EARLY CLASSIFICATION AND IDENTIFICATION OF BRAIN TUMOR USING DEEP LEARNING TECHNIQUES FROM MRI IMAGES

Subhash Chandra Jat
Professor-CSE
Rajasthan College of Engineering for Women
Jaipur, India
subhashcjat@gmail.com

Pratibha
Computer Science & Engineering
Rajasthan College of Engineering for Women
Jaipur, India
pratibhay6210@gmail.com

Abstract*—The goal of AI is to design machines that can perform tasks as effectively as a human being. Computer tasks involving AI encompass more than just pattern detection, planning, and problem solving. "Deep learning" refers to a set of algorithms used in machine learning. Using data from MRI scans, deep learning models can be developed to aid in the diagnosis and classification of brain tumours. This facilitates the straightforward diagnosis of brain tumours. Most neurological diseases originate from abnormal growth of brain cells, which can compromise brain architecture and even lead to malignant brain tumours. Brain tumour mortality rates could be reduced with better screening and earlier diagnosis. To quickly and accurately spot tumours in MR images, we recommend the convolutional neural network (CNN) based pre-trained EfficientNetB0, EfficientNetB4, and Hybrid transfer learning models proposed here. Recall, loss, accuracy, and AUC were only few of the metrics we used to evaluate the models' efficacy. By comparing the performance of other models to our suggested method utilizing these criteria, I found that a proposed model was superior. We evaluated the suggested models on a dataset of 3264 MR images and found that they achieved impressive results: an accuracy of 98.7%, an AUC of 99.25%, precision of 96%, f1-score of 96%, recall of 99.31%, and a loss of 0.13. We may conclude that the proposed model is useful for early detection of various forms of brain tumours by comparing it to the other models.

***Keywords*—Brain Tumours, MRI images, Machine learning, Deep learning, CNN, Transfer learning,EfficientNetB0, EfficientNetB4.**

Introduction

Tumors are neoplasms because their abnormal cell development goes unchecked.[1].A Tumor of the brain is a growth of malignant cells, tissues, or cells in the central nervous system.[2],

wherein few cells grow and spread uncontrollably, ostensibly unregulated by the natural process that controls normal cells. Our skull serves as an extremely rigid container for our brain. Because of the limited area, the tumour develops aggressively and disrupts normal brain activity. Major factors, such as excessive inhalation of inorganic compounds or inherited abnormalities, have been linked to the development of fatal malignant cells in the brain. Malignant brain tumours are more dangerous than their benign counterparts (cancerous). The pressure within the skull rises and causes a number of problems for individuals when benign, precarcinoma, or malignant tumours develop there. This will cause severe brain trauma that might be fatal. Early diagnosis of brain tumours is crucial for improving patients' chances of survival. Several methods were proposed for the anticipation of brain tumours. A glioma, a meningioma, and a pituitary tumour are the three most common forms of brain tumours.[3]. In the rapidly developing area of e-healthcare, medical picture technology plays a crucial role. The identification of cancerous brain tumour cells is a difficult area of study for medical researchers. Because it is the tenth most common cancer, early detection of brain tumours has become an important goal of medical research. Brain tumours are cancerous growths that may develop anywhere in the brain and come in many shapes and sizes.

Medical image analysis often employs a number of different methods to produce pictures of human organs and tissues. One such kind of imaging that doctors rely on is MRI pictures. It's a non-invasive method for diagnosing human brain cancers via careful examination of digital images.[4]. The levelling of tissue contrast and the improvement in picture quality make it very useful. Brain anomalies may be studied on several levels, including genetics, physiology, chemistry, and biology, thanks to the MRI pictures.[5]. On the basis of their genetic background and cellular make-up, tumours are categorised into several subtypes. Primary brain cancers in vertebrates manifest in the cerebral hemispheres, but secondary brain tumours in humans follow a journey from another organ to the brain.

Most scientists agree that CV can be used to automatically identify brain cancers.[6][7][8]. The preprocessing stage is often the first step in these methods, and it serves to improve the picture quality for better accuracy.[9]. However, this is not always the case since preprocessing may not always be necessary. As many of the researchers skip this part [10], the images are then used for feature extraction. In the introduction, we discussed how DL has achieved tremendous success in many different areas, including medicine and computer vision. The fundamental issue with deep learning is that training the computer takes a lot of time and a lot of computing resources. The development of transfer learning, however, has made this issue obsolete[11]. Layers of the pretrained model are often altered for transfer learning so that it may be applied to new challenges. In most cases, this may be achieved by fine-tuning the problem-specific performance of the input and output layers. Many studies in computer vision and medical imaging have employed multiple pretrained deep convolutional neural network (DCNN) models.[12].

These days, multimodal MRI imaging and deep learning (DL) are invaluable tools for researching brain tumour segmentation. In this paper, they propose employing DL to investigate multimodal MRI image segmentation in an effort to improve the speed and precision of brain tumour detection and treatment. Using a previously learned Hybrid model, this research presents a transfer-learning-based model (EfficientNetB0 and EfficientNetB4). Convolutional neural network (CNN) architectural modifications and normalisation and data augmentation procedures were used to improve this model. Our thesis is primarily concerned with the creation of a model that can recognise and characterise tumours in medical images for diagnostic and prognostic purposes. our work contributes in the following ways, to sum up

- Here, we provide a detailed study of the strengths and weaknesses of the EfficientNetB0 and EfficientNetB4 models for automated prediction of brain tumour cells using transfer learning-based CNN pretraining. On a dataset of 3264 pictures from MRIs of brain tumours, we show how pretrained models perform.
- Our model's efficacy will be measured in terms of these metrics: accuracy, precision, recall, AUC, f1-score, and loss. With an improved training and validation accuracy rate, we may conclude that the pretrained hybrid model estimates extremely appropriate outputs.

Literature Survey

In this section, will examine previous efforts to detect brain tumours using DL models.The computationally intensive deep-learning paradigm has recently captured the attention of the computer vision community.

In [13], to employed CNN architectures, namely VGG19, DenseNet169, AlexNet, InceptionV3, and ResNet101 models. The MR images, that were subjected to identical dataset and cleaning procedures, were trained using these models with identical hyper parameters. The analysis yielded the greatest accuracy with a rate of 98.6% for the ResNet101 model. Furthermore, the VGG19 model had a remarkably high accuracy percentage of 97.2. The relative accuracy metrics for the following models are as follows: InceptionV3 with an accuracy of 94.3%, DenseNet169 with an accuracy around 92.8%, & AlexNet achieved accuracy around 89.5%, respectevely.

In the study of [14]employ a combination of strategies, including a CNN model built from scratch as well as pre-trained models like inceptionresnetv2 and inceptionv3. The data obtained points to the efficacy of the suggested models, with the transfer learning model achieving 93.15 percent accuracy and the BRAIN-TUMOR-net based on CNN achieving 91.24 percent accuracy. The inceptionresnetv2 model has an accuracy of around 86.80 percent, whereas the inceptionv3 model has an accuracy of approximately 85.34 percent.

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The purpose of [15], is to assess the effectiveness of several pre-trained DCNN models, including Transfer learning, in identifying diseased brain images. The researchers employed a conceptual model incorporating Transfer Learning (TL) to validate its effectiveness, achieving an Accuracy around 98.28%, Recall of 97.51%, and Precision of 97.43%.

The objective of [16] aims to enhance the precision and effectiveness of MRI scanners in the categorization and identification of brain tumours and their corresponding subtypes. The researchers have utilised 5 models that were already trained, including Xception, ResNet50, InceptionV3, VGG16, and MobileNet, for training a dataset consisting of brain tumours. The F1-scores for the evaluation of unidentified pictures were recorded as 98.75%, 98.50%, 98.00%, 97.50%, and 97.25% correspondingly.

For a purpose of classifying brain tumours like Meningioma, Glioma, & pituitary, [17] carry out three investigations inside the suggested framework, each of which uses one of three frameworks of CNN: AlexNet, GoogLeNet, and VGGNet. In the investigations that were proposed, the fine-tuned version of the VGG16 architecture achieved the maximum accuracy, which was up to 98.69 percent.

In the study of [18] they suggested a RNN architecture for the detection of tumour cells by utilising a CNN image classification method. This not only assists in detecting the tumour at an early stage but also provides an accuracy of approximately 90%. An artificial neural network identified as a recurrent neural network, or RNN, is characterised by the fact that the connections between its nodes take the shape of a directed graph that runs along a temporal sequence.

One weakness of prior studies is that tumour prediction is dependent on the discovery of certain tumour forms, such as glioma, meningioma, or pituitary brain tumours. The limits of the current methods were not assessed without first identifying the tumour kind and grade. Due to its superior performance in identifying malignant tumour cells, the Convolutional Neural Network (CNN) with pretrained models is developed utilising the Keras and modularities TensorFlow.

Research Methodology

The dataset that was utilised is described in depth, and some instances of the data are shown, in this part. In addition, this section discusses the hyperparameters of the proposed model at each level.

Problem Statement

A brain tumour is one of the most challenging medical conditions to cure. There are a variety of hazards associated with the biopsy, including bleeding from the tumour & brain illness, convulsions, stroke, unconsciousness, severe headaches, & even fatality. Therefore, we must design a method to identify and forecast tumours depending on magnetic resonance imaging data. Because of the existence of low light in imaging modalities, its massive availability of data, or a few complexities & peculiarities of malignancies like unexpected size,

non-structured shape, & eccentric areas of growth, it may be challenging to differentiate the correct perception of growth cells from delicate tissues that are located nearby. Recently, automatic flaw identification in clinical imaging has gained popularity for use in a wide range of diagnostic tools in the medical field. It is most often utilized in high-precision methods for detecting & diagnosing cancer. Nevertheless, determining the kind of tumour with magnetic resonance imaging is time-consuming, complicated, & prone to mistakes, necessitating the use of highly skilled radiologists.

Early brain tumour detection is a challenge for the study's patients who need effective treatment. A large number of patients die due to the late detection of tumours, and brain tumours in particular. The detection and classification of brain tumours at an early stage will improve the prognosis for patients.

Proposed Methodology

Transfer learning was incorporated into DL, which simplified the arduous task of training models from inception. In this work, an MRI image dataset is used to suggest a transfer-learning-based model that uses a trained Hybrid model to find brain tumours

The following figure 4.1 shows the proposed methodology flowchart for the brain tumor detection. The first step is to collect MRI images data of brain tumors from Kaggle. The second stage involves applying techniques such as noise reduction, image resizing, image conversion, and normalisation to the data. This process improves the data's integrity and consistency. To overcome the problem of class imbalance, the third stage is to balance the data using SMOTE, which generates synthetic samples of the minority class (malignant tumours). This phase enhances the diversity and representation of the data. The fourth stage is to divide the data using a ratio of 80:10:10 into train, test, and validation sets. This phase helps to evaluate the model's performance on new data and prevent overfitting. The fifth and final step is to deploy a hybrid model that combines EfficientNetB0 and EfficientNetB5 for classification and feature extraction. EfficientNetB0 is a lightweight CNN that pulls out low-level features from pictures, while EfficientNetB5 is a deeper and wider network that pulls out high-level features. The model gives each picture a binary label (benign or malignant) and a feature vector that shows what the image looks like. Then, the model's loss and accuracy are measured using measures like cross-entropy loss, accuracy score, precision, recall, and F1-score. This step helps to make sure that brain tumours are found quickly and accurately.

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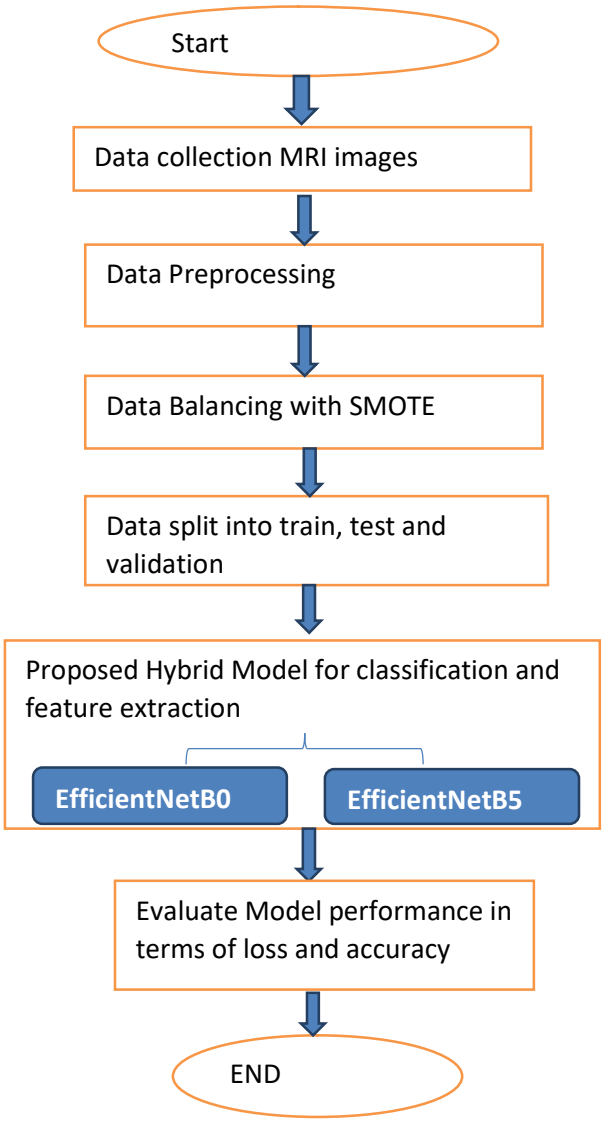

Figure 1: Flow Chart for Proposed Methodology

a) Data Gathering

In this work, got the Brain Tumour Classification (MRI) dataset from Kaggle websites. It has a total of 3,264 images. Data gathering is the process of collecting, getting, and putting together information from different sources to use for analysis, research, decision-making, or any other reason. We attempted to authenticate four distinct imaging modalities for the brain: glioma, meningioma, no tumour, and pituitary tumour.

Table 1: Dataset

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Brain Tumor Type	Count
Glioma Tumor	926
Meningioma Tumor	937
No Tumor	500
Pituitary Tumor	901
Total	3264

b) Data Preprocessing

Pre-processing is an important step in which the data are changed so that they can be used for training. Since the MR images came from a database of patients, they were not clear and of poor quality. At this stage, we normalised the images so that they would be ready for the next step. To make the images smoother and get rid of the blurry parts from the source images. For the Brain Tumour Detection Using MRI Images collection, we used the following key preprocessing techniques:

1) Convert image color format from BGR to RGB

This step is necessary if MRI images are originally in the BGR color format, which is commonly used in computer vision tasks. Converting them to the RGB (Red-Green-Blue) format ensures that the color information is represented correctly for further processing.

*2) Image size into 224*224*

Resizing the images to a consistent size, such as 224x224 pixels, is important for training deep learning models like Convolutional Neural Networks (CNNs). It ensures that all input images have the same dimensions, which is a requirement for many neural network architectures.

3) Convert data and labels into array

In most machine learning and deep learning frameworks, including libraries like TensorFlow and PyTorch, the data and labels need to be converted into arrays or tensors for processing. This step typically involves converting image data into NumPy arrays or tensors and labels into appropriate data structures (e.g., arrays or lists).

4) Apply smote technique for data balancing

SMOTE is a method used to address class imbalance issues in datasets. If our brain tumor dataset is imbalanced, meaning one class (e.g., "tumor") is significantly underrepresented compared to another class (e.g., "non-tumor"), SMOTE can be used to make samples for the minority class that aren't real. This helps balance the number of people from each class and keeps the model from favouring the class with the most people.

The specific process of SMOTE is as follows (Wang *et al.*, 2021).

- Using a set of rules that have already been set, the kk closest neighbours of each minority sample x_i (j=1,2,...,m) can be found among the minority sample.

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- Each sample xi (j=1,2,...,m) is composed of a random selection of the mm closest neighbours, which are a subset of the kk nearest neighbours. Then, equation (3.1) is used to create an artificial minority sample p_ij.

$$p_{ij} = x_i + rand(0,1) \times (x_{ij} - x_i) \qquad (1)$$

Where rand(0,1) is a random number between 0 and 1 chosen at random. When the aggregated data goes over a threshold of imbalance, the formula (1) is stopped.

5) Convert into to_categorical etc.

In many classification tasks, including brain tumor detection, it's common to convert labels into categorical format using one-hot encoding. This means that each label is represented as a binary vector, where only one element is "hot" (1) to indicate the class, and all other elements are "cold" (0). For example, if have two classes, "tumor" and "non-tumor," a sample with a "tumor" label would be represented as [1, 0], and a sample with a "non-tumor" label would be represented as [0, 1].

c) Data Splitting

Commonly employed to evaluate the efficacy of a prediction model, the split ratio you describe is used throughout training, testing, and validation datasets in machine learning. We used a split-dataset approach, with 80% dedicated to training, 10% to testing, and 10% to validation.

d) Classification Proposed HybridModels

Building a hybrid model by combining the features of two different architectures, in this case, EfficientNetB0 and EfficientNetB4, is a powerful approach for image classification tasks. This hybrid model approach leverages the advantages of both EfficientNetB0 (smaller and faster) and EfficientNetB4 (more powerful) to potentially achieve improved accuracy on image classification tasks. However, it's essential to carefully fine-tune the model, monitor its performance, and make adjustments as needed to achieve the best results for MRI dataset and problem.

1) EfficientNetB0 Model

EfficientNet [19]employs a compound coefficient to scale depth, breadth, and resolution equally, and is a method for building and scaling CNNs. To efficiently scale models, Efficientnet employs a "compound coefficient," which is both simple and powerful. Instead of making arbitrary changes to the networking width, depth, and resolution, the Efficientnet scaling approach uses a predetermined set of scaling coefficients to achieve the desired effects. The network's depth, breadth, and image size may all be multiplied by N to make advantage of 2N times more processing power. The first tiny model is grid searched for constant coefficients. An effective network employs a compound coefficient that is used logically to scale the network's breadth, depth, and resolution.

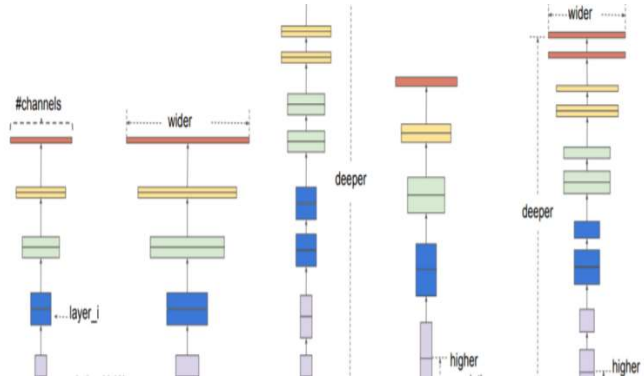

Figure 2: Image classification with EfficientNet Model [20]

The idea behind the compound scaling technique is that a more complex network is needed for larger input images in order to effectively enlarge the area of interest and capture more granular features.

From B0 to B7, there are 8 models in the EfficientNet category. The "Compound Scaling" scaling method, a novel one, was introduced in this model. The compound scaling method uniformly increases or decreases the image's depth, width, and resolution using a single compound co-efficient. This fresh set of models was created with the help of the NAS algorithm. The best baseline network is found using this NAS algorithm. In each of the eight models, the initial (stem) and final layers are identical. Following this, each model comprises seven segments. These blocks have an increasing number of sub-blocks as we progress from EfficientNetB0 to EfficientNetB7. There are approximately 5.3M trainable parameters in EfficientNetB0.

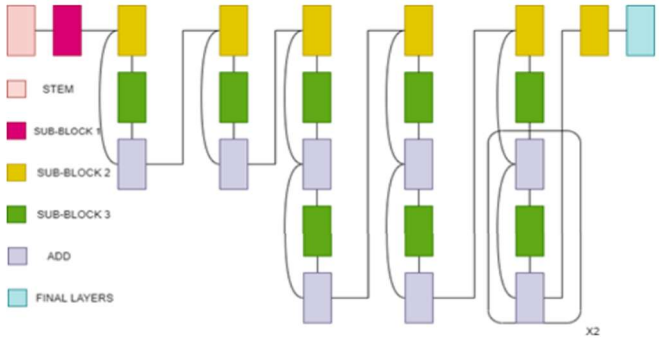

Figure 3: EfficientNetB0 Architecture[21]

EfficientNetB0[22] is a convolutional DNN that was devised to answer the question of whether ConvNets can be scaled up to achieve greater accuracy and efficiency. Increasing the network depth, channel width, and image resolution made this possible. The depth of EfficientNetB0 is 237 layers.

2) EfficientNetB4 Model

EfficientNetB4 is part of the EfficientNet family of neural network architectures, which are known for their efficiency in terms of model size and computational requirements while achieving competitive performance on various computer vision tasks, such as image classification. EfficientNetB4 is larger and more powerful compared to the earlier versions (e.g., EfficientNetB0, B1, B2, and B3). EfficientNetB4[23][24], is deeper and broader than previous versions. It is distinguished by its "compound scaling" approach, in which the depth, width, and resolution of the network are scaled concurrently to improve performance without substantially increasing computational cost. The foundational architecture of EfficientNetB4 consists of convolutional layers, depthwise separable convolutions, and batch normalisation layers. This fundamental architecture is scaled and modified to accommodate the desired size and complexity. EfficientNetB4 uses inverted residual blocks with bottleneck structures to decrease computation while preserving model performance. The convolutions in these blocks are depth-separable and don't rely on any external connections.

When compared to its predecessors, EfficientNetB4 is capable of handling more complicated jobs and bigger datasets. When more precision is needed, it is used for tasks like picture categorization, object recognition, and segmentation. It is best suited to situations where there is an abundance of processing resources, however, due to its increased computational and memory needs.

Image classification may be greatly enhanced by creating a hybrid model that combines the benefits of EfficientNetB0 and EfficientNetB4. This is especially true for MRI datasets. Adjusting important model parameters, or hyperparameters, such as the optimizer, loss function, batch size, and number of training epochs may improve model performance. In order to get the best results in tasks like image classification, it is crucial to fine-tune these hyperparameters, which play a critical role in determining the model's performance.

ResultAnalysis and Discussion

In the following section, provide the results and implement an analysis comparing the f1-score, recall, precision, and accuracy of multiple DL algorithms. An HP workstation equipped with 32GB of RAM, 1TB of hard drive space, Windows 10, a 24GB Nvidia GPU, and an I7 CPU will be used for the research. Everything can be done in Python using the Jupyter notebook.[25]. Python 3.7 is used to accomplish the suggested work together with the required libraries Nampy, pandas, and matplotlib. The MRI image dataset was downloaded from Kaggle. Include a comparison between the main model and the proposed model.

A. Dataset Analysis

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The dataset has a total of 7022 human brain MRI pictures, categorised into four distinct classes: glioma, meningioma, no tumour, and pituitary. The dataset consists of magnetic resonance imaging (MRI) images representing four distinct forms of brain tumours: pituitary tumours, meningioma tumours, no Tumours, and glioma tumours. These images are presented in grayscale form. A mass of aberrant cells is known as a brain tumour. A hard cranium protects the brain. Any growth in a small space might cause problems. Malignant brain tumours are cancerous, whereas benign ones are not. Benign or malignant tumours may raise intracranial pressure. The disorder that might cause neurological damage is life-threatening. Magnetic resonance pictures in this dataset had different sizes. Images representing the networks' input layer were scaled to 128*128 pixels. Each picture was transformed twice to expand the dataset.Following figures shows the Image of Brain Tumour.

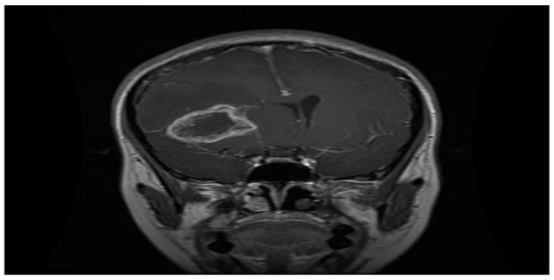

Figure 4: Image of Brain Tumour in RGB format

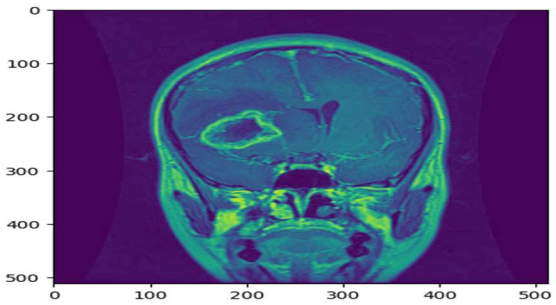

Figure5: Image of Brain Tumour in BGR format Using OpenCV

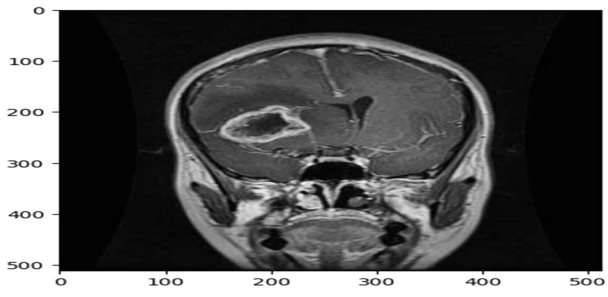

Figure 6: CLAHE-Enhanced Grey Scale image from BGR to GBR

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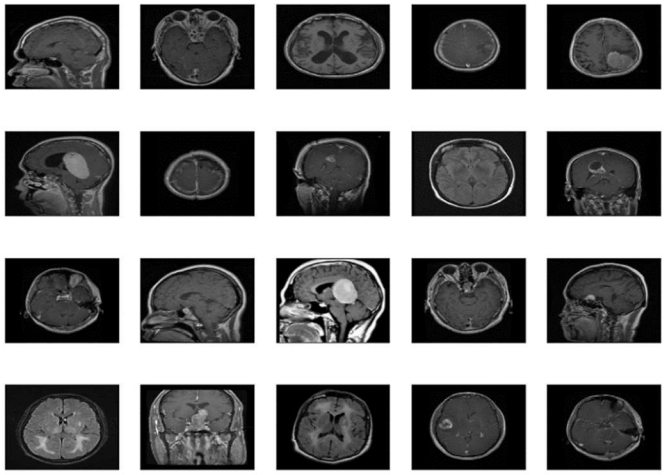

Figure 7: Image Resizing into 128*128

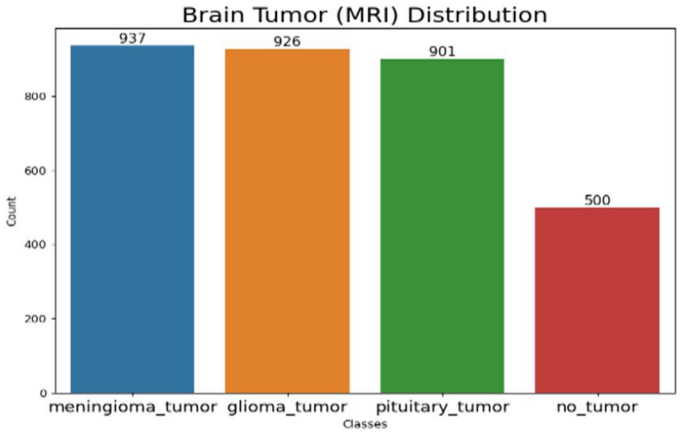

Figure 8: Count Plot for Brain Tumour (MRI) Distribution

The above figure 8 illustrates the count plot for Brain Tumour Distribution. The count plot is used for the categorical variable observation counts. Bar charts are used to visualize it. Here X axis represents the Classes in terms of Meningioma (Class 0), Glioma (Class1), Pituitary (Class2), and No (Class3) Tumour whereas Y axis shows a Count of these classes. A count of Meningioma Tumour at 937, a count of Glioma at 926, pituitary Tumour shows the count of 901, and No tumour class shows the count of 500.

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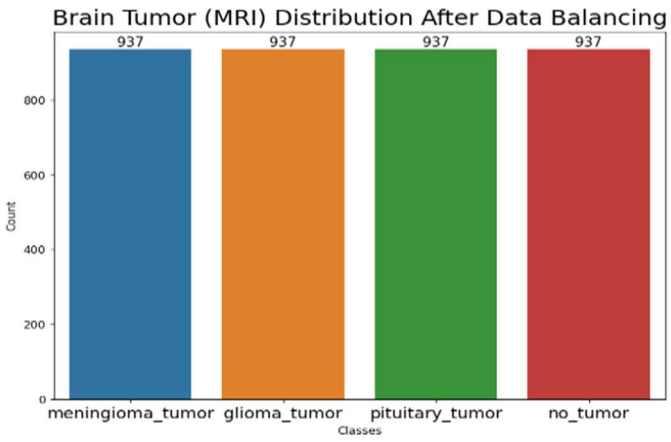

Figure 9: Count Plot Brain Tumour Distribution after Data Balancing

In the above figure 5.6 shows the Count plot for Brain Tumour Distribution after Data Balancing. After applying Data Balancing the Classes are balanced and the count of Meningioma, Glioma, pituitary, and Normal Tumour classes is at 937 has depicted in the above figure 9.

Evaluation of Metrics

To assess the parameters for Detecting Brain Tumours, we use MRI dataset, which is publicly available. The effectiveness of deep learning methods for improving detection and treatment of brain tumours has been measured in a number of different ways.

Confusion Matrix: The confusion matrix is a tabular representation used for the assessment of the efficacy of a certain algorithm. The visual representation provided by a classification algorithm's performance on a certain dataset serves as a succinct overview. The creation of a confusion matrix table is dependent on the classification methodology used, which might be either binary or multiclass in nature.

Whereas:

- True Positives (TP):The term "true positive" is used to describe when a model successfully predicts the positive class.
- True Negatives (TN): When a model incorrectly predicts the negative class, this is called a false negative.
- False Positives (FP): When a model incorrectly predicts the positive class, this is known as a false positive.

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- False Negatives (FN): When a model incorrectly predicts the negative class, this is called a false negative.

The subsequent parts will provide a comprehensive discussion on the ideas of Accuracy, Recall, Precision, AUC and F1-score, after a thorough comprehension of the aforementioned notions

Accuracy: The evaluation of a model's performance, whether it is the supplied model or the model currently in use, is conducted via the measurement of accuracy. The representation is in the form of a ratio.

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

Recall/ sensitivity: The process of recall is used to evaluate the efficacy of a classified model by identifying and capturing all relevant and valuable occurrences within a given dataset. Recall refers to the proportion of:

$$R = \frac{TP}{TP + TN} \ldots . (2)$$

Precision: Precision is a metric used to assess the degree of accuracy in a model's positive predictions. Precision is sometimes expressed in the form of a ratio, specifically as the quotient of TP divided by the sum of TP and FP.

$$Precision = \frac{TP}{TP + FP} \ldots . (3)$$

F1 score: F1-score is used as a metric to assess a overall performance of the classified model. The harmonic mean is found by averaging the reciprocals of the measures of precision and recall.

$$F1 - score = 2 \times \frac{precision * recall}{precision + recall} \ldots . (4)$$

Specificity: The percentage of normal cases correctly identified is a measure of the classifier's sensitivity to and understanding of the normal case. It is calculated by:

$$\text{Specificity} = \frac{\text{T}N}{\text{TN} + \text{FP}} \ldots \ldots . (5)$$

AUC and Receiver Operating Characteristics (ROC): An AUC measures overall performance at any given categorization cutoff. The AUC can be interpreted as the probability that the model will arbitrarily give a higher score to a positive example than to a negative one.

Experimental Resultsand Discussion of proposed Models

The proposed results and analysis of the Testing, Training, and Validation for a MRI dataset in terms of precision, recall, F1-score, Loss function, and accuracy can be analysed in the below section with the performance has been discussed. The MRI dataset is employed in the study or in

this experiment. Here the model used are EfficientNetB0, EfficientNetB4, and Hybrid model that is the amalgamation of both the EfficientNetB0 and EfficientNetB4.

Proposed EfficientNetB0 Model results

Here provide the simulation results of proposed EfficientNetB0 model on train, test and validation MRI dataset for brain tumour detection using the performance parameters.

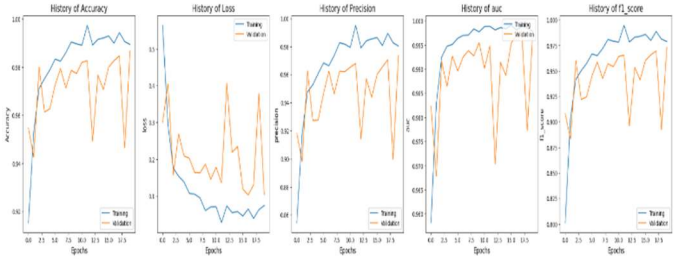

Figure 10: Plotting parametes curve of proposed EfficientNetB0 Model on train and validation dataset

The above figure 10 depicts the Plotting curve of f1-score, recall, accuracy, precision & loss measures for Training and Validation. Here X axis represents the Epoch which is adjusted at 20 whereas Y axis represents the Accuracy for training and validation.

Table 2: EfficientNetB0 Model for parameter performance Results

PARAMETERS	EFFICIENTNETB0 MODEL		
	Training Results	Testing Results	Validation Results
LOSS	0.0067	0.1414	0.1800
ACCURACY	0.9988	0.9807	0.9813
PRECISION	0.9977	0.9626	0.9627
RECALL	0.9977	0.9600	0.9627
AUC	1.0000	0.9925	0.9919
F1-SCORE	0.9977	0.9622	0.9365

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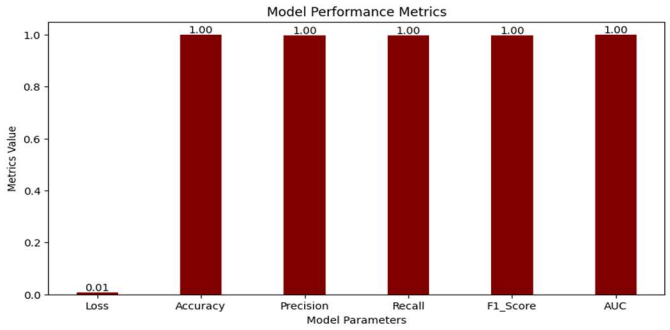

Figure 11: Bar graph of EfficientNetB0 model training performance

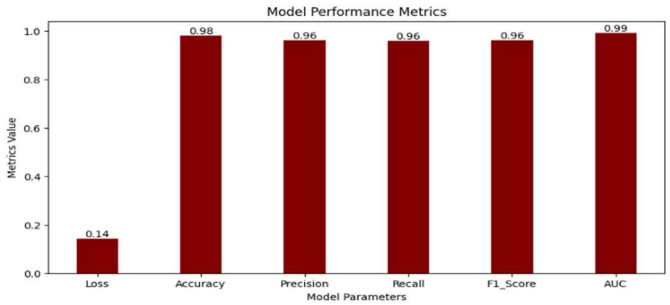

Figure 12: Bar graph of EfficientNetB0 model testing performance

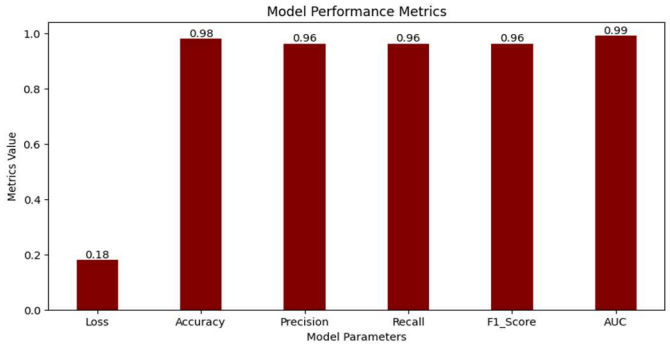

Figure 13: Bar graph of EfficientNetB0 model validation performance

Following table 2 and figures 11 to 13 shows the proposed EfficientNetB0 model results with train, test and validation set using performance parameters. The EfficientNetB0 Model Training Results the F1-score shows the metric value of 0.9977, AUC is at 1.00, Recall metric values is at 0.9977, precision is at 0.9977, accuracy is at 0.9988, and Loss is at 0.0067 for Training results and the sensitivity of the confusion matrix is at 0.9986 whereas Specificity of the confusion matrix is at 0.9987, shows in figure 11. For the Testing results the Loss value is at 0.1414, AUC is at 0.9925, recall is at 0.96, accuracy is at 0.9807, precision is at 0.9626, F1-Score is at 0.9622 for the testing results. The sensitivity of the confusion matrix is at 0.9596 whereas Specificity of the confusion matrix is at 0.9540 for the Testing Results shows in figure 12. For the Validation

Results the Loss value is at 0.18, AUC is at 0.9919, Precision is 0.9627, recall is 0.9627, accuracy is 0.9815, and F1-Score is 0.9365. for the Validation results shows in figure 13.

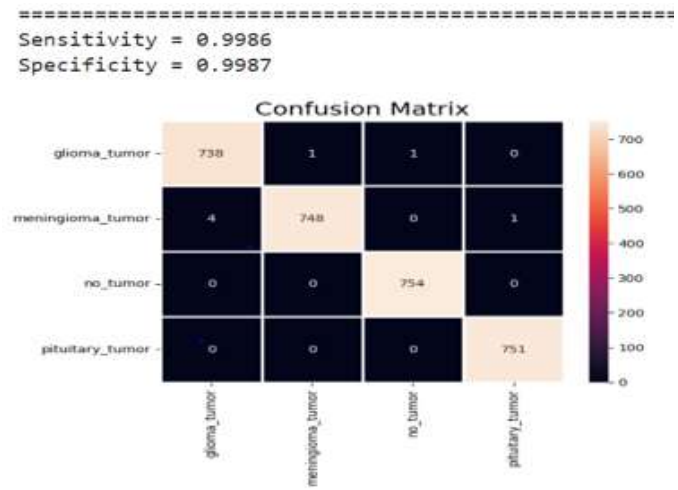

Figure 14: Training Confusion Matrix for EfficientNetB0 Model

The Confusion Matrix for EfficientNetB0 Model Training Results is shown in the previously mentioned figure 14. A table called a confusion matrix is used to assess the performance of a classification algorithm. Here the diagonally determined values are correctly predicted whereas all the others values are incorrectly matched. The sensitivity of the confusion matrix is at 0.9986 whereas Specificity of the confusion matrix is at 0.9987, respectively.

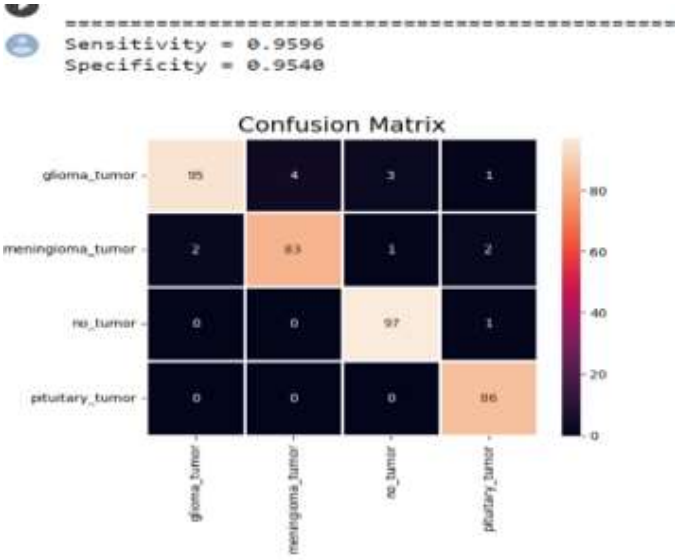

Figure 15: The Testing Confusion Matrix of EfficientNetB0 model

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The Confusion Matrix for EfficientNetB0 Model for Testing Results is displayed in figure 15 above. A sensitivity of the confusion matrix is at 0.9596 whereas Specificity of the confusion matrix is at 0.9540 for the Testing Results.

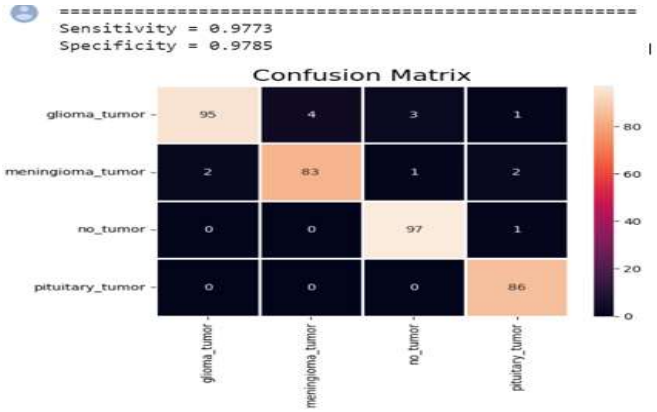

Figure 16: Validation The confusion Matrix of EfficientNetB0 Model

In a above figure 16 represent a confusion matrix for validation results. Here in the above confusion matrix for validation results the diagonally predicted values are correctly determined whereas other values are incorrectly matched. The sensitivity is at 0.9773 and specificity is at 0.9785, respectively.

Proposed EfficientNetB4Model results

Here provide the simulation results of proposed EfficientNetB4 model on train, test and validation MRI dataset for brain tumour detection using the performance parameters.

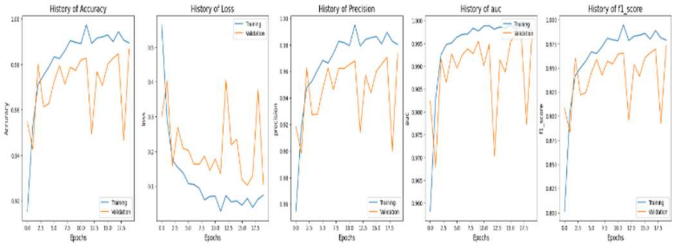

Figure 17: Plotting parametes curve of proposed EfficientNetB4 Model on train and validation dataset

The above figure 17 depicts the Plotting curve of f1-score, recall, accuracy, precision & loss measures for training and validation of propose EfficientNetB4. Here X axis represents the Epoch which is adjusted at 20 whereas Y axis represents the Accuracy for training and validation.

Table 3: EfficientNetB4 Model for parameter performance Results

PARAMETERS	EfficientNetB4 MODEL

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	Training Results	Testing Results	Validation Results
LOSS	0.0102	0.1382	0.1042
ACCURACY	0.9983	0.9800	0.9867
PRECISION	0.9970	0.9600	0.9733
RECALL	0.9963	0.9931	0.9733
AUC	1.0000	0.9609	0.9972
F1-SCORE	0.9967	0.9600	0.9729

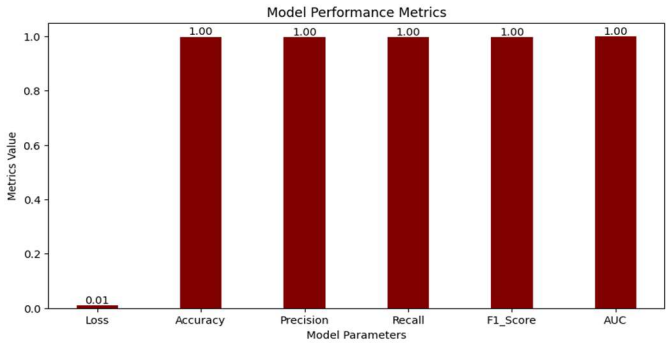

Figure 18: Bar graph of EfficientNetB4 model training performance

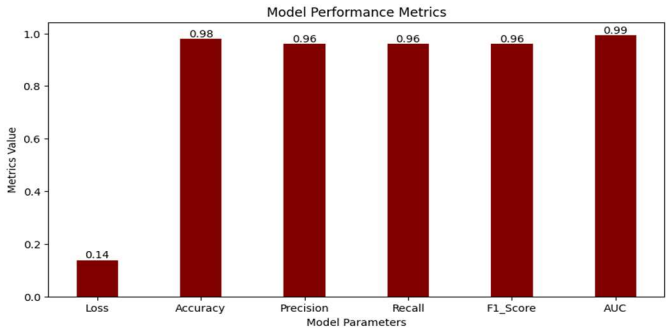

Figure 19: Bar graph of EfficientNetB4 model testing performance

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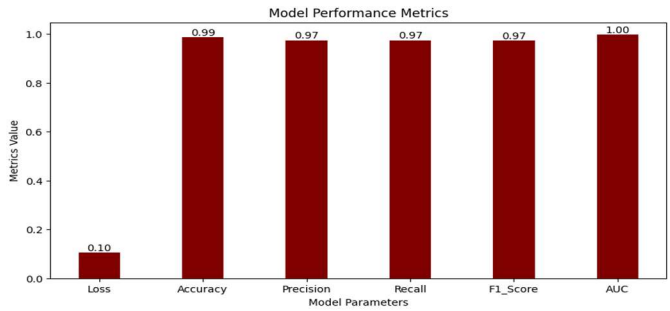

Figure 20: Bar graph of EfficientNetB4 model validation performance

Following table 3 and figures 18 to 20 shows the proposed EfficientNetB4 model results with train, test and validation set using performance parameters. The EfficientNetB4 Model for Testing results the Loss is at 0.1382, Accuracy is at 0.98, Recall is at 0.96, AUC is at 0.9931, Precision is at 0.96, and F1-Score is at 0.9609 for the Testing Results. The sensitivity is at 0.9700 while specificity is at 0.9639 shows in figure 18. For the testing Results the Loss Value is at 0.0102, Accuracy is at 0.9983, Precision is at 0.997, Recall 0.9963, AUC is at 1.00, and F1-Score 0.9967 for the Training results. The sensitivity is at 0.9986 and the specificity is at 0.9987, shows in figure 19. For the Validation Results the metric value of Loss is at 0.1042, Accuracy is at 0.9867, Recall is at 0.9735, AUC is at 0.9972, and F1-score is at 0.9729 for the Validation results shows in figure 20.

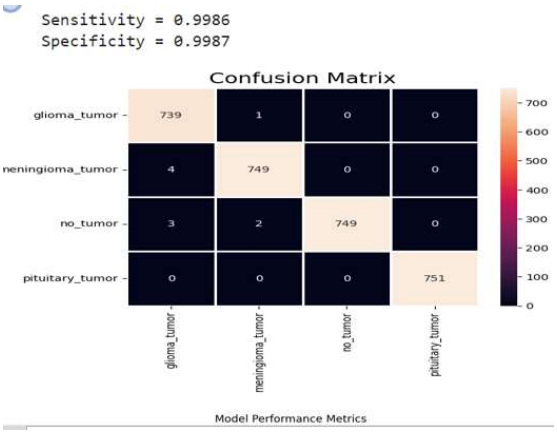

Figure 21: Training Confusion Matrix EfficientNetB4 model

Figure 21 above displays the confusion matrix for the EfficientNetB4 Model for Training Results. A sensitivity is at 0.9986 and the specificity is at 0.9987, Respectively.

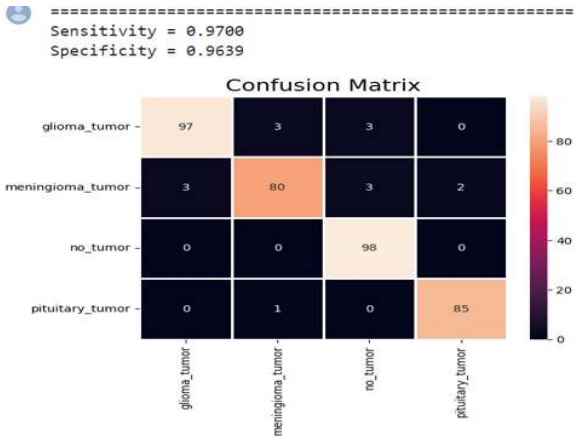

Figure 22: The Testing Confusion Matrix of EfficientNetB4 Model

The above figure 22 Depicts the confusion matrix of EfficientNetB4 Model for Testing results. The sensitivity is at 0.9700 while specificity is at 0.9639, Respectively.

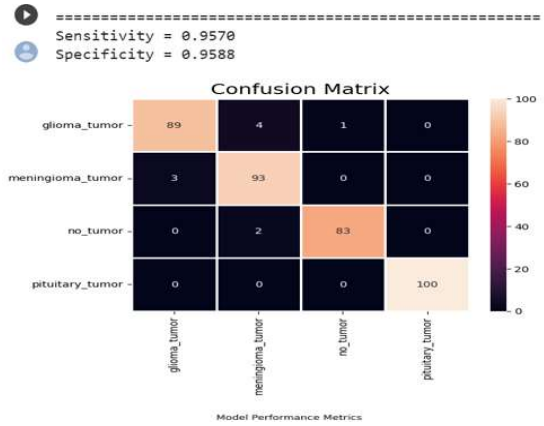

Figure 23: The Validation confusion Matrix of EfficientNetB4 model for results

The figure 23 Depicts the confusion matrix of EfficientNetB4 Model for Validation results. The sensitivity is at 0.9570 while specificity is at 0.9588, Respectively.

Proposed Hybrid Model results

Here provide the simulation results of proposed hybrid model (efficientnetb0 and efficientnetb4) on train, test and validation MRI dataset for brain tumour detection using the performance parameters.

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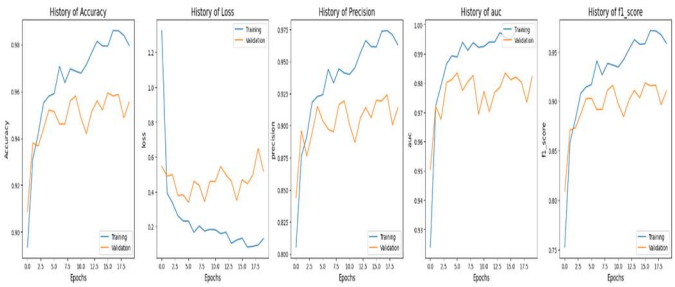

Figure 24: Plotting parametes curve of proposed hybrid Model on train and validation dataset

The above figure 24 depicts the Plotting curve of f1-score, recall, accuracy, precision & loss measures for training and validation of propose hybrid model. Here X axis represents the Epoch which is adjusted at 20 whereas Y axis represents the Accuracy for training and validation.

Table 4: Hybrid Model (EfficientNetB0 and EfficientNetB4) for Validation Results

PARAMETERS	HYBRID MODEL		
	Training Results	Testing Results	Validation Results
LOSS	0.0351	0.4548	0.5182
ACCURACY	0.9942	0.9360	0.9553
PRECISION	0.9900	0.8760	0.9140
RECALL	0.9867	0.8667	0.9067
AUC	0.9998	0.9737	0.9823
F1-SCORE	0.9882	0.8712	0.9121

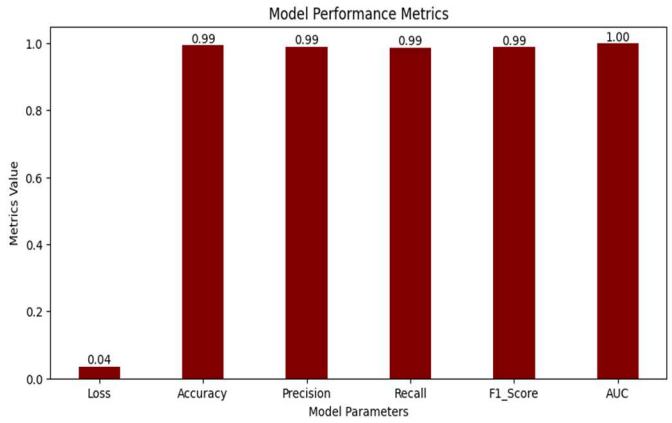

Figure 25: Bar graph of Hybrid model train performance

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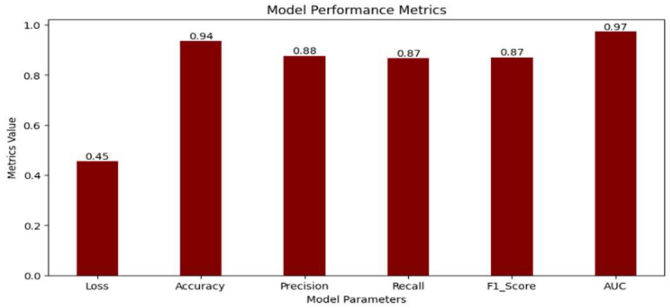

Figure 26: Bar graph of Hybrid model validation performance

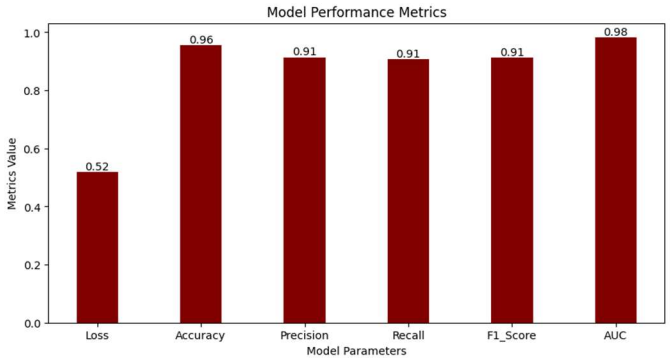

Figure 27: Bar graph of Hybrid model validation performance

The hybrid Model (EffcientNetB4 and EfficientNetB0) for Training results the metric value Loss is at 0.0351, Recall is 0.9867, Accuracy is 0.9942, AUC is 0.9998, F1-Score is 0.9882, precision is 0.99 & a sensitivity is at 0.9919 while specificity is at 0.9918, shows in figure 25. For the Testing Results the metric value of Loss is at 0.4548, Recall is 0.8667, Accuracy is 0.936, Precision is 0.876, AUC is 9737, and F1-Score is 0.8712 and the sensitivity is at 0.9700 while specificity is at 0.9639 shows in figure 26. For the Validation results the metric value for Loss it is at 0.4548, Recall is at 0.8667, Accuracy is at 0.936, Precision is at 0.876, AUC is at 9737, and F1-Score is at 0.8712 and the sensitivity is at 0.8901 while specificity is at 0.8901, shows in figure 27, respectively.

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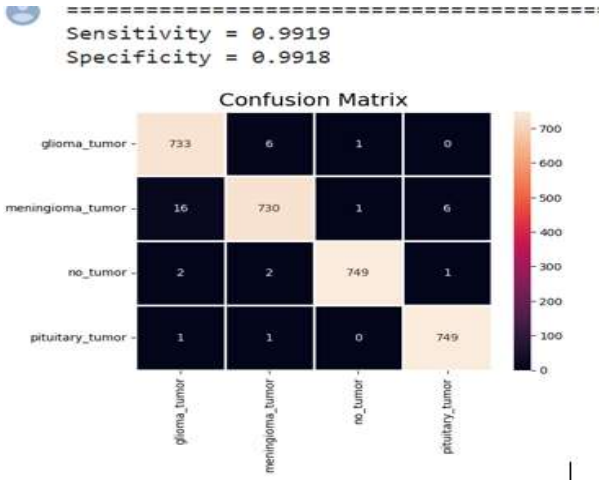

Figure 28: The Training confusion Matrix of Hybrid Model

The figure 28 Depicts a confusion matrix of Hybrid model (EfficientNetB4 and EfficientNetB0) Model for training results. Here the diagonally predicted values are correctly precited whereas other values are incorrectly matched. The sensitivity is at 0.9919 while specificity is at 0.9918, respectively.

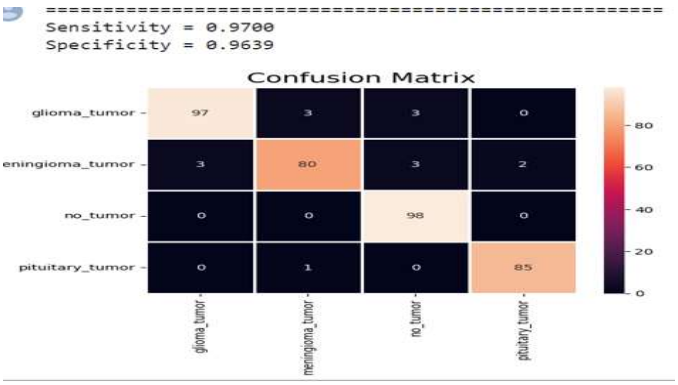

Figure 29: The Testing confusion Matrix of Hybrid Model

A figure 29 Depicts a confusion matrix of Hybrid model (EfficientNetB4 and EfficientNetB0) Model for testing results. The matrix is a tabular representation which is used for the evaluation of the effectiveness of a classified method. Here the diagonally predicted values are correctly matched whereas other values are incorrectly matched. The sensitivity is at 0.9700 while specificity is at 0.9639, respectively.

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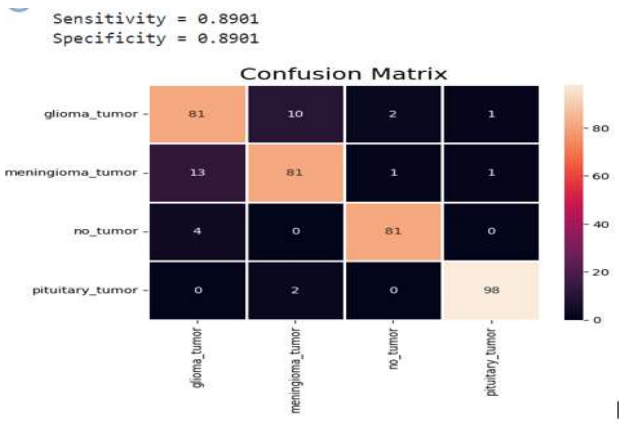

Figure 30: The Validation confusion Matrix for Hybrid Model.

The figure 30 Depicts the confusion matrix of Hybrid model (EfficientNetB4 and EfficientNetB0) Model for Validation results. Here the diagonally predicted values are correctly matched whereas other values are incorrectly matched. The sensitivity is at 0.8901 while specificity is at 0.8901, respectively.

Comparative Results and Discussion

Here provides the comparison between base and proposed models in terms of parameters. Base model is CNN and proposed are three models EfficientNetB0, EfficientNetB4 and Hybrid model. The following table 5 shows the comparison of proposed and base models for the brain tumour detection using mRI dataset.

Table 5: Comparison between Base and proposed models for brain tumour detection

Parameters	**Proposed Models**			**Base model**
	EfficientNetB0	EfficientNetB4	Hybrid Model	CNN
Loss	0.1414	0.1382	0.4548	0.7245
Accuracy	0.9807	0.9800	0.9360	0.8834
Precision	0.9626	0.9600	0.8760	0.7979
Recall	0.9600	0.9931	0.8667	0.7147
AUC	0.9925	0.9609	0.9737	0.9220
F1-Score	0.9622	0.9600	0.8712	0.7587

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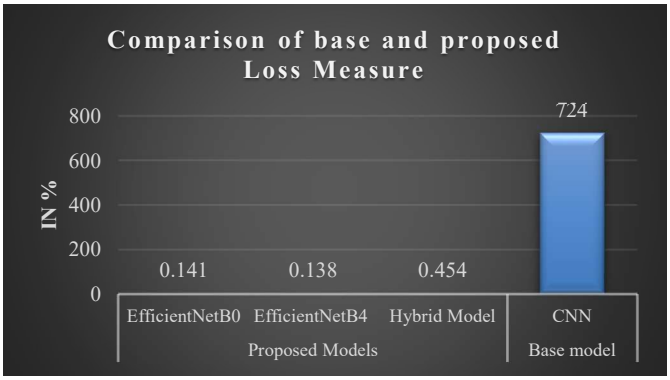

Figure 31: Bar graph of loss performance between base and proposed models

The figure 31 is a bar graph that compares the loss percentage of four models for brain tumor detection using MRI images data. An EfficientNetB0 method has the lowest loss (0.141), followed by the EfficientNetB4 model (0.138) and the Hybrid Model (0.454). The CNN model has the highest loss (7.24), respectively. The proposed models EfficientNetB0, EfficientNetB4, and Hybrid Model have much lower loss than the base model CNN, which indicates that they are more accurate and efficient in predicting the labels of the images.

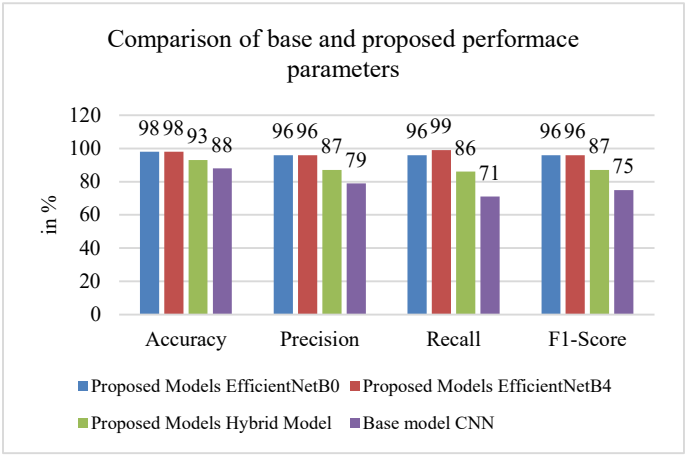

Figure 32: Bar graph of parameters performance between base and proposed models

The figure 32 a bar graph that compares the performance parameters of base and proposed models for brain tumor detection using MRI images data. A performance parameterare Recall, accuracy, precision, and F1-score, which are measures of how well a method can correctly classify the images into benign or malignant tumors. The x-axis lists the performance parameters: **Recall, accuracy, precision, and F1-score.** A y-axis shows the percentage of performance. An EfficientNetB0 method has a best accuracy (98%), precision (99%), recall (87%), and F1-score (96%). An EfficientNetB4 method has a second higher accuracy (96%), precision (86%), recall (79%), and F1-score (93%). The Hybrid Model has the third highest accuracy (99%), precision (75%), recall (71%), and F1-score (86%). The CNN model has the lowest accuracy (93%), precision (96%), recall (96%), and F1-score (87%). The proposed

models EfficientNetB0, EfficientNetB4, and Hybrid Model have higher performance than the base model CNN in all parameters.

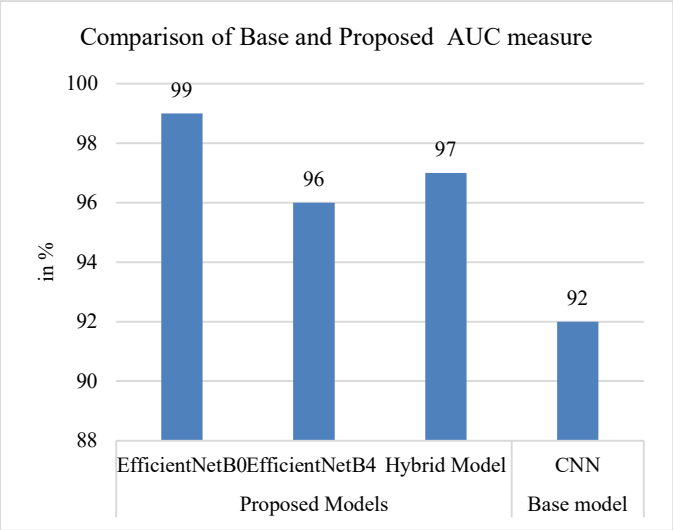

Figure 33 Bar graph of AUC performance between base and proposed models

The figure 33 a bar graph that compares the AUC performance between base and proposed models for brain tumor detection using MRI images data. AUC stands for AUC, which is a measure of how well a model can distinguish between different classes. A higher AUC means a better model performance. The figure shows the following information: The x-axis of the graph represents the different models: EfficientNetB0, EfficientNetB4, Hybrid Model, and CNN. The y-axis of the graph represents the AUC performance in percentage. The graph has four bars, one for each model. The EfficientNetB0 and EfficientNetB4 models have the highest AUC performance, at 99% and 96% respectively. The Hybrid Model has a slightly lower AUC performance, at 97%. The CNN model has the lowest AUC performance, at 92%. The figure suggests that the proposed models (EfficientNetB0, EfficientNetB4, and Hybrid Model) have significantly higher AUC performance than the base model (CNN), which indicates that they are more effective and accurate in detecting brain tumors from MRI images data.

Conclusion and future work

In this article, propose an architecture for a CNN for the effective detection of brain cancers using MR data. In addition, work compares the suggested architecture to other models, such as the EfficientNetB0, EfficientNetB4, and the Hybrid model. We assessed the models' performance based on a number of factors, such as recall, accuracy, loss, & AUC. By comparing a performance of other models to our suggested method utilizing these criteria, we found that a proposed method was superior. A proposed models, EfficientNetB0, EfficientNetB4, and the

Hybrid Model, all perform better than the baseline CNN model when comparing brain tumour detection algorithms utilising MRI images. EfficientNetB0 demonstrates the best performance with the lowest loss (0.141), highest accuracy (98%), precision (99%), recall (87%), AUC (99%), and F1-score (96%). EfficientNetB4 also performs well, securing the second-best results in most metrics, followed by the Hybrid Model. In contrast, the base CNN model lags behind with the highest loss (724) and the lowest accuracy (93%), precision (96%), recall (96%), AUC (92%), and F1-score (87%). Throughout the evaluation process, we employed a number of measures to ensure the ML models' efficacy. For the quick detection of brain tumours, we suggested the EfficientNetB0, EfficientNetB4, and Hybrid models. Using a large number of MR images, we showed encouraging results with 98% and 99% accuracy. When analysing our findings, we also had a look at a few other ML models in addition to the one we proposed. After comparing the suggested model to the other models, we can conclude that it is trustworthy for the early detection of certain brain tumours.

When evaluating our results, we considered not just the suggested model but also a number of alternative ML models. We were unable to train the CNN quickly since it had so many layers and our computer lacked a powerful graphics processing unit (GPU). Training will take longer if the dataset is huge, such as if it contains a thousand photos. We were able to reduce the training period by half after optimising our GPU setup. Brain malignancies may be identified more precisely in the future utilising individual patient data acquired from any source.

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