How to Cite:
Raja, K., Duela, S. J., Kundra, I., Bhatt, P., & Kagot, A. (2022). AI to automate brain tumor classification using visual geometric group (VGG) 16. *International Journal of Health Sciences*, *6*(S3), 3889–3901. https://doi.org/10.53730/ijhs.v6nS3.6648

AI to automate brain tumor classification using visual geometric group (VGG) 16

Raja K.
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

Shiny Duela J.
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

Ishant Kundra
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

Aneesh Kagot
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

Prakrati Bhatt
Department of Computer Science and Engineering, SRM Institute of Science and Technology, Ramapuram Campus, Chennai, India

***Abstract*---**A brain is the most important part of our body, which authorize the center capacities which attributes inside actual body and predictable with the National mind tumor Society, around 700,000 individuals acknowledge a cerebrum tumor, and in this manner, the figure will ascend to 787,000 by the peak point of 2020. Clinical imaging for medical diagnosis of a variety of disorders has benefited from ongoing advancements in the field of deep understanding. Task CNN is the most common and widely used AI computation for visual learning and image identification. Essentially, we show the Convolutional Neural Network (CNN) strategy, together with Data Augmentation and Image Processing, to sort cerebrum MRI examination images into carcinogenic and non-harmful categories in our hypothesis. A programmable mind tumour layout based on deep learning-based Visual Geometric Group (VGG) 16 is shown in this study. The model (VGG-16) has a 96 percent and 96 percent accuracy for both training and testing photos respectively.

International Journal of Health Sciences ISSN 2550-6978 E-ISSN 2550-696X © 2022.
Manuscript submitted: 27 Dec 2021, Manuscript revised: 09 March 2022, Accepted for publication: 18 April 2022

***Keywords*---**brain tumor, deep learning, classification, tensorflow, VGG-16, transfer learning, computer vision, convolutional neural network.

Introduction

In recent past years of Artificial Intelligence and Deep learning, great advancement is achieved in clinical science like the Medical Image Handling method which help specialists analyze sickness to the earliest and effectively, as before those, it was drawn-out and tedious. In-order to determine such sort of restrictions helped innovation is genuinely necessary since Medical Field needs productive and solid procedures to analyze hazardous infections like disease, thus the most important cause of death for patients worldwide. By the investigation with the assistance of Brain MRI Images [1], we give a strategy to the characterization of Cerebrum Tumors into harmful and non-carcinogenic utilizing the information enlargement method and Convolutional Neural Organization model. A brain tumor is set apart as Benign and Malignant. Generous tumors does not have cancer cells and grow gradually. They do not spread and generally stay in one locale of mind, while threatening cerebrum tumors contain malignancy cell which develop rapidly and spread through to the mind and spine districts additionally. A dangerous neoplasm is always perilous and unsafe. World Health Organization (WHO) has reviewed cerebrum [2] tumors reliable with mind wellbeing conduct, into grade 1 several tumors that are poor quality tumors likewise alluded to as generous tumors, or evaluation 3 and 4 tumors which are high-grade tumors additionally alluded to as dangerous tumors [3]. The cerebrum tumor is analyzed utilizing a few procedures like CT examination, and EEG, yet Magnetic Resource Image (MRI) is the awesome broadly utilized strategyto gain inner photos of the structures from the inside of the person, X-ray uses extraordinary and effective attracting fields and radio frequencies. X-ray produces more useful information., inside organs and is, in this manner, more straightforward than CT or EEG examining.

Learning approach [4] is currently very popular in deep learning as it can train deep learning models with very little input, and it is especially useful for data science since most practical issues need the use of previously learned models. Because we don't have massive amounts of data to train these complicated models, we can't train them. We should take a look into transfer learning. how it works, why and when to use it. Contains several resources for models that have already been trained in the transfer of learning Training a basic classifier to foretell whether a picture includes a backpack gives you the ability to utilize the model's training data to identify beverages. Other items, such as sunglasses, are recognized. When we talk about teaching the most important thing, we note is what we learned and how we can apply it in particular situation. Weights learned in "task A" are transferred to "task B" in the same way. The idea is to use models that have learned from business in a new business with a lot of data training cards available and with little data [5]. Instead of starting with learning processes from the beginning.

Learning is mainly used for natural language processing [6] tasks such as computer vision and emotion analysis due to a large amount of computing power required [7].The methodology of Brain Tumor [8] Classification is shown in the below figure 1:

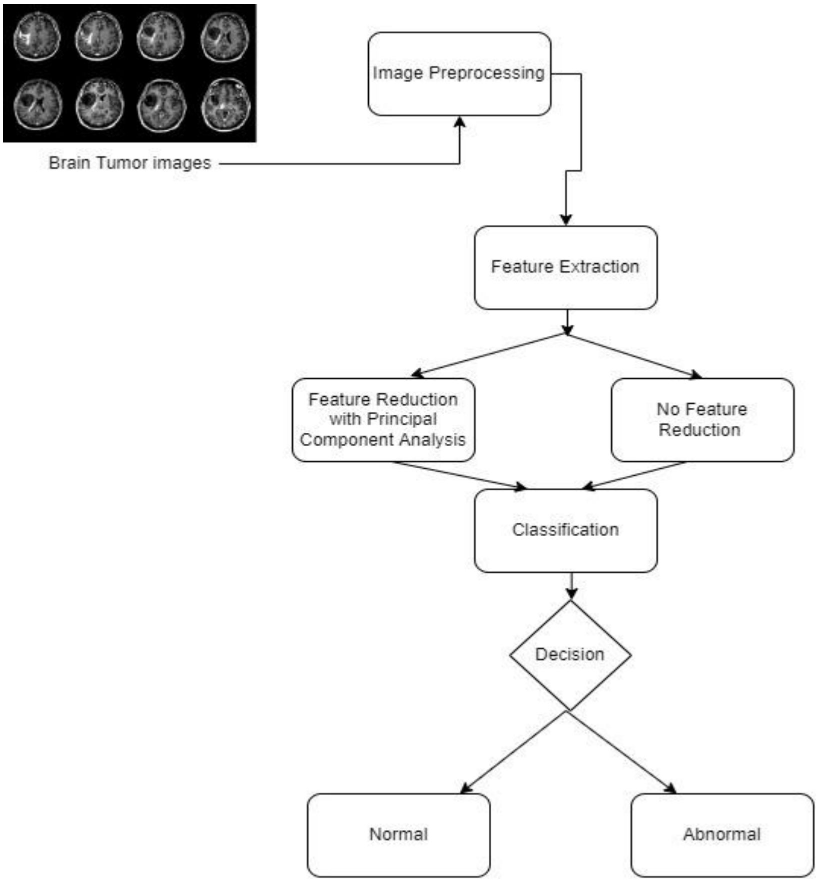

Fig 1. Methodology of Brain Tumor Classification

The induced method describes mainly the workflow of the system i.e. we have collected the data, the next step was data pre-processing as the dataset contains images, hence the pre-processing steps include cropping images and filling the images to full, and making the size of images equal resizing the images to a standard size, as data is prepared for the training, While distributing and evaluating the algorithm, we will train it on a cleaned database and training it to a certain amount of periods of history. Features of Brain Tumor as shown in figure 2:

- Headaches that are new or have changed in pattern
- A progressive increase in the frequency and severity of headaches.
- Anxiety-induced dizziness or fainting spells.
- This includes blurry vision, multiple vision, and loss of peripheral vision.
- Movement or feeling lost in an arm or leg over time.
- Unsteadiness of gait.

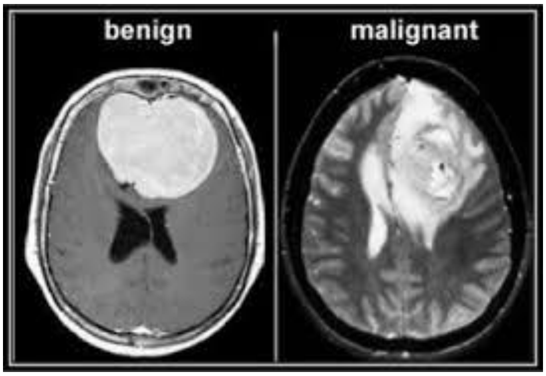

Fig 2. Different types of Brain Tumor (i.e. Malignant and Benign)

Data set

We used the dataset Brain MRI [9,10] Images for the Brain Tumor Classification which is divided into two categories i.e., Malignant and Benign [11,12]. The data is made up of 253 images, we split the data into 3 parts 155 training images,50 validation images, and up to 10 test images. All images are rescaled. The data consists of three main parts: training, validation, and testing [13,14,15]. To increase efficiency of our system we take pre-processed image.First, we resize all our images to 240*240*3, which will increase processing time and will also fit in model. Pre-processing techniques are applied. Using open-source computer vision (CV), canny edge detection algorithm [15], we first take the image and trim the dark edges, during which we would analyze the region of the brain from the image. It's a multi-set approach for detecting object edges in images. Using the Canny Edge Detection approach [18,19], we were able to trim the brain portion of the picture and reveal the true MRI brain edges. [20,21,22]

Literature review

We Objective of this audit segment is to introduce a writing study of picture division strategies. The fundamental objective is to feature the benefits and restrictions of these techniques. Key image processing procedures for cerebrum MRI picture division are delegated k-implies, SVM, FCM, k nearest neighbor, neural organization, AdaBoost, hereditary and different strategies, and so on. Parveen Amritpal Singh's [22] designed computation is a half breed method for predicting cerebrum lesions that combines SVM with fluffy c-implies. Enhancement of contrast and mid-range stretch are used to improve the image here. For skull striping, two-step thresholding and morphological tasks are used. The image division is done by fluffy c-implies (FCM) bunching. Highlights are extracted using the dim level run length framework (GLRLM). Linear, Quadratic, and Polynomial are the terms used at that time. The SVM algorithm is used to group the MRI images of the brain. To distinguish between 'tumour' and 'non-tumor' MRI pictures. The researchers employed a true interesting set of 120 victims' Structural MRI scans.

The SVM classification is performed using 128 MRI images of the brain, and the educated SVM was evaluated using the lowest 25 MRI images. The SVM classifier yields 91.66 percent, 83.33 percent, and 87.50 percent accuracy on linear, quadratic, and polynomial feature work, correspondingly, also 100 percent particularity. Prof. Chandrakant Mahobiya [14] suggested a convincing programmed order technique for cerebrum MRI using the Adaboost AI computation in Astinaminz. Preprocessing, Feature Extraction, and Classification are the three aspects of the proposed system. The gathered information is cleaned up, the Image was converted to monochrome, a middle stream is added, and background subtraction subdivision is applied. 22 features successfully recovered from an MRI using the GLCM approach for extracting the features. For description, the boosting method was utilised (Adaboost). It can detect healthy, dangerous, or harmless tumours with an effectiveness of 89.90 percent. We can work on quadratic and polynomial components in the future.

Preparing information base photos will improve the framework's accuracy. Furthermore, the framework may be used for a variety of purposes. As an example, Glioma and malignant tumors are two types of cancer. Garima Singh and Dr. M.A. Ahmed [31] proposed a novel technique that combines statistical normalisation with K-implies identification. The supplied image is first well before to eliminate any unwanted signals or noise. Channels like Average, Adaptive, Combining, Un-sharp Coverage, and Gaussian are being used to remove the noise in MRI images. The MRI order is complete when the histogram of the resulting image is standardized. Finally, the image is split using the K-implies method to remove the tumour from the MRI. To provide exact prediction and categorization, the MRIs are characterised effectively using the NB Classifier and SVM. The Credulous Bayes and SVM Classifiers are both 87.23 percentage and 91.49 percent competent, accordingly. SVM provides more precise categorization. MATLAB is used to run the programme. The suggested method has a few limitations, including the inability to determine the exact boundary of the tumour district. Later on, dealing with the obstructions should allow progress in the suggested computation, and the nature of the yield pictures may be enhanced by using better morphological jobs.

Table 1
Comparative Study of Different Brain Tumor Detection and Classification Techniques Using MRI Images

S.NO	NAME	FEATURES	DESCRIPTIONS
1.	Tazin, Tahia [22]	MobileNetV2	This paper depicts the examination of the convolutional brain organization (CNN) to recognize mind growths from X-beam pictures.. With the use of a transfer learning method, the provided model aims to improve accuracy..
2.	Kausar, Nabeela, et al [23]	Majority Voting Ensemble	For multiclass skin cancer classification, we created deep learning-based ensemble classification models. Even if individual

		Models	models perform well, the building of an ensemble is a relevant strategy as it boosts classification accuracy.
3.	Mehrotra, Rajat, et al [24]	AlexNet	Pretrained CNN models are used to execute TL to extract characteristics that are visually identifiable and vital. Finally, the categorization of these characteristics is done by employing the softmax layer.
4.	Benedetti, Priscilla, et al [25]	Inception-ResNet-v2	A CNN with transfer learning, tailored data augmentation, and a non-adaptive optimization technique was used. We were able to create a final model that could accurately distinguish several categories.
5.	Shahidi, Faezehsadat, et [26]	ResNetV2	This paper has a two-overlay reason. The underlying object is to investigate the different profound learning models in classifying breast cancer disease histopathology photographs. The second objective of our paper is to dissect the ongoing models that have a bit or restricted examination done in earlier works.
6.	Aslam, Muhammad Aqeel, and Daxiang Cui [27]	CNN	In this work, we presented a Deep Convolutional Neural Network supplemented by a Softmax layer as a CAD methodology for diagnosing the disease.
7.	Z. N. K. Swati et al [28]	Capsule networks	VGG-19 features and closed-form metric learning for similarity assessment are used in a content-based retrieval approach to return comparable brain tumor pictures.
8.	Y. Yuan et al., [29]	VGG	Developed a multi-parametric magnetic resonance transfer learning technique for detection of prostate cancer using MRI.
9.	Z. N. K. Swati et al [30]	VGG-19	A block-wise fine-tuning technique was used to classify multi-class brain tumours, which is more difficult than binary classification.
10.	Alom, Md	NABLA-N	The NABLA-N network features improved

Zahangir, et al [31]	Network	feature fusion approaches in decoding units for dermoscopic image segmentation applications. This paradigm offers superior feature representation for semantic segmentation using a mix of low to high-level feature mappings.

Proposed Methodology

This section focuses on the construction process of the Brain Tumor Classification [21,22]. The construction process of the model is done using the Transfer Learning VGG-16 model.

Data collection

The Brain MRI Images for Brain Tumor Classification dataset is divided into two categories: malignant and benign. There are 253 photographs in all, which we divided into three sections: 155 preparation images, 50 approval images, and up to 10 test shots. All of the images have been resized. The information is divided into three sections: preparation, approval, and testing.

Information preprocessing

To improve the effectiveness of our framework, we've implemented some image pre-handling strategies. To begin, we resized all of our images to 240 x 240 x 3 in order to reduce handling time and fit them into our model. We followed the related photo pre-handling methods from then on. Regardless, we used the Open-source Computer Vision (CV) Canny Edge Detection approach to remove the weak borders from the photos and extract only the cerebrum area from MRI images. A multi-stage algorithm called Cautious Edge detection is the process for detecting the corners of objects in photographs. The corners of the Real MRI mind have been depicted in the graphic using the watchful edge validation process and a short duration later just the cerebrum a piece of the picture has been trimmed.

Data augmentation

Data Augmentation [16] is one of the strategies for improperly growing the aggregate and complexity of current information. We recognise that establishing a key brain network needs a large amount of data in order to change the cutoff criteria. Because our dataset is small, we used the layout of information addition to our plan dataset by making tiny adjustments to our images, which are flipping, turning, as well as quality. It will collect our plan information size, and our model will consider these minor changes as an unmistakable picture, allowing our model to learn better and perform better on hidden data. As a result, presents the several expanded photos from a single photograph.

VGG-16 Model

As shown in figure 3, VGG16 is a convolutional neural network (CNN) design that won the ILSVR(ImageNet) problem in 2014. It is thought to become one of the best amazing vision model blueprints ever produced. The nice thing regarding VGG16 is also that they focused on having 3x3 channel cnn architectures with stage 1 or using a near buffering and Maximizing pool layers of 2x2 channel stage 2 all the same, rather than having a handful of model parameters. The VGG16 convolution cerebrum net (CNN) design, having won the 2014 ILSVR (ImageNet) challenge, constantly follows this picture of compression and max pooling stages. When it comes to vision models, this one is right up there with the finest.A remarkable part of VGG16 is that rather than using a couple hyper-limits, it relies upon a single 3x3 channel convolution layer with a phase 1 and a comparable cushioning and Max pool layer with a phase 2 for every one of its subsequent endeavors generally through the designing, the convolution and max pool layers are used dependably. For yield, there are two FC (completely associated layers) followed by a SoftMax. 16 layers with weights may be found in VGG16, which is shown by the number 16. 138 million (around) borders make up this tremendous affiliation. VGG16 is a convolutional frontal cortex connection model suggested by K. Simonyan and A. Zisserman of the Oxford university published "Astoundingly Deep Convolutional Networks for Large-Scale Image Identification." The model performs 92.7 percent top-5 test accuracy in Datasets, a collection of over 14 million pictures with 1000 classifications. It was one of the most visually appealing models entered in the 2014 ILSVRC. This also generates AlexNet with swapping a large number of investigated streams (11 during the first convolutional and 5 in the intermediate convolutional layer, accordingly) with diverse 33-piece assessed touchpoints. VGG16 was equipped with NVIDIA Titan Black GPUs and was ready for a legitimately postponed deadline.

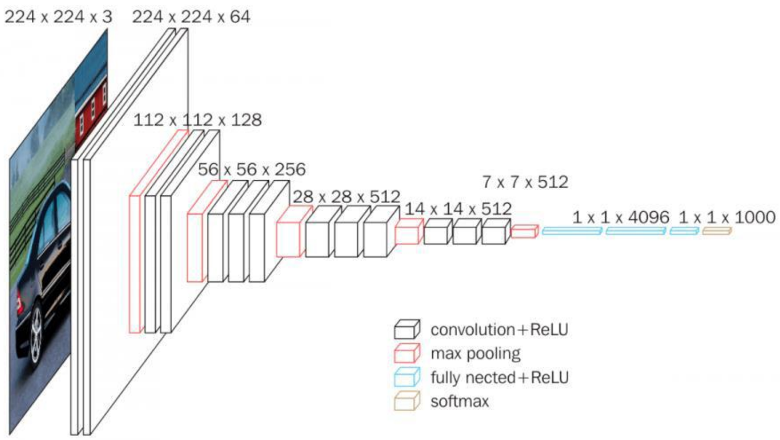

Figure 3. VGG-16 Architecture

The VGG-16 technique is used to assign a 224 by 224 RGB graphic of predetermined size to the cov1 layer in Figure 3. The image was layered with a large number of convoluted (Conv.) layers, only with pathways having a tiny region of interest: 33 (the lowest amount to identify a possibilities of left/right, up/down, and middle). Another of the models also includes an 11 convolution channel, which must show up as a brief change in the information channels (followed by non-linearity). The spatial padding of Conv. layer input is for the sole purpose of protecting the space objective post integration, i.e., for a 33 percent Conv. Layer, the shock absorption is 1-pixel. To accomplish spatial pooling, five max-pooling provides the following definition a segment of the Conv. stages (not all the Conv. layers are followed by max-pooling). Max-pooling is done in stage 2 over a 22-pixel window. Following a store of fully connected layers (which has varied meanings in different models), 3 Layers (FC) layers are added: the first couple have 4096 windows each, whereas the third does a 1000-way ILSVRC join and so has 1000 channels (one for each class). The last level is the hypersensitive maximum layer. The game design for the entirely linked stages is akin to bringing all connections together through a broad perspective.

Results and Discussions

For producing and testing photographs, the model (VGG-16) produced overall exactness (i.e., the percentage of properly perceived pictures to total pictures) of 96 percent and 90 percent, respectively. Figure 4 models clustering algorithm, which shows both true positive, real negative, false positive, and false negative values.

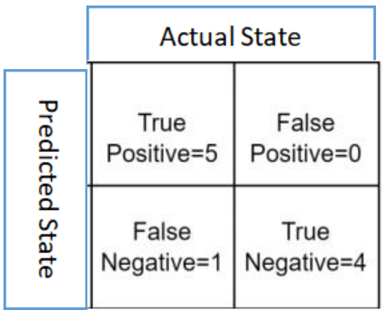

Fig 4. Confusion Matrix

Figure 5 shows the validation loss of the model which is continuously reducing on each epoch.

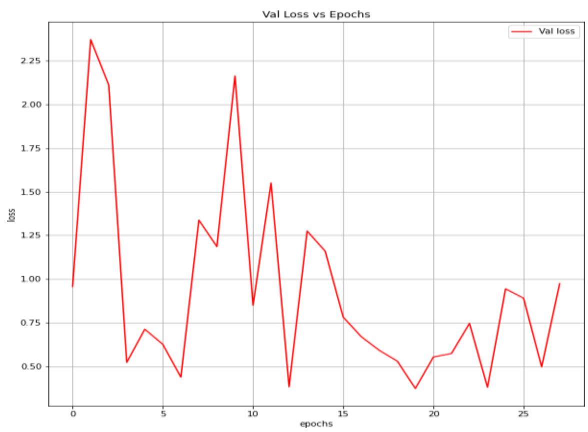

Fig 5. Val Loss

Figure 6 represents the validation accuracy of the model which is continuously increasing on every epoch.

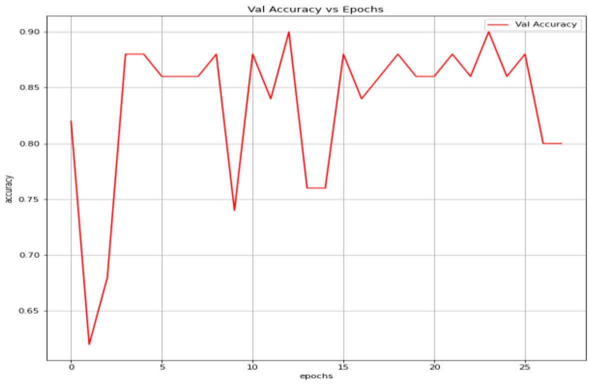

Fig 6. Val Accuracy

Figure 7 shows the training loss of the model which is continuously reducing on each epoch.

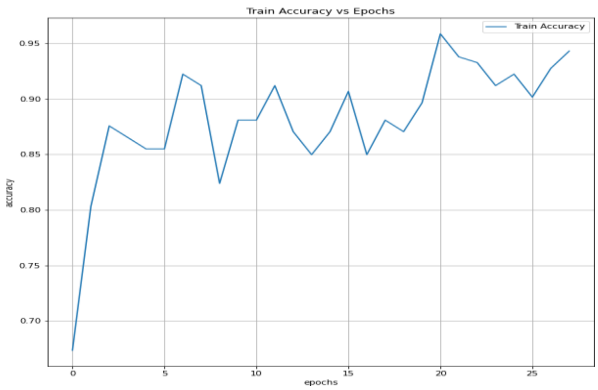

Fig:7 Train Loss

Figure 8 represents the training accuracy of the model which is continuously increasing on every epoch.

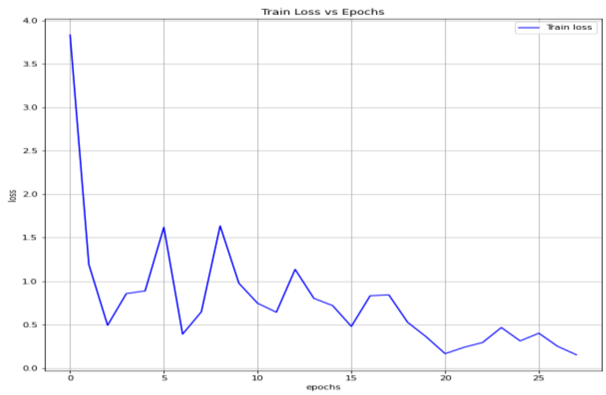

Fig 8. Train Accuracy

Conclusion

Another strategy for arranging cerebrum tumours was introduced in this study. To commence, we employed the picture edge pretty essential to locate and trim the objects of interest in MRI scans. Then, to enhance the quantity of our prepared data, we applied the informational extension approach. Second, we offer a Transfer learning model VGG-16 to supply a productive philosophy to cerebrum tumour order. Although neural organisation requires a large amount of data to prepare for refined and accurate results, our trial results demonstrate that we can attain full exactness and a good accuracy rate even with a little dataset. Our suggested framework has the potential to aid in the detection of malignancies in patients with cerebrum tumours. For additional upgrades, the model effectiveness, exhaustive hyper-boundary tuning, and a superior preprocessing procedure can be considered.

References

1. NBTS, National Brain Tumor Society: Quick brain tumor facts, 2020. Available from: https://braintumor.org/brain-tumor-information/brain-tumor-facts/.
2. Cancer. Net, Brain Tumor: Staticstics, 2020. Available from: https://www.cancer.net/cancertypes/brain- tumor/statistics.
3. [3] NHS, National Health Service: Brain Tumours, 2020. Available from: https://www.nhs.uk/conditions/brain-tumours/.
4. S. Basheera, M. S. S. Ram, Classification of brain tumors using deep features extracted using CNN, J. Phys., 1172 (2019), 012016.
5. M. Sajjad, S. Khan, M. Khan, W. Wu, A. Ullah,
6. S. W. Baik, Multi-grade brain tumor classification using deep CNN with extensive data augmentation, J. Comput. Sci., 30 (2019), 174-182.
7. R. Carlo, C. Renato, C. Giuseppe, U. Lorenzo, I. Giovanni, S. Domenico, Distinguishing Functional from Non-functional Pituitary Macroadenomas with a Machine Learning Analysis, Mediterranean Conference on Medical and Biological Engineering and Computing, Springer, 2019, 1822-1829.

8. S. Khawaldeh, U. Pervaiz, A. Rafiq, R. Alkhawaldeh, Noninvasive grading of glioma tumor using magnetic resonance imaging with convolutional neural networks, J. Appl. Sci., 8 (2018), 27.
9. N. Abiwinanda, M. Hanif, S. Hesaputra, A. Handayani, T. R. Mengko, Brain tumor classification using convolutional neural network, World Congress on Medical Physics and Biomedical Engineering, Springer, Singapore, 2019.
10. S. Das, R. Aranya, N. Labiba, Brain tumor classification using convolutional neural network, 2019 1st International Conference on Advances in Science, Engineering and Robotics Technology (ICASERT), 2019.
11. V. Romeo, R. Cuocolo, C. Ricciardi, L. Ugga, S. Cocozza, F. Verde, et al., Prediction of tumor grade and nodal status in oropharyngeal and oral cavity squamous-cell carcinoma using a radiomic approach, Anticancer Res., 40 (2020), 271-280.
12. M. Talo, U. B. Baloglu, O. Yldrm, U. R. Acharya, Application of deep transfer learning for automated brain abnormality classification using MRI images, Cognitive Systems Research, 54 (2019), 176- 188.
13. Latchoumi, T. P., Swathi, R., Vidyasri, P., & Balamurugan, K. (2022, March). Develop New Algorithm To Improve Safety On WMSN In Health Disease Monitoring. In 2022 International Mobile and Embedded Technology Conference (MECON) (pp. 357-362). IEEE.
14. A. Cinar, M. Yldrm, Detection of tumors on brain MRI images using the hybrid convolutional neural network architecture, Med. Hypotheses, 139 (2020), 109684.
15. N. Chakrabarty, Brain MRI images dataset for brain tumor detection, Kaggle, 2019. Available from: https://www.kaggle.com/navoneel/brain-mri- images-for-brain-tumor-detection.
16. J. F. Canny, Canny Edge Detection, Open Source Computer Vision, OpenCVhttps://docs.opencv.org /trunk/da/d22/tutorial_py_can ny.html.
17. C. Shorten, T. M. Khoshgoftaa, A survey on image data augmentation for deep learning, J. Big Data, 6 (2019), 60.
18. Keras, Image data preprocessing keras API, Keras documentation. Available from: https://keras.io/api/preprocessing/image/.
19. V. Nair, G. Hinton, Rectified linear units improve restricted boltzmann machines, ICML, 2010.
20. S. Mannor, D. Peleg, R. Rubinstein, The cross entropy method for classification, Proceedings of the 22nd international conference on Machine learning, 2005.
21. Latchoumi, T. P., & Parthiban, L. (2021). Quasi oppositional dragonfly algorithm for load balancing in a cloud computing environment. Wireless Personal Communications, 1-18.
22. Banu, J. F., Muneeshwari, P., Raja, K., Suresh, S., Latchoumi, T. P., & Deepan, S. (2022, January). Ontology-Based Image Retrieval by Utilizing Model Annotations and Content. In 2022 12th International Conference on Cloud Computing, Data Science & Engineering (Confluence) (pp. 300-305). IEEE.
23. Tazin, Tahia, et al. "A Robust and Novel Approach for Brain Tumor Classification Using Convolutional NeuralNetwork.“ Computational Intelligence and Neuroscience 2021 (2021).

24. Kausar, Nabeela, et al. "Multiclass Skin Cancer Classification Using Ensemble of Fine-Tuned Deep Learning Models." Applied Sciences 11.22 (2021): 10593.
25. Latchoumi, T. P., & Parthiban, L. (2021). Quasi oppositional dragonfly algorithm for load balancing in a cloud computing environment. Wireless Personal Communications, 1-18.
26. Benedetti, Priscilla, et al. "Skin cancer classification using inception network and transfer learning." International Conference on Computational Science and Its Applications. Springer, Cham, 2020.
27. Shahidi, Faezehsadat, et al. "Breast cancer classification using deep learning approaches and histopathology image: a comparison study." IEEE Access 8 (2020): 187531-187552.
28. Aslam, Muhammad Aqeel, and Daxiang Cui. "Breast cancer classification using deep convolutional neural network." Journal of Physics: Conference Series. Vol. 1584. No. 1. IOP Publishing, 2020.
29. Z. N. K. Swati et al., "Content-based brain tumor retrieval for MR images using transfer learning," IEEE Access, vol. 7, pp. 17809–17822, 2019.
30. Y. Yuan et al., "Prostate cancer classification with multiparametric MRI transfer learning model," Med. Phys., vol. 46, no. 2, pp. 756–765, Feb. 2019.
31. Z. N. K. Swati et al., "Brain tumor classification for MR images using transfer learning and fine-tuning," Computerized Med. Imag. Graph., vol. 75, pp. 34–46, Jul. 2019.
32. Alom, Md Zahangir, et al. "Skin cancer segmentation and classification with NABLA-N and inception recurrent residual convolutional networks." arXiv preprint arXiv:1904.11126 (2019).