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Augmented MRI Images for Classification of Normal and Tumors Brain through Transfer Learning Techniques

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Abstract A brain tumor is a severe malignant condition caused by uncontrolled and abnormal cell division. Recent advances in deep learning have aided the health business in Medical Imaging for the diagnosis of numerous disorders. The most frequent and widely used deep learning algorithm for visual learning and image recognition. This research seeks to multi-classification tumors in the brain from images attained by Magnetic Resonance Imaging (MRI) using deep learning models that have been pre-trained for transfer learning. As per the publicly available MRI brain tumor dataset, brain tumors identified as glioma, meningioma, and pituitary, are accounting for most brain tumors. To ensure the robustness of the suggested method, data acquisition, and preprocessing are performed in the first step followed by data augmentation. Finally, Transfer Learning algorithms including DenseNet, ResNetV2, and InceptionResNetv2 have been applied to find out the optimum algorithm based on various parameters including accuracy, precision, and recall, and are under the curve (AUC). The experimental outcomes show that the model's validation accuracy is high for DenseNet (about 97%), while ResNetv2 and InceptionResNetv2 achieved 77% and 80% only.

Index Terms: Brain Tumors Classification, CNN, Transfer Learning.

I. INTRODUCTION

Our brain is a complex organ that controls and coordinates our reactions. The brain is the largest complex organ in the human body that is composed of more than 100 million nerve cells. A tumor in the brain is a group of atypical growth of cells. The abnormal cells have been grown from 2 or 4 to 8 until they form a lump of abnormal cells. Primary and secondary brain tumors are also known as benign (non-cancerous) and malignant (cancerous) tumors. As non-cancerous tumors are not malignant, they do not metastasize to other regions of the brain. Malignant tumors are cancerous tumors, and they spread rapidly to other parts of the body, resulting in death immediately. These tumors develop beneath the region of the skull where they exert pressure on the brain, causing headaches; therefore, headache is the primary symptom that a person exhibits to indicate whether or not he has a brain tumor. Misdiagnosis of brain tumor types reduces the efficacy of medical treatment and the patient's chance of survival. One way to figure out what kind of brain tumor a patient has is to look at MRI images of their brain. However, for doctors, looking at many images is nearly impossible, takes a long time, and can lead to mistakes. Using approaches based on deep learning, the classification of brain tumor types becomes simpler, and one can achieve a higher rate of accuracy with minimal error. The main aim of this paper is to train our model for more accurate brain tumor classification. Patients' brain tumors vary in size and severity, so the data are initially divided into training and validation sections. Another important aspect of developing a CNN model is classifying brain tumors based on the images provided during training, with sufficient precision for medical-grade software. Existing methods require doctors to manually perform image recognition and identify the tumor's location, which is time-consuming and causes patients to wait longer than necessary; however, the proposed CNN model provides a solution at an earlier stage. Existing systems differentiated brain tumors by having a medical expert manually examine MRI images of the patient's brain, with the accuracy dependent on the expert's level of experience. The dataset of MRI images was used to classify the brain tumor because it provides more detailed information about the organs of a body than a CT scan or electroencephalogram (EEG).

II. RELATED WORKS

Deep learning (DL) and artificial intelligence (AI) are widely used in image processing techniques to divide, recognize, and categorize brain cancer detection from MRI images. There have already been many studies on classifying and dividing MRI images of the brain, but none of them have used the DenseNet, ResNetV2, and InceptionResNetV2 algorithms and compared them to find out how accurate they are using the parameters accuracy, precision, recall, and area under the curve (AUC).

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Moving ahead, the literature survey has been discussed as follows:

In [1] a novel unsupervised model based on classification is proposed that merges texture and color. Another neural network-based Methodology has been developed by authors in [2] that claims to have an accuracy of 73% detection in comparison to recommended medical professional decision. In [3], the researchers combine the visual information fidelity and spatial interdependence matrix and then employed a Gaussian-based distance along with the optimum path forest classifier for classification of lung diseases. The authors in [4] and [5] classified brain tumors by applying support vector machines and fuzzy approach respectively. [5] worked on Gliomas dataset to represent distinct shapes of tumor, its shape, its location, size, and the intensity of image. Moreover, in order to improve the segmentation process, [6] presented an algorithm (novel tissue segmentation) that segments the images of brain MRI into tumor, edoema, white matter, and grey matter for the detection of diseased tissues for investigating the change in treatment planning. Further, in [7], a learning-based architecture is proposed for automatic and robust segmentation of the nucleus with the significant advantage of its applicability to various staining histopathology images. A new algorithm for extracting spatially varying multifractal features using a segmentation technique based on multifractal features was proposed in [8]. [9] talked about the challenges and future directions of multi-sensor fusion in the body sensor networks domain. Learning-based Deep-Q-Networks are introduced in [10] to reduce malware-based attacks, and further research is conducted on information pertaining to the medical field on multiple layers. It also minimizes intermediary attacks with reduced complexity. Besides this, in [11], a new technique is built for reducing the stone's image dimension along with its gray level range without losing any substantial information. In [12], the authors developed a "significance-weighted principal component analysis" technique for reducing deviations in intensity and boosting the statistical power to detect group differences.

[13] proposed a robust segmentation system based on neighborhood attraction for improving the performance of segmentation and the attraction is further optimized using a neural network model. The authors claim that the proposed technique is superior in comparison to the other fuzzy c-means-based techniques. However, the automatic segmentation issue is a major drawback for heterogeneous images. Therefore, in [14], the authors presented a novel technique for automated segmentation of such images which have heterogeneous properties. The traditional methods are computationally slow in comparison to the claimed algorithm, thereby giving improved results. However, the researchers in [15] found that the texture characterization is not performed in the given work, therefore, the stochastic model is proposed in [15] for tumor texture characterizing MRI-based images and using the data set named low-grade glioma BRATS2012 the proposed segmentation results on an average are better than the existing ones. On the other hand, the concern of an imbalanced dataset still exists, therefore the investigators in [16] addressed these challenges by achieving an easy, reasonably priced, and focused diagnosis of oligodendroglioma. The diagnosis is performed through data mining which outperforms the standard methods. The proposed technique can successfully overcome the imbalanced medical data features. However, the current methodologies are not consistent for feature selection and for decisions making, therefore, the authors in [17], proposed a system named "sparse representation-based radionics" also known as SRR for identifying tumors in the brain. They also set up a sparse technique for solving the redundancy issues. Still, the complexity makes the researchers reluctant in using the technique. Thus, the researchers in [18] analyzed using infra-red sensor imaging, the machine learning-enabled back propagation neural networks. Some scientists, for example in [19] still realized that the training of machines is not performed in an efficient manner, therefor they applied data augmentation techniques for increasing the data samples which resulted in effective EfficientNet-B0 that outperformed other models of CNN by achieving classification accuracy of 98.87%. Similarly, in [20], several transfer learning-based DL methods have been used for analyzing and detecting tumors in the brain tumor. Here also the overall accuracy of the best model turns out to be 99.39%. Better precision while analyzing the tumors in the brain is still not that efficient according to the authors in [21]. Therefore, the high-grade malignant tumor in the brain is the focus of [21] which resulted in an increased accuracy of 2% in the case of K-nearest neighbor algorithm, 3% in the case of support vector machine, and 4% in the case of neural networks. In [22-25], the authors worked on predicting the various diseases using different ML/AI techniques.

III. METHODOLOGY

A. Proposed Methodology

This study used image preprocessing and data augmentation at the initial stage on a small acquired dataset of 394 brain MRI images of three brain tumors and one normal brain. We apply transfer learning-based training and then used a dense layer network to evaluate how well they performed relative to pre-trained versions of deep learning models like DenseNet, ResNet-50, and InceptionResNetv2. The dataset contains 100 photographs of Glioma tumors, 115 photos of Meningioma tumors, 74 photos of Pituitary tumors, and 105 photos of normal skin. We divided the dataset into two sections for training and validation. Training data is used for model learning, whereas validation data is used for n and parameter adjustment. The proposed method has more than one step. The proposed method is summed up in Figure 1.

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B. *Data Pre-processing and Augmentation*

By employing Open-source Computer Vision methods like scaling, greyscale conversion, and image quality enhancement, we were able to first crop out the unwanted background from MRI scans, leaving only the brain section. Data augmentation increases data volume and complexity. We are aware that training a deep neural network requires a huge amount of data to fine-tune the network's parameters. We used data augmentation on our training dataset to flip, rotate, and brighten our images because we didn't have enough data. Our model will treat each of these variants as a new image, allowing it to learn more quickly and effectively deal with data that has never been said before.

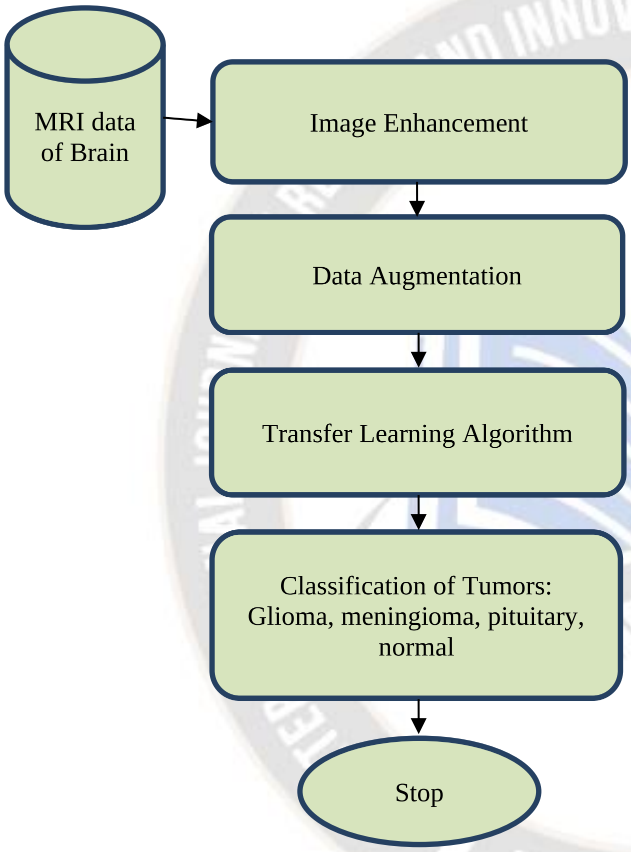

FIGURE 1. The methodology behind the proposed work of Classifying the tumorous and non-tumorous.

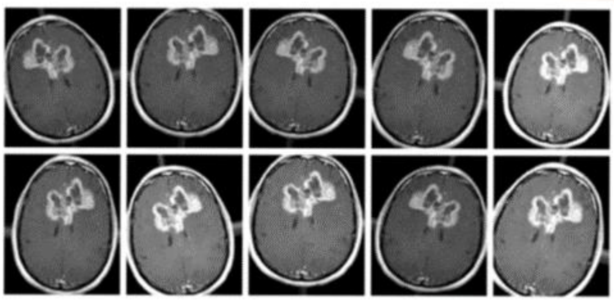

FIGURE 2. Augmentation Process.

C. *Deep Learning*

In our study, we advocated the extraction of augmented MRI image data of 75 75 input size with RGB grey scale channels and 32 batches. We started with a single 16-filter convolutional layer with 3-by-3-pixel filters. Having only 16 filters makes it easier to find edges, corners, and lines. Then, we added a max-pooling layer with a 2 2 filter to obtain the most exhaustive summary of that image, and we raised the number of convolutional layers and filters to 32, 64, and 128, while keeping the filter size at 33. (Refer to Figure 3). These little patterns merge to generate larger patterns, such as circles and squares, as the number of filters grows. We added max-pooling layers on top of the convolutional layers to get the most information from the data. Finally, we employed a fully connected dense layer of 256 neurons and the softmax output layer to calculate the probability score for each class categorizing the input MRI picture as cancerous in three categories or normal in the fourth category.

Rectified Linear Unit (ReLU) activation function was used in every convolutional layer. According to Vinod and Hinton [18], an activation function changes the input weighted sum into the output of that node. Rectifier Linear unit function is often used in hidden layers of convolutional neural networks.

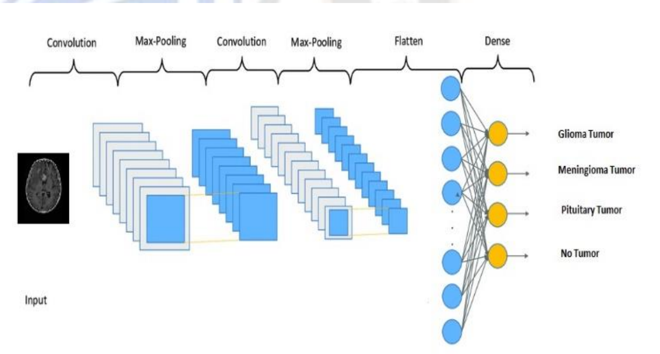

FIGURE 3. The reference architecture of CNN model.

D. *Transfer Learning Models*

Transfer learning (TL) is a type of deep learning in which trained models are applied to new training datasets. To improve accuracy and reduce losses, new training information is added to a benchmark model that has already been learned. TL is a machine-learning strategy that aims to give a faster and better answer while making it easier to collect the training data and rebuild the model. New research on deep learning shows that the TL can improve its classification performance by using data and information from other people. This is in addition to the big improvements that have been made in classifying documents, speech, and images. Figure 4 depicts the transfer learning architecture in detail.

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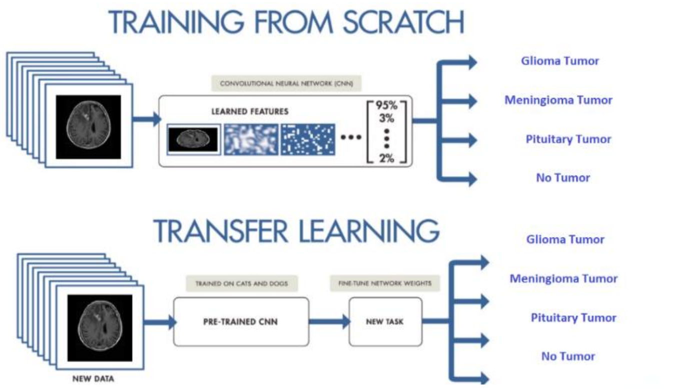

FIGURE 4. The reference architecture of CNN model.

Definition. Given a source domain DS and learning task TS, and a target domain DT and learning task TT, TL aims to help improve the learning of the target predictive function f(•) in DT using the knowledge in DS and TS, where DS ≠ DT, or TS ≠ TT.

VGG16, ResNet152V2, InceptionV3, DenseNet201, InceptionResNetV2, and more transfer learning models are offered. For implementing deep learning methods, Tensorflow and Keras are applied in this study. A thick layer and a Softmax layer are also added at the end, in addition to the Transfer Learning trained weights. The new dense layer was accountable for transforming output into the necessary prediction classes, while the Softmax layer was accountable for predicting class based on the Softmax threshold. ResNet is an artificial neural network consisting of residual neural connections (ANN). It is a deep feedforward neural network with hundreds of layers that is gateless or open-gated, significantly deeper than prior neural networks. The InceptionResNetv2 convolutional neural network was trained with over a million images from the ImageNet collection. The network has 164 layers and can divide images into a thousand different types of objects, like keyboards, mice, pencils, and different kinds of animals. InceptionResNet separates processing by size, combines the outputs, and repeats the process. ResNet uses a single-scale processing unit that has data pass-through connections. InceptionResNet generates 1,536 characteristics per image, whereas ResNet generates 2,048.

IV. RESULTS AND DISCUSSION

Preliminary for comparison purposes as mentioned in table 1, training accuracy and validation accuracy is measured on the dataset of MRI images of the brain. Initially, basic CNN was implemented and analyzed as shown in figure 5. CNN results and a high difference in training and validation metrics, so overfitting was identified.

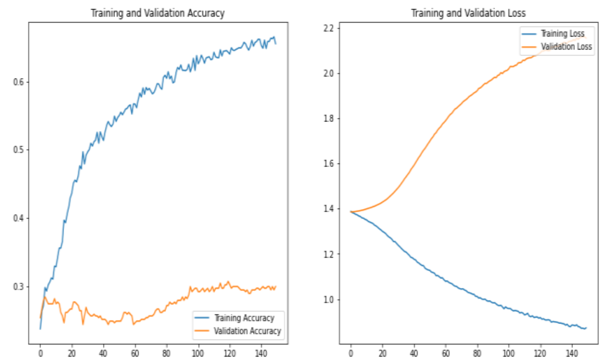

FIGURE 5. The accuracy and losses result for training and validation of CNN.

Further, the accuracy of training and validation is computed using DenseNet, ResNet5.0, and InceptionResNetv2 (See Fig. 6 and Fig. 7). As a result of analysis, all the outcomes of training accuracy and validation accuracy come out to be similar when the number of epochs increased from 1 to 14. This indicates the accuracy of the algorithms as shown in table 1.

TABLE I

COMPARISON OF TRAINING ACCURACY AND VALIDATION ACCURACY FOR VARIOUS ALGORITHMS.

Epochs	Training Accuracy			Validation Accuracy		
	DN	RN	IRN	DN	RN	IRN
1	0.83	0.26	0.49	0.89	0.31	0.25
2	0.92	0.26	0.70	0.92	0.25	0.31
3	0.94	0.32	0.77	0.82	0.30	0.24
4	0.96	0.47	0.77	0.87	0.52	0.73
5	0.97	0.60	0.82	0.93	0.58	0.64
6	0.98	0.65	0.87	0.94	0.69	0.78
7	0.98	0.68	0.89	0.88	0.70	0.82
8	0.98	0.69	0.91	0.91	0.71	0.48
9	0.99	0.72	0.92	0.88	0.73	0.85
10	0.99	0.70	0.93	0.94	0.75	0.80
11	0.99	0.73	0.94	0.95	0.63	0.88
12	0.99	0.73	0.95	0.89	0.53	0.81
13	0.99	0.73	0.96	0.95	0.60	0.83
14	0.99	0.75	0.96	0.96	0.55	0.89
15	0.99	0.74	0.96	0.95	0.79	0.74

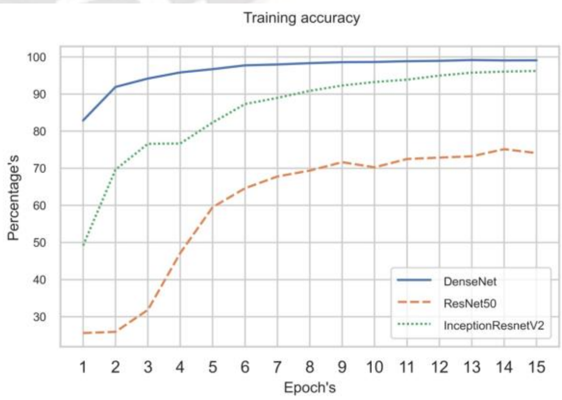

FIGURE 6. Comparison of Training Accuracy for DenseNet, ResNet50, and InceptionResNetV2.

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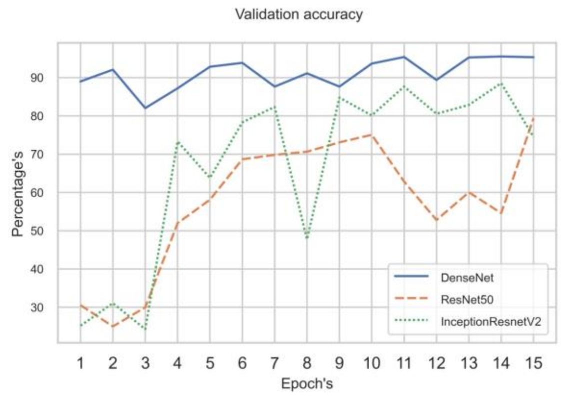

FIGURE 7. Comparison of Validation Accuracy for DenseNet, ResNet50, and InceptionResNetV2.

Therefore, the main aim of the paper is to efficiently classify the Glioma, meningioma, pituitary, and normal tumor types. For this, deep learning models including ResNet-50, InceptionResNetV2, and Recall have been used from pre-trained CNN networks to do fine-tuning based on transfer learning. The training and validation alone cannot justify the robustness or accuracy of the model until the other parameters are also worked such as the area under the curve, precision, and recall. Therefore, we analyzed the area under curve, precision, and recall parameters for the algorithms (DenseNet, ResNet50, and InceptionResNetV2) as shown in table 2. To further take a closer look, the graphs are plotted (refer to fig. 8, 9, and 10). DenseNet achieves the highest precision, recall, training, and validation accuracy, thus incurring the lowest training and validation loss.

TABLE II

COMPARISON OF VALIDATION AREA UNDER CURVE (AUC), VALIDATION PRECISION, AND VALIDATION RECALL FOR VARIOUS ALGORITHMS.

Epochs	Training Accuracy			Validation Accuracy		
	DN	RN	IRN	DN	RN	IRN
1	0.96	0.60	0.52	0.90	0.00	0.25
2	0.99	0.50	0.56	0.93	0.00	0.31
3	0.93	0.64	0.50	0.83	0.32	0.24
4	0.95	0.79	0.92	0.88	0.72	0.77
5	0.98	0.80	0.81	0.93	0.63	0.64
6	0.99	0.89	0.93	0.94	0.75	0.79
7	0.97	0.90	0.95	0.88	0.75	0.83
8	0.98	0.87	0.77	0.91	0.75	0.49
9	0.95	0.91	0.95	0.88	0.78	0.85
10	0.99	0.93	0.95	0.94	0.82	0.81
11	0.99	0.85	0.97	0.96	0.70	0.88
12	0.95	0.79	0.95	0.89	0.56	0.82
13	0.99	0.82	0.95	0.96	0.74	0.83
14	0.99	0.82	0.97	0.96	0.65	0.89
15	0.99	0.95	0.92	0.96	0.83	0.76

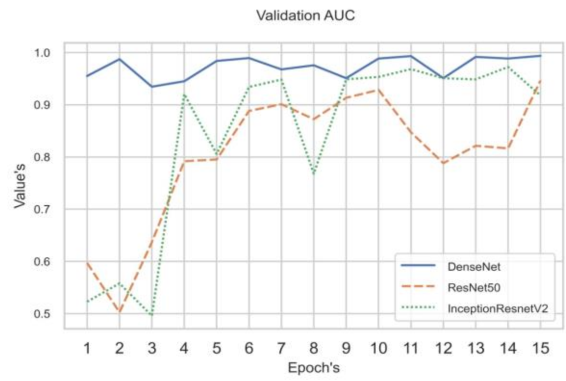

FIGURE 8. Comparison of Validation Area Under Curve (AUC) for DenseNet, ResNet50, and InceptionResNetV2.

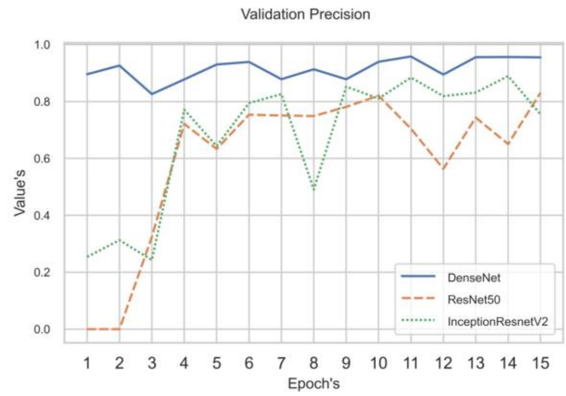

FIGURE 9. Comparison of Validation Precision for DenseNet, ResNet50, and InceptionResnetV2.

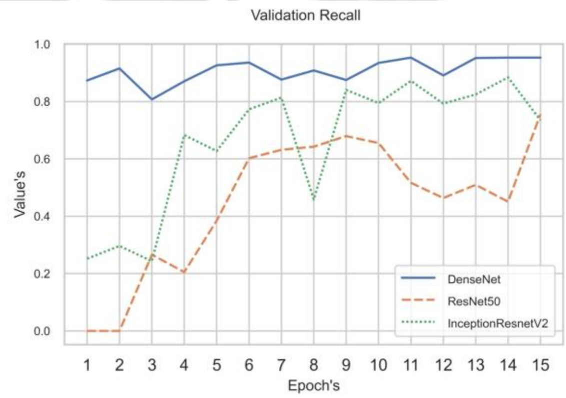

FIGURE 10. Comparison of Validation Recall for DenseNet, ResNet50, and InceptionResnetV2.

V. CONCLUSION

In this article, a novel classification system for brain tumors is presented. First, using the image edge detection technique, the region of interest in MRI images is found and cropped. Then, the data augmentation technique has been used to increase the size of the training data. Second, an efficient methodology for brain tumor classification was implemented by proposing a pre-trained deep-learning model. The experimental results show that even with a small dataset, neural networks can achieve full accuracy. When compared to other models, such as ResNet-50 and Inception-ResNetv2, DenseNet's rate of accuracy is exceptional. The average training time per epoch for the DenseNet is 205 sec, while the ResNet-50 takes 606 sec and the Inception-ResNetv3 takes 375 sec. Consequently, the proposed model requires fewer computational specifications as its execution time is shorter. In addition, the accuracy of DenseNet outperforms ResNet-50 and Inception-ResNetv2 in terms of performance. The DenseNet system can have a significant prognostic role in the detection of tumors in brain tumor patients. Comprehensive hyperparameter tuning and a better preprocessing method can be used to make the model even more useful. DenseNet is effective for binary classification problems; however, future work can extend the DenseNet method to detect skin cancer. Also, DenseNet could help in the early diagnosis of dangerous diseases in other clinical domains related to medical imaging, especially lung cancer and breast cancer, which have a very high death rate around the world. The researchers can also apply this methodology to other scientific fields.

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