Enhancing Brain Tumor Diagnosis using CNN Models: A Comparative Analysis

Prathamesh Dinesh Joshi[1]

[1]Affiliation not available

January 10, 2024

Abstract

Brain tumors, characterized by the emergence of abnormal cell growths within or around the brain, stand as a significant medical challenge with the potential for grave consequences. Regardless of their categorization as benign or malignant, the imperative for swift diagnosis and treatment remains paramount. This research explores the integration of pretrained deep learning models, particularly Convolutional Neural Networks (CNNs) including VGG16, InceptionV3, ResNet50, and NasNetMobile in automating the diagnosis process using MRI scans for the ease of patient and Healthcare Providers. This approach leverages transfer learning and Computer-Aided Diagnosis (CAD) to streamline the detection process. Hyperparameter tuning is integrated to optimize pretrained model parameters encompassing factors such as optimizer choices, activation functions, number of neurons in each dense layer and learning rates. By systematically fine tuning the hyperparameters remarkable enhancements in tumor classification accuracy are demonstrated. This research emphasizes the significance of customized hyperparameter optimization for pretrained models, advancing the accuracy and efficiency of brain tumor detection.

Posted on 10 Jan 2024 — CC-BY-NC-SA 4 — https://doi.org/10.36227/techrxiv.170491533.39709620/v1 — e-Prints posted on TechRxiv are preliminary reports that are not peer reviewed. They should not b...

Enhancing Brain Tumor Diagnosis using CNN Models: A Comparative Analysis

Prathamesh Dinesh Joshi, *Indian Institute of Information Technology Design and Manufacturing, Kurnool-518008, Andhra Pradesh, India*

***Abstract*— Brain tumors, characterized by the emergence of abnormal cell growths within or around the brain, stand as a significant medical challenge with the potential for grave consequences. Regardless of their categorization as benign or malignant, the imperative for swift diagnosis and treatment remains paramount. This research explores the integration of pretrained deep learning models, particularly Convolutional Neural Networks (CNNs) including VGG16, InceptionV3, ResNet50, and NasNetMobile in automating the diagnosis process using MRI scans for the ease of patient and Healthcare Providers. This approach leverages transfer learning and Computer-Aided Diagnosis (CAD) to streamline the detection process. Hyperparameter tuning is integrated to optimize pretrained model parameters encompassing factors such as optimizer choices, activation functions, number of neurons in each dense layer and learning rates. By systematically fine tuning the hyperparameters remarkable enhancements in tumor classification accuracy are demonstrated. This research emphasizes the significance of customized hyperparameter optimization for pretrained models, advancing the accuracy and efficiency of brain tumor detection.**

***Impact Statement* — This research introduces an innovative method for brain tumor detection using advanced Convolutional Neural Networks (CNNs), significantly enhancing the diagnostic accuracy and efficiency. By employing pretrained deep learning models like VGG16, InceptionV3, ResNet50, and NasNet Mobile, and optimizing them through hyperparameter tuning, the study achieves a remarkable F1 score of up to 99.28%. This approach facilitates a more accurate and rapid diagnosis process, crucial for effective treatment. The use of transfer learning and computer-aided diagnosis systems in MRI scans is a pivotal step in medical imaging, potentially impacting over 1 million Americans living with brain tumors and addressing a global health concern. The technology's readiness for broader applications promises to revolutionize medical diagnostics, offering a reliable tool for healthcare providers and potentially improving survival rates by enabling earlier detection and treatment of brain tumors.**

***Index Terms*— Brain Tumor, Convolutional Neural Networks, Deep Learning Models, Hyperparameter tuning, transfer learning**

I. Introduction

A brain tumor, known as an intracranial tumor, is characterized by the abnormal growth of cells in the brain. These tumors can be either benign or malignant, with varying growth rates. They may originate within the brain tissue itself (primary) or result from the spread of cancer from other parts of the body (metastasis). Regardless of their nature, brain tumors can significantly impact brain function and overall health when they exert pressure on surrounding nerves, blood vessels, and tissues. In the United States, the National Brain Tumor Society reports that approximately 1 million Americans live with brain tumors. In 2023, an estimated 94,390 Americans will receive a primary brain tumor diagnosis, with a disheartening 35.7% relative survival rate for malignant cases, resulting in an estimated 18,990 deaths[1]. While these statistics specifically pertain to the United States, it is imperative to recognize that brain tumors are a global concern. Addressing this issue requires a multifaceted approach, with a key emphasis on early detection and diagnosis. Timely intervention is essential in improving the chances of survival for individuals affected by these tumors, not only in the United States but worldwide.

In recent decades, medical imaging techniques, including Magnetic Resonance Imaging (MRI)[2], Computed Tomography (CT)[3] scans, ultrasounds[4], and more have undergone remarkable advancements, revolutionizing the field of diagnostic medicine. The Manual brain tumour classification from MRI images having similar structures or features is a complex and challenging task, depending on the radiologist's availability and experience to recognize and diagnose the brain tumour appropriately[5]. Figure 1 demonstrates the similarity in MRI images in presence and absence of tumor. Even with experienced medical professionals at the helm, the ever-increasing volume of medical reports and imaging data can overwhelm the diagnostic process. Consequently, there is a pressing need for Computer-Aided Diagnosis (CAD)[6] systems that can assist and support doctors and radiologists in their efforts to precisely detect and diagnose brain tumors at the earliest possible stages. CAD systems hold the potential to enhance diagnostic accuracy and streamline the process, ultimately contributing to improved patient outcomes.

Prathamesh Dinesh Joshi is with the Department of Computer Science and Engineering, Indian Institute of Information Technology Design and Manufacturing, Kurnool, Andhra Pradesh 518008 India (e-mail: 121cs0072@iiitk.ac.in).

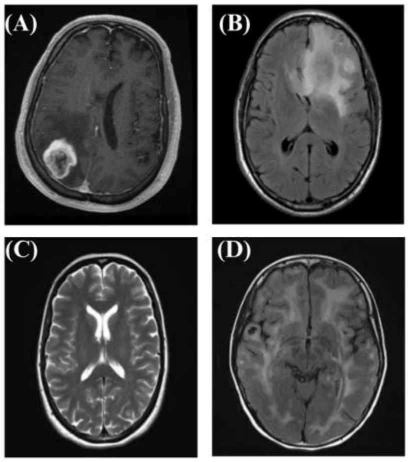

Fig. 1: Similarity in brain MRI images irrespective of the presence of a cancer tumour.

Artificial Intelligence[7] can play essential role in identifying and diagnosing brain tumors[8]. However, integrating AI into brain tumor detection within the computer-Aided Diagnosis (CAD) framework is a formidable task, primarily due to the diverse array of textures and shapes present in brain images. CAD systems consists of pre-processing, segmentation, feature analysis (feature extraction, feature selection and feature verification) and the classification. The most crucial step among these is Image segmentation which is the process of splitting an image into multiple parts. It creates various sets of pixels within the same image. Segmenting an image makes it easier for us to further analyze and extract meaningful information from it[9]. There are different methods for Image segmentation[10] (Figure 2) such as Region Based Method, Threshold Method, Edge Based Method, Watershed Method, and Clustering Method[11] but these methods often make them less suitable for complex or large-scale segmentation tasks.

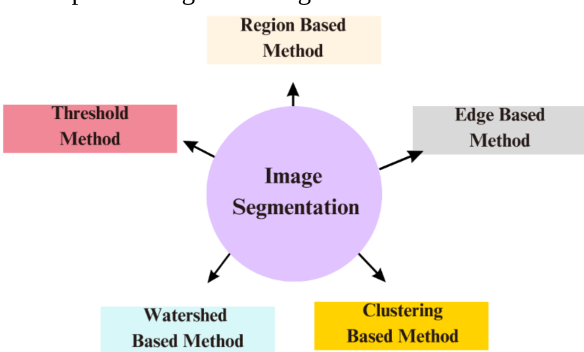

Fig. 2: Non-ML based algorithms for segmenting the MRI/CT image

To tackle this challenge, recent advancements in AI have seen the introduction of deep learning, a subfield that seeks to replicate the cognitive processes of the human brain in computer systems. Deep learning models, including Convolutional Neural Networks (CNNs)[12], have demonstrated the ability to discern intricate patterns in images, text, sounds, and other data, yielding highly accurate predictions and valuable insights. In the realm of medical image analysis, deep learning has found substantial utility in the detection of cancer cells and other medical diagnoses (Figure 3).

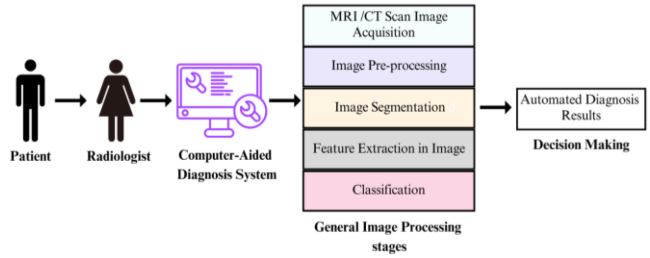

Fig. 3: How and AI/ML based system can help accurate tumour detection

Among deep learning models, Convolutional Neural Network (CNN) stands out as one of the most successful for image understanding. The CNN model is made of convolutional filters[13] whose primary function is to learn and extract necessary features for the efficient medical image understanding[14](Figure 4).

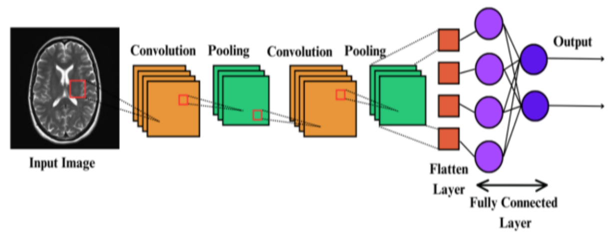

Fig. 4: General Convolutional Neural Network (CNN) architecture for classifying brain MRI/CT images into two classes.

Furthermore, a significant technique that amplifies the utility of CNNs in medical imaging is transfer learning[15]. Transfer learning involves leveraging pretrained models on large and diverse datasets and adapting them for specific tasks. In the context of medical image analysis, this entails taking a CNN model that has already acquired rich features from extensive datasets and fine-tuning it for specialized tasks such as brain tumor detection as shown in the figure 5

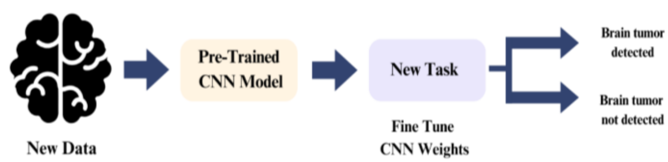

Fig. 5: General transfer learning architecture for classifying brain MRI/CT images into two classes.

Several noteworthy research studies have harnessed the power of deep learning in medical image analysis. For instance, Charron et al. employed a deep CNN to monitor brain metastases[16], while Yang et al. used AlexNet and GoogLeNet to grade gliomas from MRI images, with GoogLeNet outperforming AlexNet[17]. In a 2019 study, Zhou et al. employed a pre-trained InceptionV3 model to differentiate between benign and malignant renal tumors on CT images [18]. Additionally, Habib used an Artificial CNN to detect brain tumors, achieving an impressive 88.7% test accuracy with a unique neural network architecture[19]. Malathi M. and P. Sinthia proposed fully automated brain tumor segmentation using CNN and the TensorFlow library[20], while S. Deepak employed the pre-trained GoogLeNet framework, achieving a mean accuracy of 98 percent[21]. Majib et al. introduced a hybrid approach, VGG-SCnet, combining VGGNet with a stacked classifier for fine-tuning a VGG-16 architecture[22]. These studies collectively underscore the transformative potential of deep learning and CNNs in the critical task of medical image analysis, particularly in the context of brain tumor detection.

This study conducted a comparative analysis of pretrained CNN models, including VGG16, ResNet50, InceptionV3, and NasNet Mobile, utilizing a transfer learning approach for the detection of brain tumors. The dataset employed for this research, sourced from Kaggle[23], comprised 4600 images, primarily in JPEG format and predominantly in RGB scale. Among these images, 2513 belonged to the brain tumor class, while the remainder represented the healthy class, with an 80:20 data split for training and testing.The evaluation of these models was based on default parameters, the number of epochs, and the size of the training set, with a focus on accuracy and F1 score metrics. Subsequently, various hyperparameter tuning methods were employed, including Keras' hyperband[24] tuner, Random Search[25], Bayesian Optimization[26], and manual techniques. The results revealed the highest F1 score[27] of 99.28% achieved by InceptionV3 using Keras tuner Hyperband, while the lowest was recorded at 59.58% for ResNet50 with Keras tuner Bayesian Optimization.

II. Results

A. *Data Pre-Processing*

Before employing any image classification techniques, it is imperative to consider preprocessing steps. In this study, the dataset sourced from Kaggle consisted of a total of 4,600 images, with 2,513 images classified as belonging to the Brain tumor category and 2,087 images representing the healthy class. To facilitate efficient mini-batch training and model convergence, a batch size of 64 images was employed. All images underwent resizing to a standardized dimension of 150x150 pixels, a measure taken to mitigate computational complexity. Additionally, the images were uniformly converted to the RGB format, as the majority of CNN pretrained models necessitate RGB input. Consequently, the input shape was configured as (150,150,3), signifying that each input image consists of a 3-channel RGB composition. Class labels were meticulously assigned to align with the binary classification task's requisites. Furthermore, the dataset was partitioned into an 80:20 ratio for the purposes of training and testing, ensuring the robustness and integrity of the experimental setup.

B. *Use Of CNN Architecture*

CNN is one of the best techniques for image classification because they are designed to automatically learn hierarchical features from the images. As we can see from Figure 4 that it consists of multiple layers including convolutional layers which scan and filter an input image. In order to obtain a new feature, the input feature maps are first convolved with a learned kernel and then the results are passed into a nonlinear activation function. We will get different feature maps by applying different kernels[28].The typical activation functions are Relu[29] ,tanh and Sigmoid[30].

After Convolutional Layer, there is a pooling layer which are often applied to reduce spatial dimensions of the feature maps while retaining important information. Common pooling techniques include max-pooling and average-pooling[31]. Feature maps are then flattened into a vector to be fed into one or more fully connected layers[32] where flattening layer helps to convert data into 1-dimentional array for feeding next layer. Lastly, we have fully connected layer where final fully connected layer in a CNN is responsible for making predictions or classification. In context of Image classification, these layers typically output probabilities for different classes, and the class with the highest probability is considered the predicted class.

Transfer Learning, a technique with the help of which a model can be taught and refined for one activity and then applied to a different one which is closely connected to it.[33]. Transfer learning aims to improve learning in the target domain by leveraging knowledge from the source domain and learning task[34].Figure 5 demonstrates how we can apply the transfer learning method, which combines the insights gained from pretrained models with fine-tuning on new data, improves the model's accuracy in classifying new data.

For this study, focusing on brain tumor detection, we have created a Convolutional Neural Network (CNN) model using TensorFlow’s Keras Library. Specifically, an instance of a Sequential model is initialized. The model architecture is built using the one of architecture from InceptionV3[35], Resnet50[36], VGG16[37], NasNet Mobile[38] which had been trained on ImageNet dataset. The pretrained model is loaded with the specified weights and is configured not to include top classification layer which gives us more flexibility and control over how can we use the model for the specific task and input shape is chosen to match the requirements of pretrained models (Figure 6).

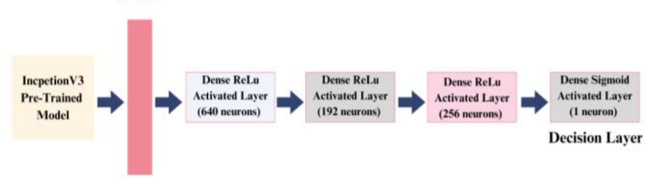

Fig. 6: Architecture of the InceptionV3 model with the hyperparameters used.

The next step involves freezing the weights of all layers in the pretrained model by iterating through each layer which ensures while using transfer learning, pretrained weights are not updated during training on new dataset. Then output is flattened to transform the multidimensional output into one dimensional tensor. Subsequently, a stack of three densely connected layers is introduced to capture intricate data patterns and feature. These layers vary in number of neurons and activation functions. Finally, a single neuron equipped with a sigmoid activation function is appended, serving as the output layer for the binary classification task, specifically aimed at detecting the presence or absence of a brain tumor.

In order to enhance model performance, an extensive hyperparameter tuning[39] strategy was systematically applied to all the pretrained models under investigation. Three stacked dense layers with varying neurons and the activation functions, including ReLu, tanh, and sigmoid were systematically explored using Keras tuner Random Search, Bayesian Optimization, Hyperband. The search space for hyperparameters encompassed layer units, optimizer choices (adam, sgd, rmsprop)[40], and learning rates. The best performing set of Hyperparameter was extracted out of 5 trials for each Keras Tuner Additionally manual hyperparameter settings were tested for comparison. In particular, models with 1024, 512, and 128 neurons in the respective layers, each employing SELU[41] activation for the first two layers and either SELU or ReLU for the third, were examined. All models underwent training for a fixed number of epochs, specifically 10 during the experimentation process. Later Accuracy[42] and f1 score were consider as a metrices for evaluating the performance of all the proposed models.

III. Observations

From Figure 7, it is evident that VGG16 outperformed other models when trained with our custom default hyperparameters, achieving an impressive F1-score of 0.9892. NasNet Mobile closely followed with a score of 0.9821. Among the Keras Tuner hyperparameter functions, Hyperband, in conjunction with InceptionV3, exhibited outstanding performance, achieving an exceptional F1-score of 0.9928. VGG16 also performed well with Keras Tuner Hyperband, attaining a score of 0.9916.

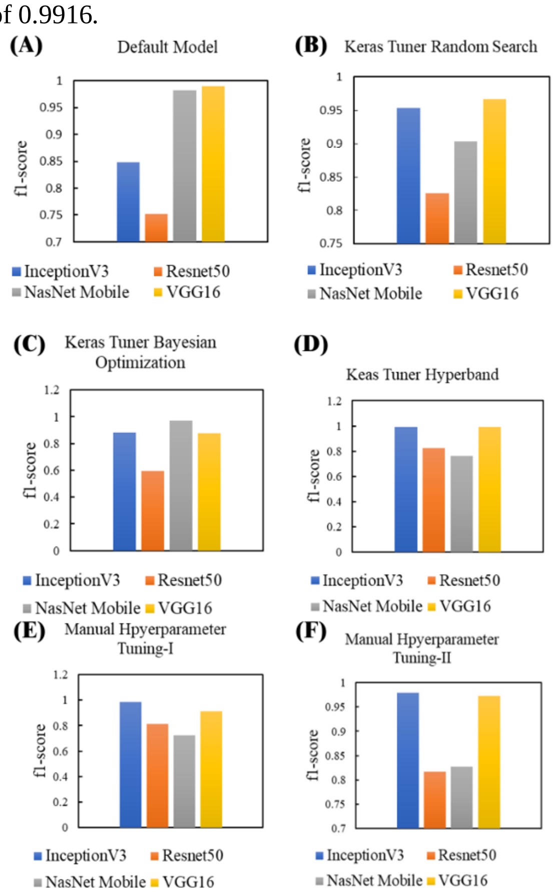

Fig. 7: Comparison of f1-score for Inception V3, Resnet50, NasNet Mobile and VGG16 for various hyperparameters. (A) Default, (B) Keras Tuner Random search (C) Keras tuner Bayesian optimization (D) Keras Tuner Hyperband (E) Manual Hyperparameter tuning 1 and (F) Manual hyperparameter tuning 2.

Among all the models and their respective hyperparameter sets, InceptionV3 combined with Keras Tuner Hyperband delivered the best performance. This configuration included a first stacked layer with 640 neurons using ReLU activation, followed by a layer with 192 neurons also employing ReLU activation. The final layer consisted of 256 neurons with ReLU activation, and the output layer featured a single neuron using the Sigmoid activation function.

When analyzing the test set accuracy, a notable distinction emerges, ranging from the impressive 0.9935 achieved by the InceptionV3 model with Keras Hyperband to the relatively modest 0.8422 attained by the best-performing Resnet50 model. Figure 8 provides a visual representation of the test set accuracy across all models when employing Keras Tuner Hyperband.

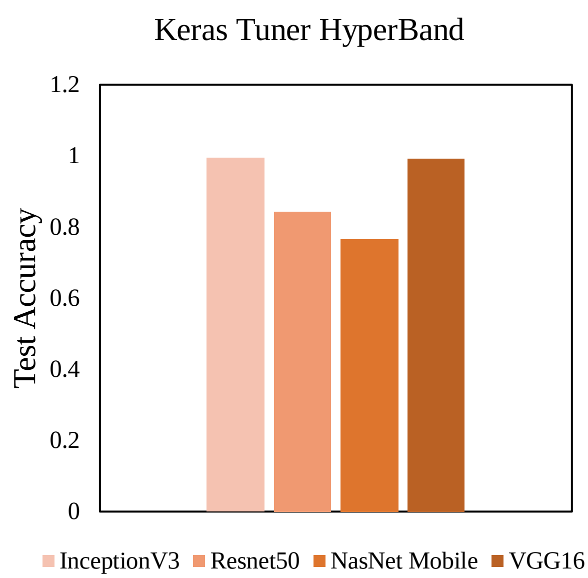

Fig. 8: Test accuracy for various models for Keras Tuner Hyperband

Figure 9, shows the test set accuracy of the InceptionV3 model, considering all the sets of hyperparameters employed. It is worth noting that InceptionV3, known for its intricate architecture compared to other models, consistently demonstrates remarkable performance with diverse hyperparameter configurations. This suggests that the complexity of InceptionV3 contributes to its adaptability across various hyperparameter settings. Furthermore, the efficacy of Keras Hyperband, utilizing Successive Halving[43], plays a pivotal role in achieving these high-performing results across the models.

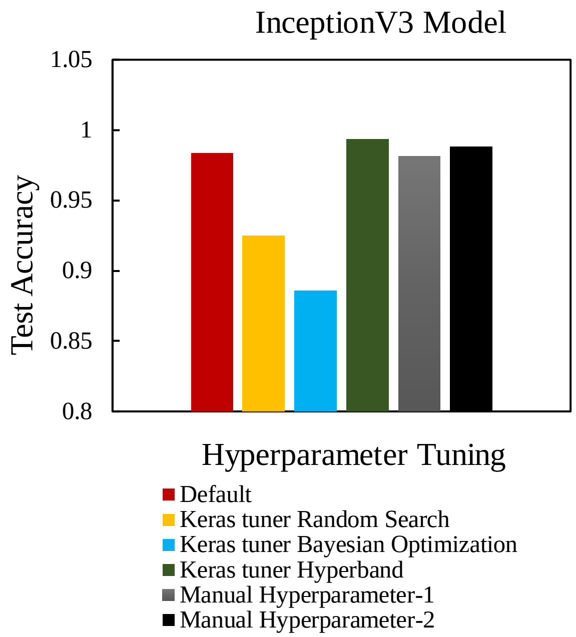

Fig. 9: Test accuracy of InceptionV3 model for various hyperparameters

IV. Conclusion

In this study focused on brain tumor detection, we harnessed the capabilities of Convolutional Neural Networks (CNNs) through TensorFlow's Keras Library. Leveraging transfer learning with pre-trained CNN architectures including InceptionV3, ResNet50, VGG16, and NasNet Mobile, fine-tuned for our specific task. Employing an extensive hyperparameter tuning strategy, we explored various combinations of hyperparameters, encompassing custom defaults and Keras Tuner's Hyperband function. This comprehensive approach revealed that InceptionV3 consistently outperformed other architectures across diverse hyperparameter settings, while VGG16 also demonstrated notable performance. The Hyperband function proved instrumental in enhancing these models' performance. Conversely, ResNet50 showed relatively lower accuracy throughout, and NasNet Mobile exhibited mixed results, particularly with manual hyperparameters. This research underscores the pivotal role of architecture choice and hyperparameter optimization in creating effective brain tumor detection models, conducting a comprehensive comparative analysis among different models to gain valuable insights. These advancements in computer-aided diagnosis systems not only contribute to early and precise brain tumor detection but also hold the promise of reducing the burden on medical professionals, ultimately leading to improved patient care and outcomes. In the pursuit of enhancing model accuracy, there lies a compelling opportunity for further refinement and advancement in this critical domain, fostering a brighter future for brain tumor detection and patient well-being.

References

[1] "Brain Tumor Facts." Accessed: Sep. 16, 2023. [Online]. Available: https://braintumor.org/brain-tumors/about-brain-tumors/brain-tumor-facts/

[2] V. P. B. Grover, J. M. Tognarelli, M. M. E. Crossey, I. J. Cox, S. D. Taylor-Robinson, and M. J. W. McPhail, "Magnetic Resonance Imaging: Principles and Techniques: Lessons for Clinicians," *J Clin Exp Hepatol*, vol. 5, no. 3, pp. 246–255, Sep. 2015, doi: 10.1016/J.JCEH.2015.08.001.

[3] O. Schillaci, L. Filippi, C. Manni, R. S.-S. in nuclear medicine, and undefined 2007, "Single-photon emission computed tomography/computed tomography in brain tumors," *Elsevier*, Accessed: Nov. 05, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0001299806000584

[4] R. Sastry *et al.*, "Applications of Ultrasound in the Resection of Brain Tumors," *Journal of Neuroimaging*, vol. 27, no. 1, pp. 5–15, Jan. 2017, doi: 10.1111/JON.12382.

[5] C. L. Choudhury, C. Mahanty, R. Kumar, and B. K. Mishra, "Brain Tumor Detection and Classification Using Convolutional Neural Network and Deep Neural Network," *2020 International Conference on Computer Science, Engineering and Applications, ICCSEA 2020*, Mar. 2020, doi: 10.1109/ICCSEA49143.2020.9132874.

[6] K. D.-C. medical imaging and graphics and undefined 2007, "Computer-aided diagnosis in medical imaging: historical review, current status and future potential," *Elsevier*, Accessed: Nov. 05, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0895611107000262

[7] P. Hamet, J. T.- Metabolism, and undefined 2017, "Artificial intelligence in medicine," *Elsevier*, Accessed: Nov. 05, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S002604951730015X

[8] H. A. Shah, F. Saeed, S. Yun, J. H. Park, A. Paul, and J. M. Kang, "A Robust Approach for Brain Tumor Detection in Magnetic Resonance Images Using Finetuned EfficientNet," *IEEE Access*, vol. 10, pp. 65426–65438, 2022, doi: 10.1109/ACCESS.2022.3184113.

[9] L. Kapoor, S. T. cloud computing, & data science, and undefined 2017, "A survey on brain tumor detection using image processing techniques," *ieeexplore.ieee.orgL Kapoor, S Thakur2017 7th international conference on cloud computing, data science, 2017•ieeexplore.ieee.org*, Accessed: Sep. 16, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/7943218/

[10] Y. J. Zhang, "A survey on evaluation methods for image segmentation," *Pattern Recognit*, vol. 29, no. 8, pp. 1335–1346, Aug. 1996, doi: 10.1016/0031-3203(95)00169-7.

[11] Y. Aslam, N. Santhi, N. Ramasamy, and K. Ramar, “A Review on Various Clustering Approaches for Image Segmentation,” *Proceedings of the 4th International Conference on Inventive Systems and Control, ICISC 2020*, pp. 679–685, Jan. 2020, doi: 10.1109/ICISC47916.2020.9171125.

[12] K. O’Shea and R. Nash, “An Introduction to Convolutional Neural Networks,” *Int J Res Appl Sci Eng Technol*, vol. 10, no. 12, pp. 943–947, Nov. 2015, doi: 10.22214/ijraset.2022.47789.

[13] S. S. Du, J. D. Lee, and Y. Tian, “When is a convolutional filter easy to learn?,” *6th International Conference on Learning Representations, ICLR 2018 - Conference Track Proceedings*, 2018.

[14] D. R. Sarvamangala, · Raghavendra, and V. Kulkarni, “Convolutional neural networks in medical image understanding: a survey,” *Evol Intell*, vol. 15, pp. 1–22, 2065, doi: 10.1007/s12065-020-00540-3.

[15] F. Zhuang *et al.*, “A comprehensive survey on transfer learning,” *ieeexplore.ieee.org*, 2020, Accessed: Nov. 05, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9134370/

[16] O. Charron, A. Lallement, D. Jarnet, V. Noblet, J. B. Clavier, and P. Meyer, “Automatic detection and segmentation of brain metastases on multimodal MR images with a deep convolutional neural network,” *Comput Biol Med*, vol. 95, pp. 43–54, Apr. 2018, doi: 10.1016/J.COMPBIOMED.2018.02.004.

[17] Y. Yang *et al.*, “Glioma grading on conventional MR images: A deep learning study with transfer learning,” *Front Neurosci*, vol. 12, no. NOV, p. 415895, Nov. 2018, doi: 10.3389/FNINS.2018.00804/BIBTEX.

[18] L. Zhou, Z. Zhang, Y.-C. Chen, Z.-Y. Zhao, X.-D. Yin, and H.-B. Jiang, “A Deep Learning-Based Radiomics Model for Differentiating Benign and Malignant Renal Tumors 1,” *Transl Oncol*, vol. 12, pp. 292–300, 2019, doi: 10.1016/j.tranon.2018.10.012.

[19] “Brain Tumor Detection Using Convolutional Neural Networks | by Mohamed Ali Habib | Medium.” Accessed: Sep. 09, 2023. [Online]. Available: https://medium.com/@mohamedalihabib7/brain-tumor-detection-using-convolutional-neural-networks-30ccef6612b0

[20] M. Malathi, P. S.-A. P. journal of cancer prevention, and undefined 2019, “Brain tumour segmentation using convolutional neural network with tensor flow,” *ncbi.nlm.nih.govM Malathi, P SinthiaAsian Pacific journal of cancer prevention: APJCP, 2019•ncbi.nlm.nih.gov*, Accessed: Sep. 09, 2023. [Online]. Available: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6745230/

[21] S. Deepak, P. A.-C. in biology and medicine, and undefined 2019, “Brain tumor classification using deep CNN features via transfer learning,” *Elsevier*, Accessed: Sep. 09, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0010482519302148

[22] M. S. Majib, M. M. Rahman, T. M. Shahriar Sazzad, N. I. Khan, and S. K. Dey, “VGG-SCNet: A VGG Net based Deep Learning framework for Brain Tumor Detection on MRI Images,” *IEEE Access*, 2021, doi: 10.1109/ACCESS.2021.3105874.

[23] “Brian Tumor Dataset | Kaggle.” Accessed: Sep. 09, 2023. [Online]. Available: https://www.kaggle.com/datasets/preetviradiya/brian-tumor-dataset

[24] L. Li, K. Jamieson, G. DeSalvo, … A. R.-T. journal of machine, and undefined 2017, “Hyperband: A novel bandit-based approach to hyperparameter optimization,” *jmlr.org*, vol. 18, pp. 1–52, 2018, Accessed: Nov. 05, 2023. [Online]. Available: https://www.jmlr.org/papers/volume18/16-558/16-558.pdf

[25] J. Bergstra, J. B. Ca, and Y. B. Ca, “Random Search for Hyper-Parameter Optimization Yoshua Bengio,” *Journal of Machine Learning Research*, vol. 13, pp. 281–305, 2012, Accessed: Nov. 05, 2023. [Online]. Available: http://scikit-learn.sourceforge.net.

[26] A. H. Victoria and G. Maragatham, “Automatic tuning of hyperparameters using Bayesian optimization,” *Evolving Systems*, vol. 12, no. 1, pp. 217–223, Mar. 2021, doi: 10.1007/S12530-020-09345-2.

[27] R. Yacouby, D. A.-P. of the first workshop on, and undefined 2020, “Probabilistic extension of precision, recall, and f1 score for more thorough evaluation of classification models,” *aclanthology.org*, Accessed: Nov. 05, 2023. [Online]. Available: https://aclanthology.org/2020.eval4nlp-1.9/

[28] T. Guo, J. Dong, H. Li, and Y. Gao, “Simple convolutional neural network on image classification,” *2017 IEEE 2nd International Conference on Big Data Analysis, ICBDA 2017*, pp. 721–724, Oct. 2017, doi: 10.1109/ICBDA.2017.8078730.

[29] V. Nair and G. E. Hinton, “Rectified Linear Units Improve Restricted Boltzmann Machines”.

[30] S. Gomar, M. Mirhassani, and M. Ahmadi, “Precise digital implementations of hyperbolic tanh and sigmoid function,” *Conf Rec Asilomar Conf Signals Syst Comput*, pp. 1586–1589, Mar. 2017, doi: 10.1109/ACSSC.2016.7869646.

[31] Z. Li, S. H. Wang, R. R. Fan, G. Cao, Y. D. Zhang, and T. Guo, “Teeth category classification via seven-layer deep convolutional neural network with max pooling and global average pooling,” *Int J Imaging Syst Technol*, vol. 29, no. 4, pp. 577–583, Dec. 2019, doi: 10.1002/IMA.22337.

[32] S. H. S. Basha, S. R. Dubey, V. Pulabaigari, and S. Mukherjee, “Impact of fully connected layers on performance of convolutional neural networks for image classification,” *Neurocomputing*, vol. 378, pp. 112–119, Feb. 2020, doi: 10.1016/J.NEUCOM.2019.10.008.

[33] D. Yang *et al.*, “Deep Learning (CNN) and Transfer Learning: A Review,” *J Phys Conf Ser*, vol. 2273, no. 1, p. 012029, May 2022, doi: 10.1088/1742-6596/2273/1/012029.

[34] J. A. L. Marques, F. N. B. Gois, J. P. do V. Madeiro, T. Li, and S. J. Fong, "Artificial neural network-based approaches for computer-aided disease diagnosis and treatment," *Cognitive and Soft Computing Techniques for the Analysis of Healthcare Data*, pp. 79–99, Jan. 2022, doi: 10.1016/B978-0-323-85751-2.00008-6.

[35] X. Xia, C. Xu, and B. Nan, "Inception-v3 for flower classification," *2017 2nd International Conference on Image, Vision and Computing, ICIVC 2017*, pp. 783–787, Jul. 2017, doi: 10.1109/ICIVC.2017.7984661.

[36] I. Z. Mukti and D. Biswas, "Transfer Learning Based Plant Diseases Detection Using ResNet50," *2019 4th International Conference on Electrical Information and Communication Technology, EICT 2019*, Dec. 2019, doi: 10.1109/EICT48899.2019.9068805.

[37] H. Qassim, A. Verma, and D. Feinzimer, "Compressed residual-VGG16 CNN model for big data places image recognition," *2018 IEEE 8th Annual Computing and Communication Workshop and Conference, CCWC 2018*, vol. 2018-January, pp. 169–175, Feb. 2018, doi: 10.1109/CCWC.2018.8301729.

[38] F. Saxen, P. Werner, S. Handrich, E. Othman, L. Dinges, and A. Al-Hamadi, "Face attribute detection with mobilenetv2 and nasnet-mobile," *International Symposium on Image and Signal Processing and Analysis, ISPA*, vol. 2019-September, pp. 176–180, Sep. 2019, doi: 10.1109/ISPA.2019.8868585.

[39] L. Yang and A. Shami, "On hyperparameter optimization of machine learning algorithms: Theory and practice," *Neurocomputing*, vol. 415, pp. 295–316, Nov. 2020, doi: 10.1016/J.NEUCOM.2020.07.061.

[40] A. Kumar, S. Sarkar, and C. Pradhan, "Malaria Disease Detection Using CNN Technique with SGD, RMSprop and ADAM Optimizers," *Studies in Big Data*, vol. 68, pp. 211–230, 2020, doi: 10.1007/978-3-030-33966-1_11/COVER.

[41] A. D. Rasamoelina, F. Adjailia, and P. Sincak, "A Review of Activation Function for Artificial Neural Network," *SAMI 2020 - IEEE 18th World Symposium on Applied Machine Intelligence and Informatics, Proceedings*, pp. 281–286, Jan. 2020, doi: 10.1109/SAMI48414.2020.9108717.

[42] S. Shahinfar, P. Meek, G. F.-E. Informatics, and undefined 2020, "'How many images do I need?' Understanding how sample size per class affects deep learning model performance metrics for balanced designs in autonomous," *Elsevier,* Accessed: Nov. 05, 2023. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1574954120300352

[43] C. Goay, N. Ahmad, P. G.-I. Access, and undefined 2021, "Transient simulations of high-speed channels using CNN-LSTM with an adaptive successive halving algorithm for automated hyperparameter optimizations," *ieeexplore.ieee.org,* Accessed: Nov. 05, 2023. [Online]. Available: https://ieeexplore.ieee.org/abstract/document/9536702/

Prathamesh Dinesh Joshi was born in Akola, Maharashtra, India in 2002. He is currently 3rd year B.Tech student majoring in computer science and engineering at Indian Institute of Information Technology Design and Manufacturing, Kurnool, Andhra Pradesh, India and is expected to be graduate by 2025.

He worked as High-Performance Computing intern at Centre for Development of Advanced Computing(C-DAC), Pune, India form May-July,2023. His current research interest lies in the area of Biomedical Imaging, Deep Learning, and particularly in Computer Vision and its applications.