Hybrid CNN-ResNet50 Model for Brain Tumor Classification Using Transfer Learning

Sheenam Middha[1][a], Sonam Khattar[1][b] and Tushar Verma[2][c]
Department of Computer Science and Engineering, Chandigarh University, Mohali, Punjab, India

Keywords: Hybrid Deep Learning CNN Model, MRI Images, Brain Tumor, Classification.

Abstract: A tumor is fatal cancers that can affect both adults and minors. A brain tumor's treatment depends on an early and precise diagnosis. Finding the brain tumor with computer-aided technologies is a crucial first step for physicians. Experts can spot tumors more quickly and easily thanks to these devices. But conventional procedures also prevent mistakes from happening. This article uses magnetic resonance imaging (MRI) to diagnose brain tumors. A hybrid approach that uses CNN models—one of the deep learning networks—for diagnosis has been put forth. One of the CNN models, Resnet50 architecture, serves as the foundation.97.67% accuracy rate is achieved with this model. The model that performed the best out of all of them has been used to classify the images of brain tumors. Consequently, further analyses in the literature indicate that the suggested method is practical and useful for brain tumor detection in computer-aided systems.

1 INTRODUCTION

A brain tumor is an abnormal development of cells inside the brain. While some brain tumors are benign, some could be cancerous. Brain tumors that originate from the actual tissue of the brain are known as primary brain tumors. Metastasis is the term used to describe a malignant tumor that has moved from another area of the body to the brain. The type, location, and range of the tumor can all affect the available treatment options. Therapy or symptom reduction is the main goal of treatment. The tumor symptoms include migraines and recurrent headaches. It may still lead to visual impairment. At this point, science may not know enough about what caused the tumor's extraordinary growth in the first place. Tumors can be classified based on two factors, such as where they originated from and whether or not they are cancerous. A benign tumor is a non-cancerous tumor that does not impact any other portion of the human body (Chen, Liu, et al. 2018),(Sultan, Upadhyay, et al. 2019) (Hossain, Shishir, et al. 2019). They have a modest pace of expansion and are easily recognizable.

Malignant brain tumors, which are founded on cancer and can impact other brain regions, can be extremely violent and terrifying since they can be difficult to diagnose. When it comes to detecting a tumor, the physicians will decide between an X-ray and magnetic resonance imaging (MRI). If no examination is able to provide sufficient information, an MRI scan may be appropriate. The MRI scan uses radio waves and magnetism features to create flawless images.

MRI scan of the brain can provide a safe and painless experiment that uses magnetic fields and radio waves to provide detailed images of the human brain. As an alternative to a Computed Tomography (CT) scan, an MRI scan doesn't use radiation. MRI scanners typically have a large magnet field in the shape of a doughnut with a channel in the middle. The patients will be positioned on a table that slides into the channel for this testing procedure. Numerous locations with better opening in MRI machines are available, which can help individuals who are claustrophobic (Anaraki, Ayati, et al. 2019), (Özyurt, Sert, et al. 2019). A brain examination called an MRI machine is offered in radiology centers and hospitals. During the testing procedure, radio

[a] https://orcid.org/0000-0002-0639-5539
[b] https://orcid.org/0000-0002-5444-4358
[c] https://orcid.org/0000-0002-6696-4537

Middha, S., Khattar, S. and Verma, T.
Hybrid CNN-ResNet50 Model for Brain Tumor Classification Using Transfer Learning.
DOI: 10.5220/0013594400004664

In *Proceedings of the 3rd International Conference on Futuristic Technology (INCOFT 2025) - Volume 2*, pages 444-448
ISBN: 978-989-758-763-4

waves are used to pinpoint the magnetic location of the atoms in the human body. These signals can then be chosen by a powerful antenna and transmitted to a computer. The computer is capable of carrying out millions of estimations, producing clear and white photographs of the body.

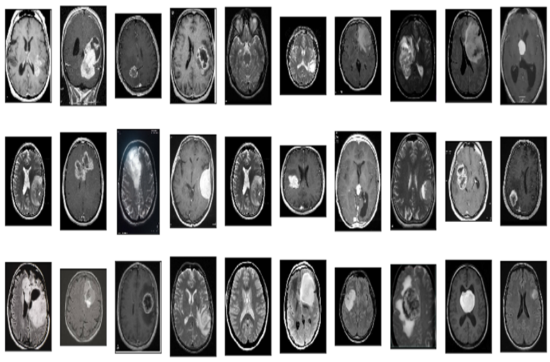

Figure 1: MRI images

Stages Of Brain Cancer

- Under a microscope, grade I tumors appear nearly normal and are characterized by sluggish growth. These tumors are classified as benign. Since these tumors usually have distinct borders, surgical removal of them is less difficult.
- Low-grade malignant tumors, or grade II tumors, develop more slowly than other tumor types and have the ability to invade adjacent brain tissue. Under a microscope, the cells of Grade II tumors appear slightly aberrant, suggesting a degree of malignancy.
- Anaplastic or malignant tumors, commonly referred to as grade III tumors, grow quickly and are more aggressive. Under a microscope, the cells in these tumors appear incredibly aberrant, and they are probably going to migrate into adjacent brain tissue. Grade III cancers include anaplastic oligodendroglioma and anaplastic astrocytoma. Aggressive treatment is needed for these tumors, which includes radiation, chemotherapy, and surgery. A thorough treatment strategy and close monitoring are crucial because the overall prognosis is less favorable and there is a higher chance of recurrence as compared to lower-grade cancers.
- Grade IV tumors that are highly aggressive include the widely recognized glioblastoma multiforme. These tumors exhibit highly rapid growth and, when observed under a microscope, the cells appear highly abnormal. Grade IV tumors often induce angiogenesis to facilitate their rapid proliferation. Despite intensive treatment, the outlook for Grade IV tumors is quite unfavorable and often involves a combination of radiation, chemotherapy, and surgery. The average survival duration for individuals diagnosed with glioblastoma is typically between 15 and 18 months.

The paper is organized in such a way that section 2 provides a full overview of the pertinent work, and Section 3 provides a thorough overview of the proposed system along with implementation details. In Section 4, the comprehensive experimental outcomes are displayed. The results are shown in Section 5.

2 LITRATURE SURVEY

(Zotin et al. 2018) proposed FCM clustering-based medical image processing system for MRI brain tumor edge identification is presented. The input image is enhanced by BCET after being denoised with a median filter. After segmenting the picture using the FCM clustering approach, the Canny edge detector is used to create an edge map of the brain tumor. The suggested approach works better since the Canny method is used on perfect set of images that are divided into homogeneous regions and have superior quality because of the FCM and BCET. Consequently, the suggested approach yields good estimators, presenting great image quality for medical specialists to analyze. An analysis of the edge maps by a medical expert revealed that the segmentation accuracy is 10-15% better in specific tumor pathology cases compared to the comparable expert estimations. The experimental study that was carried out proved how stable the edge map produced by the suggested technique was against the effects of noise.

An innovative CNN architecture that differs from the ones typically utilized in computer vision is introduced by (Havaei et al. 2017). Our CNN utilizes both local and more global contextual aspects at the same time. Moreover, our networks have a final layer that is a convolutional version of a fully connected layer, which allows a 40-fold speedup over most typical CNN implementations. To address tumor label imbalance issues, we also provide a two-phase training protocol. Finally, we study a cascade design in which a second-class CNN uses the output of a first-class CNN as an additional information source.

(Hollon et al. 2020) provided a parallel approach that uses deep convolutional neural networks (CNNs) in conjunction with label-free optical imaging technique stimulated Raman histology to detect disease at predict almost real-time. In particular, our CNNs—which were trained on more than 2.5 million SRH images—can diagnose brain tumors in the operating room in less than 150 seconds, which is orders of magnitude quicker than traditional methods (which take, say, 20–30 minutes).

(Arif F et al. 2022) In order to enhance performance and streamline the medical picture segmentation process, a deep learning classifier and Berkeley's wavelet transformation (BWT) have been the foundation of the suggested system's research. Utilizing the gray-level-co-existence matrix (GLCM) approach, significant features are identified from each segmented tissue and then optimized using a genetic algorithm. Based on factors including accuracy, sensitivity, specificity, spatial overlap, AVME, FoM, Jaccard's coefficient, and coefficient of dice, the creative outcome of the employed approach was evaluated.

(Alsaif et al. 2022) The suggested approach performs exceptionally well for the initial cluster centers and size. Segmentation is carried out utilizing BWT methods, which have lower computational speed and accuracy. This paper suggests a method to divide the brain tissue that involves very little human intervention. The primary motive of this approach is to expedite the process of patient identification for neurosurgeons or other human experts. Comparing the testing results to the most advanced technology, the accuracy is 98.5%. There is still room for improvement in terms of computational time, system complexity, and memory usage when executing the algorithms. The same methodology can also be applied to the identification and examination of various illnesses present in other bodily organs, such as the kidney, liver, or lungs. It is possible to employ several classifiers with optimization techniques.

Utilizing the Faster R-CNN deep learning architecture, (R. Sa et al. 2017) propose a method to identify intervertebral discs in X-ray pictures. Scientists employ this CNN to enhance the accuracy and efficiency of intervertebral disc recognition, a vital stage in diagnosing spinal problems. Their methodology demonstrates significant improvements in detection accuracy compared to traditional approaches, highlighting the potential of Faster R-CNN for application in medical image processing. The study demonstrates how sophisticated deep learning methods may improve radiology's capacity for diagnosis. This problem was resolved by (R. Sa et al. 2017). Traditional machine learning methods require a manually generated feature for classification. However, without requiring human feature extraction, deep learning systems can be developed to yield accurate classification results. Since there are a lot of MRI pictures in the first dataset, we use a 23-layer CNN to build our models at first.

(Alanazi, Muhannad Faleh et al. 2022) To evaluate how well convolutional neural networks (CNNs) perform on brain magnetic resonance imaging (MRI), they are built from the ground up using various layers. The 22-layer, binary-classification (tumor or no tumor) isolated-CNN model is then utilized once more to re-adjust the weights of the neurons for the purpose of classifying brain MRI pictures into tumor subclasses using the transfer-learning concept. This results in a high accuracy of 95.75% for the transfer-learned model developed for the MRI images from the same MRI machine. The created transfer-learned model has also been validated using brain MRI images from another machine to verify its general competence, flexibility, and reliability for future real-time application. The results show that the proposed model achieves a high accuracy of 96.89% for a previously unobserved brain MRI dataset. Thus, the recommended deep learning.

3 METHODOLOGY

The Hybrid approach for Brain Tumor detection using CNN with ResNet50 was proposed and detailed description is given below:

This methodology follows three step process. Firstly, trained the data. Secondly, various pooling techniques are applied and finally classifiers are used to find features. The Concatenating pooling layer from the ResNet50 model yielded the final features. Ultimately, a concatenated feature vector measuring 4096×1 is obtained. Because each pre-trained CNN model's final pooling layers seek to gather the best features for classifying the target class rather than irrelevant features.

Figure 2 presents the suggested hybrid deep learning model. It performs Radiography classification method using two base models and a heading model. Concatenating with CNN models with ResNet50 results in a single feature vector. The output metrics are examined using the deep neural network classifier. Because of their easy training times and straightforward structure, two pre-trained models are recommended.

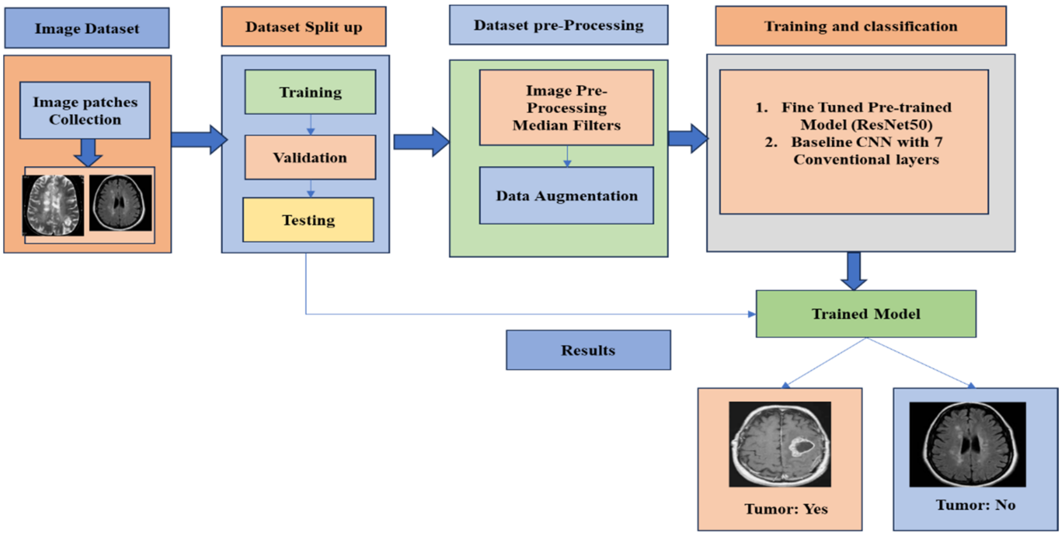

Figure 2: Proposed model for detection of Brain Tumor images

The first layer of this neural network architecture is an input layer that can handle 224x224 images with three colour channels. It makes use of a ResNet50 model that has already been trained and produces 7x7 feature maps with 2048 channels. These characteristics are then further refined by a Conv2D layer with 16 filters, which adds non-linearity while lowering complexity. The spatial dimensions are then reduced to 3x3 while maintaining the depth using a

MaxPooling2D layer. Following the application of another MaxPooling2D layer that further decreases the dimensions to 1x1, another Conv2D layer with 32 filters is applied. The spatial data is condensed by the global average pooling layer into a 32-dimensional vector. To avoid overfitting, this vector goes through a dropout layer after passing through a dense layer with 512 units.

4 RESULTS AND DISCUSSIONS

The trials were conducted in the Google Colab environment. Computation was done with both CPU and GPU. Utilized were a Tesla K80 accelerator, Xeon CPU running at 3.35 GHz, and a 20 GB RAM.

The accuracy of our model during training and validation is shown in Figure 3. The Keras callback's function computed it. Accuracy in training and validation was observed when using varying numbers of epochs. We discovered that the Hybrid model had the maximum accuracy for both training and validation after 6 epoches.

We can observe from the previously mentioned graphs that validation accuracy increases in tandem with training accuracy. As loss decreases, so does the validation loss. To improve the results, we can adjust the hyperparameters of the learning rate, train the model on more photos, or simply train it for more epochs. Our test accuracy is 97.5 percent thanks to the evaluate () technique.

5 CONCLUSIONS

Due of various diversities of medical images, image segmentation is important in medical image processing. We employed MRI scans for brain tumor segmentation. Brain tumor segmentation and classification are the two main uses of MRI. This paper uses CNN modes with seven layers to classify photos of brain tumors. Using Resnet50 architecture as a foundation, a hybrid model is introduced. The developed hybrid model has a 97.67% accuracy rate and Loss is 0.02%. Additionally, many models are used to classify images of brain tumors. The hybrid model that was created has the highest accuracy rate. The accuracy of previous architectures, including the classical Resnet architecture, has significantly improved with the release of the upgraded Resnet50 architecture

REFERENCES

W. Chen, B. Liu, S. Peng, J. Sun, and X. Qiao, "Computer-aided grading of gliomas combining automatic segmentation and radiomics," Int. J. Biomed. Imaging, 2018.

H. H. Sultan, N. M. Salem, and W. Al-Atabany, "Multi-classification of brain tumor images using deep neural network," IEEE Access, vol. 7, pp. 69215–69225, 2019.

T. Hossain, F. Shishir, M. Ashraf, M. Al Nasim, and F. Shah, "Brain tumor detection using convolutional neural network," in Proc. IEEE Int. Conf., 2019, pp. 1–6.

A. K. Anaraki, M. Ayati, and F. Kazemi, "Magnetic resonance imaging-based brain tumor grades classification and grading via convolutional neural networks and genetic algorithms," Biocybern. Biomed. Eng., vol. 39, no. 1, pp. 63–74, 2019.

F. Özyurt, E. Sert, E. Avci, and E. Dogantekin, "Brain tumor detection based on convolutional neural network with neutrosophic expert maximum fuzzy sure entropy," Measurement, vol. 147, 2019.

Khattar, S., & Bajaj, R. (2023, December). A Deep Learning Approach of Skin Cancer Classification using Hybrid CNN-Inception Model. In 2023 Global Conference on Information Technologies and Communications (GCITC) (pp. 1-7). IEEE.

A. Zotin, K. Simonov, M. Kurako, Y. Hamad, and S. Kirillova, "Edge detection in MRI brain tumor images based on fuzzy c-means clustering," Procedia Computer Science, vol. 126, pp. 1261-1270, 2018.

H. Greenspan, A. Ruf, and J. Goldberger, "Constrained Gaussian Mixture Model Framework for Automatic Segmentation of MR brain Images," IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1233-1245, 2018.

M. Havaei, A. Davy, D. Warde-Farley, A. Biard, A. Courville, Y. Bengio, C. Pal, P. M. Jodoin, and H. Larochelle, "Brain tumor segmentation with deep neural networks," Medical Image Analysis, vol. 35, no. 1, pp. 18-31, 2017.

T. C. Hollon, B. Pandian, A. R. Adapa, E. Urias, A. V. Save, S. S. S. Khalsa, D. G. Eichberg, R. S. D'Amico, Z. U. Farooq, S. Lewis, et al., "Near real-time intraoperative brain tumor diagnosis using stimulated raman histology and deep neural networks," Nat Med., vol. 26, no. 1, pp. 52–58, 2020.

Goudarzi, H., Pournajaf, K., & Zarrin, M. (2022). "A F. Muhammad Arif, A. S. Shamsudheen, O. Geman, D. Izdrui, and D. Vicoveanu, "Brain tumor detection and classification by MRI using biologically inspired orthogonal wavelet transform and deep learning techniques," J. Healthcare Eng., 2022

F. Muhammad Arif, A. S. Shamsudheen, O. Geman, D. Izdrui, and D. Vicoveanu, "Brain tumor detection and classification by MRI using biologically inspired orthogonal wavelet transform and deep learning techniques," J. Healthcare Eng., 2022