Multi-Classification of Brain MRI Tumor Using ConVGXNet, ConResXNet, and ConIncXNet

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Multi-Classification of Brain MRI Tumor Using ConVGXNet, ConResXNet, and ConIncXNet

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Abstract: *A brain tumor is a cancerous disease that can be fatal. The classification of brain tumors in clinical methods is time-consuming and error-prone. This paper proposes three deep convolutional neural network (CNN)-based architectures, ConVGXNet, ConResXNet, and ConIncXNet, by utilizing the concept of transfer learning. The proposed models extricate diversified features from magnetic resonance images (MRI). Many multi-class brain MRIs corresponding to glioma, pituitary, and no tumor patients are used to train the proposed models. This study also carries out data pre-processing and data augmentation for the models' effectiveness. A proper training configuration monitors the performance of the models. ConIncXNet is the most accurate of the architectures proposed. The accuracy of the ConIncXNet architecture is 97 percent. The models are also evaluated based on weighted F1 score, precision, and recall. This proposed CNN architecture can improve the classification of brain tumors in medical image diagnosis systems.*

Keywords: ConIncXNet; Multi-Classification; Brain Tumor; Data augmentation; Transfer Learning

1. INTRODUCTION

Brain tumor discovery is challenging in starting stage because it cannot discover the exact estimation of the tumor. Hence, the location of the brain tumors remains challenging due to the brain's complex structure compared to other heart, lung, kidney, and bone cancer discoveries in therapeutic areas. To prevent the disease from being fatal, early detection of tumorous and non-tumorous cells is critical [1]. The most outstanding issue with classifying the MRI images with a few neural networks lies within the number of images in the dataset. Computer-aided systems can reduce typical error phenomena in conventional methods [2]. However, the earlier artificial neural network also served the purpose of brain tumor classification using traditional segmentation techniques such as activity level set contour [3]. The convolutional neural network has been used recently for classification and detection problems due to its proper feature extraction [4-6]. The medical image diagnosis system uses the deep learning network of CNN as it automatically evaluates the model's performance on the image dataset [7,8]. The power sectors also utilize the deep network [9].

The deep CNN model consists of various layers with layer parameters. Among these are the input, convolutional, pooling, flatten, and dense layers [10]. The SoftMax layer utilizes the purpose of classification at the end of the CNN layer. Gupta et al. executed brain tumor classification in which they used discrete wavelet transform DWT), principal component analysis (PCA), and SVM algorithm [11]. The obtained accuracy for their implementation is 80%. Vani et al. claimed in their study to acquire 81.48% accuracy for classifying brain tumors using SVM [12]. Shahzadi et al. utilized the CNN-LSTM to classify a brain tumor [13]. They have used the Alex net-LSTM, Resnet-lstm, and VGG-lstm and found the highest accuracy of 84% with VGG-lstm.

This paper proposes three deep CNN architectures named ConVGXNet, ConResXNet, and ConIncXNet to classify brain tumors. The novelty of this work lies in the developed fine-tuned models. Pre-processing and data augmentation also carry proper significance. The following way describes the rest of the paper: section 2 indicates the related works; section 3 depicts the description of the proposed methodology. Section 4 explains the result analysis of this proposed hybrid CNN model; section 5 illustrates the conclusion and then the references.

2. LITERATURE REVIEW

This section describes some related works associated with the deep CNN model. Afshar et al. proposed a method for classifying a brain tumor using 64 featuring maps [14]. The acquired accuracy of their study is 86.56%. Charfi et al. proposed a technique using histogram equalization to segment images [15]. Then, they used PCA for dimension reduction of the image dataset. Lastly, they used a back-propagation feed-forward neural network to classify normal and abnormal brain images. The acquired accuracy of their proposed method is 90%.

Citak et al. proposed three deep learning algorithms in their paper: multi-layer perceptron, logistic regression, and SVM [16]. The acquired accuracy of their proposed method is 93%, with a specificity of 86.7%. Mohsen et al. have suggested a deep learning model for classifying brain tumors in which they have used discrete wavelet transform (DWT) [17]. They also compared their deep learning model with the KNN classifier, showing that their model achieved 93.94% accuracy.

In the proposed method by Saxena et al., they used transfer learning with three different deep CNN models [18]. The deep CNN models are Resnet 50, Inception V3, and VGG 16, and they have achieved the highest accuracy of 95% with Resnet 50. El Abbadi et al. stated that their proposed method for brain tumor classification had acquired 96.66% accuracy [19]. They used Singular value decomposition (SVD) in their study to classify brain tumors using abnormal data images of 50 and typical data images of 20. This proposed method can achieve better accuracy and a weighted F1 score for uneven class distribution.

3. PROPOSED METHOD

The purpose of this proposed method is to classify the brain tumor from MRI images using the proposed deep

CNNs. The following illustrates the working procedure of the proposed methodology :

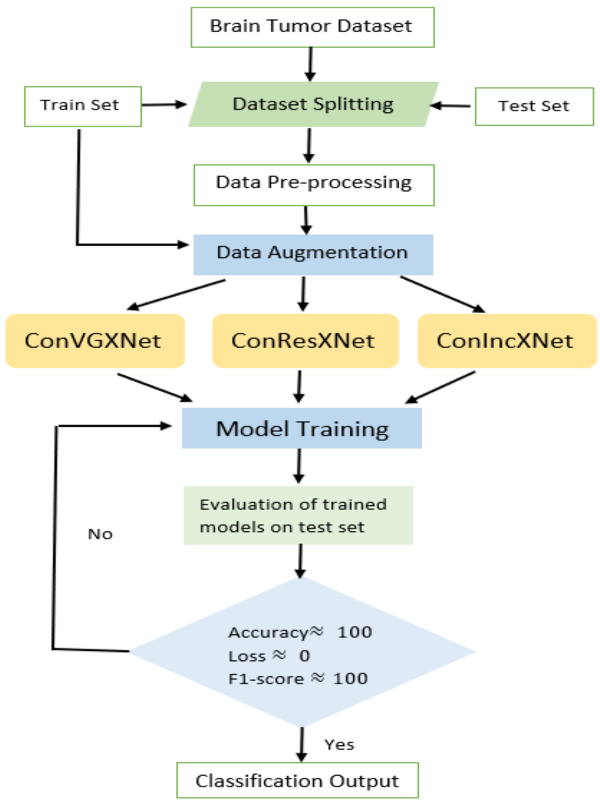


Fig. 1. Working procedure of the proposed method

Fig. 1 shows the operational flow of the proposed method for classifying brain tumors from brain MRI images. After dataset collection and splitting, the authors perform dataset pre-processing in which the MRI images have been resized and normalized. Data augmentation has been performed on the train data. For obtaining better accuracy, the pre-trained CNN architecture is tuned.
In this section, the significant steps involved in the methodology have been explained. This section contains essential steps such as dataset description and splitting, data pre-processing, data augmentation proposed CNN architecture, and training specifications.

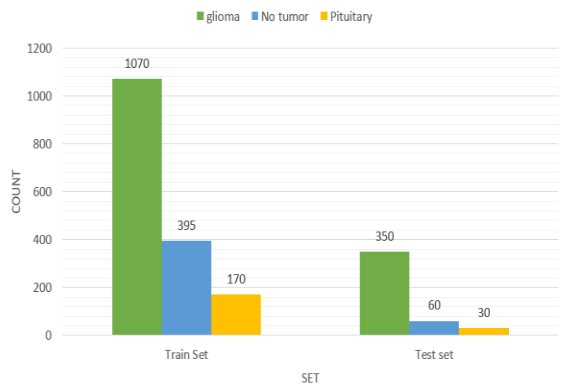


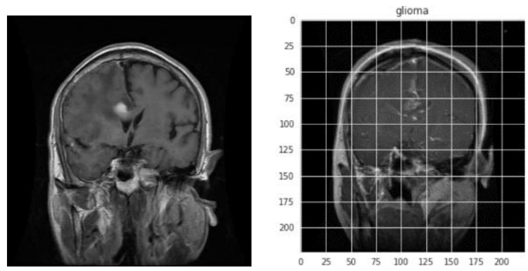
Fig. 2. The count of classes in each set

3.1 Dataset Description and Splitting

The image dataset is collected from Bhuvaji, S. Brain Tumor Dataset [20]. There is a total of 2075 MRI images in the dataset. The image height and width in the dataset are 512 pixels. All of the images in the dataset are grayscale contrast-enhanced images with T1 modality. The images are available in all three views: axial, coronal, and sagittal. The dataset's brain tumors differ in size, shape, and location. The dataset is split into two sets. One is a train set, and another is a test set. There are three folders in each set of images: glioma, no tumor, and pituitary. These are the MRI image classes. The 440 MRI images in the test set include 350 gliomas, 60 no tumors, and 30 pituitary images. Fig. 2 depicts the number of classes in the train and test sets.

3.2 Data pre-processing

In this step, the image dataset is pre-processed by resizing the grayscale images of the dataset. Then, image normalization was done. In Fig. 3, one glioma tumor image is shown after resizing.



(a) Input image (b) Resized image

Fig. 3. Visualizing image from dataset after resizing

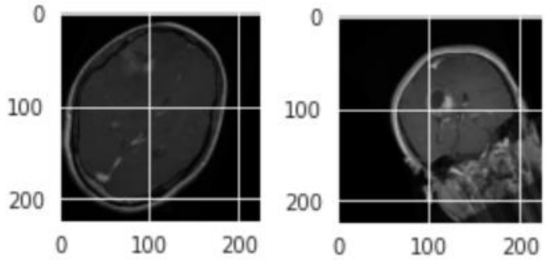
The fine-tuned CNN model's input size is 224,224,3 after resizing and normalizing. Table 1 shows various CNN models' input sizes with the proposed ConVGXNet, ConResXNet, and ConIncXNet models.

Table 1. The Input Size of Various CNN Model

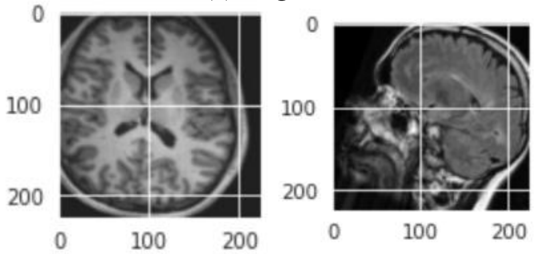
CNN Model	The Input Image Size
Resnet 50	[224 224 3]
VGG 16	[224 224 3]
Inception V3	[299 299 3]
Proposed ConVGXNet, ConResXNet, and ConIncXNet models	[224 224 3]

3.3 Data augmentation

The image augmentation is done on the train set image and through transformations like image rotation, zoom range, width-shift range, height shift range, and horizontal flip. This image augmentation is done so that the CNN model does not use the same picture twice for training. This augmentation is done by setting the parameters through 'ImageDataGenerator' in Keras. The rotation range is set as 30, which is used to rotate pictures randomly, and the value of this is from 0 to 180 degrees. The zoom range is set as 0.2 for zooming inside the MRI images. Width-shift range and height-shift range are set as 0.1, which is used for shifting the images horizontally and vertically. Horizontal flip is set as accurate, which is used to flip the images horizontally from the dataset. Each image in the training dataset is passed through this data augmentation, and a new train set is obtained for the deep CNN model. In Fig.4. various types of augmented images have been shown after applying image augmentation to the training dataset.



(a)Image rotation



(b) Image zooming

Fig. 4. Augmented image from dataset after applying various augmentations.

3.4 ConVGXNet, ConResXNet, and ConIncXNet models:

The convolutional layer is used for feature extraction as it goes deep. The feature map is extracted using a filter kernel for convolution of the input image. In one-layer convolutional network,

$$z^{[1]} = w^{[1]} a^{[0]} + b^{[1]} \quad (1)$$

$$a^{[1]} = g(z^{[1]}) \quad (2)$$

Where $a^{[0]}$ denotes the input layer of the CNN model, $w^{[1]}$ denotes the weight of the filter and $b^{[1]}$ represents the bias, and $z^{[1]}$ is the output of the first convolutional layer.

Table 2. The fine-tuning layer with layer name and output shape

Layer	Layer Name	Output Shape
1	Input layer	224,224,3
2	Conv2d	111,111,32
311	Concatenate	5,5,2048
312	Flatten	51200
313	Dense (ReLu activation)	512
314	Batch Normalization	512
315	Dropout	512
316	Dense (SoftMax)	3

The CNN models are created for diversified feature extraction from the pre-processed and augmented data input MRI images. ConVGXNet, ConResXNet, and ConIncXNet models are made up by fine-tuning the VGG16, Resnet50, and Inception V3 models, respectively. In the fine-tuned CNN models, five layers have been added in the last of pre-trained weights, which were initially trained on the ImageNet [21] dataset. ConIncXNet has frozen the last three layers of the Inception V3 model and added five, constituting 316 layers. The fine-tuning layers in the ConIncXNet model are shown in Table 2 with output shape and layer name. The ConIncXNet architecture is shown in Fig. 5. The last indicated five layers are the fine-tuned layers of the model.

3.5 Training Specifications and Error Metrics:

Multiple iterations are needed to train the CNN models, known as epochs. Epochs are used during model training for the optimization of the model. The error that occurs in the training data can be reduced by using the epochs. However, during the continuation of multiple iterations of epochs, the loss in the validation dataset may be higher than the training set, which causes the overfitting of the model. For solving this issue, early stopping criteria are used [22]. Using this, the CNN models can be regularized in which it prevents the training as soon as the validation error reaches the minimum value. The customized early stopping criteria have been done using patience six and maximum mode, monitoring the validation accuracy. Patience 6 means that the training is terminated when performance is degrading. The mode maximum implies that it will be stopped training when the validation accuracy has reached the maximum value and is not increasing anymore. In Table 3, the training specifications are given.

Table 3. Training Specifications of the model

Training Parameter	Value
Epoch	10
Optimizer	“Adam”
Dropout Probability	30%
Learning Rate	0.001
Loss	Sparse Categorical Cross entropy
Batch Size	32

The model has been trained using the 'Adam' optimizer as it combines the RMSprop and AdaGrad algorithms to maintain the sparse gradients properly. 'Sparse categorical cross-entropy loss' is utilized because this study deals with a multi-classification problem and each sample on the dataset belongs to only one class. The batch size and epoch are selected based on the model's performance. Fig. 6 illustrates the training and validation accuracy with the loss of the proposed ConIncXNet model.

Precision, recall, and F1 score are critical metrics that can be calculated using the following equations:

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

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1\text{-}score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

$$Classification\ Error = 1 - Accuracy \quad (6)$$

$$Weighted\ F1\ score/\ Recall = \frac{\sum_{i=1}^{n} Recall/F1\ score\ of\ n\ classs \times Images\ in\ n\ class}{Total\ Image\ Classified} \tag{7}$$

TP, FP, TN, and FN represent the number of classified cases of true positives, false positives, true negatives, and false negatives, respectively.

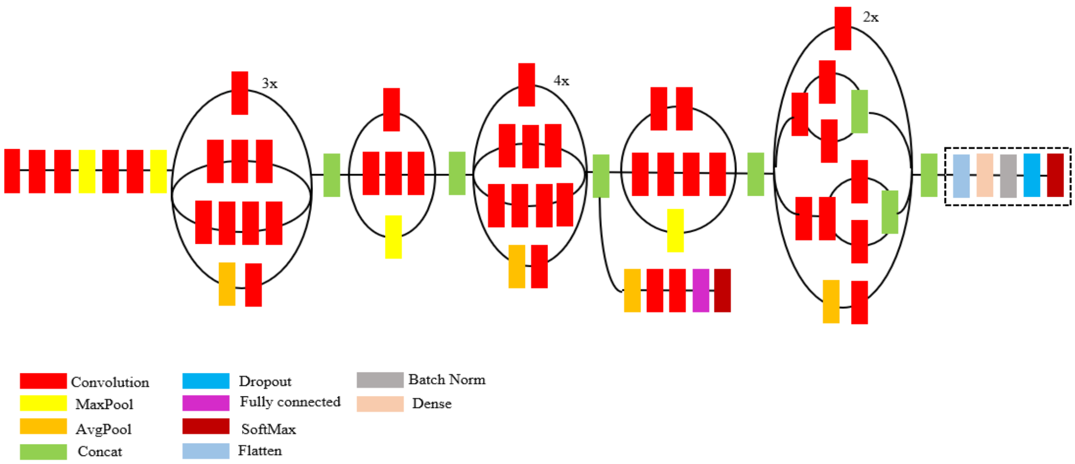
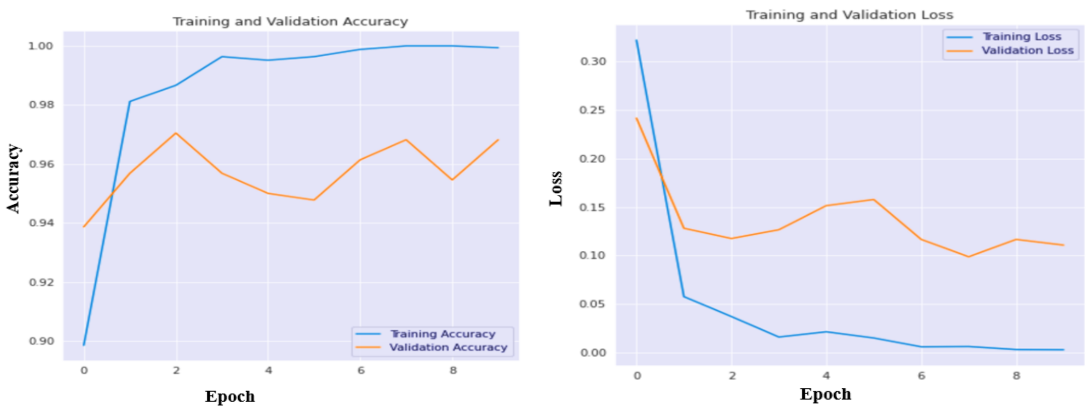


Fig. 5. Architecture of **ConIncXNet** model



(a) (b)

Fig. 6. Accuracy and loss plot of the proposed **ConIncXNet** model (a) Accuracy versus epoch (b) Loss versus epoch

4. RESULTS AND DISCUSSION

4.1 Computational Experimental Environment

The proposed method is implemented in Python, and the GPU is used for training. The necessary library for building the deep CNN model and data pre-processing and augmentation has been imported. The libraries mainly used are Keras, TensorFlow, Numpy, and Scikit-learn. Keras is a high-level neural network library that is written in Python. TensorFlow is an open-source machine learning library that provides API (Application Programming Interface). Google's Brain team created it. The Numpy library for Python supports large and multidimensional arrays of mathematical operations. The Scikit-learn library is used for classification. The included packages in these libraries are cv2, os, Keras model, Keras pre-processing, Keras layers, and Keras optimizers. These packages have been used for various operations on an image, such as array-related tasks, zooming of image, image show, resizing, and fetching images from the path of the folder.

4.2 Performance Evaluation

The confusion matrix shows the correct and incorrect estimation of classes in a tabular format. The confusion matrices of the proposed three models are shown in Table 4, in which the row-wise column denotes the predicted class label, and the column-wise row is the actual one.

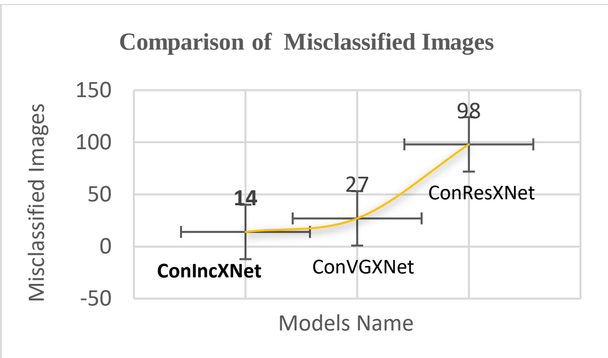


Fig. 7. Comparison of the models based on misclassified images

Table 4 shows that the ConIncXNet model can identify the glioma class more accurately than the other two models. Among 350 glioma test MRIs, the proposed ConIncXNet model can accurately identify 342 images as glioma class. The total number of misclassified images by the ConIncXNet model is 14, whereas for the ConVGXNet model, 27. Fig. 7 depicts the visual representation of the models' comparison of the misclassified images. The ConResXNet model provides the highest number of misclassified images which is 98. Thus, the ConIncXNet model outperforms the other two models. The ConResXNet model provides the lowest performance due to the inability to make a smooth decision on the test MRIs.

Table 4. Confusion matrix of all the models where G, N, and P mean glioma, no tumor, and pituitary, respectively

		Predicted								
		ConIncXNet			**ConVGXNet**			**ConResXNet**		
		G	N	P	G	N	P	G	N	P
Actual	Glioma (G)	342	4	4	326	6	18	280	66	4
	No tumor (N)	0	60	0	0	60	0	0	60	0
	Pituitary (P)	5	1	24	3	0	27	11	17	2

Table 5. Evaluation of all models based on performance

CNN Models	Classes	Precision	Recall	F1 -score	Accuracy	Loss
	Glioma	0.96	0.80	0.87		
ConResXNet	No tumor	0.42	1.00	0.59	0.78	0.5
	Pituitary	0.33	0.07	0.11		
	Glioma	0.99	0.93	0.96		
ConVGXNet	No tumor	0.91	1.00	0.95	0.94	0.2
	Pituitary	0.60	0.90	0.72		
	Glioma	0.99	0. 98	0.98		
ConIncXNet	No tumor	0.92	1.00	0.96	**0.97**	**0.1**
	Pituitary	0.86	0.80	0.83		

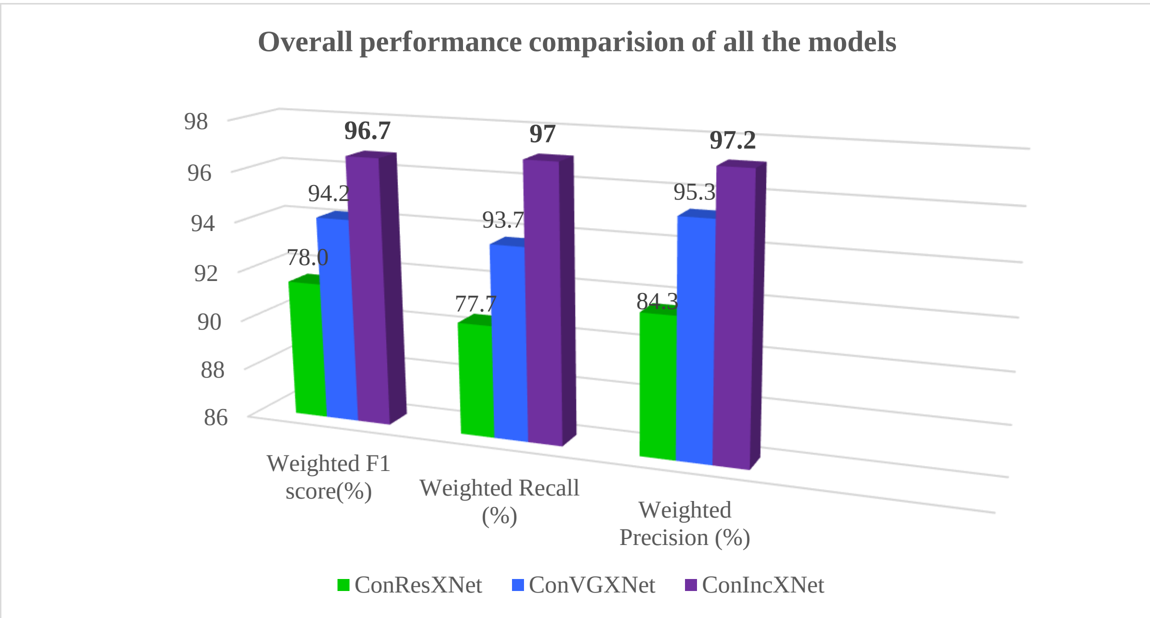


Fig. 8. Comparison of the models based on performance metrics

Table 5 depicts the class-specific performance of the models. Recall with inadequate precision can sometimes be found in training. However, excellent precision has been found in this proposed ConIncXNet model, along with good recall (Table 5). ConIncXNet model converges to the minimum loss (0.1) and also ensures satisfactory performance. Table 5 shows that the pituitary class performs poorly compared to the other classes in all the three models due to the lowest number of samples of the pituitary class in the image dataset. For this uneven dataset distribution, weighted performance matrices are measured for the model performance evaluation (Fig. 8). Fig. 8 depicts the overall performance of the proposed deep models. The ConIncXNet model achieves the highest weighted F1 score, indicating that the deep features extricated by the ConIncXNet model can smoothly decide on the test MRIs. The weighted F1 score of the ConIncXNet model is high due to the highest weighted precision and recall. The ConVGXNet model's weighted performance measure is higher than the ConResXNet model but lower than the ConIncXNet model. Fig. 9 illustrates the comparison of the model's classification error. The ConIncXNet model obtains the lowest classification error among the other two models.

4.3 Comparison with Existing State-of-arts Method

The comparison of the developed three CNN models with existing state-of-arts methods is shown in Table 6. From Table 6, it is observed that two researchers used VGG Net [13] and Resnet 50 [18], but those results in poor accuracy compared to the developed model (ConIncXNet) in this study.

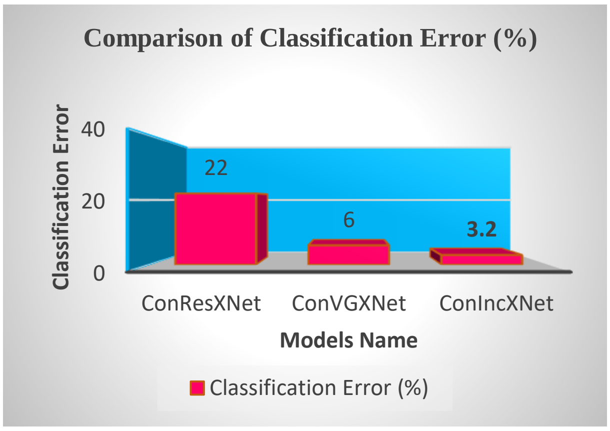


Fig. 9. Classification error comparison of all models

Table 6. Comparison of the proposed model with existing methods

References	CNN Model/Method	Accuracy
Gupta et al. [11]	DWT, PCA, SVM	80%
Vani et al. [12]	SVM	81.48%
Shahzadi et al. [13]	VGG Net-LSTM	84%
Afshar et al. [14]	Improved Method	86.56%
Charfi et al. [15]	PCA	90%
Citak et al. [16]	SVM	93%
Mohsen et al. [17]	DWT	93.94%
Saxena et al. [18]	Resnet 50	95%
EI Abbadi et al. [19]	SVD	96.66%
Proposed model	ConResXNet	78%
Proposed model	ConVGXNet	94%
Proposed model	**ConIncXNet**	**97%**

Among the ConResXNet, ConVGXNet, and ConIncXNet models, the ConIncXNet model is finally proposed in this work, providing a better-weighted F1 score and accuracy. Although the proposed model provides better performance on this dataset, another dataset's performance variation can occur, which is the limit of this work.

5. CONCLUSION

This proposed CNN model aims to classify brain tumors from brain MRI images. For this purpose, pre-processing and augmentation are performed on the image dataset. The image dataset consists of a train and test set, and the data augmentation is applied to the train set. This work utilizes three different deep CNN models. The novel aspect of this work is the fine adjustment of the VGG16, Resnet 50, and Inception V3 models. Five layers have been added to the last of the three models for fine-tuning the pre-trained weights. Customized early stopping criteria are used where the number of epochs is 10. The ConIncXNet model has obtained 97% accuracy with 0.10 loss. The 'Adam' training optimizer is used, and the model's required training time is also less compared with other existing methods. In the future, the authors are interested in the ensemble of in-depth features from pre-trained models.

Conflicts of Interest:
The authors declare no conflict of interest.

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