data Balancing

SMOTE was used in the classification of brain tumor dataset where data imbalance was experienced. For balancing the class distribution, SMOTE deals with minority classes by creating synthetic samples through interpolate of

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instances. This step is important in a way that it minimizes prejudice in the predictions made by the model most especially when it comes to rare types of tumor. As a result, by using SMOTE, the ratio of the instance density for all classes would increase and, thus, enhance the original dataset's performance and robustness for the model. This technique works in parallel with the data preprocessing phase of the project, so that the next phase of training phase acquires a balanced dataset which is critical to derive an appropriate classification of the different types of brain tumors.

Specifically, as Figure 2 showing, the type of brain MRI scans in the dataset is divided into four categories and each category is represented using different colored bars in the bar chart. There seems to have been a fair division of the dataset over the three types of tumor with meningioma tumours having the largest number of cases approximately around 900 (green bar) while pituitary tumours had cases nearly 850 (blue bar) and glioma tumours a little over 850 (red bar). The no_tumor compound, depicted by orangish bar, indicates, albeit, discovered a relatively low approximate likened to the tumor cases of about 500 cases and this maybe because of intentional sampling of normal compounds in relatively lower intensity as compared to tumor compounds. This distribution suggest a pattern of dataset design in which tumor cases are given importance while there is still a large non-tumor scan base.

As shown in figure 3, after applying the SMOTE technique there is proportionate distribution of tumor types in the present dataset. The bar plot shows an equal count of approximately 900 samples across all four tumor categories: preoperative diagnosis included pituitary tumor, no tumor, meningioma tumor and glioma tumor. To handle the problem of the initial class imbalance in our dataset, SMOTE was applied next to add synthetic samples for the under-represented tumor categories so that each category has the same number of instances. It eliminates model bias in the classification process while improving the performance of our classification system because the model is trained with an equal proportion of all tumor types.

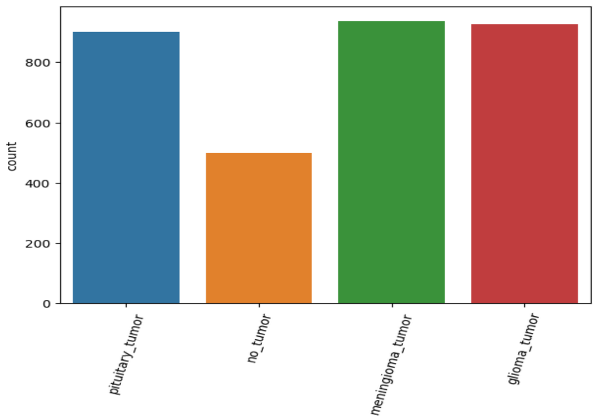

Figure 2: Distribution of MRI Scand Before SMOTE

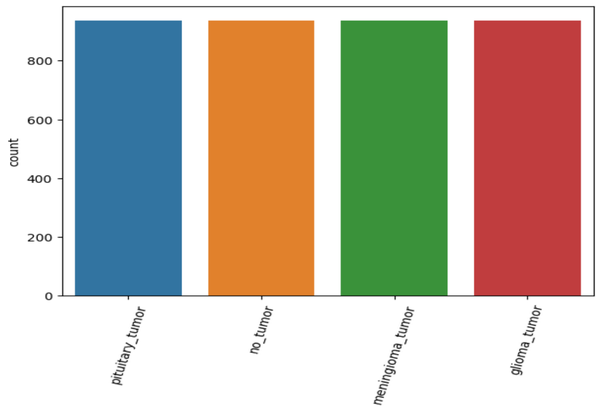

Figure 3: Distribution of MRI Scand After SMOTE

D. Exploratory Data Analysis

MRI scans of the brain of four different subjects with different types of brain tumors are illustrated in figure 2 along with a normal control. The first image at the top left is a glioma tumor where the brain tissue is irregular in density, and it is a mass; the top right is a meningioma tumor rounded and is closely associated with the dura mater. The control to check for abnormalities is the bottom left image with the brain scan of no tumour, normal, bilateral, symmetrical structures and normal depiction of gray and white matter. The last image at the bottom right is of Pituitary Tumor; this cancer is found in the pituitary gland in the brain's base. All of these images are in black and white, inherent to MRI scans, the pituitary and meningioma scans are in sagittal view and glioma scan and normal brain scans are in various planes to depict the required topographical landmarks. Every picture is marked and measured on the axes with numbers, which indicates that these are ordinary diagnostic treatment slices.

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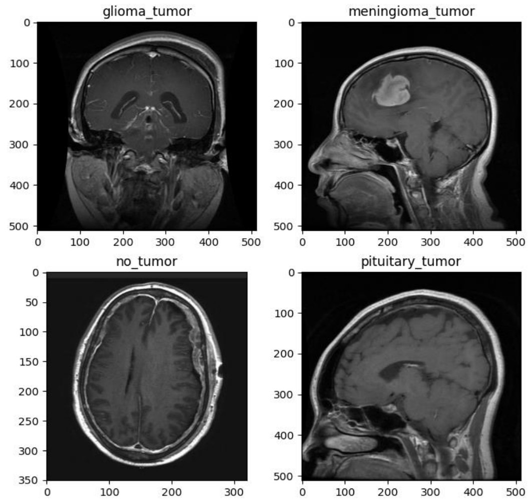

Figure 4: Representative MRI scans showing different types of brain tumours and normal brain tissue

E. Data Splitting

The dataset is divided into training and testing subsets using an 80:20 split ratio to guarantee the extremity of both models during the assessment of the model. The training sample includes 80% of all data and the rest 20% to compose a testing sample for the deep learning models. This subdivision guarantees a model that works on most of a data set yet saves enough for an objective validation. This kind of splitting is used to ensure that the distribution of the classes of the tumours is also replicated in the partitions.

Figure 5 is showing proposed workflow diagram of this study which starts from data collection to model evaluation.

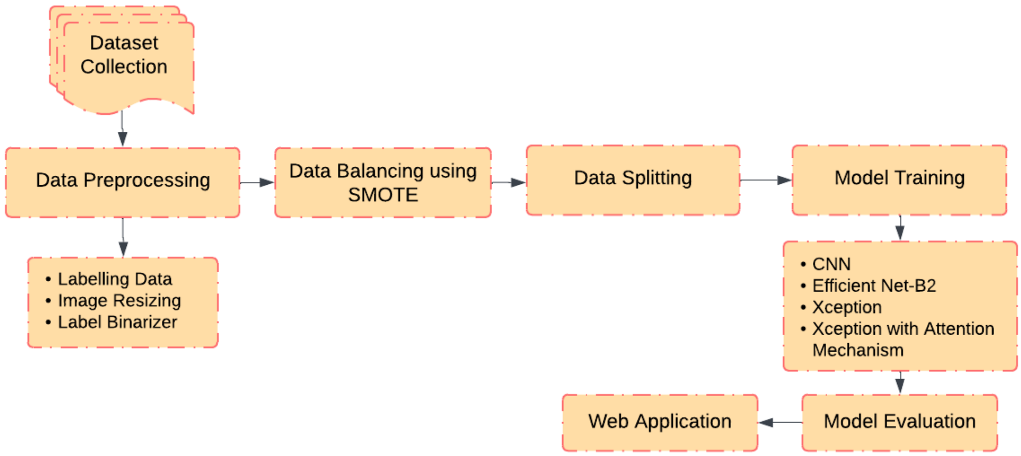

Figure 5: Proposed Workflow Diagram

EVALUATION RESULT

A. Classification Performance of CNN Model

Illustrated in figure 6 is the confusion matrix of the CNN model classification accuracy for 4 classes labeling from 0-3. The diagonal values (169, 67, 179, 178) are correct classifications indicative of high classification rates of classes particularly, class 0, class 2 and class 3. Negative elements show the percentages of misclassified samples, especially between classes 0 and 1 took place in 64 samples and between classes 1 and 2 took place in 43 samples. The colors close to black denote small misclassification in case of low value while high correct classification is represented by bright yellow supporting the general good performance of the model with few areas for improvements.

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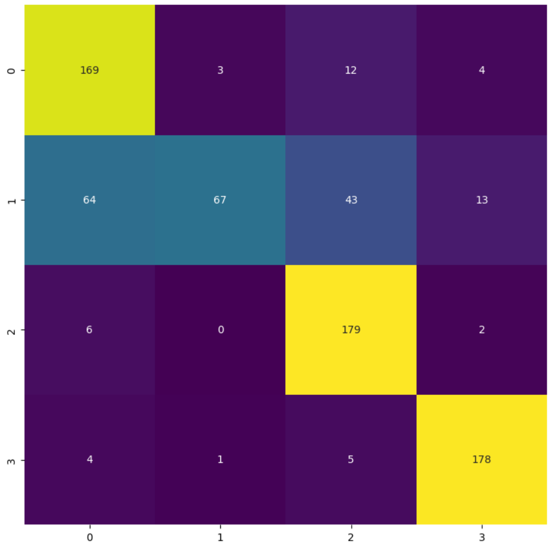

Figure 6: Confusion Matrix

B. Classification Performance of EFFICIENTNET-B2 Model

Figure 7 presents a confusion matrix of the classification effectiveness with using EfficientNet-B2 model over 4 classes, from 0 to 3. Correct classifications are presented as diagonal elements of the confusion matrix, which equal 151, 115, 158, 176 and show good performance of the model for each of the classes, with a focus on class 3. The off-diagonal entries define misclassifications, with generous confusion between classes 0 and 1 whereby 23 and 22 samples of them are classified correspondingly and between classes 1 and 3, with 32 samples. The gradient range from dark purple indicating low misclassification to yellow green representing high correct classification provides an effective visualization of the models classification regime.

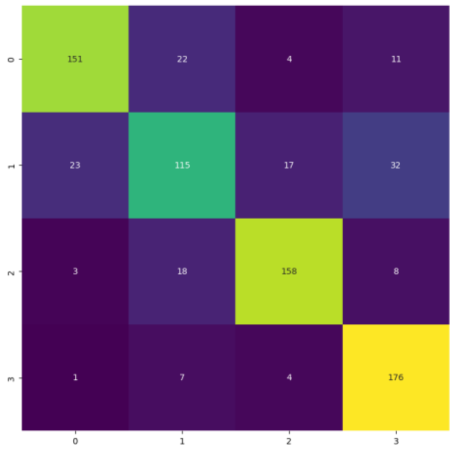

Figure 7: Confusion Matrix

C. Classification Performance of the Xception Model

In this study, the confusion matrix in order to evaluate the performance of the Xception model is shown in the Figure 8 with 4 classes ranging from 0 to 3. Schedule 12 also depicts diagonal values that highlight correct, such as 158, 47, 155, 183 with best performance in classes 0, 2, and 3. Some of the significant misclassification can be observed between class 0 and class 1 where 69 samples were mistakenly placed and class 1 misclassifies 34 samples as class 2 and 37 as class 3. The shades go from dark purple (low misclassifications) to bright yellow/green (high correct classifications), classifying class 1 as one of the most complicated to be classified correctly by the model.

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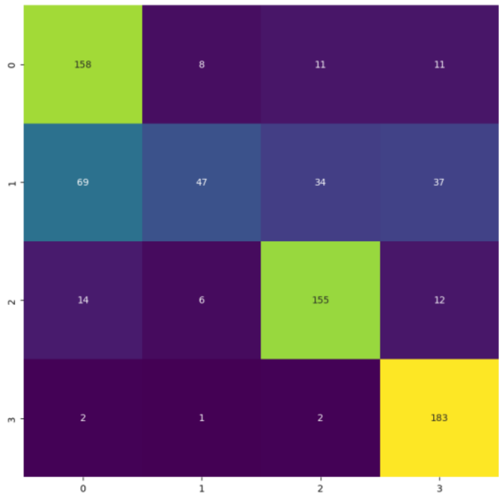

Figure 8: Confusion Matrix

D. Classification Performance of Xception with Attention Mechanism Model

In Figure 9 we shown confusion matrix for the classification performance based on the Xception model with the attention mechanism trained over 4 classes ranging from 0 to 3. The diagonal elements (highlighted in yellow/lime) represent correct predictions: Out of all the predictions made: class 0 had 179 correct, class 1 had 168, class 2 had 182 and class 3 had 183. Misclassification, shown in purple on the off-diagonal elements, have relatively low error rates; for example, there are sixteen class labels that were incorrectly predicted as the other class label of class 1 and six class labels of class 0 were predicted as class 1. The confusion matrix filled shows a high level of accuracy of the model through out the different classes.

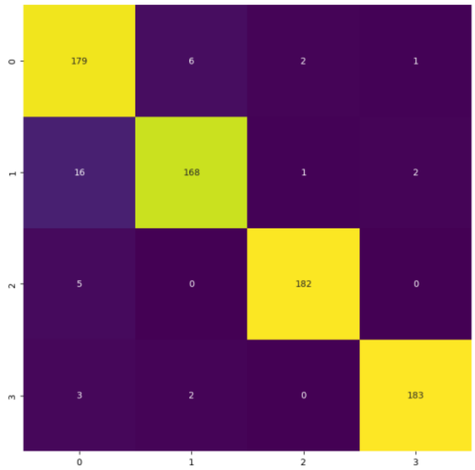

Figure 9: Confusion Matrix

This table 1 is showing all four models accuracies respectively.

Table 1: Model Accuracy Comparison for Brain Tumor Detection

Model	Accuracy (%)
Convolutional Neural Network (CNN)	79
EfficientNet-B2	80
Xception	72
Xception with Attention Mechanism	95

CONCLUSION & FUTURE SCOPE

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This study proves that deep learning models, especially the proposed Xception-based model with attention, can effectively classify brain tumor from MRI images. In the tested models, including CNN, EfficientNet-B2, and standard Xception, Xception with attention mechanism of 95% accuracy was obtained which is significantly higher compared with others. This brings out the fact that with transfer learning techniques and use of attention schemes the details in the medical images are captured well to enhance the accurate identification of the tumors. This helps alleviate the utilization of highly skilled radiologists, especially in developing countries so that patient's diagnosis would be attended to and achieved faster than it would take a radiologist to flag up an error. Moreover, when implemented in the Flask-based GUI, the system is easily embedded in the clinical workflows due to its appealing user interface.

For future work the following changes are suggested; First, data set can be further enlarged in terms of the types and numbers of tumor, and the subjects with images from different age, gender, or races. Second, radiation exposure could be minimized, and other techniques such as multi-modal learning, whereby MRI is combined with patient information including metadata could improve the diagnosis. Third, it is possible to deploy the system using other cloud based platforms which support real time processing of the data making it possible for the healthcare providers all over the world to access it. Furthermore, the adoption of the XAI methodologies can assist with improving trust in the constructed models by informing the selection process which the models use. Further, longitudinal research can be done to measure the effectiveness of the system in objective clinical environments for the specific consequences it has on patient treatment results. The following are ways in which the proposed system if developed, can advance and improve into a reliable large-scale and interpretable tool for the detection of Brain Tumour Candidate Regions from Multi-modal MRI:

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