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Deep Learning Models for Brain Tumor Classification

Sunitha EV[1] and Jiby TC[2]
[1] KL University, Vijayawada, India
Email: sunithaev@gmail.com
[2] IIIT Surat, Surat, Gujarat
Email: jiby@iiitsurat.ac.in

***Abstract*—Applying Deep Learning (DL) models in Brain Tumour (BT) classification helps the doctors to do the diagnosis accurately. Many research works are being done in this area. Convolutional Neural Network, Recurrent Neural Network, and Transformer based models are the main DL models dealing with BT classification. Different datasets are available which provides MRI images of brain with and without tumour. Our aim is to find the best model from these three for the BT classification. The conclusion of our study is that CNN based models perform well in BT classification. Transformer based models also have the potential. Hence, these two models can be used as a hybrid model in BT classification for a better performing system.**

***Index Terms*— Brain Tumor classification, Deep Learning models, Vision Transformer, Convolutional Neural Network.**

I. INTRODUCTION

Revolutionary developments are being made in the field of Brain Tumour (BT) detection and classification through the application of Deep Learning (DL) techniques. Researches are rapidly progressing by harnessing Convolutional Neural Networks (CNNs) and employing Transfer Learning (TL) strategies to boost the precision of identifying BT from MRI scans. Moreover, there is a joint effort to integrate Machine Learning (ML) methodologies with DL, targeting to fine-tune the accuracy and efficacy of the detection and classification process. The main objective is to enable early and accurate diagnosis, and thereby enabling prompt medical interventions and ultimately improving patient outcomes. The integration of DL methodologies in BT detection and classification shows promising potential for the development of robust and reliable investigative tools. In our literature study, we have observed many works related to the detection and classification of BT, finally selecting 25 papers based on their relevance. Our investigation explores into the datasets used, the proposed architectures, and the performance metrics of each model. This study intentions to identify the optimal model for effective BT detection and classification. We have done a comparative study on the performance of CNN and ViT (Vision Transformer), both have significant role in the image classification.
The majority of studies utilized datasets from figshare.com and Kaggle, while a few papers opted for datasets from the Cancer Imaging Archive [1]. These datasets consist of brain MRI images captured from various perspectives. Figshare encompasses a total of 3064 images, and Kaggle comprises 3762 images. Some works, such as those by Kang [2] and Shahin [3], incorporated three distinct datasets featuring images of varied sizes and classes: (1) BT-small, a small dataset with two classes (tumour or normal), (2) BT-large, a large dataset with two classes (tumour or normal), and (3) a large dataset with four classes (normal, glioma tumour, meningioma

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tumour, and pituitary tumour). In order to fulfil the requirement for a substantial training dataset for deep learning models, various image augmentation techniques, including rotation, shearing, scaling, and reflection, were applied to the available datasets. In some literatures, the deep learning model is trained using one dataset and tested using another dataset.

II. DL Models for BT Classification

In the era of medical imaging, the incorporation of DL models has marked substantial steps, particularly in the field of BT detection and classification. Deep Learning which is a subset of Machine Learning, has proved supreme competence in deciphering complex patterns within medical images, resulting in remarkable developments in diagnostic accuracy and efficiency. Unambiguously, within the domain of BT, the application of DL models presents a promising way for early and precise detection, and enabling rapid medical interventions and ultimately elevating patient recovery.

The study of DL models for BT detection and classification involves the implementation of sophisticated algorithms, with a noteworthy prominence on CNNs and ViTs. These models pull their inherent capability to learn complex features from wide-ranging datasets, particularly Magnetic Resonance Imaging (MRI) scans of the brain captured from various angles. The consolidation of these cutting-edge technologies not only amplifies the exactness of tumour identification but also contributes significantly to the progression of robust and reliable diagnostic tools. The DL architecture proposed in the literature can be classified into four (i) CNN based (ii) RNN based (iii) Transformer based (iv) Hybrid models.

A. CNN based architectures

Various CNN-based models are suggested in the literature, each categorized by distinct layer configurations, activation functions, loss functions, and dropout strategies. One prominent approach involves the utilization of CNN with Hard Swish ReLU[8]. In this study, Histogram Oriented Gradient (HOG) is employed for feature extraction, followed by inputting it into a CNN with Hard Swish ReLU. The MRI scans undergo improvement through normalization and histogram of oriented gradients, resultant in the extraction of feature vectors. The histogram descriptor effectively captures edge and contour features. These extracted features are then fed into convolutional neural networks for the classification of meningioma, glioma, and pituitary tumours.

The integration of a Hard Swish-based ReLU activation function proves contributory in enhancing classification performance and learning speed. Notably, the Hard Swish ReLU surpasses Sigmoid and tanh in precision, recall, and f-measure with an 80:20 train-test split. The study shows impressive metrics claiming a precision of 99.6%, recall of 98.6%, and an f-measure of 99%. The proposed model exhibits proficiency in predicting three distinct classes: glioma, meningioma, and pituitary.

In the study [10], ReLU is used for activation, and SoftMax is used for classification. The architecture comprises a sequence of Conv-ReLU-dropout-max-pool combinations repeated four times, followed by Fully Connected Network (FCN), ReLU, FCN, and finally Softmax. A 50% dropout rate is applied, and a 10-fold cross-validation is used. The model exhibits an average performance on the given dataset, achieving an accuracy of 92.72%, recall of 90.61%, precision of 90.13%, and an F1-Score of 90.14%.

In their study [9], the authors introduce a CNN architecture using ReLU and max-pooling with varying layers for three distinct classifications. These classifications encompass (1) Tumor/No Tumor, (2) Normal/glioma/meningioma/pituitary/metastatic, and (3) Grade II/Grade III/Grade IV. The proposed CNN model for Classification-1 contains 13 weighted layers, incorporating 1 input, 2 convolutions, 2 ReLU, 1 normalization, 2 max-pooling, 2 fully connected, 1 dropout, 1 Softmax, and 1 classification layer, with a 30% dropout. This model effectively categorizes input images as Tumor or No Tumor.

In the Classification-2 model, the Conv-ReLU-Max pool layers are repeated 5 times, predicting five classes: Normal/glioma/meningioma/pituitary/metastatic. For the Classification-3 model, the Conv-ReLU-Max pool layers are repeated 2 times. The Grid Search algorithm is applied to determine optimal values for parameters such as the number of layers (Conv, Maxpool, FCN), number of filters, filter size, and activation function.

The stated metrics for Classification-1 include an accuracy of 99.3%, sensitivity of 0.994, specificity of 0.994, and precision of 0.9925. For Classification-2, the values are 0.98 specificity, 97.06% accuracy, 0.9174 sensitivity, and 0.9202 precision. Finally, for Classification-3, the reported metrics are 98.76% accuracy, 0.983 sensitivity, 0.99 specificity, and 0.9831 precision.

In their study [11], the authors used a combination of CNN, FCN, feature fusion, and SVM for the purpose of classification. The CNN model incorporates Convolution, ReLU, Batch Normalization, Average Pooling, and Max Pooling layers. The CNN is followed by an FCN with a 50% dropout is utilized. The deep and static features are fused in the feature fusion step, and then the resulting combination is applied to SVM for the classification of three classes (glioma, meningioma, and pituitary). They [11] claimed performance values of 99.2% accuracy, 0.9913 precision, 0.9906 recall, 0.9909 F1-Score, and a 0.999 AUC-ROC.

Abd[6] and Kibriya[7] applied CNN for BT detection in their respective studies. They stated accuracies of 98.63% and 97.2%, representing the effectiveness of their methods. Both approaches utilized a dataset sourced from FigShare, comprising 3064 data points collected from 233 distinct patients.

B. RNN based architectures

RNN based models are not so prevalent in the field of image classification, because these models are originally developed for the text based applications like sentiment analysis.

In their paper [8], the authors introduce both CNN-based and RNN-based models. The RNN-based model incorporates RNN with three different activation functions: sigmoid, tanh, and hard swish ReLU. However, the performance of the RNN-based model falls short compared to the CNN-based model. The conveyed accuracies for the RNN-based model are as follows: sigmoid - 97.6%, tanh - 98.3%, and hard swish ReLU - 98.3%.

C. Transformer based architectures

Transformers are originally designed for Natural Language Processing (NLP). But then, Transformer models expanded their scope in 2020 to include image data. This expansion helped the integration of Transformers into the field of Computer Vision (CV), which giving rise to Vision Transformers (ViT). ViT adopts a strategy of dividing an image into steady patches and linearly embedding each patch and at the same time retaining positional information. These patches are processes using a standard Transformer encoder, which allows the model to capture both local and global features within the image. ViT exhibits proficiency in tasks such as image classification, segmentation, object detection, visual reasoning, and generative modelling.

In the study [12], a Vision Transformer model is fine- tuned for the BT detection. The algorithm uses a strategy of dividing the MRI scans into patches in order to process by the model. It applies grid-based splitting, in which individual patches are flattened into elongated vectors, which will be given as input for the model. Afterward, these flattened patches undergo additional processing, including transformation into lower-dimensional feature vectors through linear mappings. The authors report a notable accuracy of 98.13%.

In their work [13], researchers used pre-trained and fine-tuned ViT models (B/16, B/32, L/16, and L/32) These models are originally trained on ImageNet for image classification purposes. The outstanding model among these was L/32, which is showcasing a remarkable accuracy of 98.2% on the test set at a resolution of (384×384). Moreover, combining all four ViT models into an ensemble model yielded even more amazing results, overall testing accuracy of 98.7% at the same resolution. Interestingly, this ensemble model works well with images having (224 × 224) resolution as well.

In [14], the authors propose a model, MedNeXt, an innovative segmentation network inspired by Transformers. This model integrates a ConvNeXt 3D Encoder-Decoder Network, using Residual ConvNeXt blocks to preserve semantic details across various scales. Moreover, it includes a unique approach of gradually increasing kernel sizes, mitigating performance sluggishness when dealing with limited medical data. MedNeXt uses compound scaling across depth, width, and kernel size, leading to cutting-edge performance across four tasks involving MRI and CT modalities and diverse dataset sizes. This advancement in architecture signifies a current approach to deep learning, specifically designed for the particulars of medical image segmentation. The success of MedNeXt marks a substantial progress in using deep architectures for accurate medical image analysis and segmentation tasks.

D. Hybrid models

Researchers examined different combinations of deep learning models to enhance performance in BT detection. Many studies in this field tried different adaptations and amalgamations of CNN, experimenting with different activation functions and network layers. Transfer learning plays an important role in achieving promising results. Amran[4] and Raza[5] utilize a hybrid architecture, combining GoogleNet with CNN, achieving claimed accuracies of 99% and 99.67%, respectively.

In [16], a concise five-step strategy for BT classification is presented. It begins with a linear contrast stretching method to underscore edges in the source image. Afterward, a dedicated 17-layer deep neural network is designed for Tumor segmentation, followed by the application of a altered MobileNetV2 architecture for feature extraction through transfer learning. The method integrates an entropy-based method with a multi-class support vector machine (M-SVM) for best feature selection. Finally, M-SVM is used for classifying meningioma, glioma, and pituitary images. Assessments on BraTS 2018 and Figshare datasets gives outstanding performance, better than other methods with a visual accuracy of 97.47% and a quantitative accuracy of 98.92%.

[17] introduces a technique for multi-class BT classification using two modules; feature extraction module with unsupervised convolutional PCANet and classification module with a supervised CNN. Improvements to the PCANet, such as non-linear activation on convolutional maps and the computation of 3D PCA filters, enhance feature expressiveness in comparison to traditional PCANet and deep CNNs. The unsupervised PCANet requires less training data than its supervised CNN counter-parts and integrates flawlessly into a straight forward CNN classification module. Performance evaluation over four datasets, showing various characteristics and image sizes, reveals consistently high overall accuracy: Cheng Dataset - 0.9673, Brats-small-2C-Dataset - 0.9796, Brats-large-2C-Dataset - 0.9883, Brats-large-4C-Dataset - 0.9402.

[18] presents a method for multi-class BT classification that emphases on deep feature fusion. The initial preprocessing includes min-max normalization of MR images, followed by comprehensive data augmentation to address challenges related to limited data. Deep CNN features from transfer-learned architectures such as AlexNet, GoogLeNet, and ResNet18 are integrated into a unified feature vector. This vector is then fed into Support Vector Machine (SVM) and K-nearest neighbour (KNN) models for the final output prediction. The consolidated feature vector, containing more information than independent vectors, significantly enhances the classification performance of the method. The proposed framework undergoes training and evaluation on an extensive dataset comprising 15,320 Magnetic Resonance Images (MRIs) and achieves an impressive accuracy rate of 99.7%.

[19] designs a investigative system for BT using 5 leading deep learning architectures: DenseNet121, Xception, ResNet152V2, DenseNet201, and InceptionResNetV2. The final layers of these architectures undergo modifications, introducing a deep dense block and a softmax layer to improve classification accuracy. The study did two experiments: one measuring results for three classes (glioma, meningioma, and pituitary images) and another evaluating four classes, which include images from healthy patients. Among these architectures, the Xception-based model stands out, achieving notable classification accuracy rates of 99.67% on the 3-class dataset and 95.87% on the 4-class dataset.

III. Comparison of Performance of the DL Models for BT Classification

The research highlights the vital influence of dataset quality and various hyperparameters, including activation function, layer count, loss function, and filter size, on the effectiveness of DL models. A comparative study of methodologies across the literature highlights the greater performance of hybrid models. The remarkable performance of ViT stands out and is considered a key focus for future research developments.

Succeeding studies will order the enhancement of ViT's performance and research into the study of ViT-based hybrid models. Moreover, there are intentions to conduct experiments with HOG to refine the feature extraction process. Table 1 presents a comparison of various DL models, arranged in ascending order based on their accuracy. Across all studies, the classification objective remains multi-class classification, with the class names being Glioma, Meningioma, and Pituitary, except for Amran[4]. In the case of Amran[4], a two-class classification (Tumor/No Tumor) is conducted. From the literature, it is understood that CNN and ViT give promising results in the BT classification. So, we have done a comparative study on both the architectures. We have done it in two different ways.

In the first method, we have used same dataset for training and testing CNN and ViT models. In the second method, we trained the models with one Kaggle dataset and then tested with a different dataset. The orientation of the MRI images is totally different in the second set as shown in Figure 2.

Multiclass classification with 3-class and 4-class datasets are done. The classes are glioma, meningioma, pituitary, and No-tumour. Both CNN and ViT models are trained on the same datasets and noted their performance. From the result, we can see that the ViT architecture is giving a consistent performance with different datasets. The basic architecture of CNN used in all the experiments is as follows. We used two Conv2D layers([None,119,119,32] and [None,29,29,32]) interleaved with MaxPooling2D layers([None,59,59,32] and [None, 14,14,32]). It is attached with two dense layers and one drop out layer.

A. Performance of CNN and ViT on 3-class dataset

The performance of CNN and ViT on 3- class dataset is given below. CNN model gives 0.93, 0.86, 0.89mfor precision, recall, and F1-score respectively for class 0. For class 1, precision, recall and F1-score are 0.88, 0.7 and 0.78 respectively. For class 2, 0.75, 0.97, 0.85 for precision, recall and F1-score respectively. CNN gives

TABLE I. PERFORMANCE OF DIFFERENT DL MODELS ON BRAIN TUMOR CLASSIFICATION

References	Architecture	Classification Target	ClassesNames	No.of.Images	Accuracy	Precision	Recall	F1-score	Year
Badža [10]	CNN+ ReLU+ Drop(50%)+Maxpool+Softmax	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	92.7	90.13	90.61	90.14	2020
Alhassan[8]	CNN+Hard Swish ReLU+HOG RNN+Hard Swish ReLU+HOG	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	98.6 98.3	99.6 99	98.6 98.3	99 98.6	2021
Irmak [9]	CNN+ReLU+Maxpool+dropout(50%)+softmax	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3950	97.06	92.02	91.74	-	2021
Amran[4]	CNN+Batch_Norm+Clipped_ReLU+FCN+Softmax	two class	Tumor/No Tumor	3000	99	98.7	98.6	98	2022
Zahoor [11]	CNN+ReLU+AvgPool+Batch_Norm+FCN+feature_fusion+Softmax + SVM	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	5058	99.2	99.13	99.06	99.09	2022
Kibriya [7]	CNN+ReLU+Batch_Norm+MaxPool+dropout(50%)+FCN+Softmax	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	97.2	97	96	-	2022
Raza[5]	**CNN+Batch_Norm+Clipped_ReLU+Global_avg_pool+FCN+Soft**	Multi-Classification (Tumor	Glioma, Meningioma, Pituitary	3062	**99.67**	99.6	100	99.66	2022
Abd[6]	CNN+AvgPool+FCN+Softmax	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	98.63	98.72	98.83	98.77	2023
Tummala[13]	ViT(B/16.B/32,L/16,L/32)	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	98.7	-	-	-	2022
Asiri [12]	Fine tuned ViT	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	5712	98.13	98	98	98	2023
Maqsood[16]	CNN+ReLU+Max pooling +Softmax+Segmentation+MobileNetV2_SVM MobileNetV2 and LSTM hybrid network	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	97.47% 98.92%	-	97.22	-	2022
Kibriya [18]	**AlexNet, GoogLeNet, and ResNet18 + SVM, KNN**	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064	**Fused 99.7 99.7**	**99**	**100**	**99**	**2022**
Asif [19]	Xception, DenseNet201, DenseNet121, ResNet152V2, and InceptionResNetV2 deep dense block based on the Xception [Xception + DDB]	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	3064 3264	95.87	96.25	95.6	95.92	2023
Shahin [17]	PCANet+CNN+batchnorm+ReLU+avgPool--> Softmax	Multi-Classification (Tumor Type)	Glioma, Meningioma, Pituitary	9581	96.73	93.9	96.55	96.35	2023

precision 86% and recall and F1-score 84% , on average of three classes. The total number of images used is 3000.
For class 0, ViT gives 0.97 precision, 0.98 recall and 0.98 F1-score. For class 1, 0.96 precision, 0.97 recall and F1-score. For class 2, 0.98 precision, 0.97 recall and 0.98 F1-score. The overall performance of ViT is 97% precision, recall and F1-score. Total support is 3000 images. The performance is shows in Fig 1 and 2.

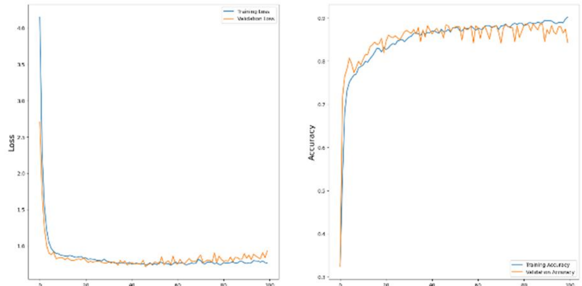

Fig. 1. Performance of CNN model on 3-class dataset

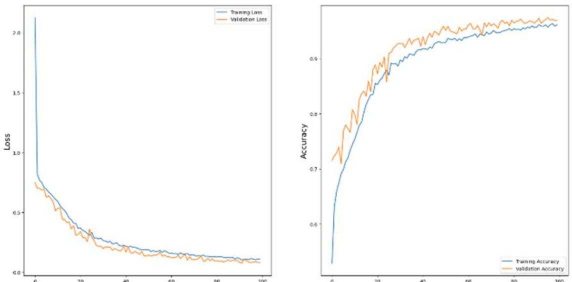

Fig. 2. Performance of ViT model on 3-class dataset.

B. Performance of CNN and ViT on 4-class dataset

The performance of CNN and ViT is measured on 4-class dataset. Figures 5 and 6 gives the comparison of these two models on 4-class dataset. CNN model gives 93% precision, recall and F1 score, whereas the ViT model gives 97% for precision, recall and F1-score.

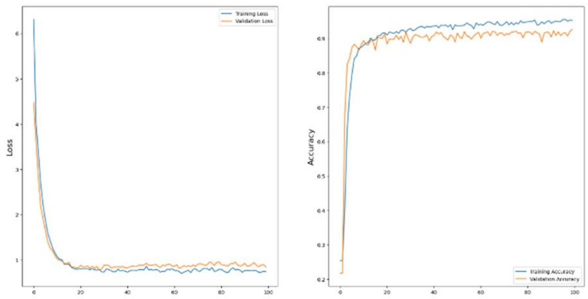

Fig. 3. Performance of CNN model on 4-class dataset

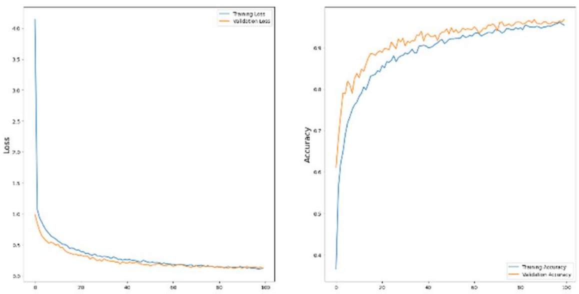

Fig. 4. Performance of ViT model on 4-class dataset.

The CNN model gives 0.97 precision, 0.98 recall and 0.97 F1-score for class 0. For class 1, 0.96 precision, 0.88 recall, and 0.92 F1-score. For class 2, 0.82 precision, 0.87 recall, and 0.84 F1-score. For class 3, 0.95 precision, 0.96 recall and 0.95 F1-score. The overall accuracy is 0.93. Total support is 1143 images.
The ViT model gives 0.98 precision, recall and F1- score for class 0. For class 1, 0.98 precision, 0.93 recall, and 0.95 F1-score. For class 2, 0.92 precision, 0.96 recall, and 0.94 F1-score. For class 3, 0.98 precision, 1.00recall and 0.99 F1-score. Overall accuracy is 0.97. Total number of images used is 1143. The performance is shown in Fig 3 and 4.

IV. CONCLUSION

In the literature study, we have gone through many research works which propose different BT classification methods using CNN, RNN, ViT and hybrid models. Out of these four approaches, CNN is the most popular and well performing model. ViT also has its potential since it performs consistently with different datasets. The comparative study with CNN and ViT over 3-class and 4-class datasets shows that ViT gives a consistent performance. In CNN models, ResNet is one of the best performers in BT classification. As a future work, we concentrate on a hybrid model based on CNN and ViT.

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