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A Comparative Study of Alzheimer Detection Techniques

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Abstract: Alzheimer's disease is one of the neurodegenerative disorders. It initially starts with innocuous symptoms but gradually becomes severe. This disease is so dangerous because there is no treatment, the disease is detected but typically at a later stage. So it is important to detect Alzheimer at an early stage to counter the disease and for a probable recovery for the patient. There are various approaches currently used to detect symptoms of Alzheimer's disease (AD) at an early stage. The fuzzy system approach is not widely used as it heavily depends on expert knowledge but is quite efficient in detecting AD as it provides a mathematical foundation for interpreting the human cognitive processes. Another more accurate and widely accepted approach is the machine learning detection of AD stages which uses machine learning algorithms like Support Vector Machines (SVMs) , Decision Tree , Random Forests to detect the stage depending on the data provided. The final approach is the Deep Learning approach using multi-modal data that combines image , genetic data and patient data using deep models and then uses the concatenated data to detect the AD stage more efficiently; this method is obscure as it requires huge volumes of data. This paper elaborates on all the three approaches and provides a comparative study about them and which method is more efficient for AD detection.

Keywords: Alzheimer's Disease (AD), Fuzzy System , Machine Learning , Deep Learning , Multimodal data

I. INTRODUCTION

Alzheimer's disease can be a result of both genetic disorder and environmental factors that can affect a person's brain over time .This disease affects the brain tissues by breaking them and typically occurs in people above the age of 65. The approaches that we have noted use data like MRI (Magnetic Resonance Imaging) , Genetic data , Electronic health record to detect the AD stage.

The Fuzzy system approach uses magnetic resonance imaging (MRI) neuro imaging study for AD diagnosis. It provides for precise volume measurements of brain regions in three dimensions (3D). The major function of MRI in the diagnosis of Alzheimer's disease is to assess volume changes in specific areas. The main classifier, Neuro-Fuzzy classification, aids in the classification of images into normal and abnormal. The neuro-fuzzy system shows how to analyze MRI images and segment aberrant ones.

Higher accuracy is found in detection of Alzheimer's disease using machine learning algorithms. Conditions of patients are highlighted in various forms of cognitive impairment. The combination of MRI images and other factors like psychological will help further to obtain results with more accuracy then it is obtained now. Further, the results obtained at earlier stages will be improved because of advancement achieved due to this combination.

The Deep learning approach is a more dynamic approach as compared to the fuzzy system and machine learning approach as it does not require expert knowledge like in fuzzy and it can produce more accurate results than machine learning approach by using multi-modal data which cannot be processed by shallow models. This approach uses image data (MRI) and processes image segmentation to get the regions in the brain affecting AD. The genetic data which has around 2 million classes and the patients clinical data which includes generic medical data about a patient are processed using denoising-autoencoders and the output is concatenated with the output generated by the 3D CNN using MRI to generate the intermediate data. This data is finally fed into a shallow classification model to generate predictions we will be viewing all this process in detail in this paper.

II. FUZZY SYSTEM APPROACH

Fuzzy Logic (FL) is a type of machine intelligence (AI) that allows computers to create colourful images of the uncertain world. Fuzzy sets were created as a way to represent and manipulate data that isn't precise but rather fuzzy detection of Alzheimer is done by using Magnetic Resonance Imagining (MRI) data. The approach of using fuzzy system for detection of Alzheimer is one of the most common yet highly concerning in neuroscience. The main classifier, Neuro-Fuzzy classification, aids in the classification of images into normal and abnormal. The neuro-fuzzy system shows how to analyze MRI images and segment aberrant ones. Neuro-fuzzy modeling is known as a flexible framework. This tool gathers data and required information from current experimental models as a source, and then applies fuzzy logic such as "if then else rules" to create successful models for picture analysis.

Basic Tools	Example Application
Filters	1.Noise Suppresion 2.Edge Detection
Segmentation	1.Object Recognition 2.Image Retrieval
Interest Operators	1.Image Matching 2.Motion Analysis 3.Object Recognition
Photogrammeteric Operation	3D Reconstruction

Fig 1. Classification of computer vision [1]

A. Image Segmentation

Fuzzy system employs Image Segmentation, and the integration of its algorithms simplifies the diagnosing procedure. Because of its complicated architecture and inherent image difficulties, segmenting the brain for anomaly identification in slice images is the most difficult undertaking. where photos are first pre-processed and enhanced, with the goal of removing noise, adjusting intensity levels, and improving contrast and extracting the brain from the skull. Pre-processing aids in more accurately separating desired regions and improves classification accuracy. Images are segmented into homogenous regions with similar qualities after pre-processing, and features are extracted in the feature extraction step.

B. Image Segmentation Techniques

Thresholding: The image is segmented using the Thresholding approach by comparing pixel values to a preset threshold limit. Based on the intensity levels, the picture is automatically divided into distinct sections.

Edge based segmentation: In this technique rapid variations in intensity near edges are used to segment a picture. Two of the most used edge-based segmentation approaches are the grey histogram and the gradient-based method.

Region based segmentation: Each image is segmented into regions that are similar to a set of predefined criteria. This technique uses such region based images with different methods for segmentation.

Classifiers: Different types of classifiers are used for this segmentation technique. Prime classifiers can be stated as KNN(K-Nearest Neighbor),SVM(Support Vector Machine),PCA(Principal Component Analysis).

Clustering: Image pixels are used extensively in clustering technique. This technique classifies pixels into classes.

Artificial Neural Network: A picture is initially mapped into a Neural Network in this approach. The two most critical phases in neural network segmentation are feature extraction and neural network-based picture segmentation.

1) Network of Feed Forward
2) Network of Feedback

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Hybrid: This method basically consists of all the other techniques present.

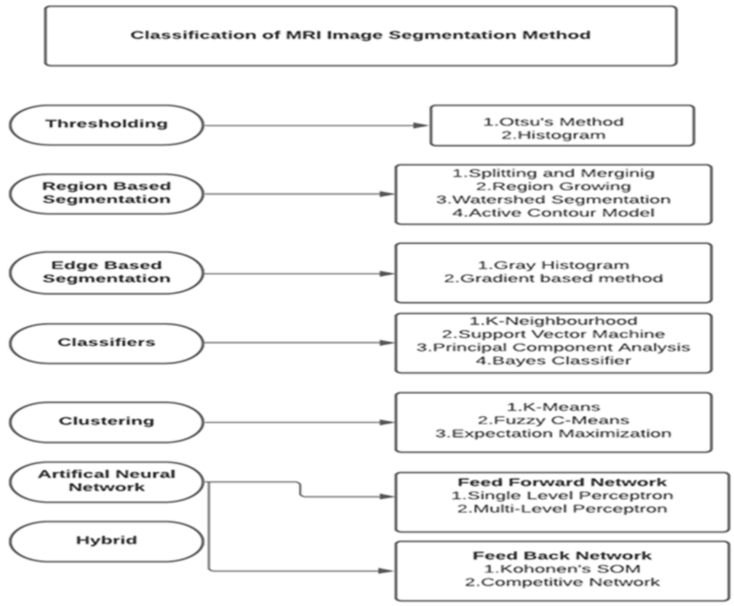

Fig 2. Image Segmentation Techniques [1]

III. MACHINE LEARNING APPROACH

A. *Support Vector Machine*

The support vector machine (SVM) is a supervised, non-probabilistic linear classifier that can learn to distinguish data from two classes by looking for the linear boundary (called the hyperplane) that maximizes the margin between the two known classes. It is trained by putting training data in an n-dimensional training space, then classifying test subjects based on their positions.

If the input is an array x which includes n features, which means it's far from a factor in a n-dimensional space, the SVM approach reveals a linear floor of size n-1 that divides the 2 clouds of n-dimensional factors belonging to the 2 classes. That is, optimizing the hyperplane parameters as a way to maximize its distance from the nearest factor, that's a hassle that may be decreased to minimization of a quadratic blunders function. It has been utilized in numerous neuroimaging and is understood to be one of the most effective systems in studying equipment within the neuroscience discipline in current research. SVM also can be tailored to solve multiclass troubles in numerous ways, usually with the aid of combining a financial institution of SVM classifiers. The major gain of SVM is that it is able to distinguish linear and non-linear objects.

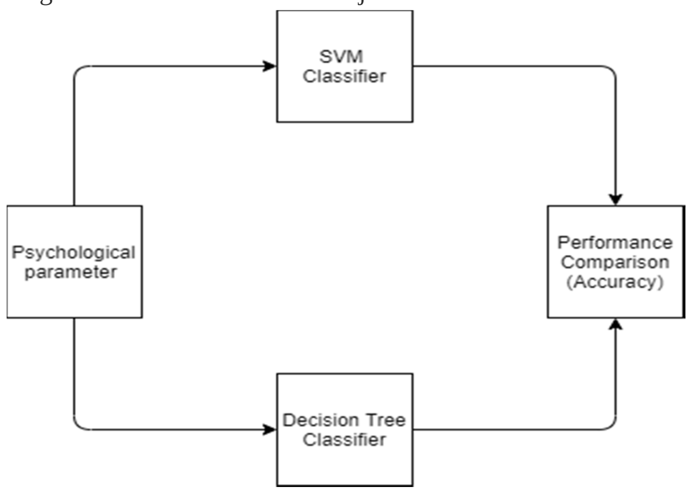

Fig 3 shows the steps in predicting Alzheimer disease using machine learning algorithms.

Classifier = svm (formula=age, visit, MMSE, EDUC .,data = train, type = 'Classification', kernel = 'linear').

The formula consists of the fields which are taken into consideration for prediction. The fundamental kind c-category and linear kernel is chosen. They each by and large depend upon the statistics used. The mental parameters are given as an input to the classifier.. When the classifier is trained and given for testing, it predicts the output with an accuracy of 85%.In mathematical representation, for a two-dimensional space, a line can distinguish linearly separable data. The equation of a straight line is y = ax + b. By renaming x to x1 and y to x2, the equation becomes a (x1-x2) + b = 0. If we specify X = (x1, x2) and w = (a,-1), we get wx + b = 0, which is a hyperplane equation. The linearly separable output with the hyperplane equation has the following form:

$$f(y) = z^T\emptyset.(y) + b$$

Where y is an input vector, z^T is a hyperplane parameter, and $\emptyset(y)$ is a function used to map feature vector *y* into a higher-dimensional space. The parameters *z* and *b* are scaled suitably by the same quantity.
In addition, in order for any decision boundary surface (hyperplane) to correspond to a unique pair of (z, b), familiarize yourself with the following constraints: where y1, y2, y3,..., YN are the given training points.[2]

$$min|z^T\emptyset.(y_i) + b| = 1, \qquad i = 1, \ldots, N,$$

B. Decision Tree

Decision trees are the conventional model of machine learning techniques and powerful classification methods. An algorithmic technique evolved that records splitting became accomplished with the aid of using wonderful situations. These situations shape an inverted choice tree whose root node is on the pinnacle of the tree. Many researchers have taken into consideration choice bushes as a top notch technique to undertake a predictive evaluation Decision tree is a supervised mastering version that makes use of a hard and fast of regulations to discover a solution. It is a remedy to any kind of problem. It also can be used for each category and regression. A small change within the records can also supply a top notch effect in the output. For a non-stop variable, regression tree may be used and for specific variable category bushes may be used.
The decision tree consists of the following nodes:
Root node: starting point of the tree.
Internal node: decision point of the problem that leads to the solution.
Leaf node: final or last nodes of the entire tree.
The algorithm for decision tree classifier is as follows:
model <- rpart (formula = age, visits, MMSE, EDUC~ ., data = alzhe, method = "class")
The formula consists of the fields which might be taken into consideration for the prediction of Alzheimer disease. The technique's elegance suggests the class trees. The applications used right here are party, rpart, and rpart.plot. The package ctree() can also be used to analyze the decision tree.
The decision tree is a predictive model for Alzheimer's disease. To our knowledge, decision tree induction has not been used to predict Alzheimer's disease in the past. We create a decision tree based on a training set that represents sample clinical data. We use entropy or information gain to determine the attributes of the branches at each level of the tree. Compared to the random selection of attributes, the use of information gain allows us to build an optimal or near optimal tree with fewer nodes and branches. Finally, after building the decision tree, the system can be used to predict Alzheimer's disease in new patients. Based on the values of the attributes related to the new patient, the decision tree is traversed from the root node to the leaf node. The nodes of the tree represent the prediction of the state of Alzheimer's disease. We believe that the decision tree should be periodically rebuilt or updated based on new cases of known disease states.

C. Comparison of Accuracy

Model	Accuracy (%)
SVM	85
Decision Tree	83

Table I. Comparison of models [3]

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Support Vector Machine 85%, Decision Tree 83%. The data set has multiple parameters, but only important parameters that are very helpful in predicting disease are used, such as MMSE score, age, number of visits, and patient education. When using machine learning algorithms such as support vector machines and decision trees, they predict diseases with different accuracy. Each algorithm uses 70% of the training data set for training and 30% of the test data set for testing. The behavior of the algorithms is compared based on their accuracy. Then divide the data set according to the ratio, and when comparing algorithms, choose the best one, which can be used in the next prediction stage.

IV. DEEP LEARNING APPROACH

Most of the current models used for detecting Alzheimer disease (AD) and its stages use single data modality for making predictions. But a more versatile approach that can yield a better outcome would be using multi-modal data (Images, Text) and processing it using neural networks. This approach lets us increase the accuracy of prediction as it works on multiple types of data unlike shallow models that can only work with a singular data. In [1] the authors have used three types of data namely magnetic resonance imaging (MRI), genetic (single nucleotide polymorphism SNPs) and finally clinical test data to detect AD or predict its stage. At the end it will be demonstrated how a deep model using multi-modal data performs better than shallow models like Support Vector Machines (SVM), K-nearest neighbors (KNN) etc.

A. Data Processing

The three types of data are processed and trained separately and then combined using different classification layers including SVM, KNN. The integration of deep models with shallow models and using multiple types of data enhances the ability of the final model. [1] Uses auto-encoders to extract features from genetic and clinical data and 3D (Convolutional Neural Networks) CNN for extracting data from MRI images. The dataset used was Alzheimer’s disease neuroimaging initiative (ADNI).The data set contains SNPs (808), Clinical data (503) and neurological test data (2004).

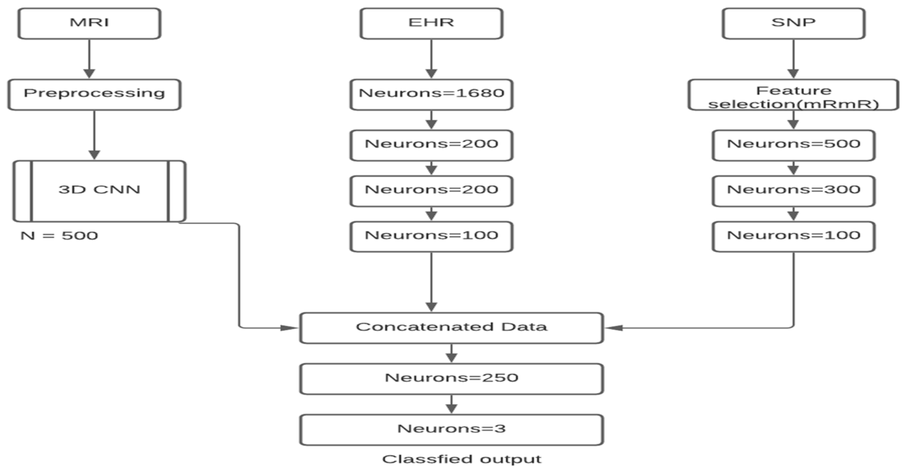

Fig.4 Training individual data

Steps

1) *Image Data:* The images are first processed to filter noise and then perform skull scripting. After these steps image segmentation is done for different brain tissues. After this process the images are normalized and then 3D areas of 21 brain regions associated with AD are extracted.
2) *Clinical Data:* 1680 common features are extracted from the data including quantitative, categorical and binary data. The quantitative data is standardized using some Scaler to be between 1 and 2 and the categorical data is made binary using one hot encoder. Finally these values are converted into 1 or 2.
3) *Genetic Data:* This is the data with the highest number of features each one having approximately 3 million features. A lot of filtration is done to eliminate SNPs with low genotype quality, low minor allele frequency, high per site missing rate. After this filtering is done, a two stage feature selection takes place i] SNPs that are located on known AD-associated genes are retained ii] Approximately 500 features are selected using minimum redundancy maximum relevance this method works well with categorical data and has been used previously with genetic data.

B. Intermediate Feature Generation

After feature extraction is completed the ready to use data is fed to the neural networks to create intermediate features for single-modality data and later the intermediate data generated by each model is concatenated. The intermediate features for imaging data are generated using 3D Convolutional Neural Networks (CNN). First the regions of interest are selected and placed in separate 3D-CNN and the weights are shared across the CNN modules. The CNN then extracts higher level features from the abstracted images which correlate better with the targets. The image data is processed using a 5x5x5 CNN layer followed by a 3x3x3 pooling layer and after that it is fed to a rectified Linear Unit layer (ReLu) to learn complex features from the data. This intermediate data is then fed to the multi-modal deep learning model. The intermediate features for EHR and SNP data are extracted using auto-encoders. Each patient's data is represented as a vector of length m (where m is the number of features).The data is then passed through two-stacked denoising auto-encoders to get a higher level representation of the data. Each auto-encoder layer takes an input I with dimensions nxd (where d=m for the first layer). This encoder then converts the input into a higher level data representation. After the auto-encoder layers are trained, network fine-tuning is done for each layer by adding a softmax activation function that predicts final classes. This intermediate data is then fed to the multi-modal deep learning model.

C. Multi-modal Data Integration

The multi-modal data is integrated with an aim to bridge the gaps of our understanding about AD and to improve the detection of AD. The intermediate data is passed to a concatenation layer followed by a classification layer which can be either KNN, SVM , decision tree or random forest to classify the AD stage.

D. Shallow vs Deep Models

Metrics	Knn	Decision Tree	SVM	Random Forest	Deep model
Accuracy	81	82	82	81	86
Precision	85	84	82	82	84
Recall	80	84	83	84	89
Mean F1	81	83	83	82	84

Table II. Model Performance [4]

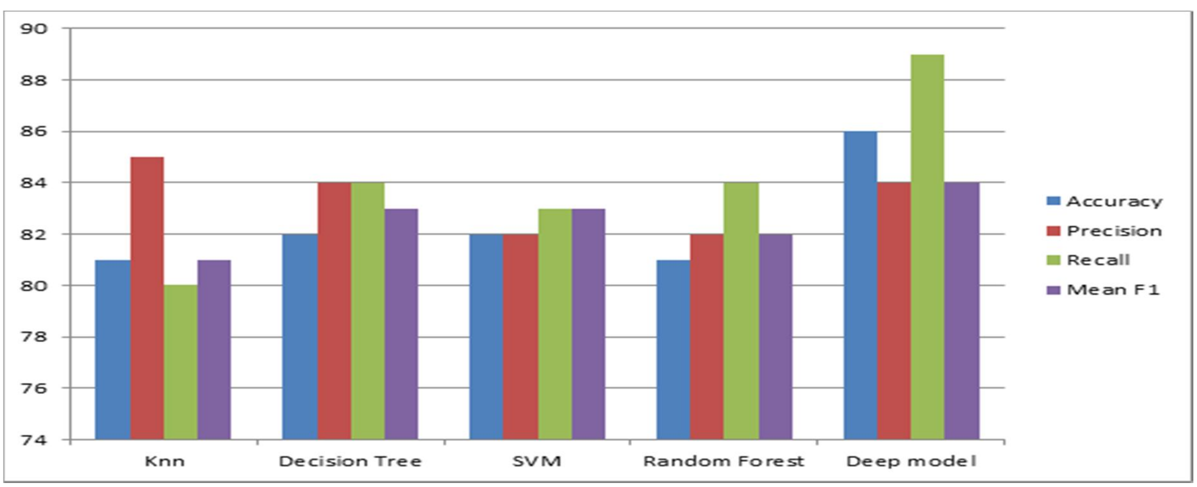

Fig.5 Model performance comparison

From the above figure it is evident that Deep models perform quite better than the shallow models currently in use for AD detection and stage prediction. Performance data was taken from [4].

V. CONCLUSION

In conclusion, from the above mentioned data about the three techniques namely Fuzzy system , machine learning and deep learning approach we can conclude that all the techniques have certain pros and cons. For a fuzzy system if we have an expert to supervise it then it's a viable option. Secondly for the Machine learning approach if we do not have a very large dataset it is a better option than Deep learning approach. Finally, if we have abundant data with millions of features like genetic data, then the Deep learning approach is the only one that can handle such data and provide best results. Overall the multi-modal data used for training the deep model gives the best accuracy in detecting Alzheimer’s disease.

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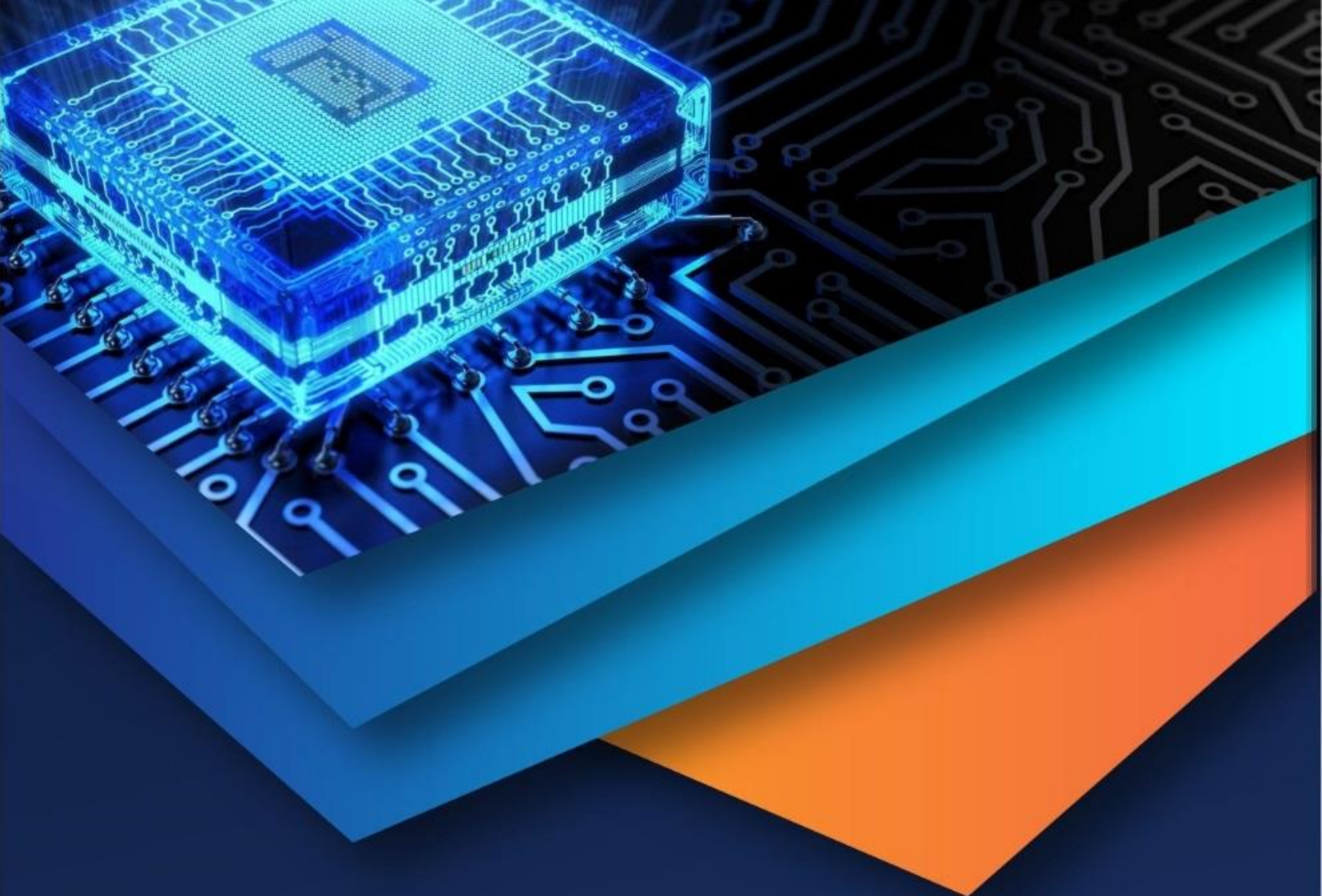

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