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Classification of Brain Tumor as Benign or Malignant Using Image Processing and Deep Learning Techniques: A Comparative Study

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Abstract: In India, the dominance of brain tumors is 5-10 per 100,000 people. According to the International Association of Cancer Registries (IARC), over 28,000 cases of brain tumors are recorded each year in India, with over 24,000 individuals dying from them each year. The proposed approach includes pre-processing of the Magnetic Resonance Imaging (MRI) scans followed by the extraction of the Region of Interest (ROI) using image processing techniques. The extracted parts are then used as input to train a deep neural network model for classification. The Convolutional Neural(CNN) is trained on a large dataset of MRI images of brain tumors, and evaluated using various performance metrics. Deep Learning models like VGG16, ResNet50 are used for the classification of images. Deep learning model with VGG16 gives 98.5 % accuracy which is better than CNN and ResNet50.
Keywords: Brain tumor, Convolutional Neural Network (CNN), VGG-16, ResNet50, Brain tumor classification, Image processing.

I. INTRODUCTION

Brain tumor is a serious medical condition that requires early diagnosis and treatment. The diagnosis of brain tumor involves the analysis of medical images obtained through various imaging modalities, such as magnetic resonance imaging (MRI). The accurate classification of brain tumors as benign or malignant is crucial for the selection of appropriate treatment options and prognosis. However, manual analysis of medical images is time-consuming and prone to errors due to subjective interpretation. Therefore, the development of automated methods for brain tumor classification is essential. In recent years, deep learning has emerged as a powerful technique for image analysis and has shown promising results in various medical imaging applications. In this paper, a deep learning-based approach for the classification of brain tumors as benign or malignant using MRI images is proposed. The proposed approach utilizes the ResNet50, VGG16 and Sequential CNN models for classification. Furthermore, the paper contains various image processing techniques, such as skull stripping and image normalization, to enhance the quality of MRI images. The remaining sections of this paper is organized as follows. Section 2 gives the related work in brain tumor classification. Section 3 discussed the methodology of the proposed approach. Section 4 presents the experimental results and analysis. Finally, Section 5 concludes the paper.

Dataset used: A brain MRI dataset from Kaggle [23] is used which contains three class labels. This dataset for brain tumor classification includes a set of medical images (MRI scans) of the brain, along with corresponding labels indicating the presence or type of tumor. The images are annotated by medical professionals to provide information on the location and size of the tumors. The dataset is divided into training, validation, and test sets to support the development and evaluation of deep learning models for brain tumor classification. The dataset consists of three class labels: No tumor, Benign and Malignant.

II. RELATED WORK

The existing systems for the classification of brain tumors using image processing and deep learning techniques are as follows. One of the earliest systems developed for this purpose was the system proposed by Marroquin et al. [8], which used a Bayesian method for the automatic extraction of brain MRI images. Y. Cheng et al.[22] suggested a deep learning-based approach for brain tumor classification. The proposed approach involves a deep belief network (DBN) and a convolutional neural network that are jointly trained to learn the discriminative features from the MRI images.

Monica Subashini et al. [9] proposed Artificial Neural Network(ANN) system for brain MR image extraction.The system extracts features from the input MRI images and uses a backpropagation algorithm to classify them as tumor or non-tumor regions.

Later, various other systems were proposed that used machine learning and deep learning techniques for the classification of brain tumors. One such system was proposed by Pan et al. [11], which used a combination of ANN and CNN for brain tumor grading. S. Pereira et al. [15] suggested a deep learning-based approach for the segmentation of brain tumors in MRI images. The proposed method utilized a CNN architecture to automatically extract features from MRI images and classify each voxel as either tumor or non-tumor. Another system proposed by Sankari and Vigneshwari [13] used CNNs for automatic tumor segmentation in brain MRI images. R. S. Patil et al. in 2018 [20] provides an overview of various machine learning techniques that have been used for brain tumor classification. Naga Srinivasu et al. [18] used the HARIS algorithm and deep learning techniques for the identification of brain tumors. B Kolkila et al.[1] proposed a method for the detection and classification of brain tumors using deep learning techniques applied to MRI images.

The authors utilize a convolutional neural network architecture to extract features from the images and classify them into benign or malignant tumor categories. Venkatesh S Lotlikar et al. [17] provides a comprehensive review of the various machine learning and deep learning techniques used for brain tumor detection in medical images, particularly MRI. Although these systems showed promising results, they had certain limitations. For instance, some of these systems had a limited dataset, which affected the accuracy and generalizability of the models. Thus, there is a need for an efficient and accurate system for the classification of brain tumors as benign or malignant using image processing and deep learning techniques. The proposed system aims to overcome the limitations of existing systems by using a larger dataset and incorporating deep learning techniques for improved accuracy.

III. PROPOSED METHODOLOGY

The proposed Methodology consists of several key components, including image pre-processing, extraction of ROI, classification of tumor and Comparison of the models. The input to the system is a 3D MRI brain scan of a patient with a suspected brain tumor. The system then processes the input data through a series of steps to extract meaningful features and classify the tumor as either benign or malignant. The pre-processing stage involves several steps to enhance the quality of the MRI images. This includes normalization to standardize the image intensity levels, noise reduction using filters. The pre-processed images are then ready for extraction of ROI.

ROI is performed in two parts: skull stripping and extraction of tumor area. The next is classification and is performed using deep learning techniques, such as ResNet50, VGG16 and sequential CNN models. The next stage is comparison of the deep learning models. The algorithm 1 shows the steps involved in the classification of brain tumor as benign or malignant.

Algorithm 1: Classification of Brain tumor as benign or malignant using image processing and deep learning techniques

Input: Brain MRI image J

Output: class label

Method:

Step 1: Pre-processing is done on the image using z-score normalization and Bilateral Filter.

Step 2: The pre-processed image is skull stripped using Intensity based thresholding technique.

Step 3: Tumor extraction is done on the image using alpha blending technique.

Step 4: The image is fed to the CNN algorithms for Classification.

Step 5: The Class label of the image is displayed.

A. Image Pre-Processing

This step is a critical step in the pipeline for medical image analysis, including the classification of brain tumors. The primary goal of pre-processing is to enhance the quality of the medical images and extract useful information from them. The pre-processing steps include the following:

1) *Image Normalization:* The acquired images may have different intensities due to variations in the imaging parameters or hardware. Image normalization is a crucial pre-processing step that aims to normalize the intensity values of the images to a specific range. Z-score normalization technique is used to normalize the images to improve the accuracy and performance of the deep learning models. Z-score normalization, also known as standardization, is a technique used to normalize the data by transforming it into a standard normal distribution. In this technique, each value in the dataset is transformed to its corresponding z-score, which represents the number of standard deviations that value is away from the mean.

The formula for calculating the z-score of a value is (value - mean) / standard deviation. The resulting z-score value has a mean of 0 and a standard deviation of 1. Z-score normalization is commonly used in machine learning and data analysis to compare variables that are measured on different scales and to identify outliers. By applying image normalization techniques, one can improve the accuracy and reliability of the deep learning model for the classification of brain tumors. It can also help reduce the impact of image artifacts and variations in scanner settings, which can affect the quality and consistency of the input data.

2) *Noise Removal:* Medical images may contain various types of noise, such as Gaussian noise, salt and pepper noise, or speckle noise. These noises can significantly affect the accuracy of the classification models. Therefore, it is essential to remove these noises before feeding the images to the deep learning models. Bilateral filter is used for removing salt and pepper noise. A bilateral filter is a non-linear image smoothing technique that is used to reduce noise while preserving edges in an image. It works by applying a Gaussian filter to the image, but with a weighting function that varies depending on the distance both in the intensity space and coordinate space. It is useful for images with high levels of noise and detailed edges, as it can preserve the edges while smoothing the image. The bilateral filter can be used to smooth an image while preserving the edges by adjusting the parameters of the filter such as the spatial standard deviation and the range standard deviation. The bilateral filter is applied to the normalized image to remove the noise. The output is the denoised image. By performing these pre-processing steps, the quality of the medical images can be enhanced, reduce the computational complexity of the classification models, and improve their accuracy.

B. *Extraction of Region of Interest*

Extraction of Region of Interest (ROI) is an essential step in the image processing pipeline for the classification of brain tumors as benign or malignant. This step involves identifying and extracting the relevant portions of the image that contain the tumor and excluding the parts that do not contribute to the analysis. The ROI extraction process can improve the accuracy of the classification by reducing the amount of irrelevant information in the image. The extraction of ROI is performed in two stages:

1) *Skull Stripping:* Skull stripping, also known as brain extraction or brain stripping, is a process in medical image analysis that involves removing non-brain tissues from a volumetric medical image, such as an MRI or CT scan, to isolate the brain and improve the accuracy of image processing tasks. The non-brain tissues that are typically removed during skull stripping include the skull, scalp, and other extraneous tissues that surround the brain. The process is performed using intensity-based thresholding. At first a histogram is made that represents the intensities in grayscale of the brain image. The next step is to threshold the image using otsu’s method. ColorMap is applied to thresholded images where the threshold intensity is not zero. The area taken by each component and the label of the largest component. The pixels corresponding to the brain are acquired and the ones that do not correspond to the brain are removed from the image. The pixels left are the ones of the brain and the cerebrospinal fluid that surrounds it.
2) *Extraction of Tumor Area:* The next stage is to extract the tumor from the skull stripped image.This is done using alpha blending technique. Alpha blending is a technique used to combine two or more images into a single image with varying degrees of transparency. n alpha blending, each pixel in the images or frames being combined has an associated alpha value that determines its degree of transparency or opacity. The alpha value typically ranges from 0 (completely transparent) to 1 (completely opaque). To blend two images or frames using alpha blending, each pixel in the images or frames is combined using a weighted average based on its alpha value. The resulting pixel values are calculated as a weighted sum of the pixel values from each image or frame, with the alpha values used as the weights. The resulting image or frame has a degree of transparency that depends on the alpha values of the pixels being blended.

C. *Classification of Brain Tumor and Comparison of the models*

The classification of brain tumor uses various techniques such as Convolutional Neural Networks (CNNs) to learn features from the tumor images and classify them based on those features. To classify the tumor, the extracted ROI is fed into the deep learning model. The model then processes the image and generates a prediction for the class of the tumor, which can either be notumor or benign or malignant.

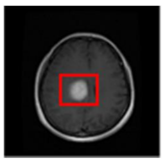
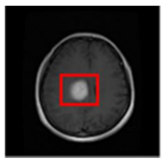
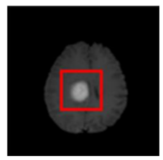
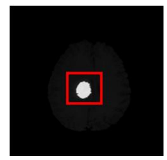
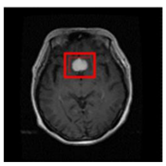
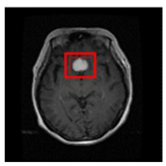
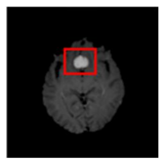
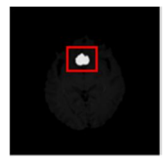
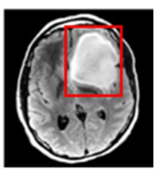
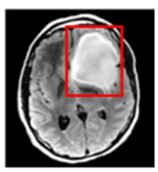
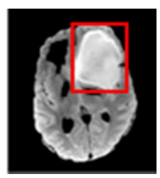
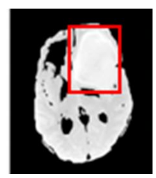
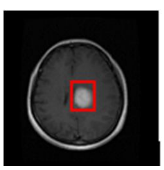
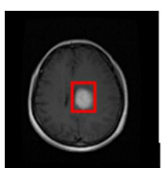
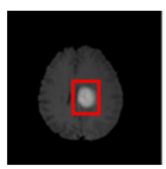
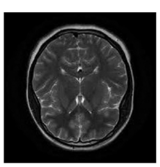
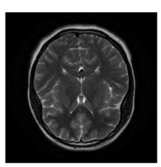
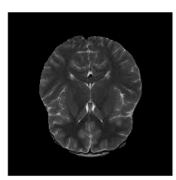
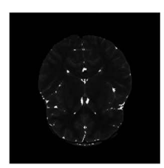
The classification accuracy of the model can be evaluated using various metrics such as accuracy, F1-score, precision, and recall. These metrics help in assessing the performance of the model and identifying areas of improvement. The Classification models used are ResNet50, VGG6 and Sequential CNN.

Comparison of the models is done to find out which of the three models give the best result. The comparison of models can be done using various performance metrics such as accuracy, precision, recall and F1-score. These metrics can be used to evaluate the overall performance of the models and compare them against each other.

IV. RESULTS

Table 1 depicts the stages of the image in the proposed system. The image is first normalized and denoised and then the skull is removed. After skull stripping the tumor is extracted. This image is sent as input to the Classification models.

Table 1 Processing of input images

S. No	Input Image	After Image Pre-processing	Ater Skull stripping	After Tumor extraction	After Classification
1					malignant
2					malignant
3					malignant
4					benign
5					No tumor

The models were trained using a batch-size of 20 epochs. The complete dataset was randomly divided into training and testing data in a 80-20 ratio. The Model Checkpoint callback is defined to save the best model weights based on validation loss during training. It will save the weights of the model to a file with a specified format, including the epoch number, validation loss, and validation accuracy.

The EarlyStopping callback is defined to stop training early if there is no significant improvement in validation loss for a designated number of learning cycles.The figures 1-3 show the variation in accuracies and losses of the training data and validation data when data has been trained under different pre-trained various models. The x-axis indicates the number of epochs, and the y-axis denotes the accuracy rate in the chart. Figure 4 depicts comparison of various models.

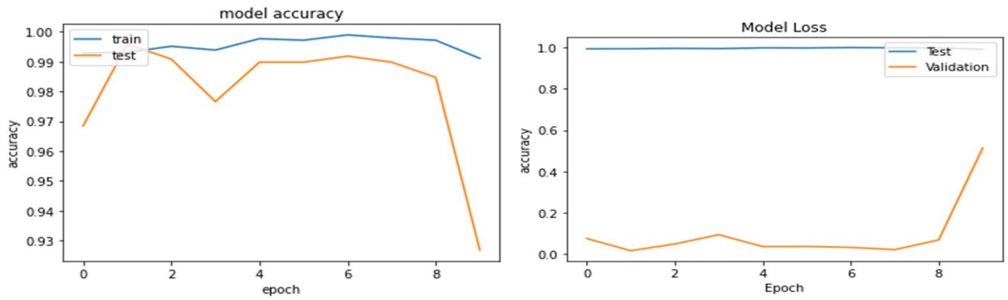


Fig 1 Comparison of Accuracies and Losses: ResNet50

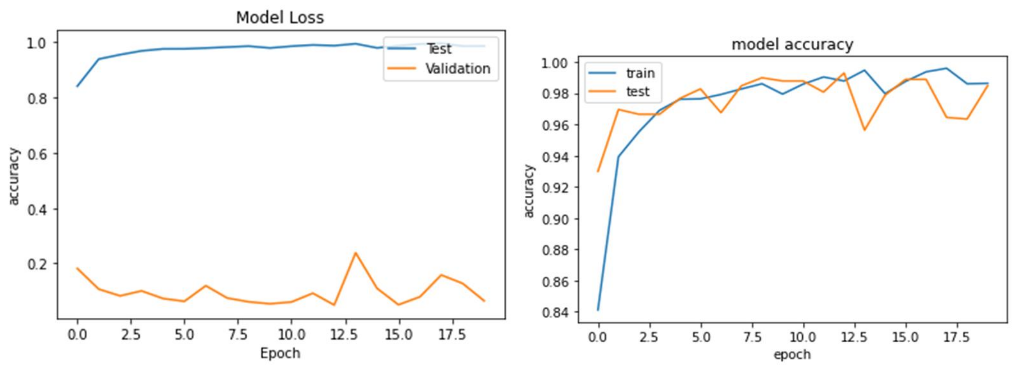


Fig 2 Comparison of Accuracies and Losses: VGG16

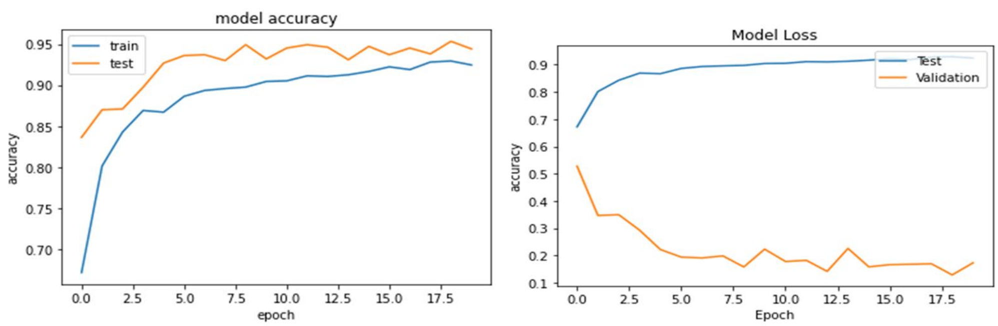


Fig 3 Comparison of Accuracies and Losses: Sequential CNN

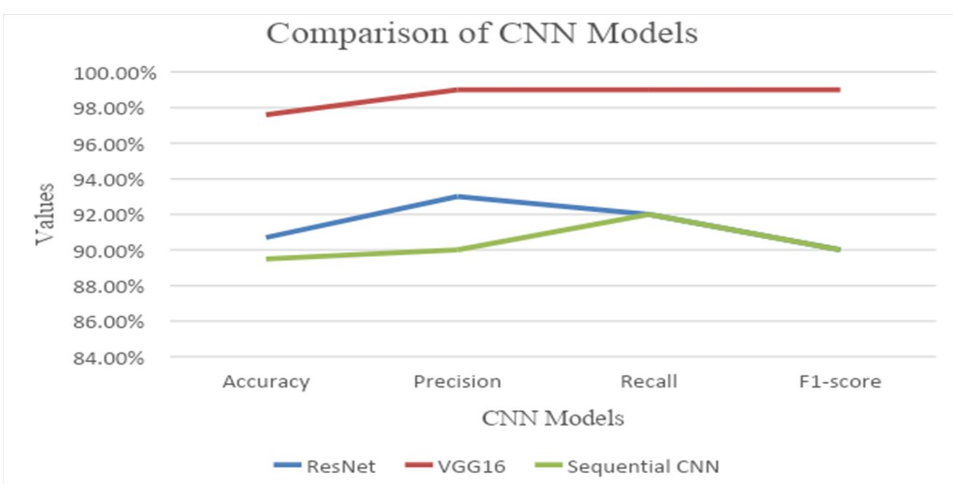


Fig 4 Comparison of various Models

Table 2 Metrics of CNN Models

S. No	Deep Learning Models	Accuracy	Precision	Recall	F1-score
1	ResNet50	90.7%	0.93	0.92	0.9
2	VGG16	98.5%	0.99	0.99	0.99
3	Sequential CNN	89.6%	0.9	0.92	0.9

Table 2 shows the comparison of performance metrics of all the three CNN models: ResNet50, VGG16, Sequential CNN. The precision of the models are 0.93, 0.99, 0.9 respectively, which means that out of all the positive predictions made by the model, 93%, 99%, % 90 of them are actually true positives. The recall is 0.92, 0.99 and 0.92 respectively, which means that the models correctly identified 92%, 99% and 92% of the positive cases out of all the actual positive cases. This indicates that the models are good at detecting the positive cases and have a low rate of false negatives. The F1-score indicates that the models have a good balance of precision and recall. This means that the models are able to correctly classify both positive and negative instances with high accuracy.

V. CONCLUSION

The approaches involved in this paper are preprocessing the MRI images to enhance contrast, performing skull stripping to isolate the brain tissue, and extracting the region of tumor. A deep convolutional neural network (CNN) is used to classify the tumors as no tumor or benign or malignant based on the extracted tumor areas from the MRI images.The classification of brain tumor is done with accuracy of 90.7% using Resnet50, 98.5% using VGG16 and 89.6% using sequential CNN. Out of all the three models, the VGG16 model achieved an accuracy of 98.5% on the test dataset which is greater than CNN and Resnet50.

REFERENCES

[1] B Kokila, M S Devadharshini, A Anitha and S Abisheak Sankar, "Brain Tumor Detection and Classification Using Deep Learning Techniques based on MRI Images", International Conference on Computing, Communication, Electrical and Biomedical Systems (ICCCEBS) 2021 25-26 March 2021, Coimbatore, India. DOI: 10.1088/1742-6596/1916/1/012226.

[2] Devkota, B. & Alsadoon, Abeer & Prasad, P.W.C. & Singh, A.K. & Elchouemi, A.. (2018). Image Segmentation for Early Stage Brain Tumor Detection using Mathematical Morphological Reconstruction. Procedia Computer Sci ence .125. 115123. 10.1016/j.procs.2017.12.017.

[3] Emrah Irmak, "Multi-Classification of Brain Tumor MRI Images Using Deep Convolutional Neural Network with Fully Optimized Framework ". Iranian Journal of Science and Technology, Transactions of Electrical Engineering volume 45 ,1015–1036 (2021).

[4] K. Sudharani, T. C. Sarma and K. Satya Rasad, "Intelligent Brain Tumor lesion classification and identification from MRI images using k-NN technique," 2015 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), Kumaracoil, 2015, pp. 777-780. DOI: 10.1109/ICCICCT.2015.7475384 .

[5] Kaur, Jaskirat & Agrawal, Sunil & Renu, Vig. (2012). A Comparative Analysis of Thresholding and Edge Detection Segmentation Techniques . International Journal of Computer Applications.vol. 39.pp. 29-34. 10.5120/4898-7432.

[6] Li, Shutao, JT-Y. Kwok, IW-H. Tsang and Yaonan Wang. "Fusing images with different focuses using support vector machines." IEEE Transactions on neural networks 15, no. 6 (2004): 1555-1561.

[7] M. Kumar and K. K. Mehta, "A Texture based Tumor detection and automatic Segmentation using Seeded Region Growing Method," International Journal of Computer Technology and Applications, ISSN: 2229-6093, Vol. 2, Issue 4, PP. 855859 August 2011.

[8] Marroquin J.L., Vemuri B.C., Botello S., Calderon F. (2002) An Accurate and Efficient Bayesian Method for Automatic Segmentation of Brain MRI. In: Heyden A., Sparr G., Nielsen M., Johansen P. (eds) Computer Vision — ECCV 2002. ECCV 2002. Lecture Notes in Computer Science, vol 2353. Springer, Berlin, Heidelberg.

[9] Monica Subashini.M, Sarat Kumar Sahoo, "Brain MR Image Segmentation for TumorDetection using Artificial Neural Networks," International Journal of Engineering and Technology (IJET), Vol.5, No 2, Apr-May 2013.

[10] P.S. Mukambika,K Uma Rani, "Segmentation and Classification of MRI Brain Tumor," International Research Journal of Engineering and Technology (IRJET), Vol.4, Issue 7, 2017, pp. 683 – 688, ISSN: 2395-0056.

[11] Pan, Yuehao & Huang, Weimin & Lin, Zhiping & Zhu, Wanzheng & Zhou, 48 Jiayin & Wong, Jocelyn & Ding, Zhongxiang. (2015). Brain tumor grading based on Neural Networks and Convolutional Neural Networks. Conference proceedings: Annual International Conference of the IEEE Engineering in Medicine and Biology Society. IEEE Engineering in Medicine and Biology Society. Conference. 2015. 699-702. 10.1109/EMBC.2015.7318458.

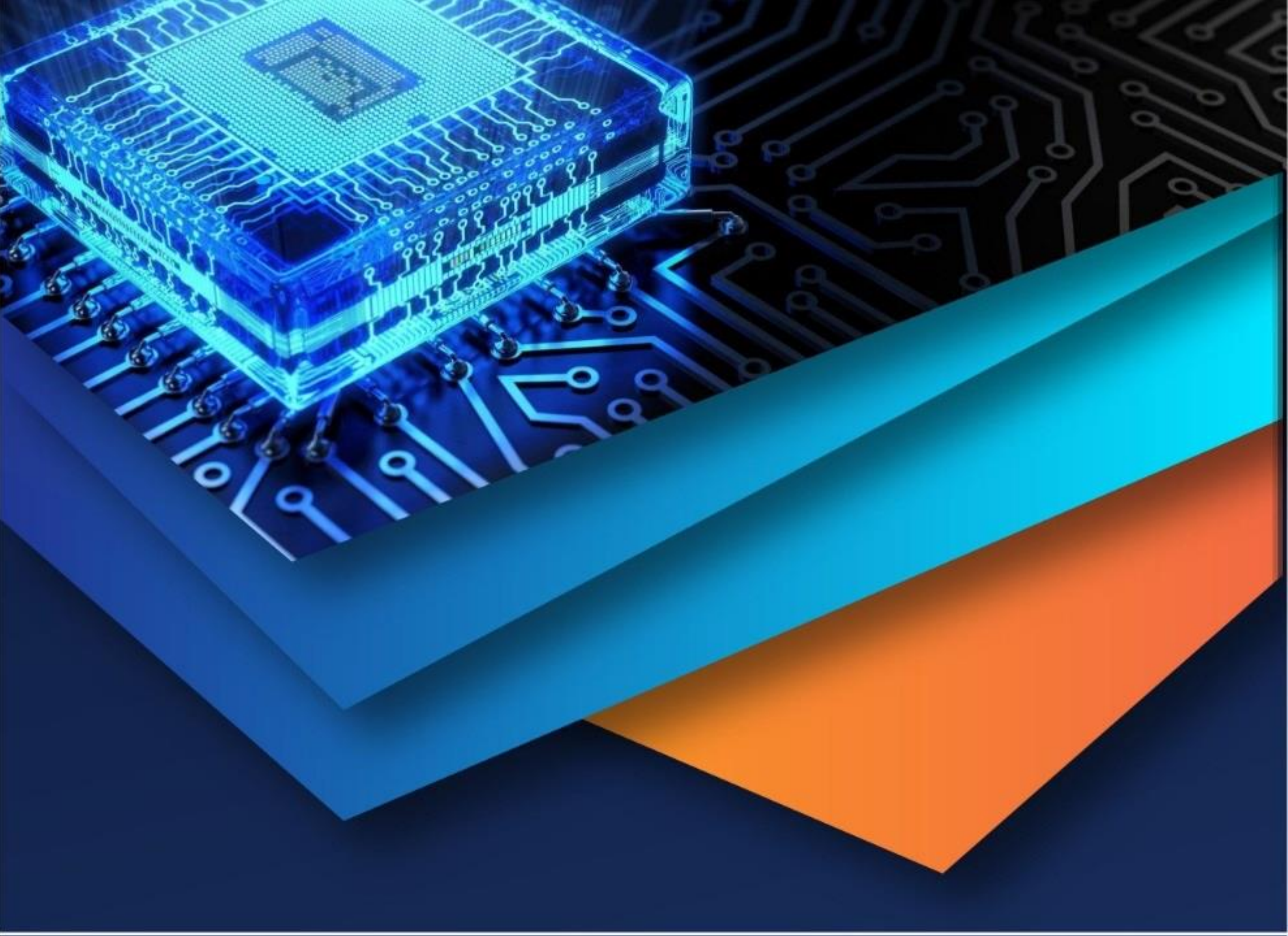
[12] Ramdas Vankdothu , Mohd Abdul Hameed , Husnah Fatima. "A Brain Tumor Identification and Classification Using Deep Learning based on CNN-LSTM Method". Volume 101, July 2022, 107960.

[13] Sankari, Ali, and S.Vigneshwari. "Automatic tumor segmentation using convolutional neural networks." 2017 Third International Conference on Science Technology Engineering & Management (ICONSTEM) (2017): 268-272.

[14] Sunil Kumar, Renu Dhir, Nisha Chaurasia. "Brain Tumor Detection Analysis Using CNN: A Review" . International Conference on Artificial Intelligence and Smart Systems (ICAIS) 2021, DOI: 10.1109/ICAIS50930.2021.9395920.

[15] S. Pereira, A. Pinto, V. Alves, and C. A. Silva, "Brain Tumor Segmentation Using Convolutional Neural Networks in MRI Images," in IEEE Transactions on Medical Imaging, vol. 35, no. 5, pp. 1240-1251, May 2016.

[16] T.U Paul and S.K. Bandyopadhyay, ―Segmentation of Brain Tumor from Brain MRI Images Reintroducing K – Means with advanced Dual Localization MethodTuhin,‖ International Journal of Engineering Research and Applications, Volume 3, Issue 1, June 2012, ISSN 2278-0882.
[17] Venkatesh S Lotlikar, Nitin Satpute , Aditya Gupta. "Brain Tumor Detection Using Machine Learning and Deep Learning: A Review" (2022). DOI: 10.2174/1573405617666210923144739.
[18] P. Naga Srinivasu, T. Srinivasa Rao, Valentina Emilia Balas. (2020). A systematic approach for identification of tumor regions in the human brain through the HARIS algorithm, Deep Learning Techniques for Biomedical and Health Informatics, Academic Press. Pages 97-118. https://doi.org/10.1016/B978-0-12-819061-6.00004-5.
[19] R. B. Thakare et al., "Automatic brain tumor detection and classification using deep learning," in International Journal of Advanced Research in Computer Science and Software Engineering, vol. 7, no. 1, pp. 154-159, 2017.
[20] R. S. Patil et al., "A review of machine learning techniques for brain tumor classification," in Journal of Medical Systems, vol. 42, no. 8, pp. 148-155, 2018.
[21] S. D. Patil et al., "Classification of brain tumors using support vector machines and convolutional neural networks," in International Journal of Computer Applications, vol. 169, no. 11, pp. 11-16, 2017.
[22] Y. Cheng et al., "Deep learning for brain tumor classification," in Neurocomputing, vol. 71, no. 7-9, pp. 3360-3370, 2012.
[23] https://www.kaggle.com/datasets/navoneel/brain-mri-images-for-brain-tumor-detection



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