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Leveraging Pre-trained Models for Precision: A Transfer Learning Approach to Brain Tumor Detection

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Abstract. Brain tumors are extremely dangerous and can lead to a drastically shortened life expectancy, making them an extremely hazardous illness. In order to create treatment programs that can prolong the lives of people impacted by brain tumors, a correct diagnosis is essential. It is difficult and time-consuming to manually identify and analyze massive amounts of MRI data. To successfully categorize brain tumors, we present a new DL method based on transfer learning in this -research. We have conceptualized a novel strategy that incorporates fine-tuning, transfer learning architecture rebuilding, and thorough pre-processing. In our transfer learning implementation, we make use of Xception, VGG19, and MobileNetV3Small, among others. Xception achieved an accuracy score of 96.84%, whereas VGG19 achieved an accuracy score of 84.98%, using the public domain Kaggle MRI Brain tumor -dataset that consisted of 253 pictures. Based on our research, Xception outperforms other models on the MRI Brain tumor -dataset, reaching an impressive accuracy rate of 96.84%. To help neurologists and physicians make quick and accurate diagnoses for patients with brain tumors, our suggested model can effectively categorize tumors in a short amount of time.

Keywords: Neuroscience; Transfer-Learning; VGG; Brain-MRI Image; Brain-Tumor.

INTRODUCTION

An accurate identification of a brain tumor is crucial for the creation of a successful treatment strategy. More than 120 distinct tumors can develop inside the neural system and specifically in the brain. Brain MR images are manually classified by neurologists according to the World Health Organization's (WHO) standards. Robots have greatly improved radiologists' ability to diagnose patients and cut down on interventions by automating the categorization process, especially for brain MRimages. Researchers now have access to a number of publicly available brain MR imaging datasets that can be used for classification. Because of this, medical researchers are able to create more efficient automated classification systems. Too much complexity during CNN's training leads to overfitting due to the small number of samples of medical datasets. Adjusting the models' extreme parameters as well as learning parameters is also necessary for successful use of deep CNNs that have been previously trained derived from transfer learning techniques in medical imaging [Mok24].

The possibility of catastrophic deaths increases after tumor cells are produced in the human brain. Brain tumors are exceedingly dangerous and difficult to treat without smart interventions because of the complexities involved. Tumors begin their development in the brain and may metastasize or propagate to different sections of the body over time. The buildup of cancer cells in the brain presents difficult issues, but there is a way to tackle them: build computers that behave like live creatures. These machines are smart enough to correct their own errors and use what they've learnt in different contexts. In this respect, Convolutional-neural-networks (CNNs) have a significant influence on artificial intelligence (AI), digital image processing, and medical imaging [Che20].

It is possible for certain brain tumors to harm brain areas that are nearby. Therefore, physicians need to pinpoint the precise part of the brain that needs treatment or surgery before they can conduct any procedure. Brain tumor segmentation involves identifying and separating malignant tumors from healthy, unaffected tissues. So far, diagnostic approaches have not met a more difficult challenge than brain segmentation. Rather than being domain-specific, many exclusionary approaches rely on generic edge-based data. Recently, algorithms based on Deep learning has been used for tasks related to tumor segmentation because of how well they recognize visual features [Sri22, Dha23, San24, Ull22, You22].

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We introduce a brain tumor-specific automatic classification system in this research. Our data comes from the Kaggle brain MRI dataset, which includes both healthy and diseased brain MR scans. We used three deep convolutional neural network (CNN) architectures—Xception, VGG19, and MobileNetV3Small— in order to extract information from magnetic resonance pictures of the brain using deep transfer learning, and this dataset served as our basis. The radiologist's work is simplified by this technique, which aids in the solution of the brain tumor categorization problem and the development of successful treatments. According to the training time and epoch number, we provide the three pre-trained architectures' total classification accuracy. We investigate the effect of the number of epochs in order to reduce the time required. We categorize the traits that were retrieved for a total of ten distinct epochs. When compared to analogous works, we acquire good outcomes [Ran23, Li23]

To assist medical professionals in determining the optimal course of action and preventing premature mortality from brain tumors, it is essential to develop a robust deep learning model that can properly predict brain cancers in a timely manner. Consequently, our research aims to establish an efficient and systematic framework for classifying brain cancers, employing various preprocessing techniques for gathering our dataset, modifying the transfer learning architecture, and incorporating additional layers. The suggested deep learning method is evaluated using the publicly accessible Kaggle MRI brain tumor dataset. To construct an effective model, we employed our innovative deep learning approach for enhanced brain tumor categorization. This research evaluates the efficacy of our recommended deep learning model using multiple performance-metrics, including preciseness, Recall, Accuracy, F1-score, with Confusion Matrix. The results indicate that our deep-learning algorithm can classify brain cancers with an accuracy rate above around 97%.

This research's primary contributions are given below:

- By including thorough preprocessing, tweaks to the transfer learning architecture, and optimization for efficiency, it showcases a new deep-learning model for the categorization of brain tumors.
- To fix overfitting problems and make use of GPU acceleration, the redesigned architecture is changed to incorporate image augmentation. Further, to quickly standardize images per configuration, which allows for the augmentation process to be reimplemented with ease.
- Fine-tuning involves incorporating layers with an altered architecture, enabling the progress of a new deep-learning system for quickly classifying brain tumors.
- Ultimately, evaluate the efficacy of our suggested models utilizing several metrics, which are Accuracy, Precision, Recall, F1-score, & Confusion-matrix, to identify the optimal model for classifying Brain tumors.

Literature review

Below mentioned Table 1 gives brief details about different published articles based on Brain-tumor Detection and Classification with the details of dataset used, methodology, findings and future scope.

Table 1

Brain Tumor Detection and Classification Related work

1	2	3	4	5	6
2024 [Mok24]	Seyed Masoud Ghoreishi Mokri et al.	MRI dataset from Tehran Faculty of Medical Sciences. 200 MRI images, 12 used for training.	Conversion to Gscale, pattern generation, and correlation calculations for tumor detection. Classification of tumor location, type.	The accuracy of the best model achieved in the study was 99% CNN.	Use advanced networks for detecting various medical issues accurately. Design network with higher power to detect different problems effectively.

1	2	3	4	5	6
2020 [Che20]	R Chelghoum, Ameur Ikhlef, et al.	Brain CE-MRI dataset with glioma, meningioma, and pituitary tumors. Public dbase from Nanfang Hospital China.	9 pre-trained deep networks applied for brain tumor classification. Deep TL with minimal pre-processing for brain MRI classification.	Achieved up to 98.71% classification accuracy using transfer learning. Overfitting observed in SENet with epochs 25 and 50.	Apply system to classify X-rays, PET, and CT for organs. Investigate the effect of epochs on classification performance.
2022 [Ran23]	Meghavi Rana, Megha Bhushan	MRI, X-Ray, infrared, CT-Scan, and lesion data sets were utilized. Public and own created datasets like brain MRI tissues.	Machine learning models use gradient boosting and DT base-learners. Deep Learning algorithms: Multiple instance learning, CNN, LSTM.	CNN and RF had better accuracy: 97.6 and 96.93, Medical image classification makes extensive use of SVM.	Denoising techniques should be used with DL models in the healthcare area. Explore more attributes of DL models used to medical pictures. Improve model potential for handling large datasets to increase accuracy.
2023 [Li23]	M. Li, Y. Jiang, Y. Zhang, H. Zhu	Dataset collection from investigations including imaging, clinical trials, and public databases Diverse, representative datasets for ML algorithm training and testing	Used a variety of models, including CNNs, RNNs, GANs, LSTMs, and hybrids. A new classification system using deep learning techniques applied to medical imaging. .	CNN:- 97.6% RF:- 96.93% SVM:- 95.05%	Multi-modal picture analysis for enhancing diagnostic precision and lowering incorrect diagnoses. Performing medical image analysis using deep learning techniques.
2022 [Sri22]	C. Srinivas, N Prasad, et al.	Kaggle dataset for brain MRI scans in the study. Brain MRI pictures classified as either benign or malignant tumors	Classification of brain tumors using CNN-pretrained VGG-16, ResNet-50, and Inception-v3 models. Machine learning using convolutional neural networks (CNNs) as a baseline	VGG -16: 0.96 Inception - v3: 0.78 ResNet50: 0.95	Examine the effect of various hyperparameters on the efficiency of the model. Enhance classi. accuracy by fine-tuning models with transfer learning methods. .
2023 [Dha23]	Tribikram Dhar, Nilanjan Dey, et al.	Synthetic datasets are created through image data augmentation techniques. Chest X-ray images, skin lesion medical images, and augmented CT images.	Decision trees, SVM, logistic regression, CNN, and black-box methods. Model-agnostic methods provide flexibility and high-level evaluation.	Challenges in deep learning healthcare adversarial attacks, data availability, trust issues.	Interactions in AI governance among organizations. IT, data, and AI governance intersections for research.
2024 [San24]	Yenumala Sankararao, Syed Khasim	Kaggle dataset: 253 images for binary classification. Figshare dataset: 3064 images for multi-class classification. BraTS sets: HGG and LGG classes.	Utilization of CNNs, RNNs, and hybrid models for tumor analysis. Evaluation of DL techniques for segmentation, prediction, classification, and assessment.	Transfer learning with Alex Net-Accuracy: 100% InceptionV3, CNN mode: 99.82%	Addressing standardization challenges in DL algorithms for brain tumor. Exploring new methodologies for dimensionality reduction in brain tumor analysis. Investigating the potential of different

1	2	3	4	5	6
					MRI modalities for tumor detection.
2022 [Ull22]	N. Ullah, J. Khan, Mohd Khan, et al.	Kaggle Brain tumor categorization (MRI) dataset for research. Image dataset includes Meningioma, Pituitary, and Glioma MRIs.	Decision trees, SVM, logistic regression, CNN, and black-box methods. Model-agnostic methods provide flexibility and high-level evaluation.	Accuracy = 98.91%, Precision = 98.28%, Recall = 99.75% and 99% -F-measure with InceptionrenNetv2 TL algorithm.	Train model with a larger dataset for improved results. Examine other deep neural networks' brain tumor detection TL.
2022 [You22]	Ayesha Li Qiang, Charles Okanda Nyatega, et al.	BRATS 2013 Dataset, World Brain Atlas, Brain MRI images.	Convolutional Neural Networks (CNNs) for image processing and categorization. Brain tumor identification using VGG 16.	CNN = 96%, VGG 16 = 98.5% and Ensemble Model = 98.14%.	Utilize diverse image modalities for brain region approximation. Enhance precision and accuracy using ensemble methods in future research.
2022 [Ata23]	Sema Atasever, Nuh Azginoglu, et al.	ImageNet, MICCAI 2012 PROMISE12, COVID-chest X-ray-dataset, IXI Dataset. BrainWeb, PPMI, BraTS, OASIS, ADNI-172, ABIDE IABIDE II.	Capsule Network-based framework (COVID-CAPS) for X-ray COVID-19 detection DenseNet based CheXNet for mammography breast cancer detection 3D-UNet for MRICT whole heart segment.	Hybrid model for disease diagnosis using a pre-trained model 92.68%.	Artificial intelligence in diagnosing gastrointestinal diseases using wireless capsule endoscopy. Transformer architectures, self-supervised learning, and few-shot learning gaining popularity.
2024 [Zi24]	Yun Zi, Qi Wang, Zijun Gao, et al.	ACDC dataset: Cardiac MRI for structure segmentation and analysis. BraTS dataset: Multimodal MRI for brain tumor segmentation. LiTS dataset: CT images for liver tumor segmentation.	Self-attention mechanism and U-Net structure for feature learning. Gradient descent optimization algorithm for model parameter updates. Cross-entropy loss function for multi-category segmentation tasks.	Achieved Dice coefficient of 85.3%, IoU of 78.9%.	Explore attention mechanism in MIS and 3D recon for optimization. Enhance model structure/parameter settings for improved performance. Combine multi-modal data for enhanced applicability.
2023 [Naz23]	Sajid Nazir and Mohd Kaleem	differential private FL TCGA. ABIDE, ADHD-200, COBRE for mental condition joint diagnosis. HAM10000 homomorphic encryption skin lesion classification dataset.	Contrastive learning, FedAvg, DenseNet, ResNet, U-Net, Capsule network.	Multiclass classification of skin diseases using FL-94.15%.	Addressing data heterogeneity in retinopathy for improved model performance. Enhancing pneumonia classification with CXR images for scalability and accuracy.

RESEARCH METHODOLOGY

We used transfer learning to classify brain tumors using three pre-trained deep networks: Xception, VGG19, and mobileNetV3Small.

VGGNet. K. Simonyan and A. Zisserman [Sim14] looked into how the depth of a neural convolutional network affected the quality of picture identification. Researchers are extending the complexity of the generated VGGNet to 11–19 weighted layers with diminutive (3×3) convolutional filters. The configurations utilizing 16 as well as 19 weight layers, designated as VGG16 and VGG19, exhibit optimal performance. The categorization error diminishes with increased depth, stabilizing until the depth reaches 19 levels. The authors state that visual representations with depth are important [You22, Ata23].

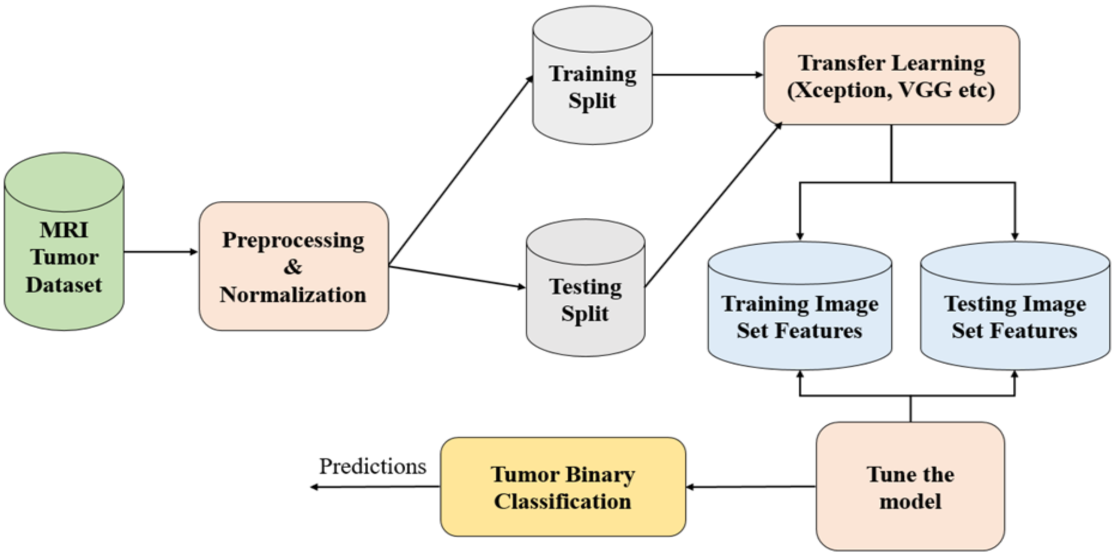


Fig. 1 Structure of Proposed Research Methodology

Xception

An Extreme Inception Deep Convolutional Neural Network (CNN) design is referred known as "Xception" for short. The Xception is compatible with images that have a dimension of 299×299×3, where the third digit stands for the number of channels in RGB photos. Xception uses depth-wise discernable convolutions, which entail a method which iteratively processes points following a depth-wise convolution, as opposed to traditional convolutions. The spatial dimensions of the output are reduced to 1×1 by applying a Universal Cumulative-pooling layer after convolutional layers.

MobileNetV3Small

An extremely effective and compact neural network architecture, MobileNetV3Small was created especially for mobile devices image classification and related tasks. This variation belongs to the MobileNetV3 family, and it includes both small and large versions in order to strike a balance between latency and accuracy.

Above mentioned Figure 1 demonstrates the proposed methodology of our research.

- First step: To run the experiment, we grab the dataset of brain tumors.
- The second step is to enlarge the image to 256×256, apply a filter to make it sharper, complement it, and finally scale it to make the data in the image normal.
- Thirdly, in the retraining transfer learning architecture stage, we truncate the layers following the activation layer and add image enhancement after the input layer.
- Fourth Step, we refine the model by adding layers that improve its ability to classify brain cancers. These layers include Global-average-Pooling, Batch-normalization, and Dense-layer.
- Fifth Step: Here, we implement our strategy by making use of Xception, VGG19, and MobileNetV3Small, three popular transfer learning algorithms.

Lastly, performance criteria i.e. Accuracy, precision, Recall, F1-score, Confusion-Matrix, and Remaining are used to assess each transfer learning method and choose the best one. In addition, we compare our findings to those of previously published publications.

Model training and preprocessing pseudocode

```
# Data Pre-processing
for img in Dataset:
    processed_img = normalize(img) # Normalize the input image
    augmented_images = apply_augmentation(processed_image) # Perform data augmentation
# Model-Structure
model1 = Sequential ()
model1.add(base_model) #Add the pre-trained base model
model1.add (GlobalAveragePooling2D()) #Use global-average-pooling layer
model1.add (Dense (128, activation='relu'))  # Add a dense-layer with ReLU-activation
model1.add(Dropout(0.5))  # Apply dropout for regularization
model1.add(Dense(1, activation='sigmoid'))  # Add output-layer with sigmoid-activation
# Transfer Learning
base_model = Xception(input_shape=(img_size, img_size, 3), include_top=False, weights='imagenet')
for layer in base_model.layers[:4]:
    layer.trainable = False  # Freeze the Starting layers of the base-model
# Training
model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])  # Compile the model with Adam optimizer
history = model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=10, batch_size=32)  # Train the model with training data
# Estimation
predictions = model.predict(X_test)  # Make estimate on Test data
evaluate_model(predictions, y_test)  # Assess model
```

Dataset

"Brain MRI Images for Brain Tumor Detection" was the dataset employed to construct the corresponding context in the given investigation. The three well-known types of brain cancer included in the dataset were meningioma, glioma, and pituitary tumors. With the use of an MRI-dataset comprising 253-Brain scans from 155 distinct patient-cases and features, Sted models were trained and evaluated. The data set containing tumor information has been sent for analysis. Fig. 2 shows the Brain MRI Images dataset structure and the classification technique, which will be explained later.

a *b*

Fig. 2 Dataset *a* contains MRI scans of the brain with black borders, while dataset *b* contains scans without such borders

RESULTS AND DISCUSSIONS

The transfer learning architecture has been reconfigured and fine-tuned by incorporating additional layers. The proposed technique for cancer in the brain identification was tested using three different transfer-learning algorithms. Performance is assessed through various indicators. The subsequent section presents the Experiment-setup, Performance-evaluation-metrics, Results-analysis, and Discussion.

Experimental Setup

The research utilizes a computer equipped with an Intel-Xeon-CPU featuring 2-cores, 13-GB of RAM, 16-GB GPU, and a 73-GB hard-drive. Experiment was conducted using Google Colab. The proposed approach is implemented using Python, along with several widely utilized libraries, including Scikit-learn, Keras, TensorFlow, Seaborn, Matplotlib, Numpy, and Pandas.

Performance-Evaluation-metrics

Multiple performance pointers, including Accuracy , precision, recall , F1-score, and confusion-matrix, assess the efficacy of our planned approach. Metrics established for the performance evaluation are as follows.

The confusion-matrix assists as a technique for assessing the efficacy of ML-categorization. This tabular structure presents four distinct groupings of the predicted & actual values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Table 2 demonstrates the confusion-matrix, which employs these labels to denote the right and wrong predictions for positive as well as negative values. A confusion matrix serves as an essential instrument for evaluating accuracy, precision, recall, and F1-score in the assessment of dependability.

Table 2

Confusion Matrix

	Actual positive	Actual negative
Predicted Positive	TP	FP
Predicted Negative	FN	TN

Accuracy is a key statistical measure, determined by the ratio of correct consequence outlooks to the entire No. of annotations:

$$Accuracy = \frac{No.\ of\ correctly\ classified\ samples}{Total\ Number\ of\ Samples} \times 100. \quad (1)$$

The accuracy rate, in percentage terms, of anticipated +ve values relative to total number of expected + ve values is called Precision. Here is a visual representation of it:

$$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}. \quad (2)$$

The accuracy rate of positive predictions relative to all other actual outcomes is called recall. The result is:

$$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}. \quad (3)$$

A degree of performance for classification problems, to get the F1-score, take the Harmonic-mean of the Precision and Recall values. A common way to express it is as follows:

$$F1\ Score = \frac{Recall \times Precision}{Recall + Precision} \times 2. \quad (4)$$

Assessment of outcomes and efficiency

We propose an approach that employs 3 transfer learning algorithms to efficiently classify Brain-tumors using the Brain-tumor-dataset. Figure 3 illustrates the efficacy and Assessment of transfer learning models' mistakes we have deployed. Figure 3 illustrates the accuracy rates, which are recorded at 96.84%, 84.98%, and 61.26%. The precision rates are 97.42%, 85.02%, 61.26%; the recall rates are 97.42%, 91.61%, 100%; the rate of F1-score is 97.42%, 88.2%, 75.90%; for Xception, VGG19 and MobileNetV3Small respectively. Among every single model, Xception attains peak performance with 99.84% -accuracy, 97.42%-precision, 97.42%-recall and 97.42%-F1-score rate.

Figure 4 displays the loss and accuracy graphs for all transfer learning models. The Accuracy rate rises, and the Loss rate decreases as the number of epochs increases. The models do not exhibit overfitting, as seen by the learning curves, as they get a solid grasp of the input at each epoch. The overfitting problem is solved by the augmentation process.

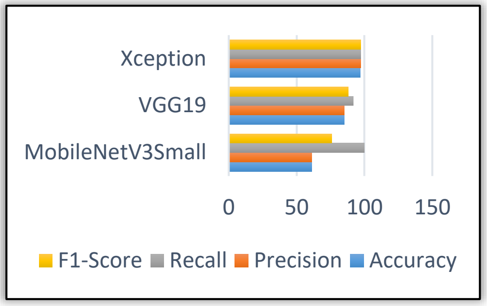


Fig. 3 Performance Analysis of all Transfer Learning Models

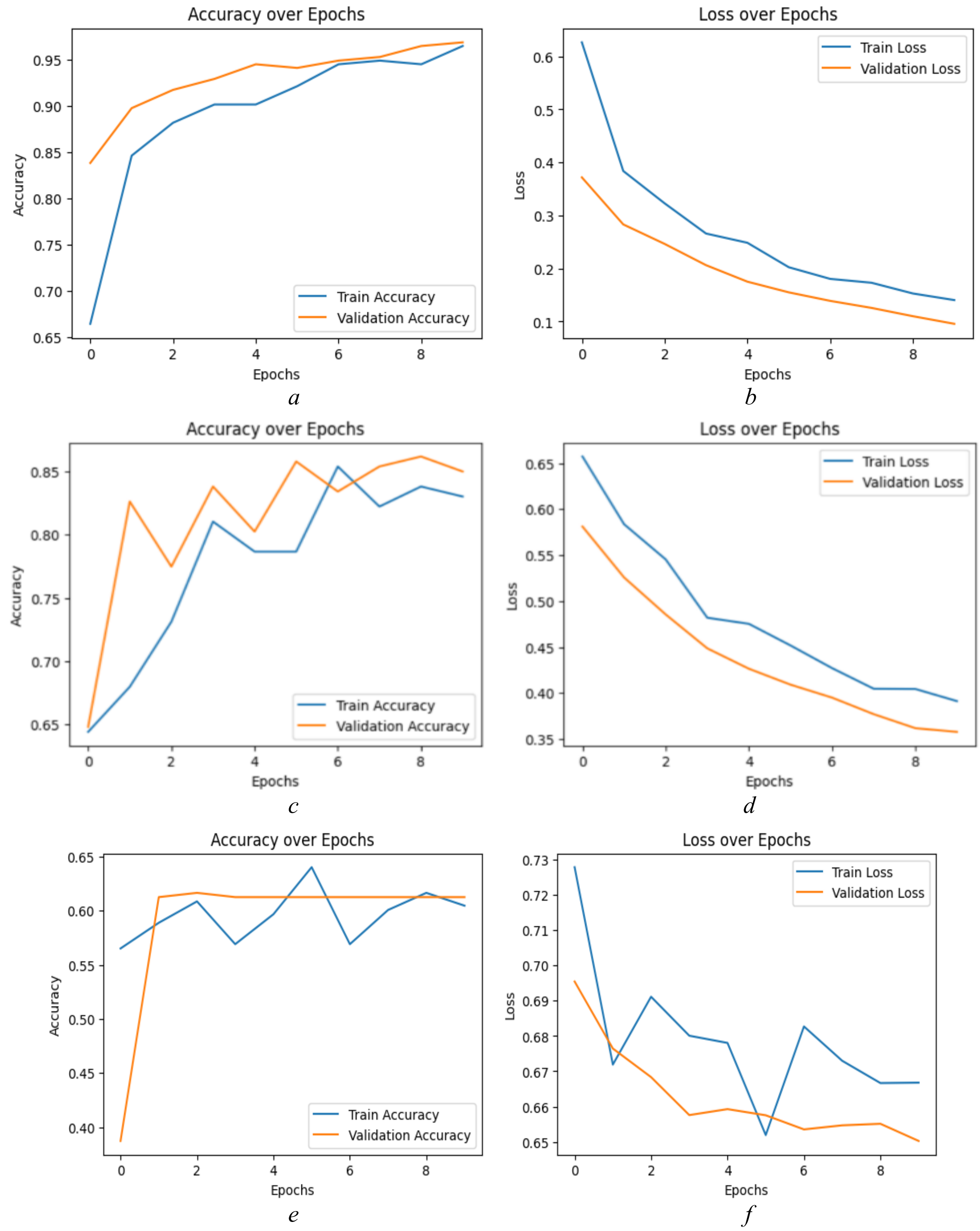
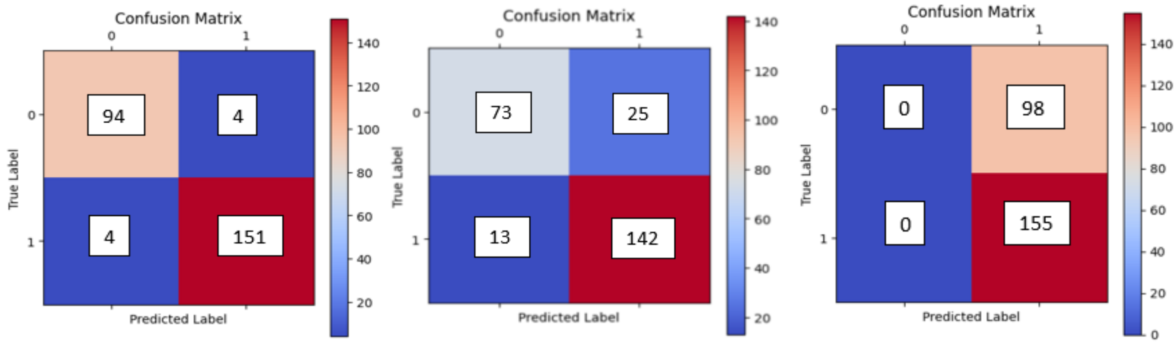


Fig. 4 Accuracy & loss for Transfer learning models:
a — *Xception Model Accuracy;* *b* — *Xception Model Loss;*
c — *VGG19 Model Accuracy;* *d* — *VGG19Model Loss;*
e — *MobileNetV3Small Model Accuracy;* *f* — *MobileNetV3Small Model Loss*

Every single transfer learning model's confusion matrix is shown in Fig. 5. A brief summary of all confusion matrices is given in this document. There are rates of 37.15% for true positives (TP), 59.68% for true negatives (TN), 0.01% for false positives (FP), and 0.01% for false negatives (FN) according to the confusion-matrix for the Xception model, which is shown in Fig. 5, *a*. In Fig. 5, *b*, we can see the VGG19 model's confusion-matrix, which shows that the rates of TP, TN, FP, and FN are 28.85%, 56.12%, 0.09%, and 0.05%, respectively. With rates of 0% for true positives (TP), 61.26% for true negatives (TN), 38.73% for false positives (FP), and 0% for false negatives (FN), the confusion-matrix for the MobileNetV3Small model is shown in Fig. 5, *c*.



a *b* *c*

Fig. 5 Every single transfer learning model's confusion-matrix:
a — Xception Confusion Matrix; b — VGG19 Confusion Matrix; c — MobileNetV3Small Confusion Matrix

After looking at all the Performance indicators, we say that Xception is the greatest transfer learning model out there. It has the lowest error rate, the peak TP and TN rates, and the fewest FP and FN rates.

The proposed research holds considerable potential for enhancing diagnosis of Brain Tumor, informing personalized-Treatment-Planning, advancing Research & drug-Development, supporting age-Guided surgery, functioning like CDS(Clinical Decision Support) System. Such Applications may enhance Patientcare, improve outcomes, and advance the field of neuro-oncology.

CONCLUSION

This paper proposes a deep learning brain cancer diagnosis method that combines preliminary processing, transfer learning structure rebuilding, and fine-tuning. Our solution used Xception, VGG19, and MobileNetV3Small transfer learning algorithms. We measured the model's Accuracy, recall, precision, and F1- score to show its remarkable improvements. We showed that our technique can accurately diagnose brain malignancies using the Brain Tumor Image dataset from Kaggle. The brain tumor classification accuracy for Xception was 96.84% and VGG19 84.98%. Later investigation showed that compared to competing models and methodologies, Xception's accuracy is significantly higher. We expect our algorithm to speed up and improve brain cancer diagnosis in clinical settings. Despite the design's improved precision, Image processing with the recommended structure could improve its suitability for this purpose. This study is limited by the lack of crisper images and better deep learning architecture, which prevents improved performance.

Recommendations

We plan to incorporate more recent data on brain tumors and more sophisticated hybrid ensemble methods into our proposed deep learning model to make it even better in the future. The adoption of explainable AI technologies could help us better understand how our deep learning model makes decisions. This would increase confidence in diagnosis for both doctors and patients.

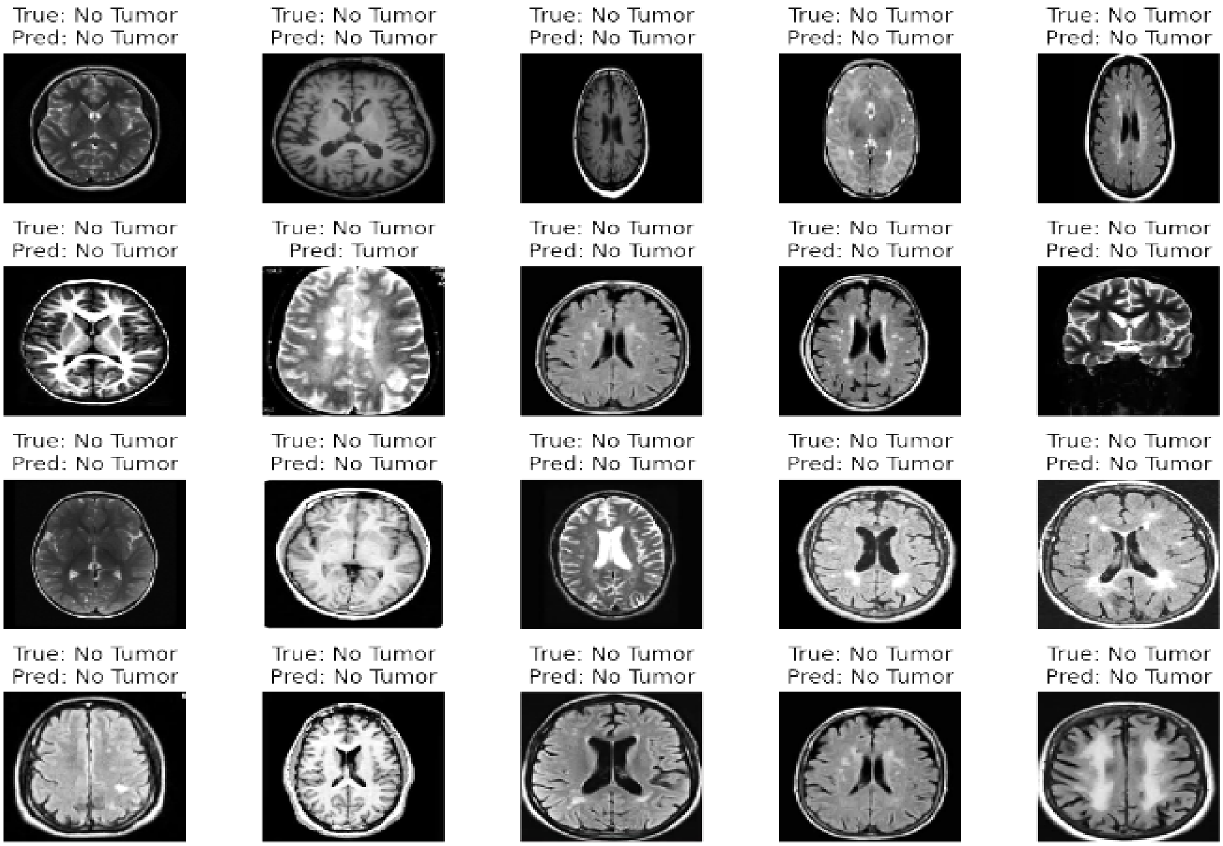


Fig. 6 Predicted Result of our suggested model

Ethical statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of interest

The authors declare that they have no conflicts of interest in this work.

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METADATA (RU) / МЕТАДАННЫЕ

Название: Использование предварительно обученных моделей для повышения точности: подход трансферного обучения к обнаружению тимуса мозга.

Аннотация: Опухоли мозга чрезвычайно опасны и могут привести к резкому сокращению продолжительности жизни, что делает их чрезвычайно опасным заболеванием. Для создания программ лечения, которые могут продлить жизнь людей, пострадавших от опухолей мозга, необходим правильный диагноз. Сложно и долго вручную идентифицировать и анализировать огромные объемы данных МРТ. Для успешной классификации опухолей мозга мы представляем новый метод DL, основанный на трансферном обучении в этом исследовании. Мы разработали концепцию новой стратегии, которая включает тонкую настройку, перестройку архитектуры трансферного обучения и тщательную предварительную обработку. В нашей реализации трансферного обучения мы используем Xception, VGG19 и MobileNetV3Small, среди прочих. Xception достиг точности 96,84%, тогда как VGG19 достиг точности 84,98%, используя общедоступный набор данных Kaggle MRI Brain tumor, состоящий из 253 изображений. На основании наших исследований Xception превосходит другие модели на наборе данных МРТ-опухолей головного мозга, достигая впечатляющей точности 96,84%. Чтобы помочь неврологам и врачам быстро и точно диагностировать пациентов с опухолями головного мозга, наша предлагаемая модель может эффективно классифицировать опухоли за короткий промежуток времени.

Ключевые слова: нейробиология; перенос обучения; VGG; МРТ-изображение мозга; опухоль мозга.

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