

A Fine Tuned Pre-trained Model for Classification of Brain Tumor using Magnetic Resonance Imaging

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Abstract— Any growth inside of the brain's restricted areas can harm humans. It is a challenging task for radiologists to classify tumor types because cancers are heterogeneous. The manifold collection of cells fosters prominent molecular squiggle with discriminative levels of sensitivity to treatment. Medical diagnosis has changed and diversified due to deep learning trends, particularly in magnetic resonance imaging (MRI). This study suggests a binary class classification and detection method for the early diagnosis of brain tumors as a solution to this issue. The pre-trained ResNet50, VGG19 and InceptionV3 deep learning models of the transfer learning approach make this possible. The different scenarios were assessed with the help of two classes of publicly available MR brain tumor datasets and with data gathered from hospitals. The accuracy rates for the pre-trained method InceptionV3, ResNet50, and VGG19 produced 99.72%, 98.84% and 94.65%, respectively. The three pre-trained models are ensembled. The highest performance accuracy in the detection of brain tumors was achieved using Inceptionv3, and VGG19 on testing samples. The results of the proposed method evaluation outperform those of existing methods.

Index Terms— transfer learning, classification, tumor, ResNet, Pre-trained model, VGG19, and InceptionV3.

I. INTRODUCTION

In the modern era, Johns Hopkins Medicine reported more than 120 distinct kinds of brain cancers, according to the brain tissue they affect. The microscopic structure of the brain is extremely multifaceted with multiple structures controlling different nervous system functions. About 25-30 adults per 100,000 have brain or cerebellum tumors [1]. Cutting-edge invasive and radiation therapies combined with improved diagnostic procedures have improved the lifespan by up to years and boosted the quality of life for patients after diagnosis. [2]. Advanced imaging and artificial intelligence (AI) image analysis demonstrated interesting differences in biological MR imaging statistics among molecularly defined tumor subgroups on newly diagnosed adult cancer patients with deep cellular characterization [3]. Due to brain tumor postoperative entirety and symptomatic hemorrhage affected 21.6% and 9.6% of patients, respectively. In univariate analysis, a needle biopsy was found to be significantly riskier for all symptomatic hemorrhages than methods that allow for adequate hemostatic manipulation (such as open and endoscopic biopsies) [4]. The management and treatment of brain tumors, one of the most challenging medical conditions to treat, depend on an early and accurate diagnosis. The most popular and effective diagnostic techniques for locating suspected primary brain tumors are computed tomography (CT) and magnetic resonance imaging (MRI), which can also assess the presence of edema, hemorrhage, and hydrocephalus [5].

Recent developments in transfer learning (TL) have enabled the recognition and classification of patterns found in medical imaging. The ability to retrieve and extract information from data without the help of radiologists and other medical professionals is a prime instance of this field's advancements. TL is proving to be a useful tool for enhancing performance in a variety of applications, such as disease prognosis and diagnosis, tumor tissue identification, and tumor grade classification [6-8]. In MR images, the most advanced technique recently used is a convolutional neural network (CNN), as the input images pass from the number of several layers to improve the accuracy if the MR images are high [9, 10].

In TL, data trained for a specific task can be reused for another related task, and it is carried out to reduce the problem of overfitting and to train fewer data with augmentation. Also, more reliable as compared to the traditional machine learning approach. Additionally, performance assessments have demonstrated that they possess excellent diagnostic precision [11-13].

Using a variety of techniques and models, numerous studies have been done on the classification of MR brain tumors [14-20]. However, some of these studies have limitations, such as a lack of performance comparison between the proposed model and machine learning methods [21]. The aim of relevant studies is to provide models for classifying two types of brain tumors without including no-tumor brains images [22-25]. Diagnosis of brain tumor is not always a straightforward mechanism to predict, not accurate and highly rely on the experiences of radiologists. There are crucial diagnostic challenges when there aren't the typical tumbling lesions [26] and limitations arise to medical experts and pathologists can benefit from computer-oriented interventions. Tremendous attempts have proposed automatic or semiautomatic techniques for brain tumor classification [27-30]. In the present study, we have tried to propose models, with constraints, and recommendations, and provide suitable solutions, which categorized brain tumors into two classes. The modeling methods have been compared to recognize significant variations that occur in terms of performance. The mentioned key points comprise our contribution:

- (1) Extensive dataset of 1926 T1C+, T2, and T1 MRI images used on our network, which are desirable for training and testing phases.
- (2) To demonstrate the concept of transfer learning by three pre-trained CNN architectures are used.
- (3) For the purpose of classifying the brain MRI images into meningioma and schwannoma classes, a standalone, layer-based CNN architecture is created from scratch.
- (4) The proposed scheme classifies brain tumor into two classes, and compared to the existing classification models.

The following subsections constitute the remainder of the paper. Information on the related work of research on brain MRI classification is detailed in Section 2. The suggested methodology and specifics of the TL algorithms are described in Section 3. In Section 4, it is further discussed how the experimental work compares to current cutting-edge TL approaches and ensemble deep learning (DL) approaches. Section 5 encompasses the research paper and discusses possibilities for the future.

II. RELATED WORK

In the recent years many methodologies related to transfer learning for classifying using MRI brain images are developed and summarized in Table I.

The study conducted by Hao et al. [31] in 2021, presented tumor diagnostic framework employed on transfer learning and reduce labelling cost to enhance the model performance. In the paper 2D slice used to train and fine tune model, consist of 203 patients for training and 66 patients for validation dataset; classification into LGG and HGG categories. The proposed model achieved AUC of 82.89% for 66 patient test datasets. TENGHONGSAKUL ET AL. [32] also employed transfer learning approach with InceptionResNet-V2, ResNet50, MobileNet-V2, and VGG16 in addition CLAHE image enhancement model used to improve the contrast. The proposed models applied using 253 MR images with split of 155 images of brain tumor and 98 of healthy brain images. The data augmentation applied and the dataset contained 1085 images of brain tumor and 980 healthy images. Data split into 70% (1445) of training, 15% (311) of test and validation of 15% (309) images. It has been analyzed from the literature that InceptionResnetV2 acquire 98.08% accuracy, MobileNet-V2 of 98.90%, ResNet50 of 99.73%, and VGG16 of 100%. MEHROTRA ET AL. [33], presented tumor identification by employing deep transfer learning approach, the pretrained models comprises of AlexNet, GoogleNet, ResNet50, ResNet101 and SqueezeNet. Total image consists of 696 MR images of T1-weighted, categorized into two classes benign (224) and malignant (472); the performance accuracy obtained ResNet101 of 94.74%, ResNet50 of 95.69%, GoogleNet of 98.09%, AlexNet of 99.04%, and SqueezeNet of 98.56%. The paper is limited to used small datasets and classification done using binary categories. ULLAH ET AL. [34], also presented deep learning approach to tumor diagnostic and classification

framework. The dataset is categorized into glioma, meningioma, and pituitary brain tumors. The author used to evaluate the performance on InceptionresnetV2, InceptionV3, Xception, Resnet18, Resnet50, Resnet101, ShuffleNet, DenseNet201, and MobileV2. The high accuracy achieved with 98.91%. Noreen et al. [35] presented a tumor diagnostic framework by employing pretrained Inception-V3 and DenseNet201 deep learning models; consist of 3064 T1-weighted contrast MR images; achieved highest accuracy in comparison to past research works. Ullah et al. [36] five CNN pre-trained models among which InceptionV3 and ResNet101 achieved 97% accuracy. The model is trained using Kaggle dataset with four tumor categories: no tumor, meningioma tumor, pituitary tumor and glioma tumor. Gomez et al. [37], proposed seven pre-trained models for classification of brain tumor and among these models InceptionV3 scored 97.12% accuracy on the datasets of Figshare, SARTAJ, and Br35H. Rajput et al. [38], employed ResNet50, VGG19 and InceptionV3 models for classification into four categories of consists of three types of brain tumor and healthy brain images using Kaggle datasets. The suggested models of Inception V3 achieved highest accuracy of 99%. Krishnapriya and Karuna [39], proposed VGG16, VGG19, ResNet50, and Inception V3 models using data augmentation on Chakrabarty 2019 datasets. It had been analyzed that VGG-19 acquired 99.48% accuracy with compare to other models. The summarized related work is shown in Table I.

TABLE I. RELATED WORK

Author	Aim	Tumor class	Dataset	Model
Hao et al. [31]	To reduce labeling cost	LGG, HGG	BRATS 2019	AlexNet
Tenghongsakul et al [32]	To enhance contrast of MR images by using CLAHE method	Tumor, Healthy brain	Kaggle	InceptionResNet-V2, ResNet50, MobileNet-V2, and VGG16
Mehrotra et al. [33]	To develop strong deep learning model of TL and investigate five models	Benign, Malignant	TCIA	AlexNet, GoogleNet, ResNet50, ResNet101 and SqueezeNet
Ullah et al. [34]	To compare the performance of hybrid approach (DL and SVM)	Glioma, meningioma, pituitary	Kaggle	InceptionresnetV2, InceptionV3, Xception, Resnet18, Resnet50, Resnet101, ShuffleNet, DenseNet201, and MobileV2
Noreen et al. [35]	To extract multi-level features from different bottom layers of the pre-trained models	Meningioma, glioma, pituitary	-	Inception-V3 and DenseNet201
Ullah et al. [36]	To automate categorization of brain tumors	Pituitary, glioma, meningioma, no tumor	Kaggle	CNN, VGG16, VGG19, InceptionV3, and ResNet101
Gomez et al. [37]	To employ optimized classifier using multi class	Glioma, pituitary, meningioma, healthy	Figshare, SARTAJ, Br35H	InceptionV3, ResNet50, InceptionResNetV2, Xception, MobileNetV2, EfficientNetB0, Generic CNN
Rajput et al. [38]	To detect and classify brain tumor	Glioma, pituitary, meningioma, normal brain	Figshare, SARTAJ, Br35H	VGG19, Inception-V3, ResNet50
Krishnapriya and Karuna [39]	To automate classification into tumor and non-tumor categories	Tumor, non-tumor	Chakrabarty 2019	VGG19, VGG16, ResNet50, InceptionV3

III. PROPOSED MODEL

In the CNN pre-trained approach, there are several models approached for brain tumor categorization, in this research we employed only three pre-trained deep neural network models, including InceptionV3, VGG19, and ResNet50, to determine how well they performed when identifying and classifying brain tumors.

The proposed model is depicted in Fig. 1., which demonstrates a concise view of TL based approach for brain tumor categorization using brain MR images. The proposed TL model for brain tumor classification comprises the following steps.

Phase 1, we collected freely available Kaggle MR image dataset for training and validation sets, including meningioma, and schwannoma MR images, and we split the dataset into the training, validation, and test directory. For testing collected data sets are utilized that is gathered from well-known Hospitals of India.

In Phase 2, we employed `train_datagen`. `flow_from_directory` to read the MR images of the dataset from the training directory.

Phase 3, the preprocessing phase is an essential task before performing data enhancing operations. It includes the following scenarios: Normalization process is carried out to perform resize operation. The input image for InceptionV3, VGG19, and ResNet50 is normalized to $229 \times 229 \times 3$.

Phase 4, a large number of datasets need to be used to train the deep learning model in order to improve accuracy. In every scenario, this method does not produce satisfactory results, especially when there are only small datasets available. The data augmentation process uses transformational techniques like rotation, scaling, and translation to increase the number of images to the database. The images in the training set are arbitrarily translated up to ten pixels vertically and horizontally, zoomed to a resolution of twenty pixels, and rotated at an angle between 90 degrees to increase the number of images. On the other hand, `featurewise_center = True` and `featurewise_std_normalization = True`, and rescaled to $1.0/255$ for the validation set of images. For this `ImageDataGenerator` function was utilized to dynamically create sets of augmented images during the training, and validation process. Furthermore, the augmented images were only used to train the proposed framework, and also for the validation phase, hence, only real images which were collected from hospitals were utilized to test the learned framework.

TABLE II. DATA AUGMENTATION

Class	Total Slices	Augmented Images	Format	Type
Meningioma	1326	3345	JPG	Grayscale
Schwannoma	465	889		

Phase 5, for evaluating the performance of the proposed model, the dataset is split into 3-fold cross-validation train-validation-test set.

Phase 6, involves unfreezing some of the top layers in order to train the final base model layers as well as the newly added classifier layers. The method enables the base model's higher order feature representations to be fine-tuned so that they are more pertinent to the given task.

Phase 7, which divides brain tumors into binary classes. In the study, a softmax layer in the transfer learning models categorized images into two classes, meningioma, and schwannoma, by using the terms.

In this study we use pre-trained CNN models to classify brain tumors in two classes of meningioma and schwannoma.

The Fig. 2. depicts the general architecture of pre-trained TL classification for identifying and classifying brain tumors. Additionally, we assessed and validated each model to determine how well various pre-trained TL algorithms performed at classifying the various types of brain tumors.

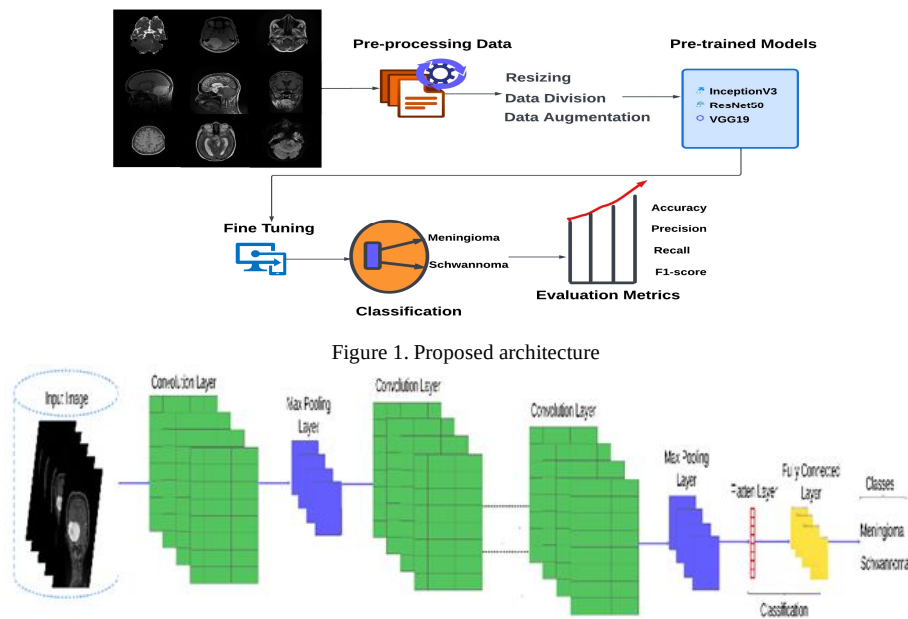


Figure 1. Proposed architecture

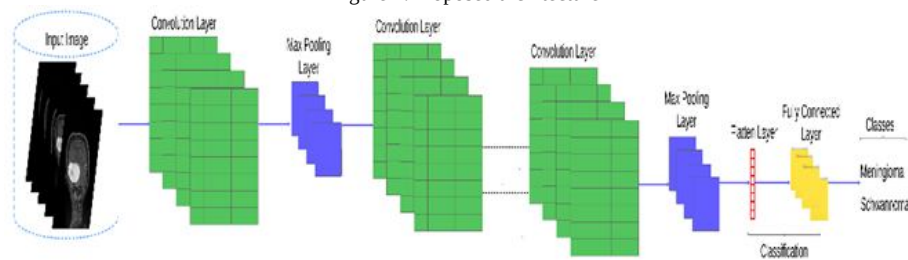


Figure 2. Architecture of pre-trained model

A. MR Dataset

In this work, the dataset exploited was downloaded from Kaggle 2020 [40] and combined with the collected dataset from Safdarjung Hospital New Delhi, PGI Hospital, and Medanta Hospital, India. Images are 512 x 512 pixels in size. For the collected dataset of every patient, radiologists examined independently the MRI image to define the pathological type. The dataset has different physiological structures, shapes, colors, and positions, etc. The sample of MRI images are given in Fig. 3. First row represents the meningioma type of brain tumor and second column shows schwannoma brain tumor, where they exhibit different appearances.

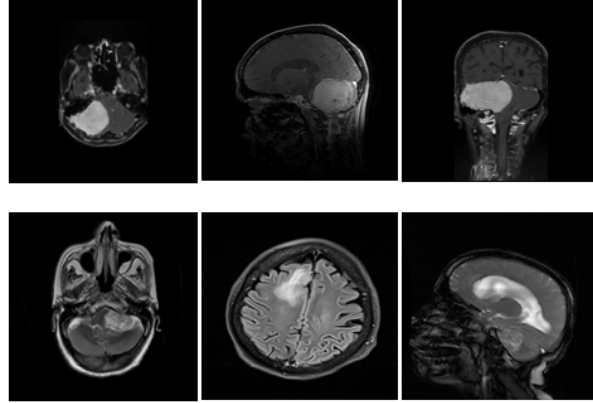


Figure 3. Sample MR images of two patients with meningioma and schwannoma brain tumor row wise

The dataset comprises of 1926 slices, including 1354 images belongs to training set and 572 images contains for validation set directory. In the Fig. 4. (a, b) shows the number of images contained in the training set for classification into meningioma and schwannoma brain tumor and validation set considered for tumor detection respectively. Further, Table III represents the dataset summary exploited in our study.

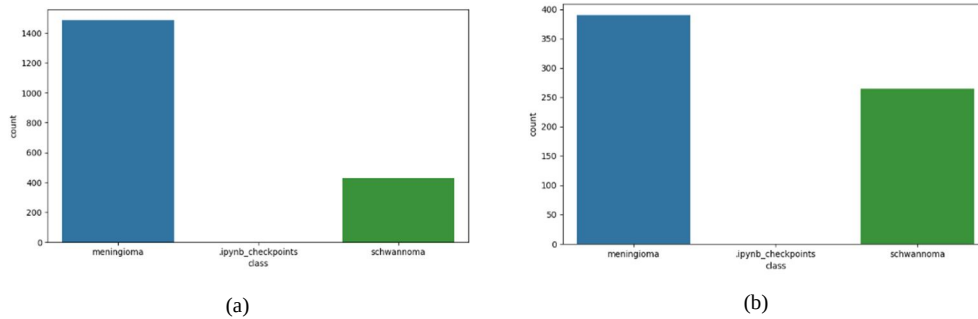


Figure 4. Total number of images (a) Training set (b) Validation set

TABLE III DATA SPECIFICATION

Data	Source	MR Sequence	Total Image	Format
Kaggle (train + Validation)	Online	T1, T2, T1C+	1926	JPG
Collected (test)	SGPGI, Safdarjung, Medanta Hospitals	T1+C, T2, Flair	26	

IV. EVALUATION

In this section, thorough information is adopted of fine-grained brain tumor classification experimentation. i.e., the TL settings and it provides an in-depth discussion of the findings to assess the performance of our model. For this, the proposed framework uses three CNN architectures, such as InceptionV3, VGG19, and ResNet50.

A. Machine Settings

The pre-trained TL networks are employed for this research, i.e., InceptionV3, VGG19, and ResNet50, which can categorize images into numerous different type classes and are trained on 1.28 million images of the ImageNet database. The aim of this study is a two-class classification of brain tumors using the brain tumor dataset. Experiments were carried out by assigning different values to the parameters to determine the optimum values for each parameter. We utilized a 0.001 learning rate and a 32-image batch size. In addition, each deep learning model was trained up to 60 epochs to conduct the TL experiments for detecting and categorizing brain tumor types, accounting for the possibility of overfitting. We performed all experimentations on a machine equipped with T4-GPU. For implementation, we used the Google Colab version of PYTHON. The refined parameters used for the classification experiments. All the TL models were trained and validated on the same TL settings indicated in Table IV for the classification of brain tumors.

TABLE IV. PARAMETERS OF TRANSFER LEARNING ARCHITECTURES

Parameter	Value
Classifier	SoftMax
Total Epochs	60
Optimizer	Adam
Verbose	1
Loss Function	Cross-Entropy
Activation Function	ReLU
Patience	10
Batch Size	32

B. Evaluation Metrics

We proposed the accuracy, precision, recall, and F1-score [6] in the study to evaluate the effectiveness of all deep transfer learning networks. These performance metrics are determined:

$$\text{Accuracy} = \frac{TP+TN}{TS} \quad (1)$$

$$\text{Precision} = \frac{TP}{TP+FP} \quad (2)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (3)$$

$$\text{F1-score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

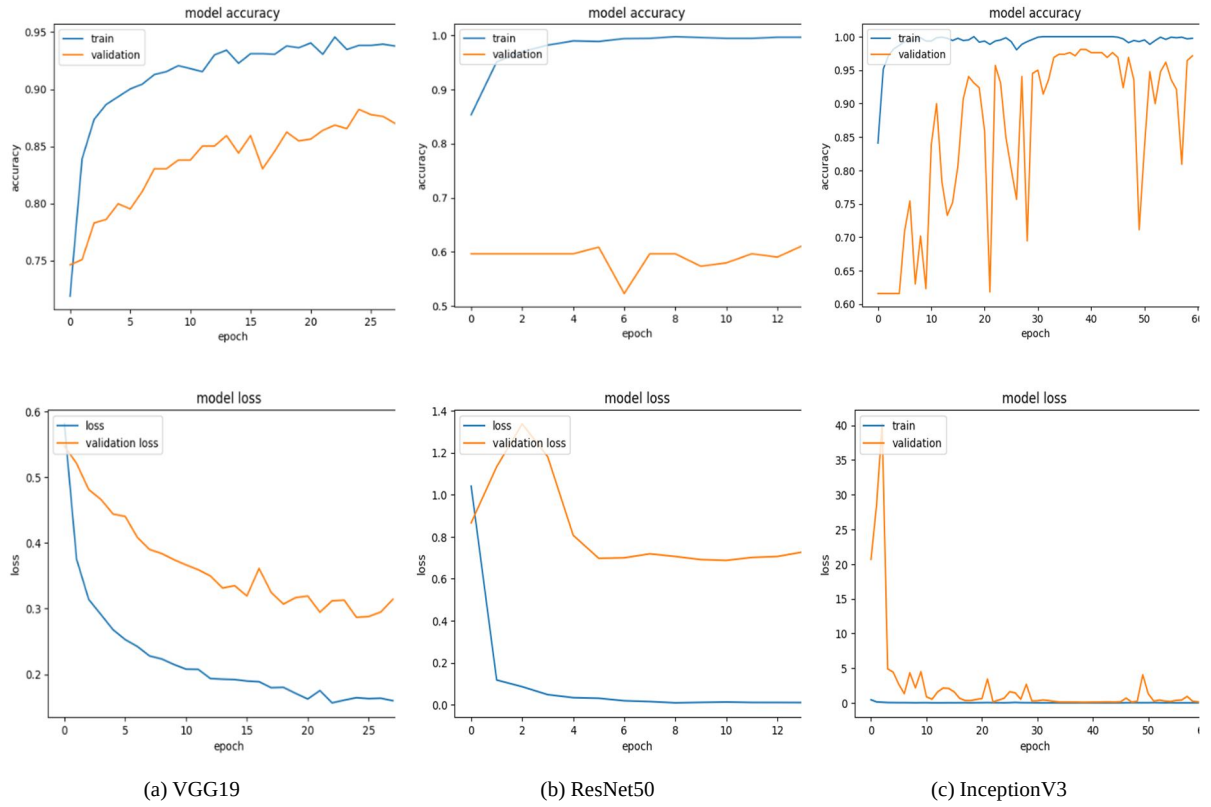
Where, TP stands for true positive, TN for true negative, FP for false positive, and FN for false negative and TS denotes the total number of images.

C. Results

This section analyses the functioning of different pre-trained TL models used to categorize the brain tumors dataset into meningioma and schwannoma. The major benefit of TL classifiers is to reduce overfitting problem and fine-tuning, which rapidly occur in deep learning algorithms when training with a smaller amount of images.

The training and testing accuracy of our best operated pre-trained models, i.e., VGG19, ResNet50, and Inceptionv3, is represented in Fig. 5. For this the data augmentation technique are used, which notably increased the size of dataset, all models took substantial time for classification. The experiment is carried out by setting number of epochs equal to 60. In each epoch, accuracy, training, and validation error is calculated. The proposed model achieves highest classification accuracy and lowest training and validation loss compared with other architectures. The accuracy and loss of each proposed model are shown in Fig. 5 column wise.

Table V represents the detailed results of various TL algorithms in classifying brain tumor images and shows that each TL classifier achieved satisfactory results. Using evaluation metrics for accuracy, precision, recall, and f1-score, we examined and assessed the TL algorithms. The results show that the InceptionV3 DL model achieved the best average accuracy of **99.72%**. Whereas, VGG16, and ResNet50 achieved the lowest average accuracy of 94.65%, 98.84% respectively. We also concatenate these three models by employing best saved model. As shown in Table V the ensemble model does not gives satisfactory results as compared to InceptionV3 model. The ensemble system, however, displays the lowest correctness metrics standard deviation, demonstrating that its



performance is more consistent when tested with threefold cross-validation. It is essential to mention that data augmentation and hyper parameter tuning of the InceptionV3 framework achieved different results. It is evaluated that the ensemble model does not gives satisfactory results as compared to InceptionV3, ResNet50, and VGG19 model. InceptionV3 model achieved effective results because of several reasons. This model can extract more robust, detailed, and discriminative, deep features. The proposed model InceptionV3 produced excellent performance in brain tumor classification which are shown in bold style in Table V. The comparison findings of Table V pre-trained models are represented in Fig. 6.

TABLE V. AVERAGE CLASSIFICATION ACCURACIES

Model	Evaluation Metrics				Total Time
	Accuracy	Precision	Recall	F1-score	
InceptionV3	99.72%	89.48%	88.55%	87.66%	25m14s
ResNet50	98.84%	95.98%	76.84%	91.50%	10m 56s
VGG19	94.65%	87.89%	84.66%	85.87%	35m20s
Ensemble Model(VGG19 + ResNet50 + InceptionV3)	85.68%	86.06%	86.76%	86.54%	10m 23s

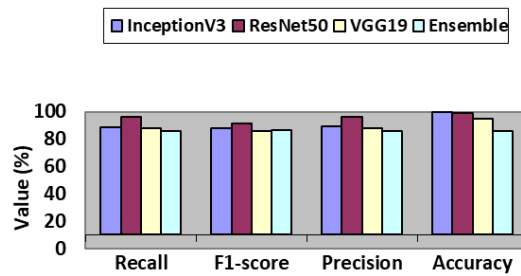


Figure 6. Comparison between pre-trained models

D. Comparison with state of art work

Table VI shows the comparison study among existing approaches and proposed work. For performance evaluation only accuracy metric more significantly evaluated in the approached research work. In the Table VI first column represents the related work, second column shows the models employed in each work. Whereas the third column shows the accuracies of the computed models. According to the Table VI, the InceptionV3 model of proposed work indicates 99.72% accuracy. Which is highest compared to existing state-of-art-work. Due to fine-tuned hyperparameter values and for testing meningioma and schwannoma brain tumor categorization includes real MRI images from Hospitals, which gives better results for tumor classification.

It is also demonstrated from Table VI that Zobeda and Nazrov [45], utilized same InceptionV3 model acquired least accuracy with 96.6% on binary classification. Whereas Srigiri & Yepuganti [39] also utilized InceptionV3 model and achieved 81.25% accuracy using 305 MR images.

TABLE VI. COMPARISON WITH PREVIOUS WORK

Work	Model	Accuracy
Srigiri & Yepuganti [39]	VGG19, VGG16, ResNet50, InceptionV3	99.48%, 99%, 97.92%, 81.25%
Mohsen et al. [41]	VGG19, ResNet101	99.98%
Fatima et al. [42]	EfficientNetB2	98.86%
Muezzinoglu et al. [43]	PatchResNet	98.10%
Anul et al. [44]	DCNNBT	99.18%
Zobeda and Nazarov [45]	InceptionV3	96.6%
Demir et al. [46]	MobileNetV2+KNN	99%
Proposed model	InceptionV3 + Augmentation + Fine tuning	99.72%

Also analysed that results acquired from other studies to classify brain tumor using CNN models ranged from 96 to 99% accuracy.

V. CONCLUSION

This paper represents a comparative analysis of InceptionV3, VGG19, ResNet50, and ensemble models for the classification of brain tumors. The goal of this effort was to automate the prediction of brain tumors by finding a better classifier for brain tumor classification. The deep learning models applied and classified brain tumors into meningioma and schwannoma using a classification MRI dataset. An accuracy of 99.72% signifies the effectiveness of InceptionV3 for reliable brain tumor classification. Despite the limited data we have achieved good results. For this, we have applied a data augmentation technique to increase the size of training and validation set. In the future, results can be further improved by training models with larger datasets.

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