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A Deep Learning Model Based on Concatenation Approach for the Diagnosis of Brain Tumor

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ABSTRACT Brain tumor is a deadly disease and its classification is a challenging task for radiologists because of the heterogeneous nature of the tumor cells. Recently, computer-aided diagnosis-based systems have promised, as an assistive technology, to diagnose the brain tumor, through magnetic resonance imaging (MRI). In recent applications of pre-trained models, normally features are extracted from bottom layers which are different from natural images to medical images. To overcome this problem, this study proposes a method of multi-level features extraction and concatenation for early diagnosis of brain tumor. Two pre-trained deep learning models i.e. Inception-v3 and DensNet201 make this model valid. With the help of these two models, two different scenarios of brain tumor detection and its classification were evaluated. First, the features from different Inception modules were extracted from pre-trained Inception-v3 model and concatenated these features for brain tumor classification. Then, these features were passed to softmax classifier to classify the brain tumor. Second, pre-trained DensNet201 was used to extract features from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Both scenarios were evaluated with the help of three-class brain tumor dataset that is available publicly. The proposed method produced 99.34 %, and 99.51% testing accuracies respectively with Inception-v3 and DensNet201 on testing samples and achieved highest performance in the detection of brain tumor. As results indicated, the proposed method based on features concatenation using pre-trained models outperformed as compared to existing state-of-the-art deep learning and machine learning based methods for brain tumor classification.

INDEX TERMS Deep learning, magnetic resonance imaging, brain tumor classification, pre-trained model, dataset.

I. INTRODUCTION

The advances in biomedical and human intelligence have overcome diverse diseases in the last few years but people are still, suffering from cancer due to its unpredictable nature. This disease is still a significant problem for humanity. Brain tumor cancer is one of the serious and utmost emergent ailments. In the USA, almost 23,000 patients were identified brain tumor cancer in 2015 [1].

In another report of cancer indicators [2], this disease is uniform in both adults and children. Approximately 80,000 fresh cases of primary brain tumors were reported in 2018 [3]: Meningioma represented 36.3% (29,320), Gliomas 26.5% (21,200), Pituitary tumors represented nearly 16.2% (13,210) and rest of the cases belonged to other types of brain tumor such as Malignant, Medulloblastoma, and Lymphomas. The principal causes of such disease are cancer-related ailment and morbidity. Effective handling of this disease is crucial which depends in its timely and accurate detection.

The dedication of a therapy modality relies upon: the degree of the tumor at the time of the investigation, the pathological type, and the category of the tumor. The brain is the most complicated and key part of the human anatomy that contains tissues and nerve cells to regulate the key actions of the whole body like breathing, the operation of our senses and muscles. A cell has its capabilities; with its functionality,

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some cells are developed normally, some decrease their capabilities, stop their growth, and then become abnormal. Such a bulk group of irregular cells produces the tissue which is described as a tumor. So, brain tumors are independent and irregular propagation of brain cells [4], [5].

The brain tumor analyzation, classification, and identification are critical issues for a neurologist who is using CAD (computer-aided diagnosis) as a supportive tool for a medical operation. There are three noticeable kinds of brain tumors: meningioma, pituitary, and glioma. Precise and timely analyzation of brain cancer is imperative for the satisfactory treatment of this ailment. The decision of a treatment depends upon the pathological type, the phase at the moment of examination, and the grade of the tumor. CAD systems have been assisting neurologists in multiple ways. Besides, CAD applications in neurology are supporting in tumor grading, classification, and detection [6].

A brain tumor is one of the most serious cancers among children and adults. Initial recognition, classification, and analyzation of brain tumors are particularly significant to treat the tumor adequately. Recently, several systems of CAD have been introduced in the field of medical imaging to help clinicians and radiologists to diagnose various types of diseases and health related issues [7]. This work used brain tumor dataset Figshare which is publicly available. Different researchers have already used this dataset to validate their models [8].

Most of the methods of brain tumors' classification depend on segmentation. Unfortunately, less importance is given to the problem of feature extraction and classification which is not only the most important step but can also improve the performance of computer-aided medical diagnosis. So, the researchers are focusing on the classification tasks by using deep learning techniques. Recently, some studies have employed deep learning to improve the performance of computer-aided medical diagnosis to investigate the brain tumor cancer. The deep learning strategies play important role in medical field and proved, as the helpful tools, in many critical diseases such as lung cancer detection [9] and image analyzation of breast cancer [10].

In the past, machine learning (ML) techniques were considered as the foundation for the purpose to take over classification and mining tasks. Recently the less accuracy in prediction models and critical nature of the medical data analyzation force researchers toward new methods of brain tumor detection to improve classification accuracy. Consequently, deep learning (DL); a sub-field of machine learning, has become the center of attraction because it is capable to provide efficient prediction models by using extensive data such as images and text. Apart from it, predicting the model on a large dataset, deep learning is capable to provide the concluded results. In medical imaging, deep learning is mostly used to identify damaged parts of any object such as effected part of the lungs, and it is also useful to classify the objects images and prediction models. Application of deep learning approaches in pattern recognition is noticeable as deep learning is nowadays used in many domains like medical analyzation, object recognition system, and object detection [11]–[18]. To identify the different patterns in cell images, the evaluation through deep learning has a significant payback. The accuracy of prediction models and data analysis through DL techniques mainly rely on the data sample and its training as it needs more accurate data for better outcomes. To overcome shortcomings in training of data samples, transfer learning can be applied to secure better performance. Transfer learning is a DL technique in which trained features of large data can be deployed to small data sets where the large data is called a source or base dataset and small data is named as target data set [18]. The fine-tune ConvNet and freeze the layers of ConvNet are considered as two main scenarios of transfer learning where we can substitute and maintain the pre-trained ConvNet on a small dataset (target dataset) to continue the back-propagation. After this, the target dataset is classified by a fully connected layer.

The motivation to use pre-trained deep learnings is time saving, because it does not need a large data set to obtain results. These models also extracted random features from images for classification. The top layers extracted lower level features such as texture, color, edges. The bottom layers of the models extracted high level features such as object and contours. In literature, normally features are extracted by using pre-trained models are from bottom layers as the features on top layers of pre-trained models are almost similar in natural and medical images. The bottom layers' features would be different from natural images to medical images. The main idea is to extract features from various layers of pre-trained models trained on our proposed dataset are combined or concatenates to extract multiscale information from input images to further enhance the features capability of the classifier model. The multi-level features information extracted from different bottom layers of the pre-trained models is the main contribution in this paper while other researchers are taking single layer to extract features, according to literature review.

This paper is divided and organized into seven sections. Section 2 provides literature review while section 3 describes dataset. Section 4 describes the proposed model. Section 5 illustrates the results of the proposed techniques and compares this model with some other existing methods. Section 6 provides discussion. Finally, last section concludes the whole discussion and present the future work.

II. LITERATURE REVIEW

Machine learning approaches have been extensively employed in various domains including medical diagnostics and preventive medicine. A limited number of studies, however, have targeted diagnosis of brain tumor especially employing magnetic resonance imaging (MRI). Mostly ML methods train and test traditional ML algorithms on MRI data. Recently, some of the approaches have employed DL for the diagnosis of brain tumor.

Rehman *et al.* [5] proposed a framework that employed a setup called tri-architectural CNN (convolution neural network) for classification of tumors of different types (GoogLeNet, AlexNet and VGGNet). This classification involved pituitary gland tumors, glioma tumors, and meningioma tumors types. The above mention algorithm sliced the brain MRI to locate regions of interests. Fine tuning and freezing were also applied to the sets of data for further classification. The authors also considered data augmentation techniques to obtain results' accuracy. This research attained an accuracy of 98.69% by employing VGG16 architecture for enhancing classification and detection.

Deepak *et al.*, [6] also adopted the concept of deep transfer for classification of images and employed the same data source discussed in [5]. The features of images were extracted, and these features were also used in aggregation of testing and classification models. Employing a 5-fold model of classification at patients' level, the authors achieved an accuracy of 98%. The study concluded that a fully automated classification can help in regions classification, and performs better than manual regions classifications. Another study, based on CapsNets as a Capsule network model, by Afshar *et al.*, [19] classified brain tumors. The study improved the level of accuracy by bringing a variation in the maps of CapsNet at some convolution layer. The study claimed a pronounced accuracy of 86.50% by using CapsNet in convolution layer. The setup was achieved by using 64 feature map to enhance the accuracy measures.

Another study by Abiwinanda *et al.* [20] adopted a deep learning model, that was based on CNN, applied to brain tumor images classification. Although the study adopted 5 classification models, it concluded model 2 as the best approximation for enhancement of images classification. The final architecture comprised of RELU layer and a maximum pool layer. This setup has 64 hidden neurons in the layered architecture. The study claimed to achieve an accuracy measure of 98.5% on training and 84.19% for validation. The authors in [21] employed a two-dimensional discrete transform based on wavelets and Gabor filters for extraction of features of brain MRI. The study achieved an accuracy measure of 91.9% by employing the aforementioned system setup with backpropagation NN.

Pashaei *et al.*, [22] developed an architecture based on CNN for features extraction. They also designed a 5 layered architecture having all layers as learnable layers with customized 3×3 layered setup. The study claimed to achieve an accuracy of 81% that was further enhanced by another featured classification model of CNN based on ELM (extreme learning machine). The study noticed a limitation in the classifiers' discrimination capability by vetting classification differences in pituitary and meningioma images.

Sajjad *et al.* [7] proposed a system based on a neural network classification that further aided a clear provision of image segments (segmenting tumor region from dataset). In addition, the study employed various noise suppression techniques by using transformation and invariance concepts. The CNN setup could tune the prediction accuracy for the prediction of tumor grades. For the prediction accuracy, the data was passed to a fine-tuned CNN. Several experiments were performed on two different sets – Radiopaedia and brain tumor. This study employed both original and augmented datasets to determine systems accuracy i.e., 90.67%. Classification of tumor into different grades from image data can be very useful in clinical practice as it can also accelerate the treatment planning for a particular grade patient by overcoming the sampling error [23]. In this regard, Pereira *et al.* [23] proposed a 3D CNN that automatically grades glioma from conventional multi-sequence MRI by defining a region of interest automatically. The anticipated grading system has dual functions: extraction of regions of interests and prediction of glioma grade. The proposed system was assessed on the publicly available dataset, called BRATS 2017 Training set in which subjects are classified as per images datasets. The accuracy of system was 89.5 %, in addition to the accuracy of predicting tumor that was achieved at 92.98% based on regions of interests.

Anaraki *et al.* [24] proposed a strategy based on CNN and GA (genetic algorithm) to classify various types of Glioma images using MRI data. The proposed system used GA for an automatic selection of CNN structure. They obtained 90.9% accuracy predicting Glioma images of three types. Besides, the study brought an accuracy of 94.2 % in the classification of Glioma, Meningioma, and Pituitary. Zhou *et al.* [25] purposed a method to use the 3D holistic image directly. First of all, 3D holistic image is converted into the 2D slices in the sequence, and then they applied DenseNet for the extraction of the features from each 2D slice. After that, Recurrent Neural Network was applied on each 2D slice which used the Long Short-Term Memory for the purpose of the classification. They performed experiments on public and proprietary datasets. They also applied pure convolutional neural network in the DenseNet as a convolutional auto encoder for the sequence representation learning. So, they used the DenseNet long Short-Term Memory and DenseNet Convolutional Neural Network to perform tumor screening and tumor type classification. Their system achieved an accuracy of 92.13% with DenseNet-LSTM.

Muneer *et al.* [26] used the real dataset from clinics of the United States. They used a customized classification algorithm based on Wndchrm. The tool has the concepts of neighborhood distance measure employing morphology and deep learning for CNN. The authors with this proposed setup achieved an accuracy of 92.86% in addition to 98.25% that was achieved through Wndchrm classification.

Banerjee *et al.* [27] discussed the convolutional neural network to enhance MRI images classification by employing a sequence of multiple MRI images. They proposed ConvNet models, that were customized to be developed from ab initio, based on concepts of slicing and patching of MRI images. The study aggregated the existing models i.e. ConvNets and VGGNet that were developed for processing of different MRI imaging. The study evaluated the performance of proposed models and claimed to achieve an accuracy measure of 97% tested on various datasets of MRI images. One of the

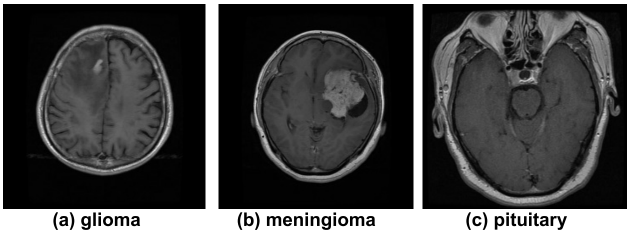


FIGURE 1. The brain tumor dataset sample for three classes: (a) glioma, (b) meningioma, (c) pituitary.

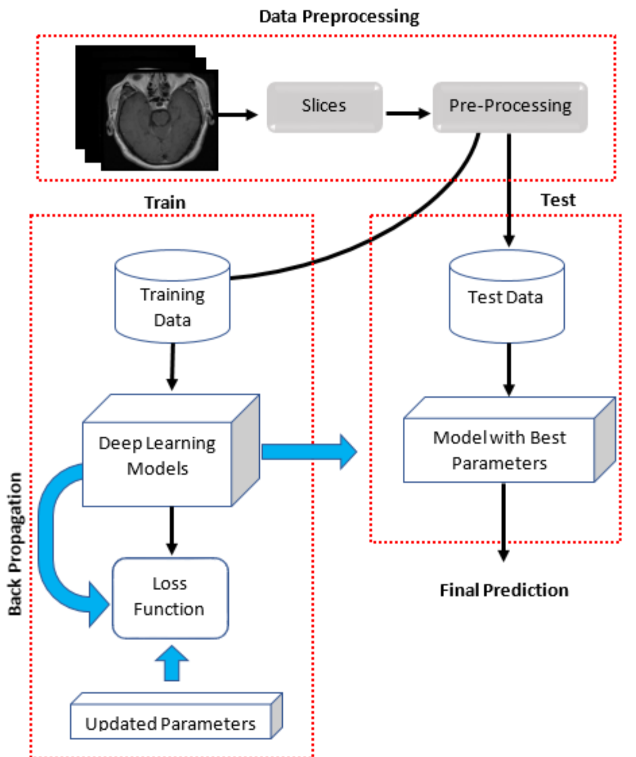


FIGURE 2. The complete training, testing and validation process based on proposed deep learning models.

limitations in exisiting approaches is feature extraction from bottom layers of pre-trained models which are different from natural images to medical images. To overcome this problem, a method of multi-level features extraction is proposed which enhances the capability of the model to classify the brain tumor.

III. DATASET

The brain dataset investigated in this study is comprised of 3064 T1-weighted contrast MR images of 233 [5]. Three different types of tumors such as meningioma, glioma, and pituitary are existing in this dataset. The image resolution 512 × 512 with voxel spacing size of 0.49 × 0.49 mm2 consisted of axial (transverse plane), coronal (frontal plane), or sagittal (lateral plane) planes has been used in this dataset. The axial plane distribution based on number of classes consisted of 708, 1426, 930 sample instances of glioma, meningioma, and pituitary tumors respectively. A min-max normalization method was used within pixel intensity value ranging between 0 to 1. The sample of three types of brain tumor is shown in Figure.1.

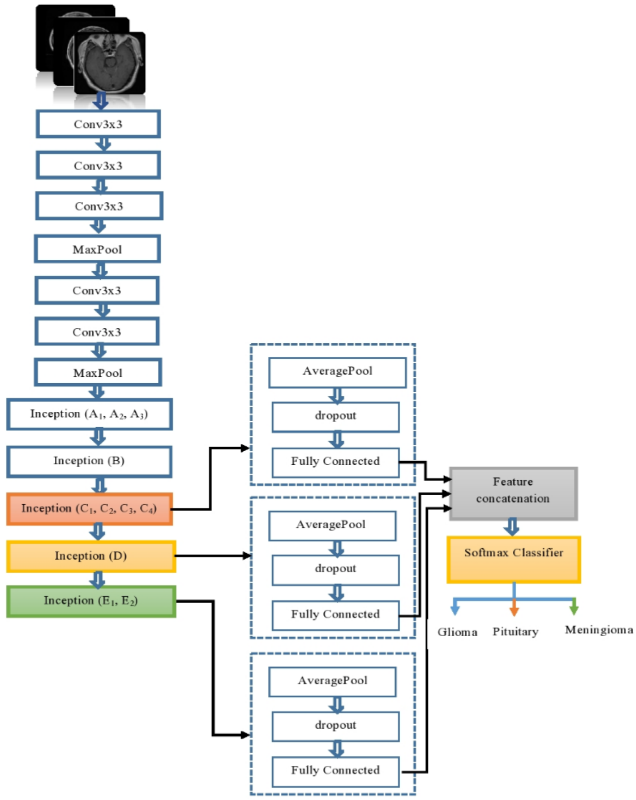


FIGURE 3. Proposed model of concatenation of features and classification of brain tumor by using Pre-Trained Inception-V3.

IV. PROPOSED MODEL

The proposed model with different number of layers and pre-trained models has been explained in the following sections in details. Figure 2 shows the process of pre-processing, training, testing, and prediction of brain tumor. The proposed model is based on deep learning which uses different hyper parameters for training and optimizes these parameters during training by using loss function and Adam optimizer. Machines learn through a loss function is a way of assessing how quite a particular algorithm models the provided data. Progressively, loss function learns to minimize the error in prediction with the aid of some optimization function. Various loss functions are available but our problem is multiclass, so, we used Cross-Entropy loss function which is also known as Softmax Loss. Adam Optimizer is an optimization algorithm that can control sparse gradients on noisy problems. Moreover, it blends the most suitable characteristics of the AdaGrad and RMSProp algorithms to attain optimize parameters.

A. PRE-TRAINED INCEPTION-V3

The proposed model of pre-trained Inception-v3 is shown in Figure 3. It consists of 11 number of inception modules and each module comprises of convolutional layer, activation layer, pooling layer, and batch normalization layer. These modules are concatenated to get multiscale maximal features from input images. We have removed most of Inception module at bottom layers of pre-trained Inception-v3 deep learning model and concatenated features at the bottom layers of proposed models for classification based on brain tumor dataset. The global average pooling, and fully connected layers are added with the last Inception module layer along with different Inception modules features for brain tumor classification. The dropout layer after global average pooling layer has been used for regularization, and this layer minimized the over fitting problem for training the proposed model. The features are extracted from fully connected layer and after the concatenation from different Inception blocks are passed to the classifier. The features taken from Inception block C, D and E modules are concatenated and passed to the traditional classifier such as softmax. The features from Inception block A and B did not produce good performance and simply these features are not extracted for classification is shown in Figure 3. The deep layers Inception module such as C, D and E Inception blocks produced better performance and these Inception module-based features have been used for classification and assessment of multiclass brain tumor types. The complete process is shown in Figure 3.

B. PRE-TRAINED DENSNET201

The pre-trained DensNet201 has been used for feature extraction by using brain tumor dataset. In this network, the features are extracted from lower dense block and upper dense block. In DensNet201, there are four denseblocks with different number of convolutional layers. The idea is to extract feature from lower block2, middle block3 and end denseblock4 of bottom layers of the DensNet201.

After feature extraction from every block, the average pooling layer and fully connected layer have been used for feature concatenation and then passed these concatenated features to softmax classifier. The softmax classifier has been applied on multilevel or fused features extracted features from pre-trained DensNet201 model. After feature extraction from different denseblocks, these features were concatenated and passed to the softmax classifier for brain tumor detection and assessment. The complete process is shown in block diagram of Figure 4.

The feature concatenation approach produced dense multiscale information from input images for brain tumor classification. The Denseblock having twelve (12) number of convolutional layers blocks, forty-eight (48) number of convolutional layers blocks and thirty-two convolutional layers blocks had been used for feature extraction and features concatenation. These denseblocks extracted from bottom layers of pre-trained DensNet201 model produced multiscale and dense information from input images of brain tumor dataset for brain tumor multiclass classification. The denseblock comprised of six number of convolutional layers did not provide efficient performance. Based on experimental

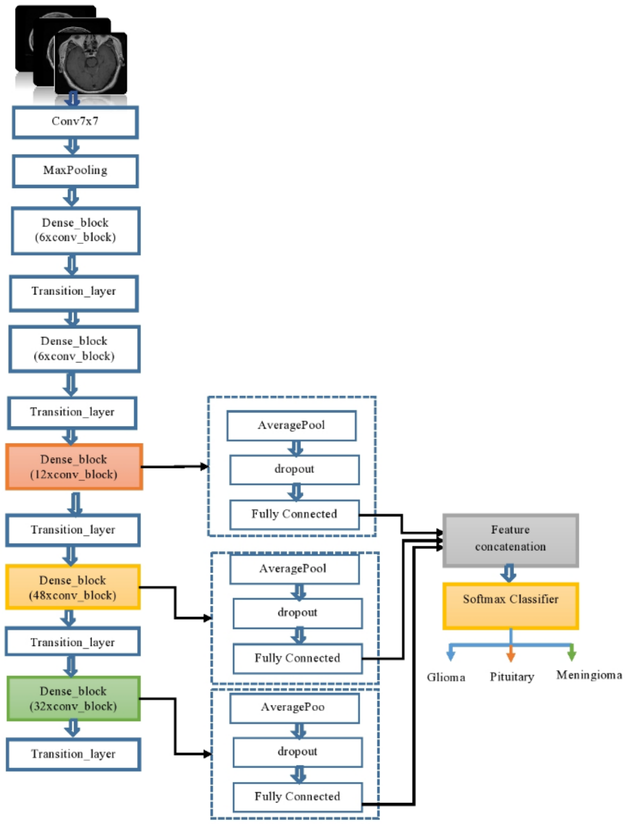


FIGURE 4. Proposed model of concatenation of features and classification of brain tumor by using Pre-trained DensNet201.

evaluation, we only used three dense blocks from pre-trained DensNet201 model which have major contribution in efficient classification of brain tumor dataset

V. RESULTS

A. PERFORMANCE METRICS

To validate the performance of the proposed model, the following performance metrics are used: the accuracy, precision, recall, and F1 score to measure true and predicted classes which have already been represented in equations 1, 2, 3, and 4, respectively. The mathematical notation of each performance metric is shown hereunder:

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recal = \frac{TP}{TP + FN} \tag{3}$$

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

Here "TP" describes true positive, "TN" represents true negative, "FP" indicates to false positive, and "FN" denotes false negative

TABLE 1. The precision, recall, and F1 score based on different densnet block features.

Algorithms	Classes	Precision	Recall	F1-score
	glioma	100.00	99.00	100
densnet_block4	meningioma	100.00	97.00	98.00
feature	pituitary	97.00	100.00	98.00
densnet_block3	glioma	100.00	99.00	99.00
feature	meningioma	100.00	95.00	98.00
	pituitary	95.00	100.00	97.00
densnet_ block2	glioma	100.00	99.00	99.00
feature	meningioma	100.00	90.00	95.00
	pituitary	92.00	100.00	96.00

TABLE 2. The precision, recall and F1 score based on different inception block features.

Algorithms	Classes	Precision	Recall	F1-score
	glioma	99.00	98.00	99.00
Inception_E	meningioma	98.00	95.00	97.00
feature	pituitary	96.00	100.00	98.00
Inception_D	glioma	100.00	98.00	99.00
features	meningioma	97.00	98.00	98.00
	pituitary	97.00	99.00	98.00
Inception_C	glioma	100.00	97.00	99.00
feature	meningioma	100.00	97.00	98.00
	pituitary	98.00	98.00	98.00

B. RESULT EVALUATION AND ANALYSIS

Various hyper-parameters were used to train our proposed models. The number of epochs 100, learning rate 0.0001, 20 batch size, Adam optimizer, categorical cross entropy loss function was used to trained proposed models. Softmax classifier was used for pre-training and scratch based proposed deep learning models. The Keras with backend TensorFlow library has been used to trained deep learning models.

The proposed models are trained by using 80 percent data for training and 20 percent for testing. The evaluation metrics have been computed for estimated labels and ground truth labels used in brain tumor dataset. The highest accuracy achieved by our proposed model based on concatenation of features. The precision, recall, and F1 score based on different densnet block features are shown in Table 1. The performance metrics for individual class of brain tumor are based on proposed model individual densnet blocks features approach as shown in Table1. The precision values of class glioma and meningioma shows highest performance of densnet block4 based features compared to other densnet blocks features. Similarly, the other performance metrics such as recall and F1-score for all brain tumor types show better performance based on proposed deep learning features extraction approach for classification of brain tumor.

The precision, recall and F1 score based on different inception block features have figured out in Table 2.

The blocks, consisted of bottom layers of Incepion-v3, have been used to extract features for brain tumor classification. The performance analysis of various bottom layers blocks of Incecption-v3 has been compared to classify different types of brain tumor and the features based on Inception C features produced excellent performance for all brain tumor classes as shown in Table.2.

TABLE 3. The precision, recall and F1 score based on concatenation of dens_block features and inception-based features.

Algorithms	Classes	Precision	Recall	F1-score
Concatenated	glioma	99.00	100.00	100.00
Desnet_block	meningioma	99.00	99.00	99.00
Features	pituitary	100.00	99.00	100.00
Concatenated	glioma	99.00	100.00	100.00
Inception	meningioma	100.00	99.00	99.00
Features	pituitary	100.00	100.00	100.00

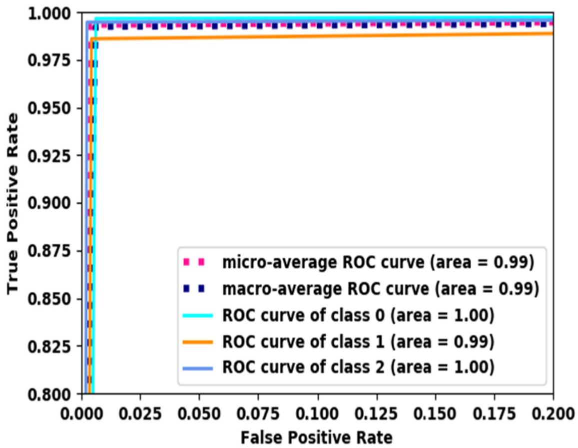
TABLE 4. Average accuracy of densnet, inception, and the combined approaches.

Model	Average Accuracy
1- dense_block4	98.44
2- dense_block3	97.4
3- dense_block2	95.83
4- Inception_E	97.4
5- Inception_D	96.88
6- Inception_C	96.28
7- combined_inception_block	**99.34**
8- combined_densnet_block	**99.51**

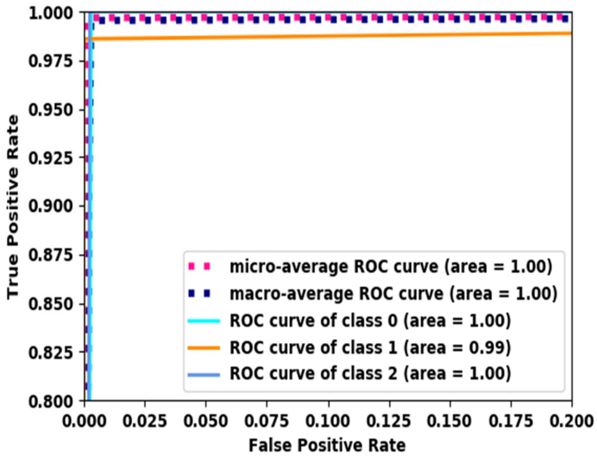
Table 3 highlights the results after concatenation of different features with densnet and inception. The performance analysis for each brain tumor class based on concatenation of features that use different bottom layers blocks. Table 3 highlights this performance. The concatenation features of different blocks of proposed Incecption-v3 and DensNet201 produced excellent performance as compared to individual block feature extraction approach which Table 1 and 2 elaborate.

Table 4 shows accuracy of densnet, inception and combined approaches. The overall performance of combined features, extracted from different layers of Inception block, is better as compared to individual Inception E, Inception D and Inception C blocks. The accuracy produced by proposed techniques, based on feature concatenation, clearly indicated the highest performance. as compared to single block (Inception E, Inception D and Inception C blocks) feature extraction methods. Similarly, the second proposed DensNet201 based features concatenation (dense block2, dense block3, dense block4) approach shows highest performance in brain tumor classification.

The combined approaches such as combined inception block and combined densnet block indicate their accuracies 99.34% and 99.51 % respectively. Bold fonts in Table 4 indicate the highest accuracy among the eight models.



(a) combined_inception_block



(b) combined_densnet_block

FIGURE 5. The ROC plot based on proposed combined_inception_block and combined_densnet_block which is further sub-divided into: (a) Combined_inception_block, (b) Combined_densnet_block.

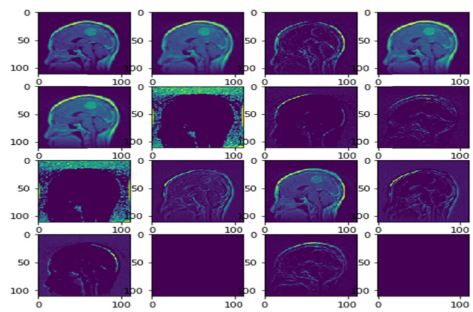
The ROC (region of convergence) in Figure 5 indicates that proposed model based on comined_features produced excellent results for each tumor class (0, 1, 2). The 0-class denoted as glioma, 1-class denoted as meningioma, and 2-class pituitary. The ROC curve for class glioma and pituitary produced true positive rate and class meningioma is less effective classified as compared toglioma and pituitary class.

Table 5 also shows comparison among other existing approaches. The proposed model based Densnet block using combined features produced excellent performance in brain tumor classification which are shown in bold fonts in Table 5. The Inception-v3 model based features concatenation method indicates 99.34% accuracy while DensNet201 model based features concatenation approach demonstrates 99.51% accuracy.

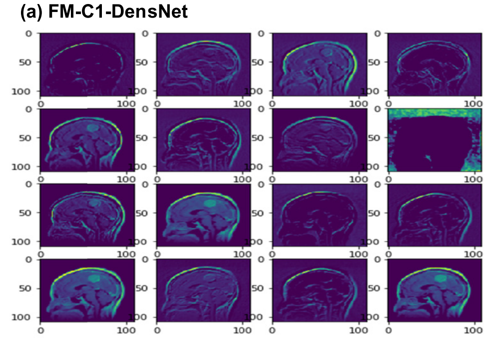
The feature map activation for convolutional layers of the best proposed model based on denseblocks feature map and Inception block feature map is shown in Figure 6. The activation map for convolutional layer has been used in proposed model which shows the reconstruction of information same like to original images.

TABLE 5. Comparison with other existing techniques.

Related work	Features	Model	Accuracy (%)
Rehman et al.[5]	Fine-tune-VGG16	Log-based softmax	98.69
Afshar et al. [19]	Model based	CapsNet	86.56
Abiwinanda et al. [20]	Model based	CNN	84.19
Ismael and Qader [21]	DWT-Gabor	NN	91.90
Pashaei et al. [22]	CNN	ELM	93.68
Proposed Model	**Combined features-based Inception block**	**Inception CNN model**	**99.34**
	Combined features-based DensNet block	**DensNet CNN model**	**99.51**



(a) FM-C1-DensNet



(b) FM-C1-Inception

FIGURE 6. The feature maps for convolutional layer1 (FM-C1) for proposed models (DensNet, Inception).

The feature extraction map for bottom convolutional layers of our proposed models provided evidence to accurately reconstruct the brain tumor information from input images.

The classification of brain tumor with different types has been discussed. The shape of glioma is different and usually encircled by edema. Meningioma commonly exists near the skull, and cerebrospinal fluid. The well-known pituitary tumor is very close to sphenoidal sinus and optic chiasma. Therefore, the discriminative features and the most relevant information related to any brain tumor is difficult to classify and the features have correlation with the position of tumor area in any MR image along-with its shape, size, and boundary is varying based on tumor types.

The deep learning based proposed models extracted are useful and discriminate features in order to classify the various type of tumor in a complex feature's estimation of different tumor types. The glioma and pituitary tumor class recovered accurately as compared to meningioma class based on proposed tumor classification models. The results are validated by using the ROC curves produced by proposed models based on predicted samples.

VI. DISCUSSION

The traditional method based on human inspection has been used for the detection and classification of MRI brain tumor and depends on the expertise of radiologists who examine and investigate the components of images. The operator-assisted classification methods are non-reproducible and unrealistic for a large amount of data because manually processing large scale dataset is a time-consuming process. To overcome such problems, computer-aided diagnosis tools are required to process a large amount of data efficiently. According to applications, the brain tumor classification is subdivided into two types: 1) classification of MRI into normal and abnormal tumor, 2) classification within abnormal brain tumors into different types of tumors. Automatic classification of brain tumors into various pathological types relatively is a difficult problem as compared to binary classification (normal and abnormal) of tumors.

Mostly, the conventional feature extraction methods employed for machine learning to obtain handcraft features depending on high-level and low-level features. This is a prime problem for a tumor analyzation using machine learning algorithms. In the CE-MRI dataset, a firm association exists between the structure of tumor and nearby healthy tissues along with edema. The shape of glioma is different and usually encircled by edema. Meningioma commonly exists near the skull, and cerebrospinal fluid. The well-known pituitary tumor is very close to sphenoidal sinus and optic chiasma. Therefore, the discriminative features and the most relevant information related to any brain tumor have correlation with the position of tumor area in any MR image along-with its shape, size, and boundary. Brain tumors have large deviations in shape, size, and intensity. So, handcrafted features based on traditional machine learning methods may not be a reasonable solution to evoke intensity of information. Recently deep-learning-based automatic feature extraction and classification approach performed admirably to highlight computer-aided medical works. Deep Learning discovered notable features in a self-learning mode with the demand of a minimum data pre-processing in the process of most significant feature extraction as well as classification. The major issue in MR image classification and recognition is to lessen the gap between the high-level data recognized by a human evaluator and a low-level visual data taken by a MRI machine. The effectiveness of this scheme for classification problem is to extract the best features that represent low- and high-level information representation by ignoring any handcrafted features. The CNN deep learning models extract important features automatically in a hierarchical learning approach that proves deep learning models delivered the better results. The deep learning-based models extract simple structural feature information in earlier layers particularly edges, shape, etc and final layers encode or construct abstract interpretations for specific features. Deep learning-based models provide an excellent self-learning feature extraction mechanism if they are compared to manual feature extraction which lessen the need of domain knowledge for enhancing the system performance. The concatenation of fusion of high level and low-level pre-trained-model layers features produced an excellent performance, if it is compared to the last layer pre-trained deep learning-based feature extraction. The combination of a lower layer and higher layer deep feature would be a better choice for assessment and classification of brain tumors.

VII. CONCLUSION

This paper discussed the application of deep learning models for the identification of brain tumor. In this paper, two different scenarios were assessed. Firstly, pre-trained DensNet201 deep learning model was used, and the features were extracted from various DensNet blocks. Then, these features were concatenated and passed to softmax classifier to classify the brain tumor. Secondly, the features from different Inception modules were extracted from pre-trained Inception-v3 model and concatenated and then, passed to the softmax for the classification of brain tumors. Both scenarios were evaluated with the publicly available three-class brain tumor dataset. Consequently, the ensemble method based on concatenation of dense block by using DensNet201 pre-trained model outperformed as compared to the current research methods for brain tumor classification problem. The proposed method produced 99.51% testing accuracy on testing samples and achieved the highest performance in detection of brain tumor. In future, we will explore and apply fine-tune techniques on pre-trained models trained with a larger number of layers and may also scratch-based models with data augmentation techniques to classify brain tumor. We will also explore ensemble method (fusion of classifiers output) based on fine-tune and scratch-based features extracted from deep learning models.

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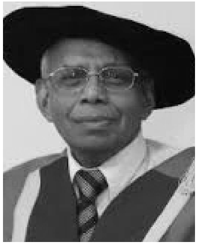

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