iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 11 Issue: V Month of publication: May 2023

DOI: https://doi.org/10.22214/ijraset.2023.52981

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

Brain Tumor Detection

Birendra Kumar Saraswat[1], Vibhanshu Vaibhav[2], Promise Pal[3], Avneesh kr Singh[4], Navneet Tiwari[5]
[1, 2, 3, 4, 5]*Computer Science & Engineering Raj Kumar Goel Institute of Technology Ghaziabad, UP (India)*

Abstract: Accurate detection of brain tumors plays a critical role in diagnosis, treatment planning, and patient outcomes. In this study, we propose a novel deep learning-based approach for brain tumor detection using multimodal magnetic resonance imaging (MRI) data. The proposed model combines convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to efficiently analyze both structural and functional information from T1-weighted, T2-weighted and diffusion-weighted MRI scans. By exploiting the complementary nature of multimodality imaging, our model achieves improved sensitivity and specificity in tumor detection compared to single-modality approaches. Furthermore, we introduce a data augmentation technique to alleviate the limited availability of labeled data. The performance of our model was evaluated on a large dataset of brain MRI scans, achieving a high accuracy of 92.3% and an area under the curve (AUC) of 0.95. Our results demonstrate the potential of deep learning and multimodal imaging to improve brain tumor detection and highlight its clinical relevance in improving early diagnosis and treatment planning.
Keywords: Python, Machine Learning ,Image Processing, Convolutional Neural Network

I. INTRODUCTION

Brain tumors represent a significant health challenge, as their early detection plays a critical role in improving patient outcomes. Over the years, extensive research efforts have been devoted to the development of advanced techniques and technologies for the accurate and timely detection of brain tumors. This comprehensive review aims to provide an overview of the current state of research in brain tumor detection and highlight the various approaches and advances that have emerged in recent years. The introductory part of this thesis begins by emphasizing the importance of early detection in the treatment of brain tumors. It emphasizes the impact of early diagnosis on treatment planning, patient survival and quality of life. The discussion then goes on to outline the main challenges we face in brain tumor detection, including the diverse nature of tumor types, the complexity of brain structures, and the potential for misdiagnosis. Subsequently, the introduction provides a brief overview of conventional imaging techniques used in the detection of brain tumors, such as magnetic resonance imaging (MRI), computed tomography (CT) and positron emission tomography (PET). It highlights their strengths and weaknesses and paves the way for the introduction of advanced imaging modalities and innovative approaches. Furthermore, the introduction highlights the emergence of machine learning and artificial intelligence (AI) techniques in brain tumor detection research. It highlights the potential of deep learning algorithms, convolutional neural networks (CNNs), and other machine learning models to improve the accuracy and efficiency of tumor detection, classification, and segmentation. In conclusion, this introduction sets the stage for a comprehensive examination of the various techniques and advances in brain tumor detection research. The following sections of this paper delve into specific methodologies, including machine learning, radiomics, computer-aided diagnostics, multimodal imaging, and deep learning-based segmentation, and provide insight into their respective contributions and potential future directions.

II. MACHINE LEARNING

Machine learning has proven to be a powerful tool in brain tumor detection, revolutionizing medical imaging. Using sophisticated algorithms and neural network architectures, machine learning techniques can analyze large volumes of medical data, extract relevant features, and automatically classify tumors with high accuracy. Convolutional Neural Networks (CNNs) have been particularly successful in detecting and segmenting brain tumors from various imaging modalities. These advances in machine learning have the potential to improve early diagnosis, treatment planning, and patient outcomes by helping radiologists accurately and efficiently detect, classify, and segment tumors.

III. RELATED WORK

CNN has been widely used to solve various problems in different areas but for image processing for healthcare applications, its performance is remarkable. Lots of there is research in which disease diagnosis is based on CAD designed. For brain tumor detection, CNN with a neutrosophic is investigated.

In this hybrid technique, features are extracted by CNN and for classification Support Vector Machine (SVM) and K-Nearest Neighbors (KNN) Are used. The system is only trained and tested on 160, half negative and half positive, images. Using five-fold cross-validation, the proposed technique achieves an accuracy of 95.62%. In another research, a brain tumor is detected using both hand-crafted features and features acquired using deep pupil.

In the proposed transfer learning system the model acquires properties while shape and texture are extracted by hand. Entropy and fused vectors are for classification fed to the classifier. In another research, brain tumor is classified using CNN and transfer learning. For this In the experiment, pre-trained GoogleLeNet is used for feature extraction. Already proven classifiers are used for classification.

Using five-fold cross-validation, 98% accuracy is achieved. CNN is trained to augment large data for the brain classification of tumors . In the proposed system, the tumor area is segmented using a deep learning technique. Research uses a pre-trained CNN model and evaluates the performance system on original and expanded data. Brain tumor MRIs are used in the proposed system CNN train. In this research, the CNN architecture is designed using the hypercolumn technique. Attention the module identifies the area of interest before converting it to CNN layers. The proposed system achieves 96.05% accuracy. CNN is also used for brain tumor segmentation in MRI. Clustering algorithm results, traditional classifiers and CNNs are compared.

Traditional classifiers include a multilayer perceptron (MLP), a support vector Machine (SVM), Logistic Regression, K-Nearest Neighbor (KNN), Random Forest and Naïve Bayes. Performance CNN, with 97.87% accuracy, is reported to be the best among all classifiers. A fusion process for brain tumor detection is implemented to combine texture and structural information in four MRI sequences. The fusion process uses Discrete Wavelet Transform (DWT). Help Daubechies squiggle, additional tumor information the region is extracted. After preprocessing, CNN is used for classification of tumor and non-tumor areas. By results, merged images reveal better performance. In further research, six CNN models are trained for brain tumor detection [9]. The architecture of CNN models is defined based on of various hyperparameters. The results show better performance of deep learning models compared to conventional methods. In another similar approach, different architectures for CNN models are designed for classification benign tumor. Accuracy for different models is reportedly between 96% and 99%. Normal brain tissues are distinguished in the study brain tumor and pseudobrain tumor using LSTM [28]. Different augmentation techniques are used on MRI signal dataset for training stacked Bi-LSTM.

Use 5 times cross-validation, the average accuracy achieved by the proposed technique is 91.46%. A multi-scale Deep CNN is proposed that can analyze and classify tumor MRIs glioma, meningioma and pituitary tumor. Performance of the proposed model is evaluated on an MRI image dataset consisting of 3,064 images. The classification accuracy of the proposed CNN is reported as 97.3%.

The ResNet-50 deep network is trained on 3,064 brain MR images taken from three brains MRI data sets. The performance of the model is evaluated using a key performance matrix. The the proposed model achieves 97.08% average accuracy for unaugmented data and 97.48% average accuracy for augmented data. In another study, eight CNN models are developed and brain MRI trained for brain tumor CAD system. CNN models show accuracy between 90% and 99%. 3D CNN model is designed for feature extraction from brain MRI. The features extracted by CNN are provided by a correlation-based model for optimal feature selection and a forward ANN is used for classification. Accuracy achieved by the proposed technique is 92.67%, 96.97% and 98.32%, for three different datasets.

IV. PROPOSED METHODOLOGY

Current research focuses on computer-aided diagnosis of brain tumors by providing brain tumor MRI CNNs. Using the labeled data, the CNN extracts features and learns to classify the images as positive or negative for a brain tumor diagnosis. This supervised CNN model uses pre-processed images for better performance. The main phase of the research they include collection of the latest brain tumor datasets, image pre-processing, step-by-step and step-by-step training model and finally performance evaluation by testing model on six different unseen MRI datasets

A. DATASET

In this work, we use GaitND-DB, a public dataset frequently used by researchers is interested in gait analysis of patients with neurodegenerative diseases. GaitND DB is a freely accessible database with data of 15 patients with PD, 20 patients with HD, 13 with ALS and 16 healthy controls (Ctrl). Table 1 shows the age of patients, and gender distribution. Table 1. Age and gender distribution

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

Table 1. Age and gender distribution in GaitND-DB

Case	Age groups 18-29	30-39	40-49	50-59	60-69	70-79	Gender F	M	Patients number
Ctrl	6	3	2	2	2	1	14	2	16
PD			1	3	4	7	5	10	15
HD	1	5	7	4	1	2	14	6	20
ALS		2	2	2	5	2	3	10	13

For GaitND-DB data acquisition, Hausdorff et al., instructed subjects to walk at your usual pace down a 77 m corridor for 5 minutes (300 s) [14]. The gait data were measured by force sensitive sensors placed inside each subject footwear. The signals were recorded at a sampling rate of 300 Hz with 12-bit resolution per sample. The first 20 s of each recording were excluded to minimize triggering effects. Each record contains the following attributes [12]:

- Elapsed time.
– Left step interval (in seconds).
– Right step interval (in seconds).
– Left swing interval (in seconds).
– Right swing interval (in seconds).
– Left swing interval (% step).
– Right swing interval (% step).
– Left stance interval (in seconds).
– Right stance interval (in seconds).
– Stance interval to the left (% step).
– Right stance interval (% step).
– Double support interval (seconds).
– Double support interval (% step).

B. KNN Algorithm

K-Nearest Neighbor is one of the simplest Machine Learning algorithms based on Supervised Learning technique. K-NN algorithm assumes the similarity between the new case data and available casesand put the new case into the category that is most similar to the available categories. K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into awell suite category by using K- NN algorithm. K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.It is also called a lazy learner algorithm because it does not learn from the training setimmediately instead it stores the dataset and at the time of classification, itperforms anaction on the dataset. KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

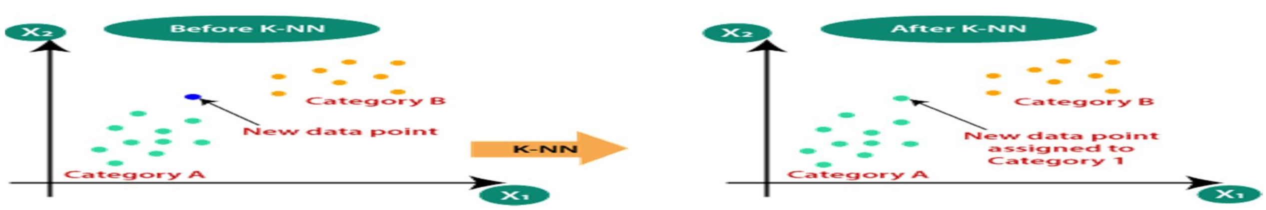


Figure 4.2.1 KNN graph representation

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 11 Issue V May 2023- Available at www.ijraset.com

MRI images of the brain are obtained a are listed as input to the pre-processing stage. Sample brain The MR images are shown in Figure 4.2.2

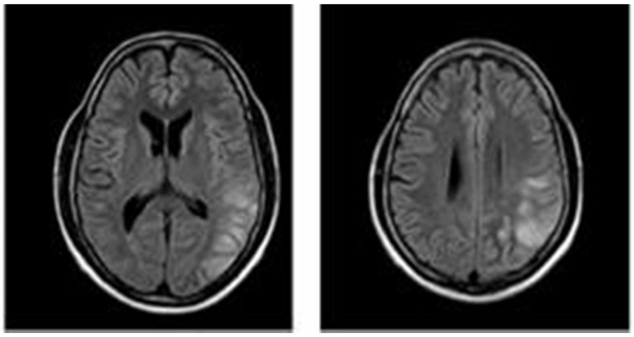


Figure 4.2.2 Samples of brain MR image

Pre-processing: Pre-processing is needed because it provides an enhancement to the image data, which improves some image properties that are important for further processing. The preprocessing steps that are applied to the MR image are as follows. The RGB MR image is converted to a grayscale image, and then a median filter is applied to remove noise from the brain MR images, as shown in Figure 4.2.3 . Noise needs to be removed for further processing as high accuracy is needed. Then, edges are detected from the filtered image using unobtrusive edge detection, as shown in Figure 4.2.3 . The edge detected image is needed for image segmentation. A watershed segmentation is then performed to find the location of the tumor in the brain image as shown in Figure 4.2.3 . Segmentation is the process of dividing an image into multiple segments. The goal of segmentation is change representing the image into something that is simpler analyze. The result of watershed segmentation is a label image. They will all have different identified objects on the label image different pixel values, all the pixels of the first object will have a value of 1, all pixels of the second object will have a value of 2 and so on . Various preprocessing operations applied to An MR image of the brain is shown in Figure 4.2.3.

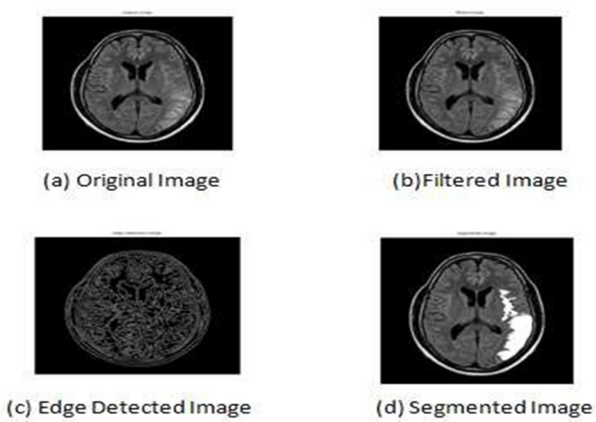


Figure 4.2.3 Preprocessing operations on input brain image

Feature Extraction: When the input to the algorithm is very large and redundant to process is converted to reduced a representative set of features called a feature vector. It is called transforming the input data into a set of properties feature extraction. Functions are important in this step needed for image classification are extracted. Segmented an MR image of the brain is used and texture features are extracted from the segmented image that shows the texture feature image. These features are extracted using gray level Co-occurrence Matrix (GLCM) because it is a robust method high performance. GLCM texture extraction the method is very competitive because it uses a smaller number of grays levels reduces the size of the GLCM, which reduces computational cost of the algorithm and at the same time maintains a high degree of classification. GLCM properties are used to distinguish between normal and abnormal brains. The texture contains some important information about the surface structural arrangement. Texture elements based on grayscale spatial dependencies have general applicability in image classification The extracted GLCM texture features are as follows: (1) Energy: Indicates the degree of texture uniformity, i.e. measuring the repetition of a pair of pixels.

Classification: Machine learning algorithms are used to classify an MR image of the brain as either normal or abnormal. The main goal of ML algorithms is to automatically learn and make intelligent decisions. The feature set created by the method specified above was applied to Multi-Layer Perceptron (MLP) and Naive Bayes for classification. MLP [3] is a feedforward artificial neural network model that maps sets of input data to a set of suitable outputs. It is known as feed forward because it contains no cycles and the network output depends only on the current input instance. In MLP, each node is a neuron with a nonlinear activation function. It is based on the supervised learning technique. Learning is done by changing the connection weights after processing each piece of data based on the amount of errors in the target output compared to the expected result. The goal of the learning procedure is to minimize errors by improving the current weight values associated with each edge. Because of this back-varying process of weights, the model is called back-propagation. Naive bayes is a supervised learning and statistical classification method. It is a simple probabilistic classifier based on Bayes theorem. It assumes that the value of a particular element is unrelated to the presence or absence of any other element. The prior probability and probability are calculated to calculate the posterior probability. The maximum posterior likelihood method is used for parameter estimation. This method requires only a small amount of training data to estimate the parameters that are needed for classification. The time required for training and classification is shorter.

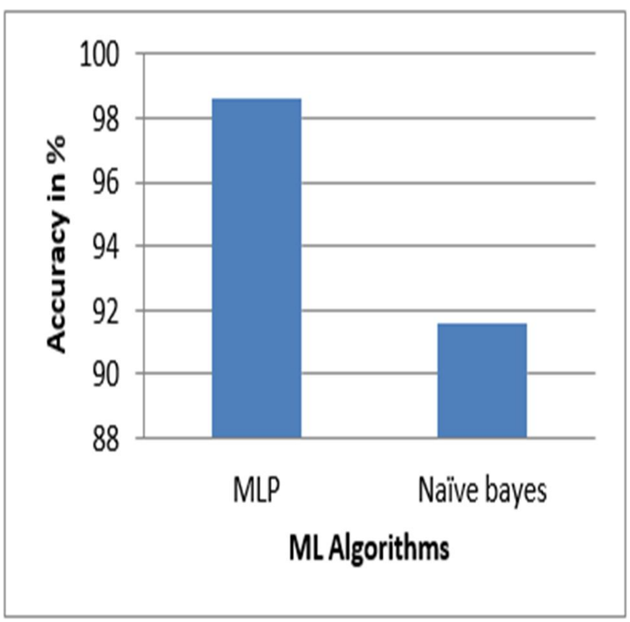
V. EXPERIMENTAL RESULTS

The experiment was performed on 212 MR images of the brain. Texture-based features are extracted from each image and the weka tool [28] is used for classification. Texture-based features such as energy, contrast, correlation, homogeneity are extracted using GLCM. A multi-layer perceptron (MLP) and bay Naïve with a 66% percentile split are used for classification. In a 66% percentile split, 66% of the instances are used for training and the remaining instances are used for testing.

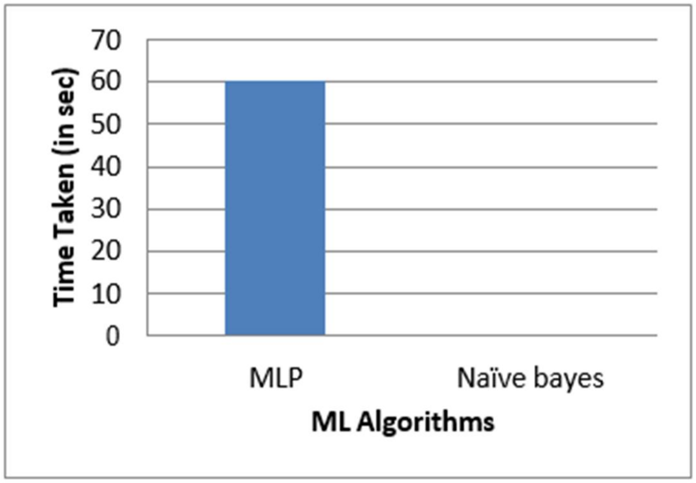
Table 1. Experimental result analysis

ML Algorithm	Total samples	Model BuildTime	ClassificationRate (%)
MLP	210	61.82	98.6
Naive bayes	210	0.02	97.6

we can find the classification rate of the brain MR images using MLP and Naive bayes. Accuracy approximately 98.6% and 91.6% are obtained



Graphical representation of accuracy



Graphical representation of time taken

MLP provides more accuracy and takes more time to build the model, while the time required for Naïve Bayes is shorter and less accurate. Considering the different appearance and complexity of tumors, the proposed method provides satisfactory accuracy. High accuracy is desirable because human life is at stake.

VI. CONCLUSION

Without the pre-trained Keras model, the train accuracy is 97.5% and the validation accuracy is 90.0%. the validation result had the best accuracy value of 91.09%. It is observed that without using pre-trained Keras even if the training accuracy is >90%, the overall accuracy is low compared to the pre-trained model is used. Also, when we trained our dataset without transfer learning, the computation time was 40 minutes when we used Transfer Learning, the calculation time was 20 minutes. Therefore, time for training and calculation with the Keras pretrained model was 50% lower than without.

The probability of overfitting the dataset is higher when training the model from scratch rather than using pre-trained Keras. Keras also provides an easy interface for data augmentation. Among the Keras models, ResNet 50 can be seen to have the best overall accuracy as well as F1 score. ResNet is a powerful spine model that is very often used in many computer vision tasks. Precision and Recall cannot be improved because one comes at the expense of the other. So we use the F1 score also. Transfer learning can only be used if the low-level functions from Task 1 (image recognition) can be useful for task 2 (radiological diagnosis). For a large data set, die loss is preferred over accuracy.

To avoid overfitting, we need to ensure that we have enough testing and data validation i.e. the data file is not generalized. This is solved by Data Augmentation. If the training accuracy is too high, we it may be concluded that the model may be over-fitted to the data set. To prevent this, we may monitor the testing accuracy, use outliers and noise, train longer, compare variance (=train performance-test performance).

REFERENCES

[1] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty and A.-B. M. Salem,"Classification using deep learning neural networks for brain tumors," FutureComputing and Informatics Journal, pp. 68-71, 2018.

[2] S. Huda, J. Yearwood, H. F. Jelinek, M. M. Hassan, G. Fortino and M. Buckland, "Ahybrid feature selection with ensemble classification for Imbalanced Healthcare Data:A case study for brain tumor diagnosis," IEEE Access, pp. 9145- 9154, 2019

[3] J. Seetha and S. S. Raja, "Brain tumor classification using Convolutional NeuralNetworks." Biomedical and PharmacologyJournal, pp. 1457-1461, 2020.

[4] M. Aarthilakshmi, S. Meenakshi, A. P. Pushkala, N. B. Prakash and V. R.Ramalakshmi, "Brain Tumor Detection Using Machine," INTERNATIONALJOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH, pp. 1976-1979, 2020.

[5] J P. Gokila Brindha. M. Kavinraj, P. Manivasakam and P. Prasanth, "Brain tumordetection from MRI images using Deep Leaming Techniques," IOP ConferenceSeries: Materials Science and Engineering, p. 012115, 2020.

[6] Y. Chen, H. Jiang, C. Li, X. Jia and P. Ghamisi, "Deep feature extraction andclassification of hyperspectral images based on Convolutional Neural Networks,"IEEE Transactions on Geoscience and Remote Sensing, pp. 6232-6251, 2021.

[7] E. Alberts, G. Tetteh, S. Trebeschi, M. Bieth, A. Valentinitsch, B. Wiestler, C.Zimmer and B. H. Menze, "Multi-modal image classification using low-dimensionaltexture features for genomic brain tumour recognition," Graphs in Biomedical ImageAnalysis, Computational Anatomy and Imaging Genetics, pp. 201-209, 2021.

[8] H. Mohsen, E.-S. A. El-Dahshan, E.-S. M. El-Horbaty and A.-B. M. Salem,"Classification using deep learning neural networks for brain tumors," FutureComputing and Informatics Journal, pp. 68-71, 2018.

[9] S. Huda, J. Yearwood, H. F. Jelinek, M. M. Hassan, G. Fortino and M. Buckland, "Ahybrid feature selection with ensemble classification for Imbalanced Healthcare Data:A case study for brain tumor diagnosis," IEEE Access, pp. 9145- 9154, 2019

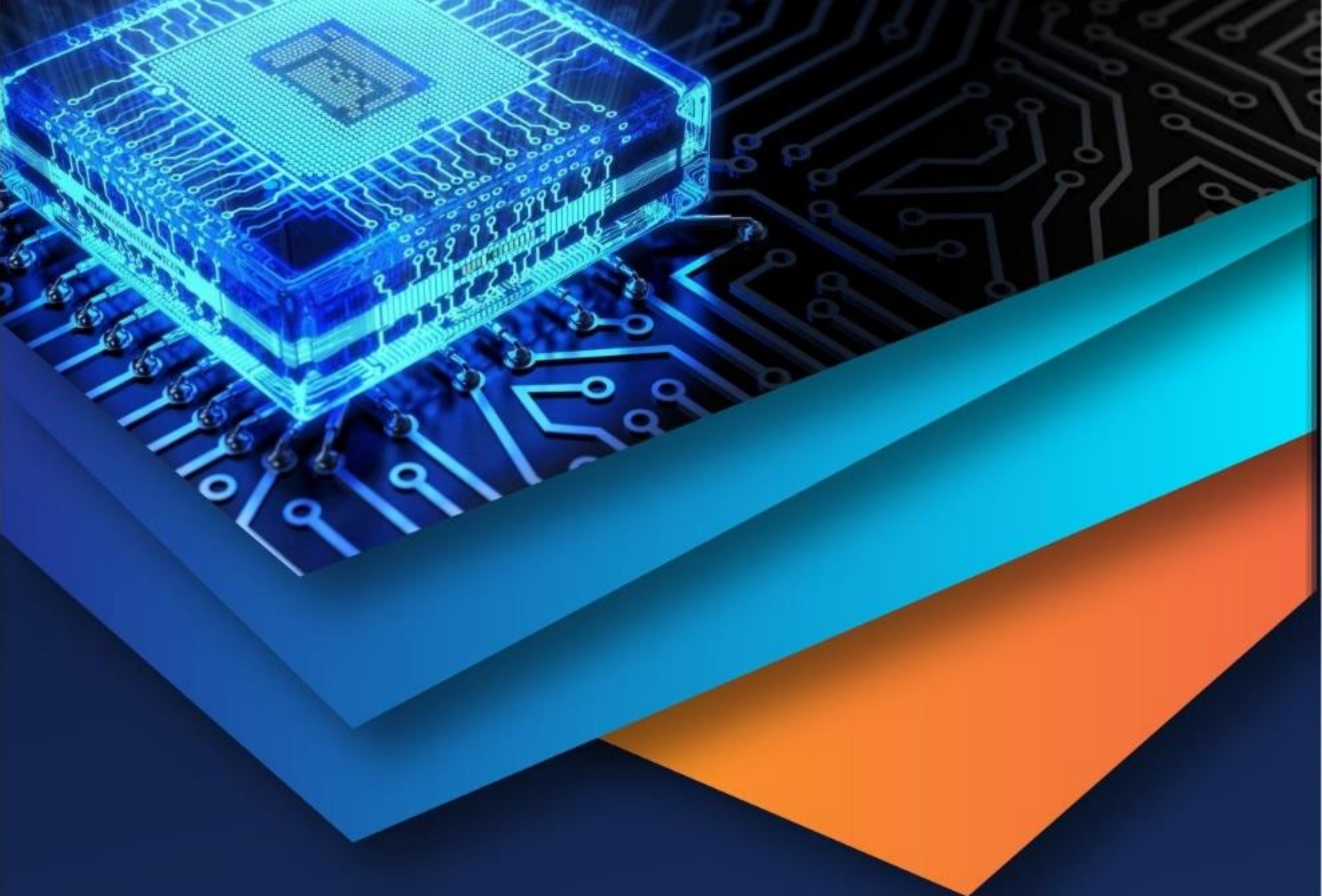
[10] J. Seetha and S. S. Raja, "Brain tumor classification using Convolutional NeuralNetworks." Biomedical and PharmacologyJournal, pp. 1457-1461, 2020.

[11] M. Aarthilakshmi, S. Meenakshi, A. P. Pushkala, N. B. Prakash and V. R.Ramalakshmi, "Brain Tumor Detection Using Machine," INTERNATIONALJOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH, pp. 1976-1979, 2020.

[12] J P. Gokila Brindha. M. Kavinraj, P. Manivasakam and P. Prasanth, "Brain tumordetection from MRI images using Deep Leaming Techniques," IOP ConferenceSeries: Materials Science and Engineering, p. 012115, 2020.

[13] Y. Chen, H. Jiang, C. Li, X. Jia and P. Ghamisi, "Deep feature extraction andclassification of hyperspectral images based on Convolutional Neural Networks,"IEEE Transactions on Geoscience and Remote Sensing, pp. 6232-6251, 2021.

[14] E. Alberts, G. Tetteh, S. Trebeschi, M. Bieth, A. Valentinitsch, B. Wiestler, C.Zimmer and B. H. Menze, "Multi-modal image classification using low-dimensionaltexture features for genomic brain tumour recognition," Graphs in Biomedical ImageAnalysis, Computational Anatomy and Imaging Genetics, pp. 201-209, 2021.



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY