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Brain Tumor Image Classification using CNN

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Abstract: We present a method for segmenting and categorizing brain tumors in the challenge of content of brain tumor with segmentation is enrolled and skull is exposed for bar graph equivalent high-level contradiction refer amount. Preprocessing, segmentation, feature extraction, optimization, and classification are used to detect tumors. The tissue is then classified using preprocessed images. We utilized leave-one-out cross-validation to generate a Dice overlap of 88 for the whole tumor area, 75 for the core tumor region, and 95 for the enhancing tumor region, which is higher than the Dice overlap reported.
Keywords: Machine Learning, CNN Algorithm, Deep Learning, Classification etc.

I. INTRODUCTION

The use of MRI to detect and define a cerebrum tumor is critical for minimizing setbacks. Because the mind is a complex creature with tightly interrelated components, cerebrum tumors are difficult to heal. Regardless of modern treatments, the vigorous and successful division of cerebrum cancer remains a major and challenging undertaking. Tumor classification and division are difficult due to the wide range of tumor forms, appearances, and sites. Because of the muddled nature of cerebrum tumors, it is difficult to totally split and categories them employing a single method of examination. The capacity of X-ray to gather many images, known as multimodality imaging, can expose the itemized structure of the cerebrum and therefore efficiently group the mental tumor. illustrates several MRI modalities for the brain.

A. Problem Statement

Brain MRI data is segmented using image processing and deep learning algorithms.

B. Motivation

Tumor segmentation is a tough job in medical image analysis. The research of scientific image analysis on brain tumors is broad. Brain tumors can be detected. Preventing the effects of early stress on human judgement Rural areas may now get health care due to the accessibility of information exchange.

II. LITERATURE SURVEY

Lina Chato , Erik Chow,” Wavelet Transform to Improve Accuracy of a Prediction Model for Overall Survival Time of Brain Tumor Patients Based on MRI Images Lina ”[1]

In this presentation, a denoising wavelet transform (DWT) method based on classification is suggested to increase the accuracy of a prediction model for overall survival time of brain tumor patients using Magnetic resonance imaging (MRI) data. This paper employs the BraTS dataset. Machine learning techniques are used to extract histogram characteristics from MRI images in order to build a prediction model. Because there are only 163 examples in the dataset, multiple machine learning approaches were applied to construct an accurate prediction model. In general, noise from the MRI imaging technology contaminated the MRI data. The results suggest that using the two-dimensional denoising wavelet transform approach increased the accuracy of a prediction model based on histogram information marginally. When patients' ages are included, Daubechies 4 level 4 (db4-L4) with a10 folds cross validation linear support vector Machine (SVM) achieves the highest accuracy. However, when the patients' age is not linked with the histogram features vector, Daubechies 2 level 1 and 3 (db2-L1, db2L3) with a 10 folds cross validation simple tree generate an enhanced accuracy. The Daubechies 2 level 3 (db2-L3) with simple tree obtains 66.7 accuracy when a 10 hold out validation procedure is applied.

In this work, we propose a novel method to improve the predication of brain tumor growth by fusing with the state-of-art tumor segmentation. The Glioma Image Segmentation and Registration (GLISTR) is known for joint segmentation and deformable registration of brain scans as well as tumor growth prediction using MRI. This paper, for the first time in literature, aims to improve the tumor growth prediction by integrating the growth patterns of different tissues such as necrosis, edema, and tumor obtained from GLISTR with our stochastic texture-based tumor segmentation methods using a joint label fusion (JLF) technique.

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We evaluate the proposed method using several adult longitudinal cases from the 2015 BRATS [1) dataset. The experimental results show difference of these tissues growth prediction by applying GLISTR and joint label fusion. ANOVA analysis suggests statistically improvement in the longitudinal tumor core prediction results.

Nowadays, brain tumor identification has shifted the focus of health care from blaming the victim to blaming the perpetrator. It is possible to describe a brain tumor as a distorted mass of tissue in which cells multiply rapidly and uncontrollably. The method of Image fragmentation is used to identify the aberrant tumor area in the brain. Segmentation of brain tissue is critical with in MRI (magnetic resonance imaging) for detecting outlines associated with a brain tumor. In the healthcare industry, there is a great deal of secret information. Any disease can be accurately predicted early with the proper application of data mining classification algorithms. ML (deep learning) and Data mining have a significant impact in the medical field. The vast majority of these ideas have been effectively applied. Specifically, the study is looking at the list of risk variables that are currently being tracked by brain tumor surveillance systems. In particular to someone being exceedingly efficient and precise in the detection, classification and segmentation of brain tumors, the method proposed promises to be highly accurate. Automated or semi-automated processes are done to gain this level of precision. Using CNN (Convolutional Neural Networks), a 3 x 3 kernel segmentation approach is suggested in this paper. Segmentation and classification can be achieved with just this one method. Layer-based results classification distinguishes CNN (a machine-learning technique) from NNs (Neural Networks). Data collection, pre-processing, average filtering, segmentation, feature extraction, and CNN via classification and identification are only a few of the stages relevant to the proposed methods. DM (data mining) techniques is being used to extract important relationships and patterns from the data. Early identification and prevention of brain tumors are made possible by the use of ML (machine learning) and Data Mining methods.

Parveen, Amritpal Singh ," Detection of Brain Tumor in MRI Images, using Combination of Fuzzy C-Means and SVM" [4], The most essential tool for identifying brain tumors is magnetic resonance imaging (MRI). Data mining algorithms are used in this paper to classify MRI pictures. For brain tumor classification, a new hybrid approach based on support vector machine (SVM) and fuzzy c-means is presented. The intended approach is a hybrid technique for brain tumor prediction that combines support vector machine (SVM) with fuzzy c means. This method improves the image by employing enhancement techniques such as contrast improvement and mid-range stretch. Skull striping is accomplished by the use of double thresholding and morphological processes. Fuzzy c-means (FCM) clustering is used in image segmentation to locate suspicious regions in brain MRI images. Grey level run length matrix (GLRLM) is utilized to extract features from brain pictures, and then SVM approach is used to classify brain MRI images, which provides more accurate and effective results for brain MRI image classification.

III. SYSTEM ARCHITECTURE

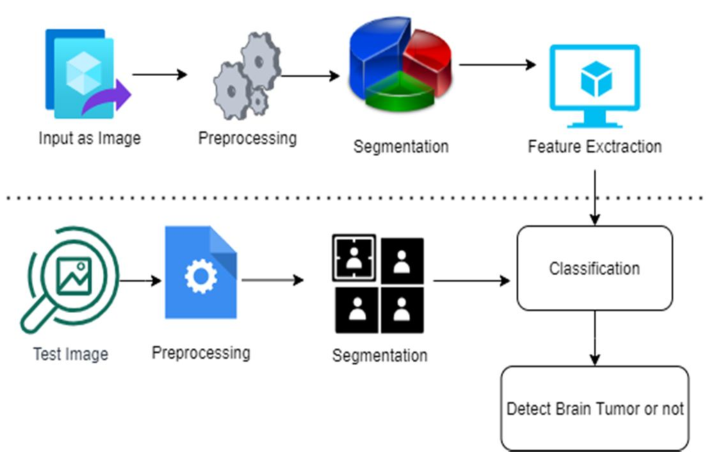

Fig. 1

Module
Pre-processing
Feature Extraction
Classification

A. Algorithm

1) *CNN:* A convolutional neural network (CNN/ConvNet) model is a deep learning model used in machine learning to analyze visual pictures. Multiplications come to mind when we think about neural networks; however, it's not the case with Convolution. It makes use of a method known as Convolution. The pooling layer is a mathematical function on two functions that yields a third function that demonstrates how the shape of one is changed by the other. A convolution neural network is made up of many layers of artificial neurons. Connections between neurons are mathematical in nature, calculating the weight value of various inputs and creating an activity value, similar to their natural counterparts. When an image is fed into a ConvNet, each layer creates a set of activation functions, which are then passed on to the next layer. In general, the first level isolates the most relevant features, such as horizontal or diagonal edges. This data is passed on to the next level, which can identify more complicated properties like corners and combinational edges. As we go deeper into the system, we learn that it can recognize more complicated elements such as objects, faces, and so on.

B. Accuracy

Accuracy is the percentage of correct predictions made by our model out of all Brain Tumor forecasts. This implies that we add the number of forecasts that were successfully forecasted as Positive (True Positive) or correctly predicted as Negative (True Negative) and divide it by all sorts of predictions, both accurate (True positive True negative) and erroneous (False Positive False Negative) (False positive and False negative).

The accuracy varies from 0 to 1. These extreme situations relate to either utterly missing or always right forecasts. For example, if our model can predict flawlessly, there will be no False Positives or False Negatives, causing the numerator to equal the denominator and bringing the Accuracy to 1. If our system is always off, inaccurately forecasting every time, the number of True Positives and True Negatives will be zero, causing the equation to be zero divided by something positive, resulting in an Accuracy of 0.

In practice, Accuracy typically fluctuates between 0.5 and 1, since if Accuracy goes below 0.5, we may simply reverse the labels of the forecasts to achieve a better prediction. However, accuracy is a poor statistic, especially when the data is skewed. Accuracy does not reveal the whole story when there is a big difference in the number of positive and negative labels. Consider the following scenario: we have 100 samples, 95 of which are labelled as belonging to Class 0, and 5 as belonging to Class 1. In this scenario, a badly constructed "dummy" model that always predicts Class 0 obtains a 95% Accuracy, indicating a fairly powerful model. However, this model is not truly predictive, thus Accuracy is not the appropriate performance indicator to assess the model's power. If we simply employed Accuracy to assess this model, we would eventually provide stakeholders and clients with a model that is neither performant nor predictive.

$$\text{Accuracy} = \text{No. of correct prediction} \,/\, \text{Total No. of prediction}$$

$$\text{Accuracy} = (TP+TN) \,/\, (TP+TN+FP+FN)$$

$$\text{Accuracy} = 60+40 \,/\, 60+40+0+5$$
$$= 0.95$$
$$= 0.95*100$$
$$= 95\ \%$$

IV. ADVANTAGES, LIMITATIONS AND APPLICATION

A. Advantages

1) High Precision
2) Low level of complexity

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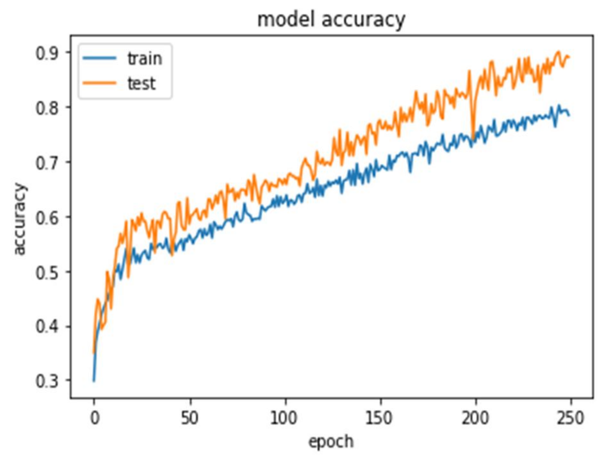
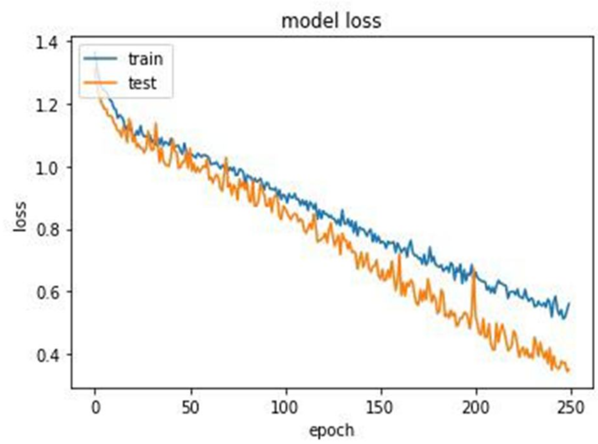
B. Limitations

The suggested algorithms are currently incapable of recognizing multiple diseases or many cases of the same ailment in a single picture. For detection, a bigger data collection is required.

C. Results



Accuracy & Epoch Graph
Fig. 2



Loss Graph
Fig. 3

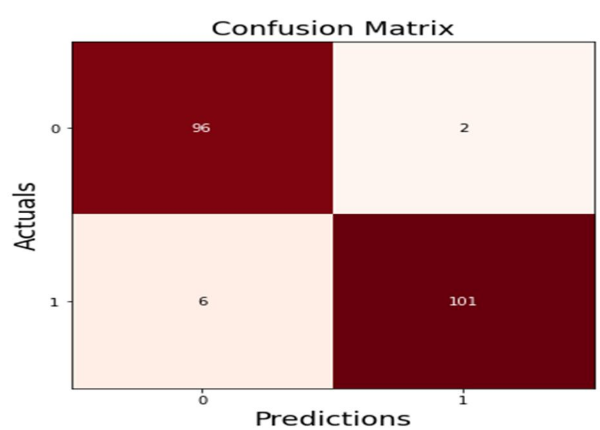


Fig. 4

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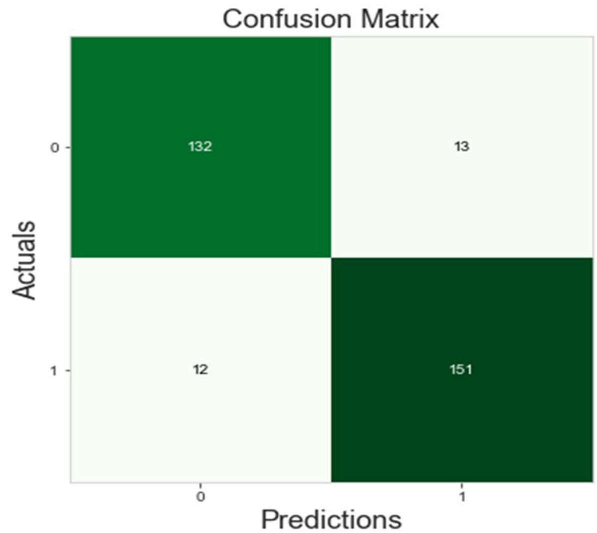

Fig. 5

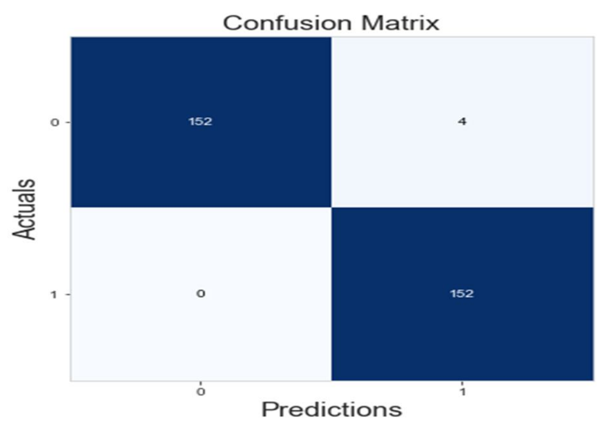

Fig. 6

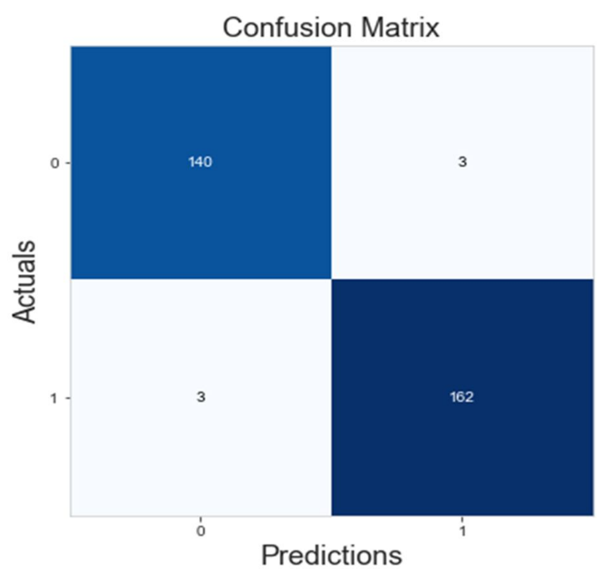

Fig. 7

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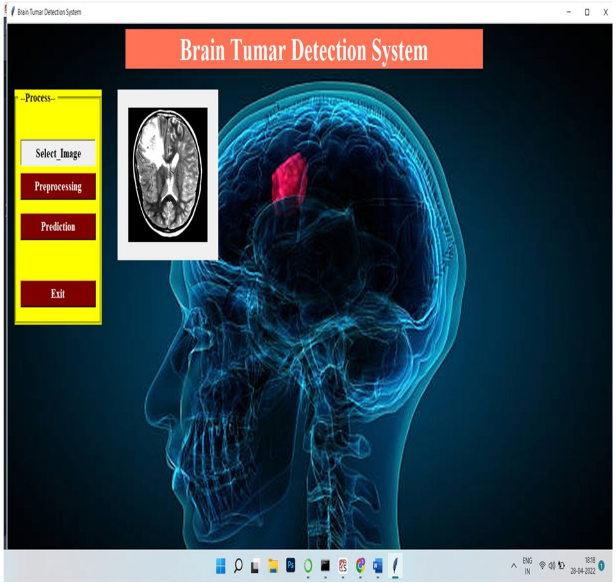
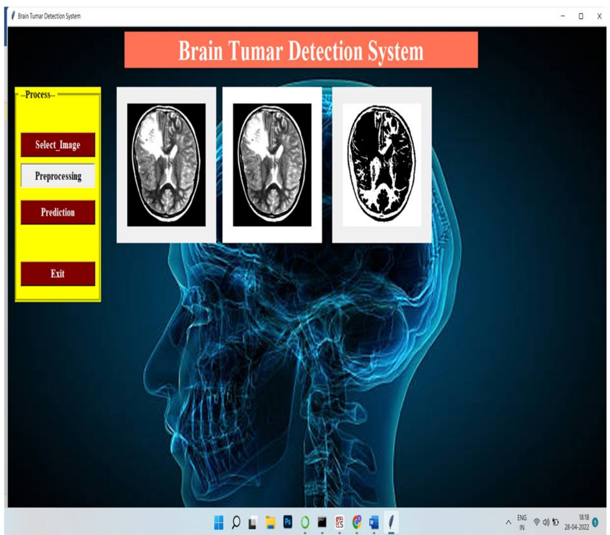
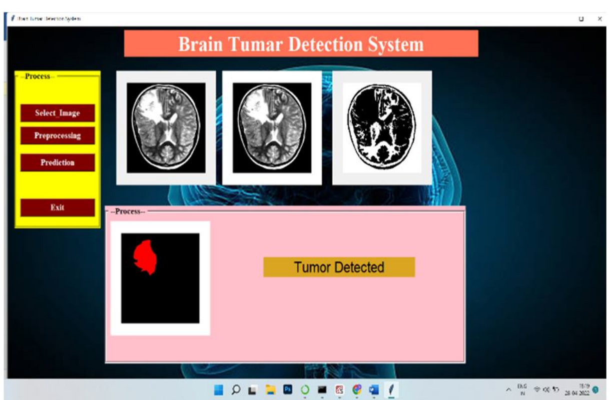
D. Test Cases



a) Sample Image Input



b) Preprocessing of Sample Image



c) Prediction of Sample Image

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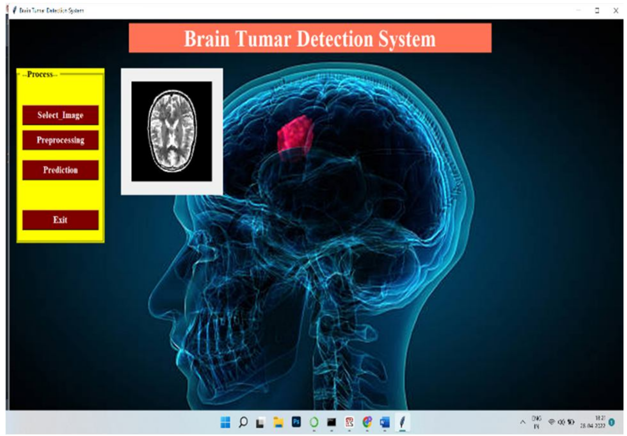
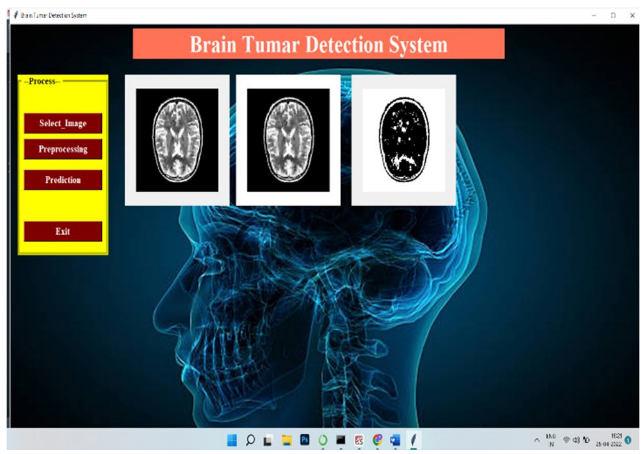
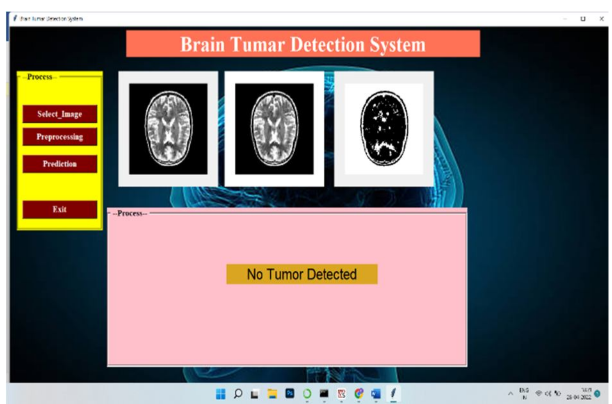
1) Case I: Brain Tumor Detected



a) Sample Image Input



b) Processing of Sample Image



c) Prediction of Sample Image

2) Case II: Brain Tumor NOT Detected

V. CONCLUSION

This study provided a method for classifying tumors into three categories: whole tumor, core tumor, and augmenting tumor. Intensity difference, neighborhood information, and wavelet features are extracted from multimodality MRI images and employed with various classifiers. The use of a CNN classifier increased classification accuracy, as indicated by quantitative results of our suggested approach that are comparable to or superior than the state of the art.

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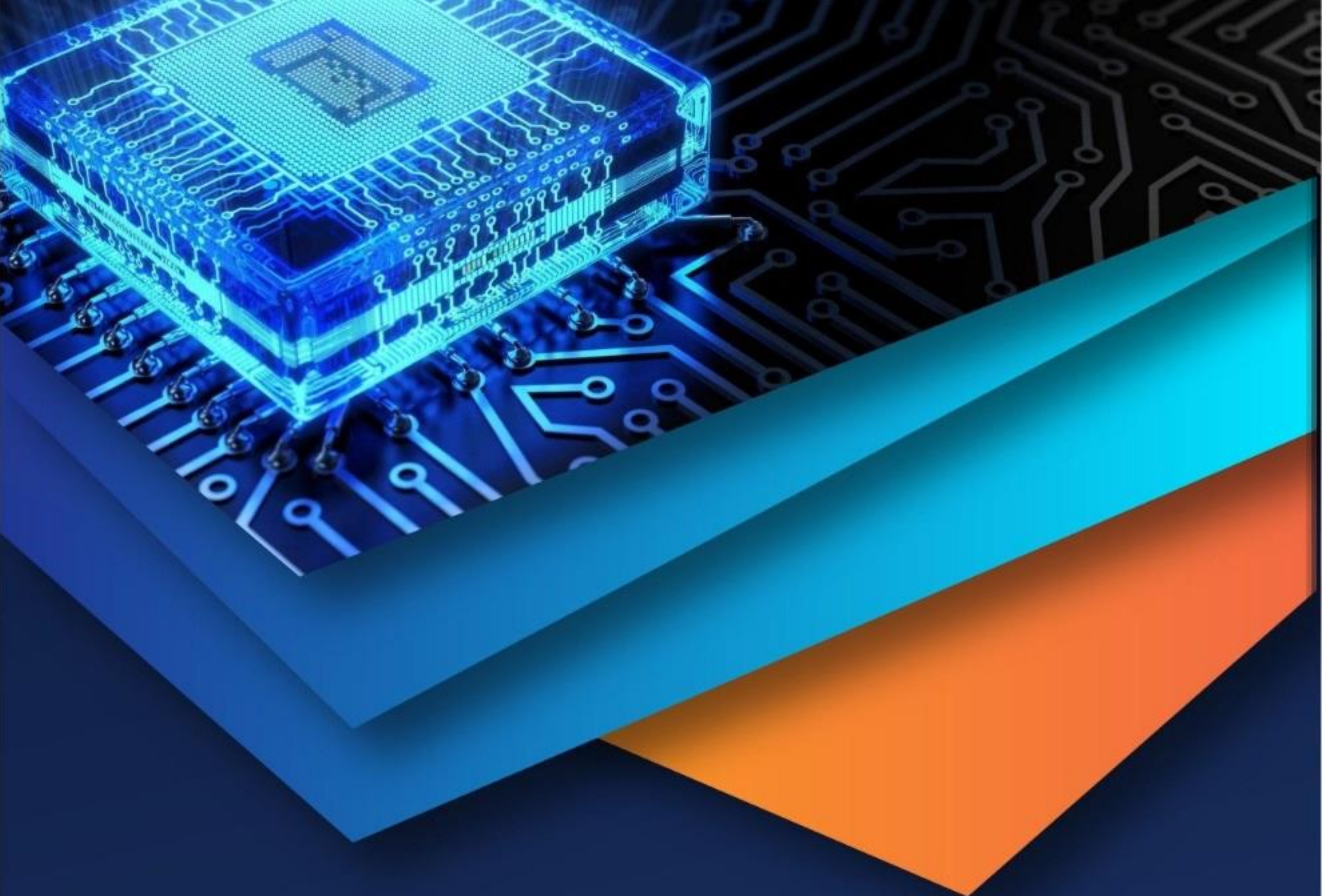

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