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Diagnosis of Chronic Brain Syndrome Using Deep Learning

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Abstract: Brain tumours, which grow within the brain or spread from other secondary tumours elsewhere in the body, have been one of the top causes of death in both adults and children in recent years. Patients can benefit from more effective treatment options if cancers are diagnosed early. Traditional feature extraction approaches concentrate on either low-level or high-level features, with some hand crafted features used to bridge the gap. By encoding/combining low-level and high-level features, a feature extraction framework can be designed to close this gap without employing handcrafted features. Deep learning is extremely powerful for feature representation because it can completely describe low-level and high-level information while also embedding the feature extraction phase in the self-learning process. A computerised technique for locating and segmenting brain tumours could help doctors make faster and more accurate diagnoses. In this paper, we propose a deep learning model that uses the VGG16 and VGG19 architectures to detect and localise cancers in MRI-based pictures. The transfer learning model was able to learn from a small number of photos and achieve a test accuracy of 92 percent for detection and a mean average precision score of 90.14 percent for segmentation.

Keywords: Tumor detection, Modules and basics Python terminologies , CNN-based algorithms

I. INTRODUCTION

Brain is one of the most vital organ of our body. It controls our deals and the functions of the body. It consists of furtherthan 100 billion jitters that communicate with each other to perform day to day working of our body. Brain excrescence is an abnormal growth of cells inside the brain or cranium.

A primary brain tumor begins in brain cells. on the other hand, secondary brain tumor cancer cell spread into brain from another body part such as lung, breast. Gliomas is called of integral tumor.[1] Brain Excrescence can be divided into two types Beningn Tumor and nasty excrescence isnon-cancerous excrescence which doesn't spread in other corridor of the body it's 1st stage excrescence.

Generally, beningn excrescences are less aggressive than nasty excrescence. still, nasty excrescences are cancerous excrescences which can spread in other corridor of the body. They're the advanced stages of brain Excrescence.

A modifed CNN armature known as capsule network, CapsNet, was used by Afshar etal. to classify brain excrescences from MR images, and a 90.89 percent bracket success has been achieved. Pashaei etal. used CNN to prize the features from brain images and used kernel extreme literacy machines(KELM) to classify brain excrescences. At the end of the tests, they achieved93.68 percent success rate. Phaye etal. proposed different capsule networks(DCNet) for brain excrescence classifcation. This frame customizes the CapsNet by replacing the standard complication layerswith densely connected complications.[2] In 2020, Figshare dataset was used in to classify brain excrescences from MR images. Ismael and Abdel- Qader presented a frame for classifcation that combines statistical features and neural network algorithms.

Computer vision and machine literacy have altered the world in every way possible during the last decade. Deep literacy is a subfield of machine literacy that has shown emotional results in a variety of fields, particularly in the biomedical assiduity, becauseto its capability to handle large quantities of data.

Its implicit and capability have also been utilised and estimated in the identification and prognostic of brain tumours utilising MRI reviews, and it has performed admirably.

The major thing of this exploration design is to give a complete critical study of former exploration and discoveries on detecting and classifying brain tumours using MRI images. This exploration is particularly useful for deep literacy professionals and those interested in the field.

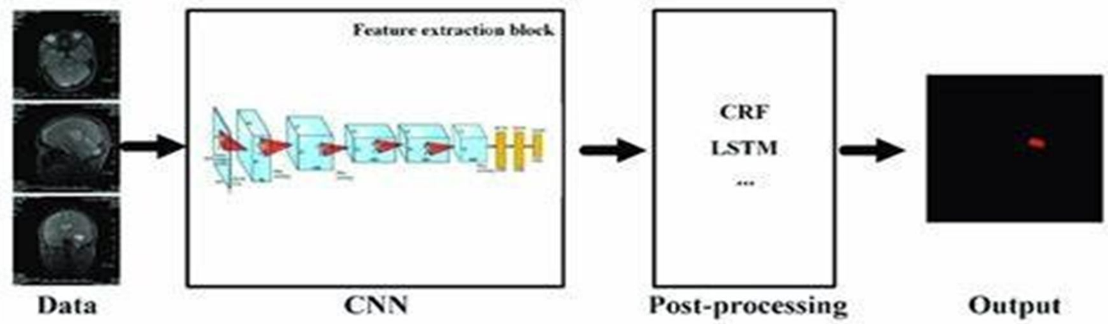

Fig. 1. deep learning approach

II. LITERATURE REVIEW

In this work we have implemented pre-trained and a improved version of and VGG19 Convolutional Neural Networks(CNN) to categories brain tumor images taken with camera into two categories namely cancerous and normal images. Research work done by nine different authors has been discussed on the basis of varied deep learning techniques and architectures adoptedby them.

1) Sakshi Ahuja et al., used transfer learning and superpixel technique for detection of brain tumor and brain segmentation respectively. The dataset used was from BRATS 2019 brain syndrome (tumor) segmentation challenge and this model was trained on the VGG 19 transfer learning model. Using the superpixel technique the tumor was divided between LGG and HGG images. The resultant is summarised to an average of dice index of 0.934 in opposition to ground truth data.[3]
2) Hajar Cherguif et al., used U-Net for the semantic segmentation of medical images. To develop a convoluted 2D segmented network, U-Net architecture was used. BRATS 2017 dataset has been used for testing and evaluating the model proposed in this model. The U-Net architecture that is proposed has 27 convolutional layers, 4 deconvolutional layers, Dice coef of 0.81.[4]
3) Chirodip Lodh Choudhury et al., made the use of deep learning (DL) techniques involving deep neural networks and also incorporated it with a Convolutional Neural Network model to get the accurate results of MRI scans. A 3-layer CNN architecturehas been proposed that was further connected to a fully Neural Network architecture. F-score equal to 97.33 and an accuracy equal to 96.05Ahmad Habbie et al., MRI T1 weighted images has been taken and using semi automatic segmentation format analyzed the occurence of a brain tumour using an active contour model.The performance of morphological active contour thathas no edge, snake active contour and morphological geodesic active contour has been analyzed. MGAC performed the best among all three as suggested by the data[5]
4) Neelum et al., used a concatenation approach for the deep learning model in this paper and the occurence of having a brain tumor was analyzed. Pre trained deep learning models which are Inception - v3 and DenseNet201 are used to detectand classify brain tumors. Inception - v3 model has been pre trained to extract the features and the same features has been concatenated for tumor classification. Then, the classification part was done by a softmax classifier.[6]
5) Ms. Swati Jayade et al., used Hybrid Classifiers. The classification of tumors has been done into types, malignant and benign.Dataset is prepared by Gray level Cooccurrence Matrix (GLCM) feature extraction methodology. A hybrid method of classifiers involves KNN and SVM classifiers was proposed to increase efficiency.[7]
6) Zheshu Jia et al., the author made a fully automatic heterogeneous segmentation in which SVM (Support Vector Machine) was used.Training and checking the possibilty of tumor detection in MRI images, a classification model as probabilistic neural network classification system had been used. Multi spectral brain dataset is used and this model focused on the automated segmentation of meningioma disease.[8]

III. PROPOSED WORK

Convolutional Neural Network which is also called as (CNN) is used to classify the data. VGG16 and VGG19 are CNN models proposed for classification of dataset. Dataset is divided into three categories which are training data, validation data and test data. Training data extracted from original data is used to train the model. The model uses the training images from the input data to train itself. Validation data from the original data is used to verify the training process and also determinethe validation accuracy. The test data from the original data is used to determine the accuracy of the model and it is unknown data which is used to test the model. Initially, a Convolutional Neural Network model is developed and dataset is imported.

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Then the VGG16 and VGG19 models are considered and since these models are pre-trained models, we use the weights of VGG16 and VGG19 architecture in the CNN model. Then the accuracy and other parameters like precision, recall and F1 score are calculated .Then the model is again trained by considering a few layers of the VGG16 architecture to improve accuracyof the model . In this section, we explain our proposed method for brain tumor detection. There are five basicsteps of our proposed method namely. Also, the model gets a feature map and defined operation is performed by the model which also tries to preserve information. This feature of aggression helps a lot to get better execution of finding brain tumors. Brain tumorswere classified using MRI data analysis in order to help the practitioners. In order to do that they used deep learning methods. VGG19 with k-means cluster was used here[9]

In this section, we explain our proposed method for brain tumor detection. There are five basic steps of our proposed method namely.

1) Data Collection
2) Data processing
3) Model Preparation
4) Model Training
5) Classification and evaluation

A. Data Collection

The concept of the VGG19 model (also called VGGNet-19) is the same as the VGG16 except that it also supports nineteen layers. The “16” and “19” in VGG-16 and VGG-19 stand for the number of weight layers in the model (convolutional layers). This means that VGG19 has three more layers than VGG16 models. We have collected our data from Kaggle. The data presented here are acquired as a part of pilot study investigation the feasibility and usefulness of functional magnetic Resonance Imaging (MRI) for surgical brain tumor planning. In the dataset ,brain imaging results are available from many patients .We collected over 3000 images containing ”yes and ”no” classes. By default, the collected data is annotated as two different classes, namely “yes” and “no”. The “Yes” class contains the images of patients who have a brain tumor. On the other hand, “no” class hasthe images of the patient who do not have brain tumor. Here,a Convolutional Neural Network (CNN) model is build thatwill classify if the given image has a tumor or not based on MRI scan segmenatation. Here we have used VGG-16 model architecture and weights to train the accurate model for this binary classification situations. The resultant following MRI Scans have no brain tumor while those given later have Brain Tumor. By default, the segmented data is annotated as two different classes, namely “yes” and “no”. The “Yes” class contains the images of patients who have a brain tumor. On the other hand, “no” class has the images of the patient who do not have brain tumor.

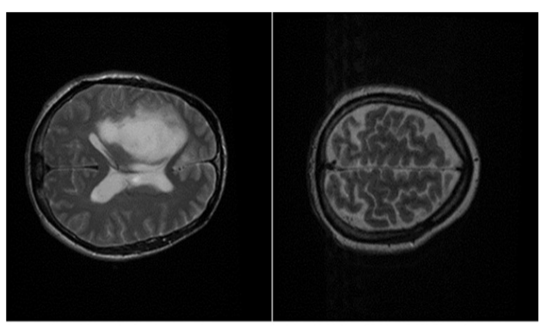

Fig. 2. Data Collected from MRI Scans

B. Preprocessing

This is done to improve the quality of the raw MRI images and transform them into a form, suitable for pro- cessing by humans or machines. This step also helps in removing undesired noise and enhancing overall appear- ance of the MRI images. Image pre-processing involves steps such as creating functions to load image datasets into arrays, resizing raw images to an established base size before feeding it to the neural network, applying normalization to rescale the pixelvalues so they lie within a fixed range, data augmentation to increase the size of the dataset if insufficient number ofimages are available, among other steps These preprocessing tasks help improve classification accuracy and also speedup the training process.

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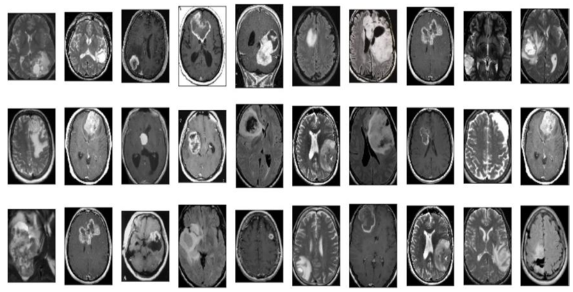

Fig.3. Images of Yes Class

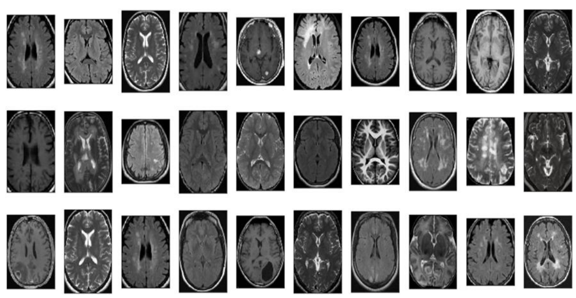

Fig.4. Images of ”NO” Class

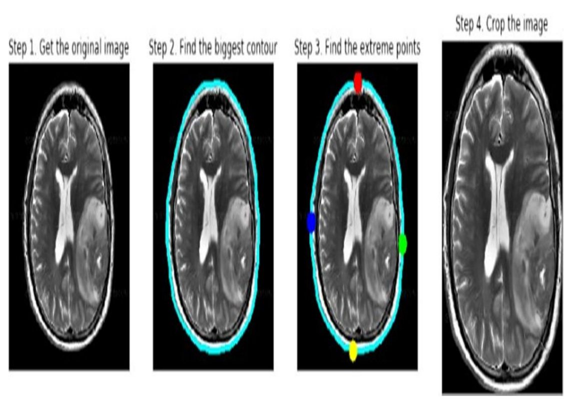

Fig.5. Images after preprocessing

C. Data Segmentation

Image segmentation can be partitioned from multiple objects/segments to a single object. It performs labeling of pixel- level for all image pixels which predicts a single label for the whole image.[10] This step aims to differentiate abnormal braintissue from the normal brain tissue. There are manual, semi-automatic and fully automatic segmentation techniques . In manual segmentation, the outline of the affected tissue area is manually traced. This method has the highest accuracy, however, it is time-consuming and cumbersome. Semi-automatic segmentation involves the users inputting some initial data to obtain the final results. In fully automatic methods, the values of the parameters do not have to be set manually and these methods can automatically detect and segment the brain tumor.

D. Data Processing

All the data we got so far from binary classification have been proposed, applying some factors these are data annotation,slice extraction, data normalization, train test split.

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E. Data Annotation

Data Annotation is the process of pre-processing the data so that it can be used for machine learning algorithm directly toget adequately trained for correct prediction. The more the image is annotated data, the better will be the level of accuracyof the model in deep learning. As we need to identify the tumor segmented region of the brain, we manually annotated the images based on the tumor position. We annotated the images based on the lobe of the tumor and the position of the tumor.

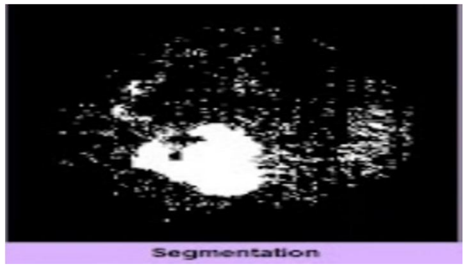

Fig.6. Data segmented

F. Slice Extraction

In general, the MRI images are i3D volume as NIFTI image format. We have transformed the 3D images into 2D images using the Nibabel library. The 3D images that we used in the slice extraction process that breaks each of the images into many different slices. Each of the part were the images of axial running state of brain. It also helps us for further classification of images and provides a structural view of data by organizing it in a format.

G. Data Augmentation

High-quality and abundant amount of data is a key for effective deployment of many different types of deep learning models. The problem of classification addressed here lacks satisfactory amount of data to fed into deep learning architecture like convolutional neural networks and acquire desired accuracy. With automatic region of interest (ROI) detection the area of brain tumor was calculated.[11]Thus, to achieve the desired accuracy we extended the existing data given earlier by applying eight different augmentation techniques presented .The possible employed augmentation techniques are rotation, flipping, skewness, and shears for geometric transformations invariance. The next four techniques such as Gaussian blur, sharpening, edge detection, and emboss are used for the noise invariance. In Table, second column refers to augmentation techniques along with their corresponding invariance parameters in third column. There are total of 30 parameters and eight augmentation techniques, which extend each sample of the dataset into 30 samples of Deep Features Extraction and Classification. The problem of classification addressed here lacks satisfactory amount of data to fed into deep learning architecture and acquire desired accuracy of the model.

H. Data Normalization

We have normalized pixel value of the images in between 0 and 1 so the when we apply neural network it converges faster. The function for normalization is Z = (x min(x))/(max(x) min(x))

I. Training And Testing Set

After normalization 70 percent of the images were sent for training and rest percent were reserved for testing purpose. The softmax, radial basis function and decision tree (DT) were used to classify the images. Two class classifier is implementedusing support vector machine with radial bass function (SVM-RBF) kernel. The proposed method can achieve an accuracy of greater than 94 percent[12]

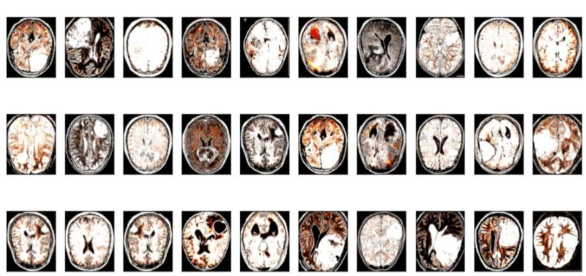

Fig.7. Resizd ”YES” Images

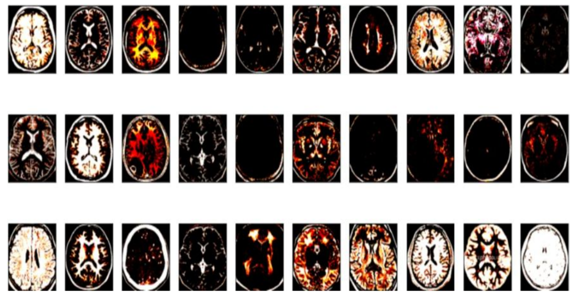

Fig.8. Resized "NO" Images

J. Model Preparation And Training

The structure of deep learning-based network is getting deeper as it is evolving[13] Once all the data are prepared , the modelswere prepared before training the data. The architectures that we are using are VGG16 and VGG19. A fully convolutional network has the capability of handling input images of any dimension and can use the de-convolution layer for interpolating the featured map of the previous layer to retrieve it to the same dimension as that of the given image, which permits calculations at the pixel-level.[14] All these architectures are selected to figure out the best performing architecture that can classify the tumor efficiently.With all the models, we used the transfer learning technique by initializing the weights from models trainedon the ImageNet dataset. By using the transfer learning, we canavoid overfitting the model and achieve faster convergence on the training data. Afterward the models were trained on the training data.

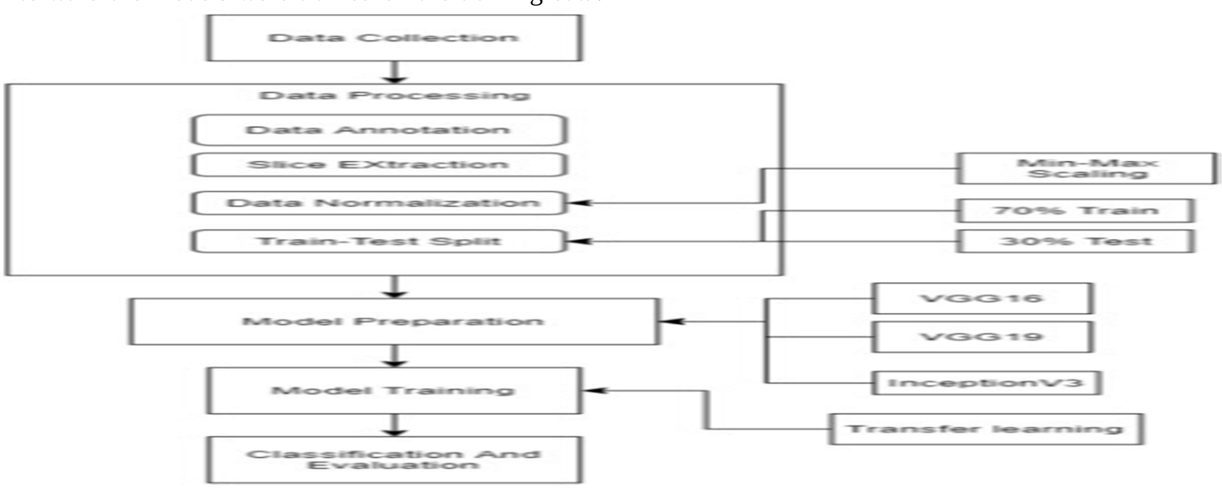

Fig. 9. Process model

K. Classification And Evaluation

After training, the model testing phase started in order to identify the accuracy of the learning. After sorting the entiredata, we apply various CNN architecture in the testing phase. We have applied two classifications for the testing phase. After training the accuracy level that we got have analyzed result has been visualized in graphs.

IV. IMPLEMENTATION RESULTS

To test the performance of the proposed algorithm we have tested it on 3200 MRI images, out of which 1835 images have brain syndrome related issues and 1365 do not have tumor. Out of those images which we selected 20 images for testing. Initially, different works on brain tumour classification were reviewed for choosing hyperparameter values [15] The findings of the suggested image segmentation in this methodology, which were achieved using real brain MR data, are presented in this section. Jupyter Notebook of the Anaconda software was used to test the suggested approach First the images were reshaped into 244×244 pixel size and passed through a convolutional layer with three filters. Subsequently, the output passes through maxpool and flattening layers. The model has been trained with 30 epochs in this process. Our model has shown an average accuracy of 92.34 from this model accuracy curve for training and testing has been shown for 30 epochs.

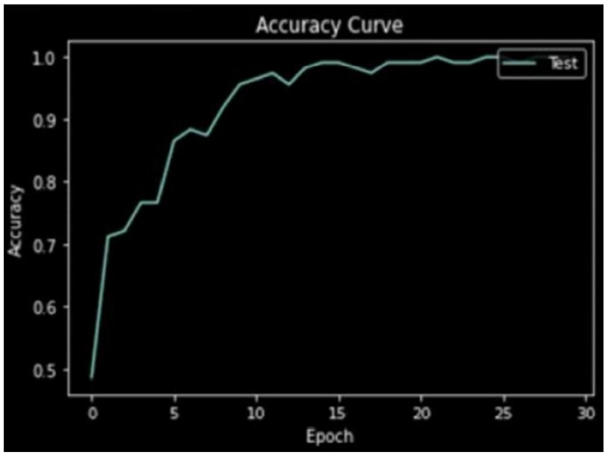

Fig. 10. Accuracy of the model

Epoch	Test Accuracy(%)		Loss Value	
	VGG16	VGG19	VGG16	VGG19
5	80.30	82.45	38.56	41.04
10	86.45	91.45	15.67	15.19
20	89.67	94.62	11.56	12.05
30	95.34	96.78	8.45	5.61

Fig.11. Testing Accuracy and Loss Function

V. CONCLUSION AND FUTURE SCOPE

A. Conclusion

In this experiment, we used MRI brain pictures to divide the brain into two sections: those with brain tumours and those without. We used a sequential model in which the MRI pictures were resized to 244 x 244 pixels, then they are passed through the convolutional layer, max-pooling layer, and flattening to transform them to vector form. We also used the ImageNet dataset, which includes a huge number of medical images and aids in feature improvement. The VGG-16 and VGG-19 architectures are employed, which are enhanced by the introduction of a dropout layer. We changed the activation functions and optimizersin these two models. We also examined accuracy across epochs. The results of the trials on numerous images reveal that the analysis for brain tumor diagnosis is fast and accurate when compared to manual detection by radiologists or clinical experts.

B. Future Scope

Our project has a promising future, with us attempting to pinpoint the tumour with greater precision. We're also experimentingwith other CNN architectures based on different activation functions, convolutional layer counts, and optimizers in order to improve accuracy. We compared two VGG models in this study and discovered that VGG-19 is more accurate. To improve accuracy, we will continue to train our model by tweaking parameters.

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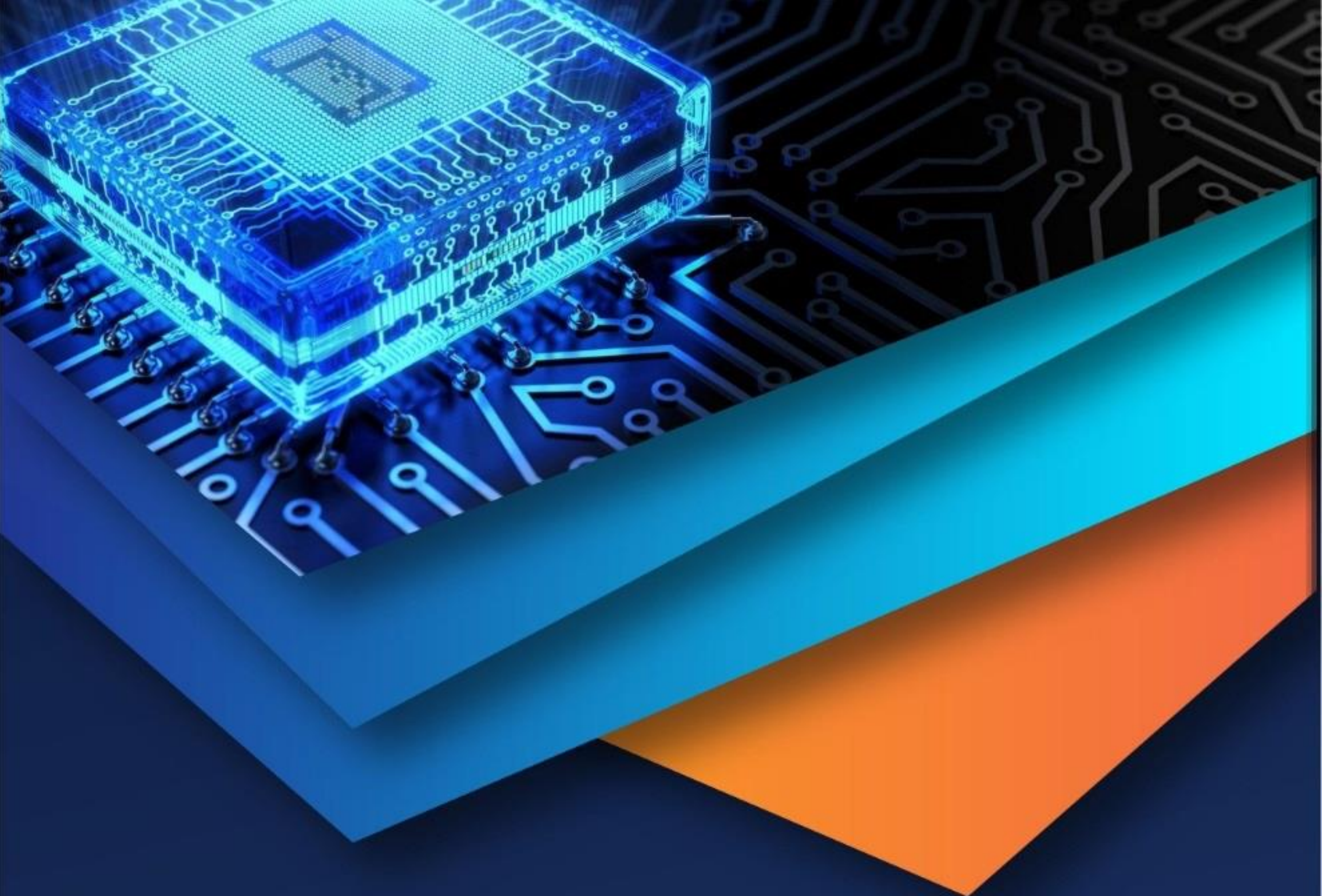

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