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Detection and Classification of Tumor Type From Brain MRI Images Using Transfer Learning

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ABSTRACT

Histopathological analysis of the extracted biological specimen has been one of the most trusted techniques to detect brain tumors in medical diagnostics. However, this analytical approach is invasive, time–intensive, and requires manual intervention; therefore, the probability of manual or human error is high. These practical limitations lay the foundation for identifying a non-invasive and automatic approach to brain tumor detection. Various effective modalities like MRI and CT scans have been discovered. These advancements have aided in gathering preliminary information in case of any suspicions of tumor manifestation. However, a diagnostic conclusion is reached by the subjective evaluation of the medical experts based on the medical images. This again raises the probability of misdiagnosis and, thus, requires an automated diagnostic system that may pitch in a 'second opinion' to reduce human error significantly. Deep learning algorithms tend to provide a solution by aiding in the designing of such computer-aided diagnostic systems. Taking this cue, brain tumor detection and classification through EfficientNet-B2 architecture, along with transfer learning, has been presented in the proposed work. Performance analysis of the model has been done by applying transfer learning through ImageNet and Noisy-student and different optimizers on two publicly available datasets. Preliminary results show that an accuracy of 97 % is achieved when EfficientNet-B2 is used for tumor classification, which is higher than other models, such as EfficientNetV2B1 (89.17 %) and EfficientNetB0 (91%). Also, it is suggestive that noisy student can prove to be an alternative for ImageNet in transfer learning mainly when binary data is being processed.

Keywords: Brain tumor; EfficientNet-B2; MRI; Deep learning; Automated diagnostics

1. INTRODUCTION

Reproduction and depletion of cells in a human body is a structured process that occurs in a regular sequence, replacing the old cells with the new cells. However, when there is a disruption in this biological process, some cells show abnormal growth, leading to the formation of lesions or tumors[1]. When this abnormal growth of cells is witnessed in the brain, leading to damage to the functioning of the organ, it is termed as a brain tumor. Medical experts have identified almost 120 types of brain tumors, broadly classifying them as benign and malignant[2]. Causal factors of brain tumors tend to span a wide range of spectrum[3]. The first visible symptoms of a probable tumor are very similar to day-to-day ailments like headaches, dizziness, and fatigue. This camouflaged behavior of tumors leads to a delay in diagnosis. Attributing to this behaviour, diagnosis at the on-setting and early stage of tumor growth is the most sought-after way of treating the ailment effectively.

Radiological modalities like MRI Imaging have proved their utility by being an effective and safe mode of getting an insight into the abnormalities in the brain structure in case of any suspicions based on the symptoms. However, the inference made is based on subjective evaluation done by the experts, which is a time-intensive and exhaustive task. This hails for the requirement of an assisted and automated diagnostic system that can aid medical personnel.

The golden truth that nobody can deny is that a machine can entirely match the medical insights provided by medical experts. But, to further aid human intelligence, the systems being designed should mimic the thinking pattern of a human brain. This is achieved using Artificial Intelligence (AI) in the underlying algorithmic approach to build automated diagnostic systems[4]. It is very well understood that every medical image being captured contains information that is of clinical importance; thus, such efficient techniques are required for medical image processing, which can process the images in a lossless as well as efficient manner[5]. This introduced the utility of deep learning in medical image processing and related research.

The healthcare community is studying deep learning techniques to harness their computational as well as analytical capabilities to design and develop models

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for tumor diagnosis by achieving accurate classification and detection. The authors have studied three different pre-trained network models for brain tumor detection, and VGG-166 achieved the highest accuracy of 96%. However, a small dataset is used for the study; thus, no remarks can be made about the large datasets. Transfer learning using ImageNet and Adam optimizer is used with EfficientNet-B2, EfficientNet-B3, and EfficientNet-B4 for tumor detection and classification[7]. However, results using transfer learning through Noisy-Student and other optimizers have yet to be explored. A CNN model is proposed for multi-class classification of brain tumors, and an overall accuracy of 96 % is achieved. However, the proposed methodology considers only two types of optimizer functions, i.e., Adam and RMSProp. Also, data augmentation has been performed through four techniques only[8]. A novel CNN architecture achieves a classification accuracy of 93.3 % for brain tumors[9].

It is evident from the existing literature that data augmentation strategies, along with cross-validation, have yet to be considered for performing the detection and classification of brain tumors. Also, the optimizers available in deep learning have yet to be explored in the studies. Only one or two optimizers have been explored in the proposed methodologies. Moreover, proposed transfer learning methodologies have used only the ImageNet dataset, and attempts have yet to be made to examine the efficacy of the Noisy-Student Dataset. This paper is targeted to analyze the overall performance of the EfficientNet – B2 model when used for classification and detection of brain tumors when MRI images are provided as the input. The proposed methodology employs transfer learning, fine-tuning, and hyper-parameterization to provide insight into the effectiveness of the said model to derive an efficient investigative architecture. The objectives of the proposed work are as follows:

1. Providing a performance analysis of the EfffcientNet-B2 model by:
   - Utilising a transfer learning approach through two different standard datasets [ImageNet and NoisyStudent]
   - Execution of the model on eight different optimizer functions
   - Subjecting the model to two different types of datasets [Binary-class and Multi-class]
2. To study the efficacy of the said transfer learning approaches combined with the optimizer function(s) in achieving classification accuracy.
3. To study the effectiveness of data augmentation techniques along with the k-fold validation strategy.
4. Providing a comparative analysis using different qualitative metrics for the model under study.
5. Providing a comparison of the model under study and the other proposed state-of-the-art models for the task of tumor classification and detection.

The remaining paper is structured and organized as follows: Section 2 presents the proposed methodology, Section 3 provides the details about the implementation, and experimental results are given under Section 4, followed by Section 5, discussing future aspects and conclusion.

2. PROPOSED METHODOLOGY

The study presented here works to provide a performance analysis of the EfficientNet – B2 network in brain tumor detection and classification from MRI Images. The performance evaluation is based on the subjection of the network to transfer learning approaches and two different datasets. Also, the network is provided with different optimizers. The accuracy of the model in classifying the images is the base factor for the determination of the efficacy of the models.

In the preliminary stage, MRI images as a part of the brain tumor dataset are treated as the inputs, which are then fed to a series of data augmentation techniques to increase the images in the overall dataset quantitatively. After that, the dataset is split into training and validation datasets, and the model under study is trained using the training data. Both the transfer learning approaches (using ImageNet and Noisy-student) are applied to the model individually, and fine-tuning is achieved using a k-fold validation strategy. Finally, the results are studied to draw valuable conclusions and analyzed using statistical metrics. The proposed methodology is depicted in Figure 1.

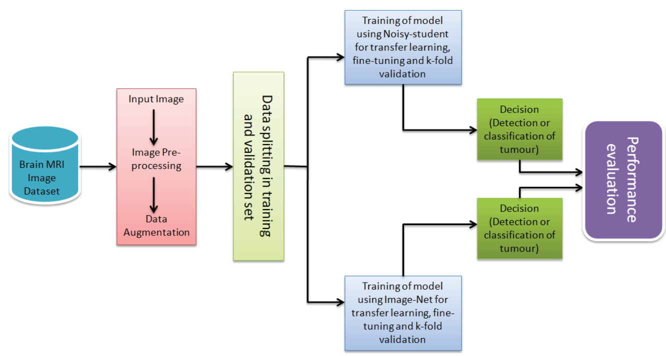


Figure 1. Proposed methodology.

2.1 Deep Learning

Deep learning is a computing paradigm that the human brain has inspired in terms of its information-processing patterns. Deep learning paradigms perform training or learning along with classification in a single step[7]. Also, deep learning techniques automate the whole feature selection process and subsequent learning.

As the whole task pipeline involved in achieving the classification task through the deep learning paradigm is automated, it helps extract and select the minor possible discriminative features, which can help obtain more accurate and precise results. Deep learning (DL) techniques can broadly be classified as depicted in Figure 2.

2.1.1 CNN Architecture

Convolutional neural networks (CNN) are the most commonly used algorithmic approach among the available

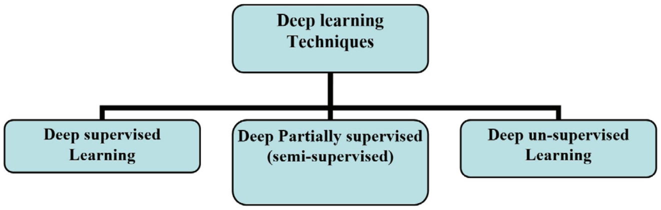


Figure 2. Types of deep learning techniques.

deep learning networks. The underlying structure of CNN is similar to that of a neural network as both draw their inspiration from the structural makeup of the human brain[8]. Processing of the images as signals leads to the utilization of a small number of parameters, which ultimately aids in simplifying the training process and also improves the processing speed. The convolution network is made up of several layers, with the significant types of layers being defined below:

a. *Convolutional Layer*: Kernels or convolutional filters are the basic forming blocks of this layer. The input image, which is treated as an N-dimensional matrix by the layer, is subjected to convolution through these kernels, producing a feature map.
b. *Pooling Layer*: Sub-sampling of the feature map obtained from the convolution layer is achieved using pooling layers. It refers to the division of large feature maps into small feature maps while preserving the commanding features at each pooling stage.
c. *Activation Function*: These functions are responsible for the learning paradigm of the network concerning the non-linear relationship between the input and output. In other words, non-linearity is introduced in the output of the network due to these functions.
d. *Fully Connected (FC) Layer*: The neurons in this layer are connected to each neuron existing in the previous layer in the whole network. The input to this layer comes from the convolution or pooling stage, which stands just before this layer.

2.1.1.1 EfficientNet Architecture

The Google Brain team proposed a new CNN architecture in 2019 to improve accuracy and efficiency. The architecture was based on the philosophy of applying a uniform scaling method to all dimensions using compound coefficients[9]. Uniform scaling was applied to optimize the depth, width, and resolution of the network for better efficiency, which is depicted in Figure 3. It was a different approach than that showcased in general convolution networks as in other networks, either one of the dimensions is scaled, which may increase the accuracy of the network but results in an overall declined accuracy of the model. This was solved by the architecture introduced in the name of EfficientNet.

2.2 Transfer Learning and Fine-tuning

It becomes practically a bottleneck to gain a large

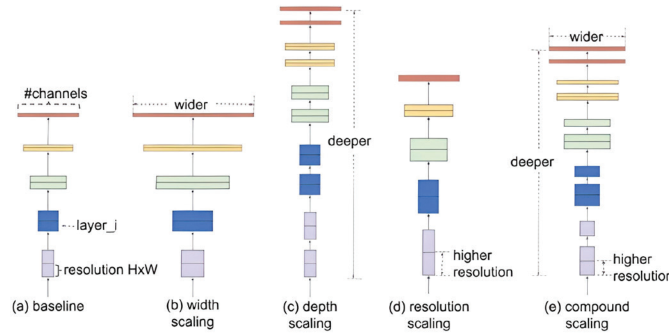


Figure 3. Different Scaling methods. (e) represents the compound scaling method used in EfficientNet architecture[12].

amount of data for some pristine fields, one such field being radiological images[8]. In such cases, transfer learning comes to the rescue, which can be defined as a technique in the field of deep learning where a model is made to train on a standard or golden dataset and then is repurposed or 'fine-tuned' to be used for the desired dataset. In this study, the model has been pre-trained through ImageNet[13] and Noisy-student[14]. The derived weights from both the 'golden' datasets are then made to be used by the base model for feature extraction, and accordingly, the model is fine-tuned to meet the required objective of achieving classification and detection of brain tumors[15].

The performance of EfficientNet-B2 is studied for both, i.e., when pre-trained weights from ImageNet and Noisy Student are applied. Fine-tuning of the model is achieved by freezing the base model and adding the pooling layer, drop-out layer, and finally, the fully connected layer as per the number of classes that are required for classification. The complete model is trained, and after successful training, the best weights are saved. Afterward, the final model is unfrozen and used along with the saved weights for the testing and prediction data for validation of the model.

2.3 Hyper-parameters and Loss Function

Parameters or settings that are not an integral part of the model but pose a significant impact on the overall performance are termed Hyper-parameters. Some of the well-known hyper-parameters are learning rate, batch size, optimizer, number of epochs, etc. Hyper-parameterization must be done before the training process is initiated, as it determines the behavior of the learning algorithm during training[15]. Proper tuning, i.e., appropriate values for the hyper-parameters, is crucial for achieving the best performance from a deep learning model.

In this work, cross-entropy has been selected for loss measurement. As the datasets that are being considered are of two different types, i.e., binary and multi-class, the loss functions are binary cross-entropy and sparse categorical cross-entropy, respectively. In the methodology being presented here, eight optimizer functions have been considered individually with the model under study. Additionally, to avoid over-fitting, a k-fold validation strategy has been employed in the overall process with the number of folds five.

3. IMPLEMENTATION DETAILS

3.1 Image Acquisition

A: It is a binary class (two classes, namely with tumor or without tumor) publicly available dataset of Brain MRI scans. There are a total of 3060 files[16]. Additionally, a total of 60 images have been provided under the name of prediction images to assess the overall prediction accuracy of the trained model.

B: It is a multi-class [four classes, namely Glioma, Meningioma, Pituitary, and No tumor (Healthy)] publicly available dataset of Brain tumor MRI scans. There are a total of 3264 files[17].

3.2 Image Pre-processing

This is a crucial stage as it prepares the input images in a suitable format for the selected deep-learning algorithmic model. There are several pre-processing techniques available, out of which two have been applied in this methodology:

a. *Resizing of the images in the dataset*: Brain MRI scan images available in the datasets mentioned under section 3.1 were resized to 224 x 224.
b. *Data augmentation*: To increase the size and diversity of the datasets being used in the study through computational methods to improve the generalization of the model, augmentation strategies like rotation, zoom, and horizontal shifts have been used.

Apart from the above-mentioned pre-processing, to avoid over-fitting and ensure that the model can generalize to unseen data, the technique of data splitting was used. The images are available as training sets in both datasets A and B and are subdivided into training and validation sets in the ratio of 4:1.

3.3 Experimental Setup

Performance analysis of EfficientNet-B2 for the task of detection and classification of Brain tumors from MRI images is done by subjecting it to the open-access datasets mentioned in section 3.1. Python with Keras and Tensorflow frameworks along with GPU runtime have been used for implementing the proposed model.

Additional proposed layers are added to devise the final proposed model as a part of fine-tuning. Checkpoints derived after applying ImageNet and Noisy-student datasets are applied to the model as a part of transfer learning. The model is then executed for each of the eight optimizers along with each of the datasets being considered by applying the transfer learning approach through each of the derived set of checkpoints.

Accuracy, Recall, Precision, and Matthews Correlation Coefficient have been taken as evaluation metrics, and a classification report is generated after the successful run of the model to obtain the summary of the performance as a whole of the model. Confusion Matrix and ROC curve have also been derived from the metrics and the same are presented in Figure 4 and Figure 5 respectively under Section 4.

3.4 Evaluation Metrics

A total of four evaluation metrics have been considered for analytical tasks of the performance of the model under different scenarios as derived based on the different conditions being taken into consideration in this study.

3.4.1 Precision

This metric can be defined as the ratio of positive instances that have been correctly predicted against the total instances that have been predicted positively by the model.

3.4.2 Accuracy

This evaluation metric gives a general overview of the effectiveness of a model being used for classification. It can be defined as the ratio of correctly predicted instances against the total number of instances.

3.4.3 Recall

Also termed as Sensitivity/True Positive Rate, the ability to be able to identify the positive cases as much as possible is analyzed through this metric.

3.4.4 F1-Score

A single value is obtained as the output, which takes both false positives (FP) and false negatives (FN) into consideration. However, it does not provide an actual number of instances under the categories of different defined categories of instances i.e. true positives (TP), true negatives (TN), false positives (FP), or false negatives (FN).

3.4.5 Matthews Correlation Coefficient (MCC)

For fields like medical diagnosis, where a true negative rate is of utmost importance, this metric proves to be a more robust measure of performance than accuracy.

4. RESULTS AND DISCUSSION

With the propositions made in the above sections, it has been established that the objective of this undertaken work is to examine the efficiency of EfficientNet – B2 in performing detection and classification activities from MRI images of brain tumors. Based on the different datasets and transfer learning approaches being considered, there are four plausible scenarios as listed below:

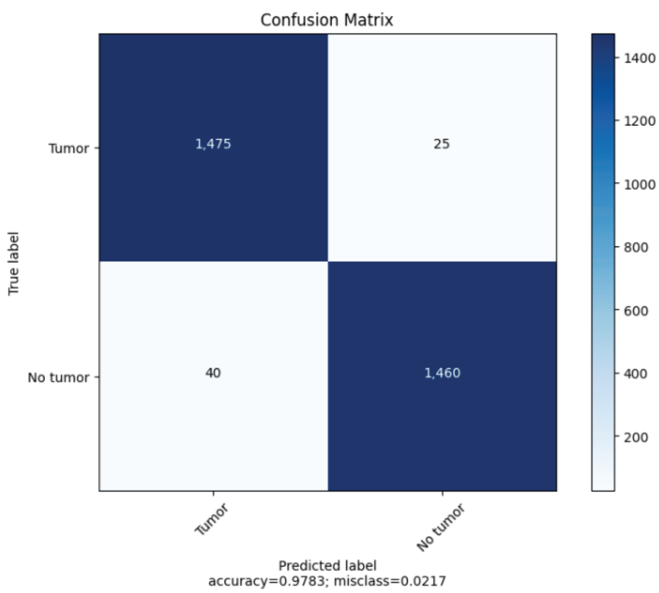
MS 1: EfficientNet – B2 with Noisy student for Dataset A
MS 2: EfficientNet – B2 with Noisy student for Dataset B
MS 3: EfficientNet – B2 with ImageNet for Dataset A
MS 4: EfficientNet – B2 with ImageNet for Dataset B

The results of the proposed study are provided in Annexure A under Table 1-4 of this manuscript. The performance of the model under study has been statistically evaluated using Accuracy, F1-score, Recall, Precision, and Matthews Correlation Coefficient. The confusion matrix and ROC curve have also been derived for the model scenarios with the best results which have been presented in Figure 4 and Figure 5 respectively. The proposed model after successful training is subjected to the prediction data available in Dataset A. As dataset A is a binary class dataset, when the model trained on a multi-class training dataset is provided with the prediction data, only detection precision i.e. whether it can detect the presence of the tumor or not has been analyzed. Each model scenario i.e. MS 1 to MS 4 is provided with prediction images from dataset A. Table 5 of Annexure A summarizes the best results obtained for the model scenarios.

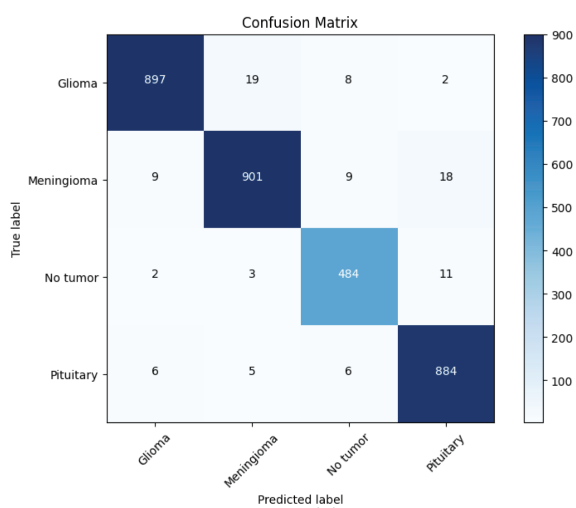
A comparison between the accuracy of the proposed classification network and previous state of art works on the same datasets is carried out to validate the obtained results. Table 6 of Annexure A summarizes the performance of the proposed methodology concerning Dataset B only.

The presented results have been used to draw the following inferences:

1. The results obtained with all the optimizers are presented in Table 3 and Table 4. Best results were obtained for EfficientNet – B2 with ImageNet and Adam optimizer. The confusion matrix drawn for the same as presented in Figure 4 also reflects the proposed model provides a high number of true positives and thus can classify the brain tumors from MRI images with appreciable accuracy. From the ROC curves presented in Figure 5, it is inferred that sensitivity i.e. True Positive Rate for the EfficientNet – B2 with ImageNet and Adam optimizer is 0.9736

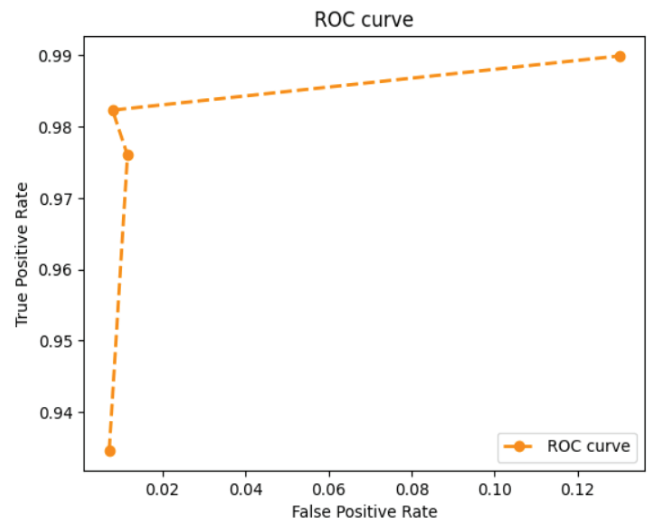


(a)

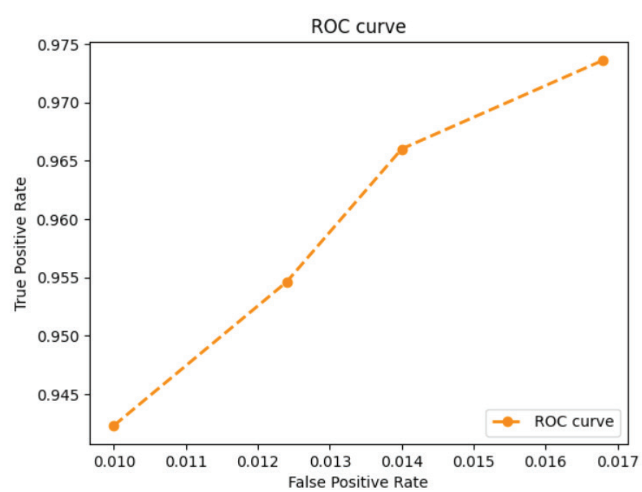


(b)

Figure 4. **Confusion matrix for the model scenarios with best results: (a) MS 3: EfficientNet – B2 with ImageNet for Dataset A, and (b) MS 4: EfficientNet – B2 with ImageNet for Dataset B**



(a)



(b)

Figure 5. **ROC curve for the model scenarios with best results (a) MS 3: EfficientNet – B2 with ImageNet for Dataset A (b) MS 4: EfficientNet – B2 with ImageNet for Dataset B**

and 0.9823 respectively for binary labeled and multi-class datasets. Thus, it can be concluded that transfer learning through ImageNet works well for binary labeled classification as well as multi-class classification as the highest accuracy of 97.85% and 97% respectively is obtained for dataset A and dataset B.

2. From the presented results in Table 1 to Table 4, it can be seen that there is a significant variation in the overall classification accuracy and other evaluation metrics as obtained for both binary and multi-class classification tasks for the optimizer functions used with the proposed model. For all the proposed model scenarios, Matthews Correlation Coefficient (MCC) is always high for the Adam optimizer i.e. a model working with the Adam optimizer has a better true negative detection rate as compared to the other seven optimizers. Also, high accuracy for the classification of brain tumors is obtained through the Adam optimizer in 3 out of 4 proposed model scenarios. Thus, this statistical behavior can be used to infer that every optimizer has its set of hyper-parameterization requirements along with dataset specifications to converge to an optimal solution. **From the obtained results, it is evident that the Adam optimizer provides the best possible loss reduction when used as the optimizer function for EfficientNet – B2.**
3. It can be witnessed through Table 1 and Table 2 that a maximum accuracy of 94% and 92% have been obtained when transfer learning is achieved through Noisy Student when used for binary labeled datasets and multi-class datasets respectively. Matthews Correlation Coefficient (MCC) of 90% has been obtained for binary labeled dataset classification, thus indicating that true negatives can be effectively identified if a model is made to work with transfer learning through Noisy Student. Thus, the potential of Noisy-student shall be further explored as an alternative to transfer learning through ImageNet.

5. CONCLUSION AND FUTURE SCOPE

One of the networks from the EfficientNet architecture family i.e. EfficientNet – B2 is under study in this work to analyze the potential usage of this model in the field of medical diagnostics. Here, the objective is to achieve the automated detection as well as classification of brain tumors from the MRI scans being provided as the input. Along with two labeled datasets, transfer learning approaches through two different standard or golden datasets are undertaken with fine-tuning of hyper-parameters. Inferences are drawn from the results and attempts were made to identify the most suitable model that can be used for automated detection and classification of brain tumors.

It is suggested through the results and inferences that EfficientNet-B2 has the potential of being utilized in designing an efficient automated diagnostic system for detection as well as classification of brain tumors from MRI images as accuracy in the range of 96% - 98% was achieved. However, it may be noted that the proposed work has been conducted with a constant number of epochs and batch size i.e. the execution environment is constrained, thus, it becomes evident that the efficacy and effectiveness of the studied model is dependent on the suitable set of parameters. The obtained results can be used to lay down the proposition of extending the undertaken study with other models available in the EfficientNet architectural family to single down the model with the best performance when used in the automation of medical diagnostics. Additionally, the effectiveness of the derived model scenarios in this study will be conducted on other publicly available labeled datasets to aid strength to the results obtained. Apart from the above, in the current proposed work, prediction images from the binary dataset were fed to the model trained on multi-labeled data which does not provide the complete picture of the actual effectiveness of the model in achieving the set objective. Taking this limitation under consideration, the authors shall acquire a multi-labeled dataset for prediction and derive the prediction results accordingly.

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CONTRIBUTORS

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Annexure–A

A.1 Performance evaluation for MS 1

Results of the pre-defined metrics for inferring the overall performance of MS 1 have been recorded in Table 1.

Table 1. Results for MS 1

Optimizer	Labels – Class	Precision (%)	Recall (%)	F1 – Score	Average accuracy (%)	MCC
Adam	0 – Affected	92.46	97.95	95.13	94.9	0.9001
	1 – Healthy	97.77	91.84			
SGD	0 – Affected	96.46	93.02	94.71	94.9	0.8989
	1 – Healthy	93.56	96.74			
RMSprop	0 – Affected	74.41	92.87	82.62	81.3	0.6480
	1 – Healthy	91.56	70.78			
Adadelta	0 – Affected	88.91	91.47	90.17	92.3	0.8386
	1 – Healthy	94.53	92.82			
Adagrad	0 – Affected	80.86	86.59	83.62	83.3	66.86
	1 – Healthy	86.08	80.19			
Adamax	0 – Affected	96.05	87.63	91.65	93.59	0.8671
	1 – Healthy	92.17	97.59			
Nadam	0 – Affected	81.28	80.78	81.06	82.03	0.6397
	1 – Healthy	82.64	83.11			
Ftrl	0 – Affected	78.64	78.08	78.36	79.89	0.5958
	1 – Healthy	80.97	81.47			

A.2 Performance evaluation on MS 2

Results of the pre-defined metrics for inferring the overall performance of MS 2 have been recorded in Table 2.

Table 2. Results for MS 2

Optimizer	Labels - Class	Precision (%)	Recall (%)	F1 – Score (in %)	Average accuracy (in %)	MCC
Adam	0 – Glioma	74	84	83	83	0.8275
	1 – Meningioma	89	82			
	2 – No tumor	76	95			
	3 – Pituitary	94	70			
SGD	0 – Glioma	68	69	74	76	0.6879
	1 – Meningioma	78	59			
	2 – No tumor	92	93			
	3 – Pituitary	65	90			
RMSprop	0 – Glioma	32	91	59	60.41	0.497
	1 – Meningioma	79	47			
	2 – No tumor	96	62			
	3 – Pituitary	28	83			

Adadelta	0 – Glioma	87	95	81	82.08	0.8893
	1 – Meningioma	80	89			
	2 – No tumor	88	96			
	3 – Pituitary	79	97			
Adagrad	0 – Glioma	91	92	92	92	0.8894
	1 – Meningioma	79	87			
	2 – No tumor	98	95			
	3 – Pituitary	97	91			
Adamax	0 – Glioma	80	93	85.77	87.81	0.8475
	1 – Meningioma	86	95			
	2 – No tumor	78	85			
	3 – Pituitary	88	96			
Nadam	0 – Glioma	81	98	88	88	0.8437
	1 – Meningioma	92	75			
	2 – No tumor	82	95			
	3 – Pituitary	97	89			
Ftrl	0 – Glioma	29	56	45	19	0
	1 – Meningioma	~0	~0			
	2 – No tumor	~0	~0			
	3 – Pituitary	~0	~0			

A.3 Performance evaluation for MS 3

Results of the pre-defined metrics for inferring the overall performance of MS 3 have been recorded in Table 3.

Table 3. Results for MS 3

Optimizer	Labels - Class	Precision (%)	Recall (%)	F1 – Score (in %)	Average accuracy (in %)	MCC
Adam	0 – Affected	98.11	97.81	98.40	97.85	0.9513
	1 – Healthy	95.52	97.93			
SGD	0 – Affected	95.50	94.94	95.27	94	0.8722
	1 – Healthy	91.49	92.41			
RMSprop	0 – Affected	82.86	88.81	85.73	83.37	0.6609
	1 – Healthy	84.14	76.38			
Adadelta	0 – Affected	80.96	84.33	82.61	92.1	0.7754
	1 – Healthy	95.47	94.33			
Adagrad	0 – Affected	86.38	89.03	87.69	83.7	0.6367
	1 – Healthy	78.22	73.72			
Adamax	0 – Affected	88	91.42	90.07	92	0.8683
	1 – Healthy	94.53	92.82			
Nadam	0 – Affected	64.34	74.59	69.08	82	0.5679
	1 – Healthy	90.03	84.74			
Ftrl	0 – Affected	77.47	81.29	79.26	79.3	0.4981
	1 – Healthy	81.22	77.39			

A.4 Performance evaluation on MS 4

Results of the pre-defined metrics for inferring the overall performance of MS 4 have been recorded in Table 4.

Table 4. Results for MS 4

Optimizer	Labels - Class	Precision (%)	Recall (%)	F1 – Score (in %)	Average accuracy (in %)	MCC
Adam	0 – Glioma	97.20	93.46	97	97	0.9657
	1 – Meningioma	96.76	97.60			
	2 – No tumor	94.56	98.23			
	3 – Pituitary	99.67	97.19			
SGD	0 – Glioma	96.80	58.67	76.37	75.98	0.6814
	1 – Meningioma	70.41	83.16			
	2 – No tumor	56.78	84.71			
	3 – Pituitary	90.12	79.07			
RMSprop	0 – Glioma	76.80	50.33	60.61	59.98	0.4693
	1 – Meningioma	42.87	55.68			
	2 – No tumor	53.21	63.93			
	3 – Pituitary	75.25	67.26			
Adadelta	0 – Glioma	93	89.60	92.06	92	0.8934
	1 – Meningioma	92.55	91.76			
	2 – No tumor	85.17	93.77			
	3 – Pituitary	98	91.98			
Adagrad	0 – Glioma	93.14	89.79	92.07	92	0.8894
	1 – Meningioma	92.70	91			
	2 – No tumor	84.87	93.64			
	3 – Pituitary	97.98	91			
Adamax	0 – Glioma	87	73.36	79.81	79.4	0.6581
	1 – Meningioma	61.4	82			
	2 – No tumor	85.17	77.9			
	3 – Pituitary	87.4	82			
Nadam	0 – Glioma	95.6	77	88	88	0.8243
	1 – Meningioma	87	92.3			
	2 – No tumor	93	89			
	3 – Pituitary	78.1	89.5			
Ftrl	0 – Glioma	~0	29	45	29	0
	1 – Meningioma	~0	~0			
	2 – No tumor	~0	~0			
	3 – Pituitary	~0	~0			

A.5 Predicted values by the model scenarios from prediction images in dataset A

Table 5

Sl. no.	Dataset	Model scenarios	Accuracy (in %)	Correct predicted values (out of 60)
1.	A (Binary Data)	EfficientNet – B2 with NoisyData and Adam optimizer	94.9	54
		EfficientNet – B2 with ImageNet and Adam optimizer	97.85	57
2.	B (Multi Class)	EfficientNet – B2 with NoisyData and Adagrad optimizer	92	50
		EfficientNet – B2 with ImageNet and Adam optimizer	97	56

A.6 Comparison with related work based on dataset B

Table 6

Model	Accuracy (in %)
EfficientNetV2B1[18]	89.17
ResNet50[18]	79.32
EfficientNetB1[18]	89.55
CNN[19]	96
EfficientNetB0 (without tuning)[8]	91
EfficientNetB7 (without tuning)[8]	95
EfficientNetB0 (with tuning)[8]	95
EfficientNetB2 (MS4)	97