Literature Review - Brain Tumor Classification

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Project Description:

The ”Brain Tumor Classification Using AI” project aims to create a system based on AI that can correctly categorize brain tumors into four groups glioma, meningioma, pituitary, and no tumor. The goal of this research is to examine medical images, such as brain MRI scans, and quickly and accurately classify tumors using modern machine learning and image processing techniques.

This study carefully examines medical images, especially Magnetic Resonance Imaging (MRI) scans of the brain, by combining cutting-edge machine learning and sophisticated image processing techniques. This project is significant because it has the potential to make early identification, treatment planning, and brain tumor monitoring easier, leading to better patient outcomes and lower healthcare costs.

The foundation of project is a powerful AI model that was painstakingly built using a sizable dataset of brain MRI scans. Convolutional neural networks (CNNs) and deep learning techniques are used by the AI system to recognize complex patterns and features in the photos. As a result, the system can distinguish between the four types of brain tumors: glioma, meningioma, pituitary, and no tumor.

For clinicians and radiologists, it is crucial to be able to appropriately classify brain tumors. For instance, severe treatment methods are necessary for gliomas, whereas hormone therapy may be necessary for pituitary tumors. Tumor classification that is swift and accurate informs treatment choices and guarantees that patients receive individualized therapy as soon as possible.

Furthermore, the project emphasis on efficiency and accuracy aims to reduce the anxiety and uncertainty that often accompanies the diagnostic process for patients. Timely identification and classification of brain tumors can alleviate the emotional burden on patients and their families, enabling them to make informed decisions regarding treatment and care plans.

By enhancing early diagnosis, maximising resources, decreasing diagnostic errors, and encouraging global collaboration in the field of medical AI, the initiative has the potential to have a big impact on Pakistan’s healthcare system. It is consistent with the overarching objective of using technology to improve healthcare accessibility and quality in the nation.

Need for Project in Pakistan:

1. **Early Detection:**
   Brain tumors represent a substantial health challenge within the country, and the early detection and accurate diagnosis of these tumors are pivotal in ensuring optimal treatment outcomes. The AI-driven classification system addresses this need by enabling the identification of brain tumors at their earliest stages, thereby enhancing patients' prospects for effective treatment.

2. **Scalability**
   In addition to early detection, the project addresses the issue of scalability in Pakistan's healthcare system. Access to medical expertise remains a challenge in remote and underserved regions of the country. The AI-powered solution presented in this project offers scalability and automation, empowering healthcare providers to extend their reach and serve more patients, even in regions with limited access to medical professionals.

3. **Resource Allocation**
   Furthermore, the project contributes to the efficient utilization of healthcare resources. By prioritizing patients based on the severity and type of brain tumor, the AI system can assist medical professionals in optimizing resource allocation, ensuring that patients receive the appropriate care and attention they require.

4. **Reducing diagnostic errors**
   Reducing diagnostic errors is another compelling aspect of this project. By leveraging AI technology, radiologists and clinicians can make more accurate and consistent diagnoses, reducing the risk of misclassification and enabling the development of tailored treatment plans that align with the specific tumor type.

5. **Research and Data Collection**
   Moreover, the project fosters the collection of a valuable dataset of brain MRI scans from Pakistani patients. This dataset can serve as a valuable resource for ongoing research into brain tumors, potentially leading to the refinement of diagnostic and treatment methods, as well as contributing to the broader global efforts in the field of medical AI.

Motivation:

The goal of advancing medical technology, raising the standard of healthcare, and saving lives is what drives the project of brain tumour classification using AI. By utilising artificial intelligence, we hope to improve the reliability, timeliness, and accessibility of brain tumour diagnosis, thereby improving the lives of patients and their families. This initiative offers a fascinating chance to use modern technology for the benefit of people and the development of medical knowledge. The project complies with the SDG 3 which is focused on ***Good Health and Well-being***

Literature Review

1 Artcle 1 - A Deep Learning Approach for Brain Tumor Classification and Segmentation Using a Multiscale Convolutional Neural Network

Received: 31 December 2020
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1.1 General Description

Location and classification of brain tumors in large medical images databases taken in routine clinical tasks by manual procedures, have a high cost both in effort and time. An automatic detection, location, and classification procedure is desirable and worthwhile. MRI is the most used technique due to its advantageous characteristics. In MRI acquisition, the scan provides hundreds of 2D image slices with high soft tissue contrast using no ionizing radiation. In this paper, a multi-pathway CNN architecture is proposed for tumor segmentation. The CNN architecture processes an MRI image (slice) pixel by pixel covering the entire image and classifying each pixel using one of four possible output labels: 0—healthy region, 1meningioma tumor, 2—glioma tumor, and 3—pituitary tumor.

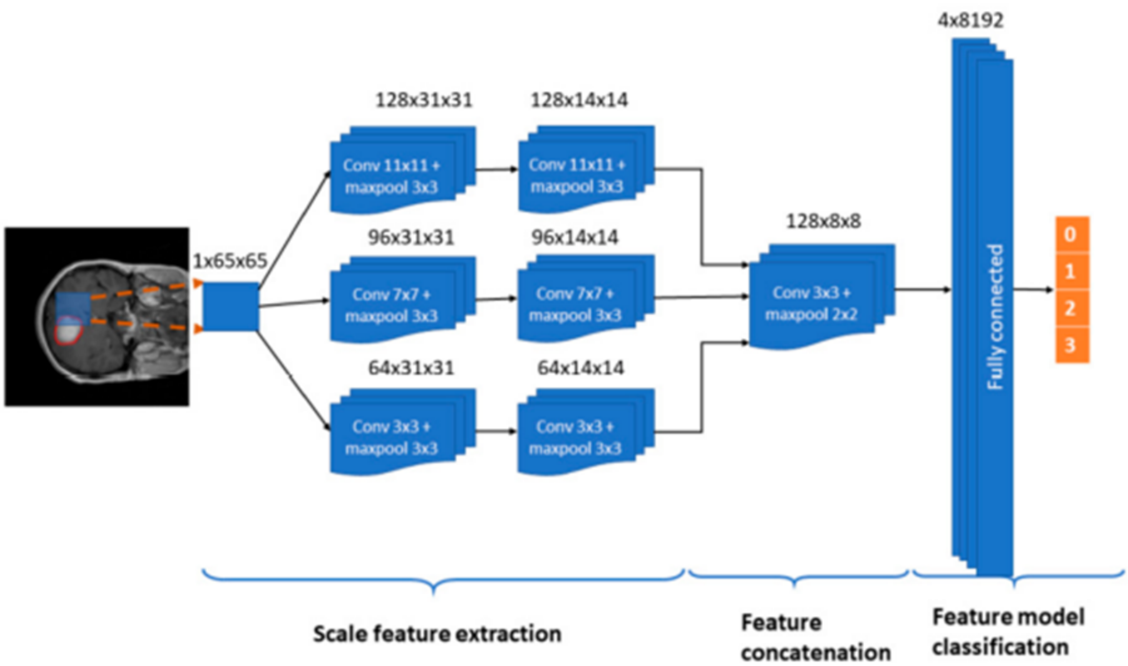

Figure 1: CNN Architecture

The proposed Convolutional Neural Networks (CNN) architecture comprises an input of 1x65x65 sliding windows. The model consists of three pathways, each featuring large, medium, and small feature scales. These pathways include two convolutional layers with max-pooling. Additionally, there is a convolutional layer that concatenates the outputs of the three pathways. The network culminates in a fully connected stage responsible for classifying the input into one of four possible output labels: 0 for a healthy region, 1 for a meningioma tumor, 2 for a glioma tumor, and 3 for a pituitary tumor. To enhance the model's robustness and prevent overfitting, a dropout mechanism is incorporated between the concatenation and fully connected stages.

1.2 Image Preprocessing

Begin by acquiring medical images using a consistent imaging protocol, standardizing orientation and resolution. Employ image enhancement techniques like histogram equalization and noise reduction to improve visual quality, followed by skull stripping to eliminate non-brain regions. Normalize image intensities to mitigate acquisition variations and resize them to a uniform input size compatible with the neural network architecture. Augment the dataset through operations like rotation and flipping to enhance diversity and prevent overfitting. Extract the region of interest (the brain tumor) using segmentation methods and consider multimodal data fusion. Appropriately split the dataset into training, validation, and test sets, addressing class imbalance with data augmentation if necessary. Standardize data to zero mean and unit variance, and implement quality control checks to ensure dataset integrity before model training. These preprocessing steps collectively pave the way for a robust brain tumor classification AI model.

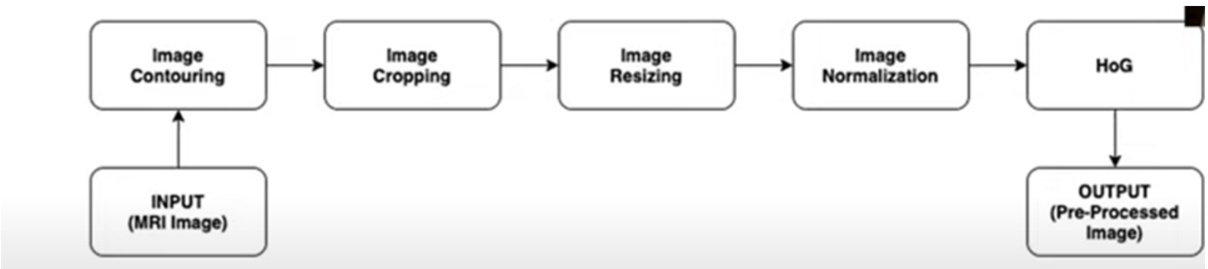

Figure 2: Image Preprocessing

Figure 3: Preprocessing Results

1.3 Misclassified Images

Following image shows some segmentations with misclassified areas; in the example of the upper row, the greater part of the detected tumor is correctly labeled (red area in the right column), resulting in a very correct segmentation (yellow area in the left column). However, there is a region detected in the non-cerebral area wrongly labeled as glioma tumor (green area in the right column). This example shows the added complexity inherent to this dataset due to the fact that it includes non-cerebral areas that can generate false positives. This complexity also manifests itself in the example of the middle row. Similarly, the segmentation is relatively correct (yellow region in the left column), but there is a misclassified area labeled as a pituitary tumor (blue region in the right column) located in the sphenoidal sinuses area, which is where pituitary tumors appear. The physical structure of the sphenoidal sinuses led to confusion to our model. The third example (lower row) shows a confusion between a real glioma (green region in the right column) and a wrongly predicted meningioma region (red area in the left column)

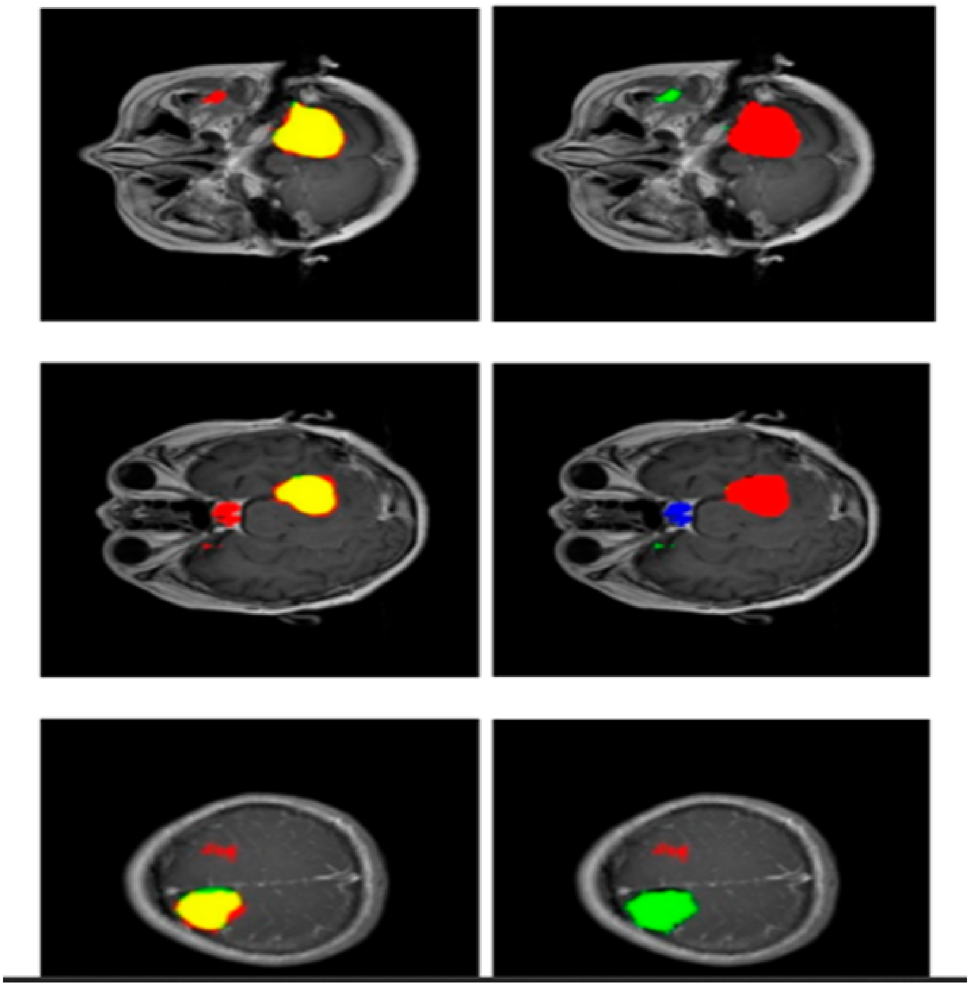

Figure 4: Wrongly predicted images

1.4 Accuracy

Comparison of the proposed approach with other approaches over the same T1-CE MRI image dataset.

Authors	Classification Method	Tumor Classification Accuracy
Cheng et al. [5]	SVM	0.912
Cheng et al. [32]	Fisher kernel	0.947
Abiwinanda et al. [24]	CNN	0.841
Pashaei et al. [25]	CNN	0.810
Pashaei et al. [25]	CNN and KELM	0.936
Sultan et al. [26]	CNN	0.961
Anaraki et al. [27]	CNN and GA	0.942
Our approach	Multiscale CNN	0.973

Figure 5: Comparison of Accuracy

2 Artcle 2 - Enhancement in Brain Image Segmentation using Swarm Ant Lion Algorithm

Published: 2019

2.1 General Description

The main motive of this research work is to provide a survey of MRI image based brain tumor segmentation techniques. The main problem is considered a complicated process, because of the variability of tumor area of the complexity of determining the tumor position, size, shape and texture. In this research work, mainly worked on interference method, feature extraction, morphological operators, edge detection methods of gray level and Swarm Ant Lion Optimization based on brain tumor shape growing segmentation to optimize the image complexity and enhance the performance. In new algorithm implemented an inspiring nature method for segmentation of brain tumor image using hybridization of PSOA (Particle Swarm Optimization Algorithm) and ALO (Ant Lion Optimizer) is also called a Swarm Ant Lion method. Swarm Ant Lion method name given to the combined approach that fuses the PSOA and ALO algorithms. the algorithm leverages the strengths of both PSOA and ALO to enhance its performance in the context of brain tumor image segmentation.

2.2 Hybridization

Hybridization in this context means that the algorithm integrates two or more optimization techniques or algorithms to improve its performance. In this case, it combines PSOA and ALO. PSOA is a nature-inspired optimization algorithm based on the social behavior of birds and fish. In PSOA, a population of particles (representing potential solutions) iteratively adjusts their positions in a multi-dimensional search space to find the optimal solution to a given problem. It's often used in optimization problems. ALO is another nature-inspired optimization algorithm inspired by the hunting behavior of antlion insects. In this algorithm, a population of ants searches for optimal solutions, and the algorithm incorporates characteristics of how antlions trap their prey. ALO is also used for optimization tasks.

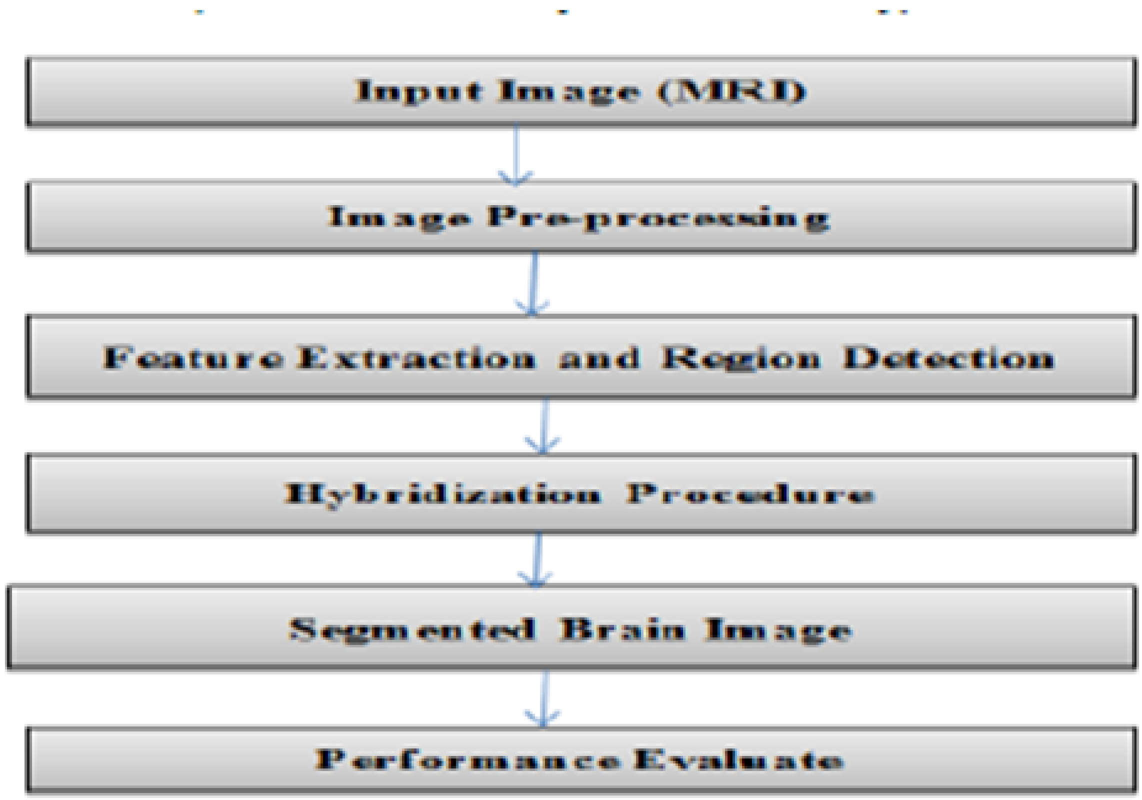

Figure 6: Proposed Flow Chart

2.3 Accuracy

Based on the provided comparison of evaluation metrics, it is evident that the "Swarm Optimization" approach outperforms the "PNN" (Probabilistic Neural Network) in terms of image quality and classification accuracy. Swarm Optimization achieves a higher Peak Signal-to-Noise Ratio (PSNR), indicating superior image quality with less distortion, while also yielding a lower Mean Squared Error (MSE), signifying less error in optimization. Additionally, Swarm Optimization demonstrates a significantly higher classification accuracy (98.5 percent) compared to PNN's 65 percent. Therefore, for the specific tasks and data involved, Swarm Optimization appears to be the more effective approach, offering better image quality and classification performance.

Metrics	Swarm Optimization	PNN
PSNR (%)	24.22	14.011
MSE	1.509	6.12
ACC (%)	98.5	65

Figure 7: Comparison of performance metric

3 Artcle 3 - MRI-Based Brain Tumor Classification Using Ensemble of Deep Features and Machine Learning Classifiers

Received: 10 February 2021
Accepted: 17 March 2021
Published: 22 March 2021

3.1 General Description

The concept of transfer learning is adopted and several pre-trained deep convolutional neural networks are used to extract deep features from brain magnetic resonance (MR) images. The extracted deep features are then evaluated by several machine learning classifiers. The top three deep features which perform well on several machine learning classifiers are selected and concatenated as an ensemble of deep features which is then fed into several machine learning classifiers to predict the final output. The traditional machine learning (ML) techniques rely on handcrafted features, which restrains the robustness of the solution. Whereas the deep learning-based techniques automatically extract meaningful features which offer significantly better performance. However, deep learning-based techniques require a large amount of annotated data for training, and acquiring such data is a challenging task. To overcome these issues, in this study, hybrid solution was proposed that exploits various pre-trained deep convolutional neural networks (CNNs) as feature extractors to extract powerful and discriminative deep features from brain magnetic resonance (MR) images, and (2) various ML classifiers to identify the normal and abnormal brain MR images.

3.2 Transfer Learning

Transfer learning can be used when it is not feasible to create a large training dataset. The concept of transfer learning can be depicted in following figure , where the model pre-trained on large benchmark datasets (e.g., ImageNet [43]) can be used as a feature extractor for the different task with a relatively smaller dataset such as an MRI dataset.

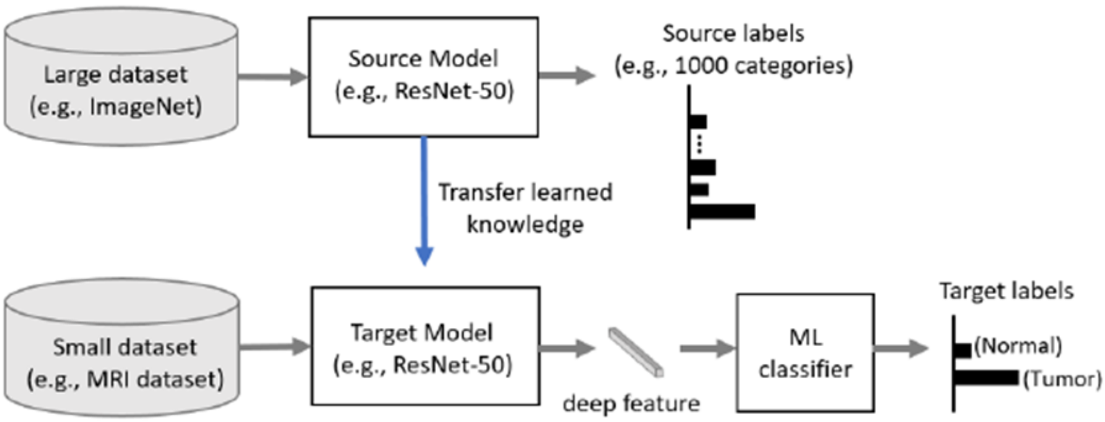

Figure 8: Concept of Transfer learning

3.3 Image Preprocessing

Almost every image in our brain MRI datasets contains undesired spaces and areas, leading to poor classification performance. Hence, it is necessary to crop the images to remove unwanted areas and use only useful information from the image. First, we load the original MR images for pre-processing. After that, we apply thresholding to the MR images to convert them into binary images. Also, we perform the dilation and erosions operations to remove the noise of images. After that, we selected the largest contour of the threshold images and calculated the four extreme points (extreme top, extreme bottom, extreme right, and extreme left) of the images. Lastly, we crop the image using the information of contour and extreme points. The cropped tumor images are resized by bicubic interpolation. The specific reason to choose the bicubic interpolation is that it can create a smoother curve.

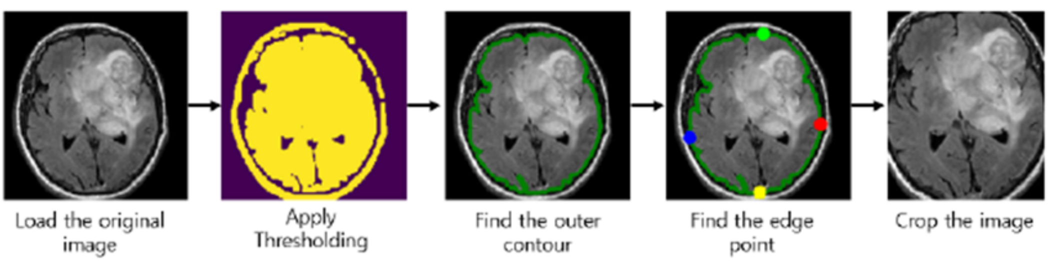

Figure 9: Steps to crop the MR images

3.4 Deep Feature Extraction Using Pre-Trained CNN Models

CNN is a class of deep neural networks that uses the convolutional layers for filtering inputs for useful information. The convolutional layers of CNN apply the convolutional filters to the input for computing the output of neurons that are connected to local regions in the input. It helps in extracting the spatial and temporal features in an image. CNN is generally comprised of three building blocks:

1. a convolutional layer to learn the spatial and temporal features
2. a subsampling (max-pooling) layer to reduce or downsample the dimensionality of an input image
3. a fully connected (FC) layer for classifying the input image into various classes

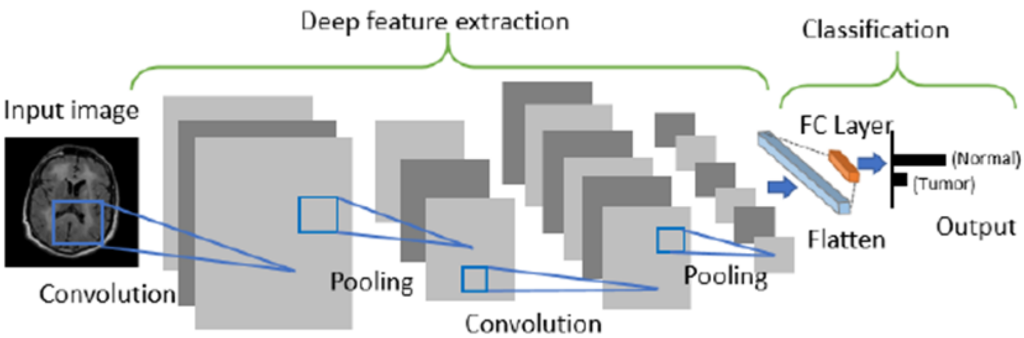

Figure 10: Architecture of CNN

3.5 Accuracy

Accuracies of pre-trained CNN models with ML classifiers on BT-small-2c dataset

Deep Feature from the Pre-Trained CNN Model	ML Classifier—Accuracy								
	FC	Gaussian NB	AdaBoost	k-NN	RF	SVM (Linear)	SVM (Sigmoid)	SVM (RBF)	ELM	Average
ResNet-50 feature	0.9216	0.8431	0.8431	0.8627	0.8824	0.8235	0.8824	0.9020	0.9020	0.8736
ResNet-101 feature	0.9216	0.8824	0.8431	0.8235	0.9020	0.8235	0.8824	0.9020	0.8824	0.8736
DenseNet-121 feature	0.9216	0.7647	0.8235	0.9216	0.8824	0.8431	0.8824	0.8627	0.9020	0.8671
DenseNet-169 feature ⋆	0.9608	0.8039	0.8627	0.9020	0.9412	0.9608	0.9608	0.9804	0.9412	**0.9237**
VGG-16 feature	0.8431	0.7451	0.7451	0.7059	0.8431	0.8627	0.8627	0.8039	0.8039	0.8017
VGG-19 feature	0.8235	0.6863	0.7843	0.6863	0.8235	0.8235	0.8235	0.8235	0.9020	0.7974
AlexNet feature	0.9216	0.7255	0.8431	0.7843	0.9020	0.8235	0.8627	0.9020	0.9020	0.8519
Inception V3 feature ⋆	0.9216	0.8824	0.9020	0.8235	0.9412	0.9020	0.9020	0.9020	0.9020	0.8976
ResNeXt-50 feature ⋆	0.9412	0.9020	0.9020	0.9020	0.9216	0.9216	0.9216	0.9216	0.9216	0.9172
ResNeXt-101 feature	0.9216	0.8039	0.8235	0.8235	0.9020	0.8627	0.9020	0.9216	0.9216	0.8758
ShuffleNet V2 feature	0.8431	0.7647	0.9216	0.8627	0.9020	0.9412	0.9412	0.9412	0.9412	0.8954
MobileNet V2 feature	0.8824	0.8431	0.7843	0.8431	0.8824	0.8627	0.8824	0.8824	0.8627	0.8584
MnasNet feature	0.9216	0.7843	0.8235	0.8235	0.9216	0.8431	0.8627	0.8627	0.9020	0.8606
Average	**0.9035**	0.8024	0.8386	0.8281	0.8959	0.8688	0.8899	0.8929	0.8989	

Figure 11: Accuracies of pre-trained CNN models

4 Artcle 4 -Brain Tumor Diagnosis and Classification via Pre-Trained Convolutional Neural Networks

Published: 27 Jul 2022

4.1 General Description

Medical Resonance Imaging (MRI), Computed Tomography (CT), and Ultrasound can be used to diagnose the tumor. MRI has shown more promising results than the other two kinds of radiology methods. In MRI the brain tumor can be spotted as the most bright part. MRI generated an image on basis of the number of hydrogen atoms in the body. If the number of hydrogen atoms is high in an area, then the area appears to be bright. In the brain, cerebrospinal fluid (CSF) is the area that has more number of hydrogen atoms and it appears brighter than the other areas. Other than CRF, tumors have the highest number of hydrogen atoms so it also appears as bright areas. If the tumor is not visible clearly with a normal MRI then a contrast agent can help to highlight the tumor. Gadolinium is the contrast agent that is used in MRI. Gadolinium has a high quantity of glucose and glucose has a high quantity of hydrogen. Tumors are known to absorb the glucose, when tumors do so they become rich in hydrogen and thus appear brighter in the MRI images.

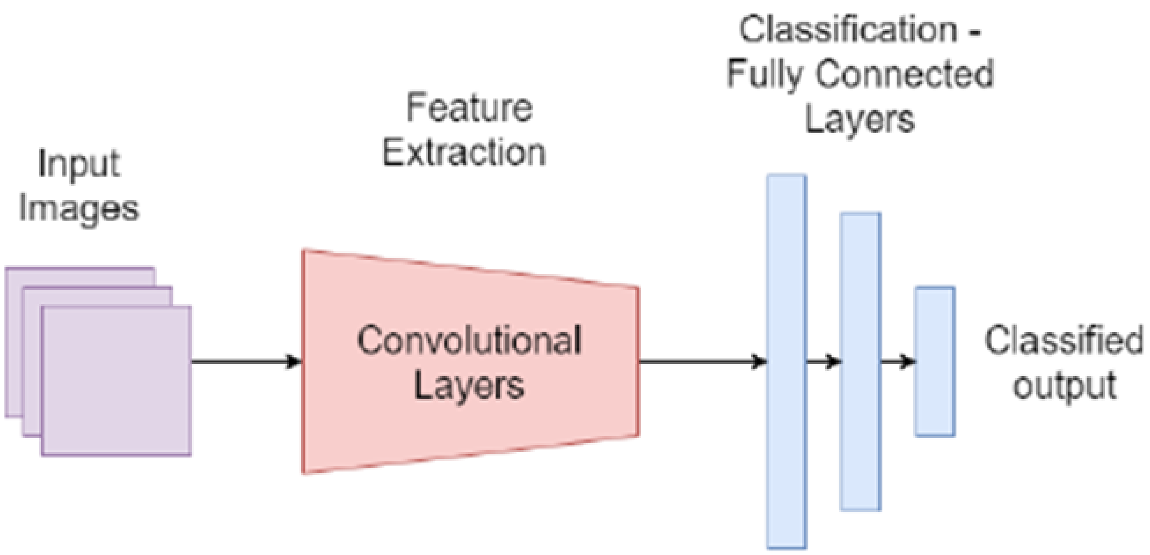

Figure 12: Division of CNN Architecture

4.2 Goals Achieved by Transfer Learning

Transfer learning is the concept where the weights of an already trained model on some dataset are used for some other application. For example, for the problem under consideration in this research, weights were used from the model that was trained on the ImageNet dataset for 1000 classes. This use of pre-trained models helps in faster convergence and the model can be trained on fewer resources and fewer datasets. This paper proposes the correct diagnosis and classification of brain tumors through MRI images by using pre-trained CNN.The goals achieved by this paper are:

1. Diagnosis of brain tumor.

2. Classification of three kinds of tumors: Glioma, Meningioma, and Pituitary.

3. Use of pre-trained models to reduce the resources used and mitigate the effect of small dataset.

4.3 Image Preprocessin

The pre-processing step includes the augmentation of the images to mitigate the effect of fewer input images. Augmentation is the process of taking an image and generating its variants by translations, rotations, scaling, shearing, and flipping (horizontal and vertical). The machine learning model treats these variants as a different image and thus the size of the dataset increases.

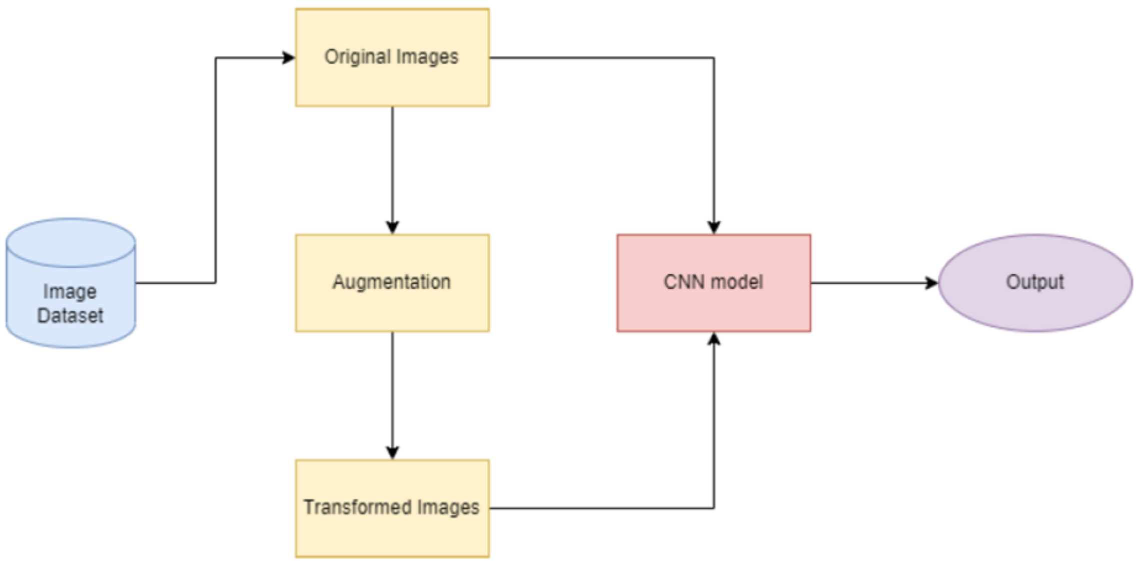

Figure 13: Classification Pipeline

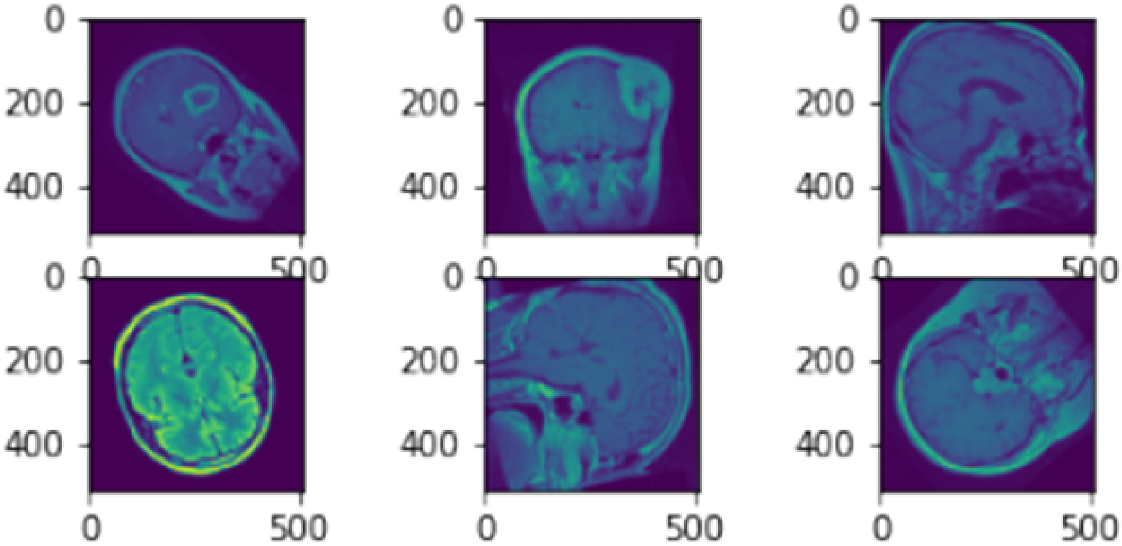

Figure 14: Few Examples of Image Augmentation

4.4 Accuracy

The performance of different models was discussed and it was shown that EfficientNet models are more effective than any other model due to their width, depth, and resolution scaling properties. EfficientNetB1 showed the best performance in terms of both training and validation accuracy.

Model	***Epochs***	***Training Accuracy***	***Training Loss***	***Val Accuracy***	***Val Loss***
EfficientNetB7	39	0.8419	0.5129	0.8818	0.2807
EfficientNetV2B1	43	0.8491	0.5695	0.8917	0.2768
EfficientNetB1	40	0.8767	0.4076	0.8955	0.3152
ResNet50	30	0.7282	0.6719	0.7932	0.4593

Figure 15: Classification Results of Different Models

Comparison

Each of the articles presents a different method and has its own advantages and limitations.

1. **Accuracy:**
   Article 3, which utilizes transfer learning and deep features with machine learning classifiers, demonstrates competitive performance. It achieves high accuracy and is a strong candidate for accurate brain tumor classification.

2. **Complexity and Resources:**
   Article 2, using the Swarm Ant Lion Algorithm (SALA), performs well in terms of image quality and classification accuracy. It offers a unique optimization technique, but it may be computationally expensive and require careful parameter tuning.

3. **Image Preprocessing:**
   Article 1 and Article 4 both emphasize the importance of image preprocessing. Proper preprocessing can significantly impact the quality of results. Article 4 discusses the use of MRI with contrast agents for enhanced tumor visibility, which can be crucial in practice.

4. **Data Augmentation:**
   Article 4 stands out for its focus on data augmentation, which helps mitigate the effects of a small dataset. Augmentation can improve model robustness and generalization.

5. **Transfer Learning:**
   Article 3 utilizes transfer learning, which is a powerful technique when dealing with limited data. It leverages pre-trained CNN models and has the potential to perform well, given the right architecture.

6. **Segmentation:**
   Article 1 and Article 2 focus on segmentation, which is a critical step in brain tumor analysis. Article 1 employs a multiscale CNN, while Article 2 introduces SALA.

Conclusion

In conclusion, there is no one-size-fits-all answer to which approach is better. The choice depends on the specific needs and constraints of the problem you are trying to address. If high accuracy is the primary concern, Article 3's approach with deep features and machine learning classifiers may be favored. If computational efficiency and unique optimization techniques are essential, Article 2's SALA approach might be considered. Furthermore, the choice of methodology may depend on the size of the dataset, availability of computational resources, and the specific challenges posed by the dataset and clinical requirements.