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Detection of Epileptic Seizures and Efficient De-Noising In Speech-Auditory Brain Waves

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Abstract: EEG measures the brain activity. EEG signals are combination of the signals i.e, pure EEG and artifacts. The presence of these noises introduces spikes and results in signal distortion. The Electroencephalogram (EEG) signal is very important in the diagnosis of epilepsy. The detection of epileptic activity is, therefore, a very demanding process that requires a detailed analysis of the entire length of the EEG data. This paper describes an automated classification of EEG signals for the detection of epileptic seizures using wavelet transform and statistical pattern recognition. On comparing with other techniques, the Conventional Wavelet transform algorithms are best auditory artifact removal technique and can be highly useful in auditory EEG data analysis .The decision making process is comprised of three main stages: (a) feature extraction based on wavelet transform, (b) feature space dimension reduction using scatter matrices, and (c) classification by quadratic classifiers (disorder such as normal, ictal and interictal). An overall classification accuracy of 99% was achieved. The proposed algorithm has a potential in the classification of EEG signals and detection of epileptic seizures, and could thus further improve the diagnosis of epilepsy.

KEY TERMS: wavelet transform, statistical pattern, epileptic seizures, EEG

I. INTRODUCTION

Brain is one of the most important organs of humans, for controlling the coordination of human muscles and nerves. The transient and unexpected electrical disturbances of the brain results in an acute disease called Epileptic seizures. Numbers of researchers have presented automated computational methods for detecting epileptic seizures from EEG signals. The word ‘epilepsy’ is derived from the Greek word epilambanein, which means ‘to seize or attack’. Seizures are the result of sudden brief, excessive electrical discharges in a group of brain cells called neurons. Transient symptoms can occur, such as loss of awareness or consciousness and disturbances of movement, sensation (including vision, hearing, and taste), mood, or mental function. The seizures occur at random to impair the normal function of the brain. [1].The prevalence of epileptic seizures changes from one geographic area to another [2]. The seizures occur at random to impair the normal function of the brain. Seizures can be classified into two main categories depending on the extent of involvement of various brain regions focal (or partial) and generalized. Generalized seizures involve most areas of the brain where as focal seizures originate from a circumscribed region of the brain, often called epileptic foci [3]. In recent years, a few attempts have been reported on seizure detection and prediction from EEG analysis using two different approaches: 1) Examination of the waveforms in the preictal EEG to find events or changes in neuronal activity such as spikes, which may be precursors to seizures. 2) Analysis of the nonlinear spatio-temporal evolution of the EEG signals to find a governing rule as the system moves from a seizure-free to seizure state [4].Some work has also been reported using artificial neural networks for seizure prediction with wavelet pre-processing.

A. Electroencephalography

Electroencephalogram (EEG) is an important means of identifying and analyzing epileptic seizure activity in humans .The identification of the epilepsy of an EEG signal is done manually. The diagnosis of an abnormal activity of the brain functionality can be analyzed with the help of EEG. EEG signals provide a great of information about the activity of the brain. But classification and evaluation analysis of these signals are limitation.EEG is most commonly used to diagnose the epilepsy which causes neurological abnormalities in EEG readings. It is also used to diagnose the coma, sleep disorders, encephalopathies and brain death and the epilepsy. EEG used to be a most important first-line method of diagnosis for tumors, stroke and other epileptic activity problems of focal brain disorders, but this use has decreased, because of the advent of high resolution anatomical imaging techniques such as MRI and CT. Despite limited resolutions, EEG continues to be a valuable tool for research and diagnosis purposes, especially when millisecond-range temporal resolution (which is not possible with CT or MRI) is required.

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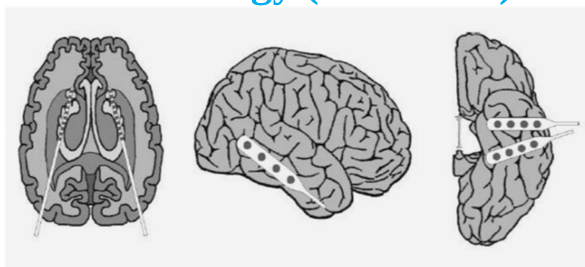

Fig1. Implanted intracranial electrodes.

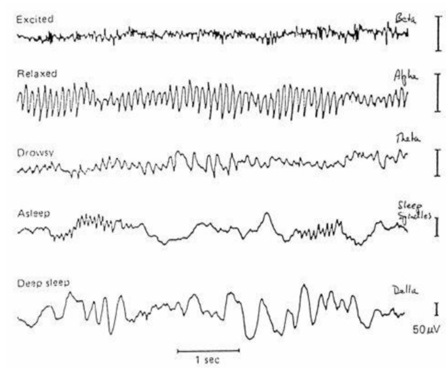

Fig.2. EEG WAVES

B. Epilepsy

Epilepsy is a common brain disorder that, according to an estimate of the World Health Organization, affects almost 60 million people around the world. Approximately one in every 100 persons will experience a seizure at some time in their life [5]. Epilepsy is characterized by the recurrent and sudden incidence of epileptic seizures which can lead to dangerous and possibly life-threatening situations [6]. The detection of epileptic seizures by visual scanning of a patient's EEG data usually collected over a few days is a tedious and time-consuming process. In addition, it requires an expert to analyze the entire length of the EEG recordings, in order to detect epileptic activity. For example, long-term treatment with antiepileptic drugs, which may cause cognitive or other neurological side effects, could be reduced to a targeted short-acting intervention . Therefore, there is a strong demand for the development of such automated systems, due to both huge amounts and increased usage of long-term EEG recordings for proper evaluation and treatment of neurological diseases, including epilepsy.

Section 2 gives the detailed description of materials and methods used in the proposed method of this project and section 3 gives the results and discussion , section 4 gives the future enhancement of the system.

II. MATERIALS AND METHODS USED

A. Materials

Three EEG data sets from three different groups were analyzed: healthy subjects with normal EEG data, epileptic subjects during a seizure-free interval with interictal EEG data, and epileptic subjects during a seizure with ictal (epileptic) EEG data. Each data set recorded with a 128-channel amplifier system contained 100 single-channel EEG segments sampled at 173.61 Hz, each of 23.6 sec duration. In addition, the segments had to fulfill a stationarity criterion described in detail in Andrzejak et al. [12].

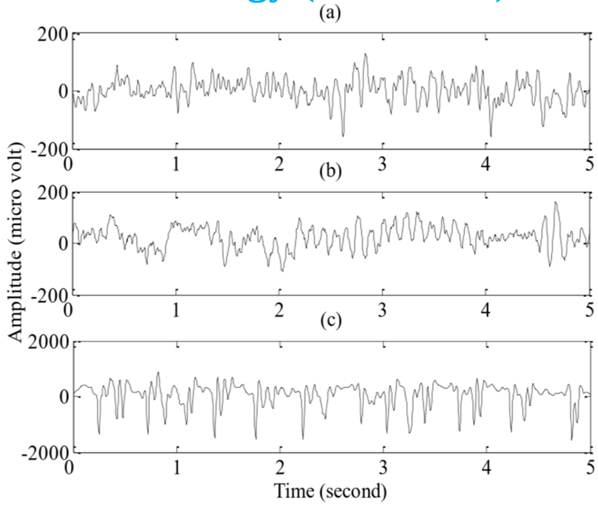

Fig3 - Segments of EEG data: (a) Normal, (b) Interictal, (c) Ictal.

There are five broad spectral sub-bands of the EEG signal which are generally of clinical interest: delta (0 - 4 Hz), theta (4 - 8 Hz), alpha (8 - 16 Hz), beta (16 - 32 Hz) and gamma waves (32 - 64 Hz). Higher frequencies are often more common in abnormal brain states such as epilepsy (i.e. there is a shift of EEG signal energy from lower to higher frequency bands before and during a seizure). These five frequency sub-bands provide more accurate information about neuronal activities underlying the problem and, consequently, some changes in the EEG signal, which are not so obvious in the original full-spectrum signal, can be amplified when each sub band is considered independently.

B. Methods

An automated classification of EEG signals for the detection of epileptic seizures based on wavelet transform and statistical pattern recognition is proposed. Finally, two quadratic classifiers are designed, which are able to distinguish all three groups of the EEG signals of interest from each other.

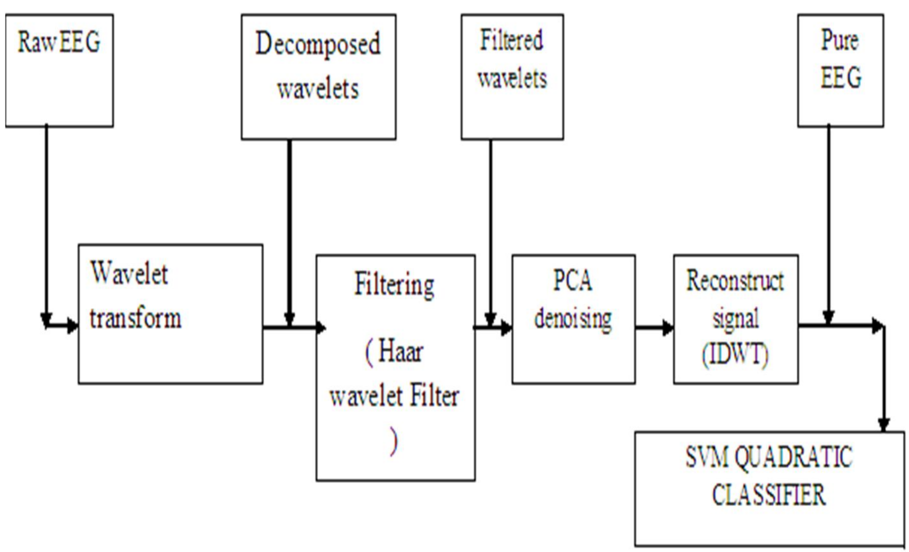

Fig 4. Block diagram

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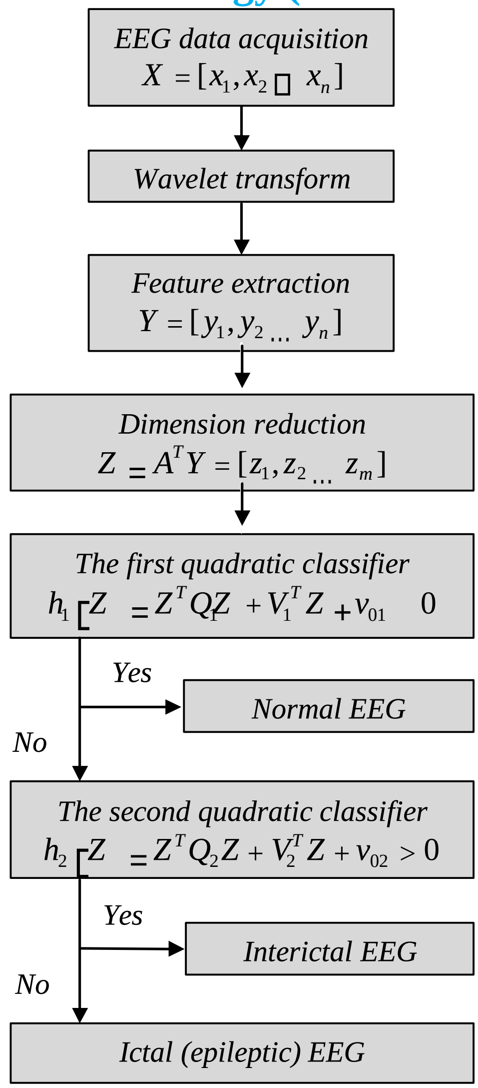

Fig 5...Flow chart of proposed system

1) Wavelet Transform and Feature Extraction: Abnormalities in EEG data during serious neurological diseases such as epilepsy are too subtle to be detected using conventional techniques that usually transform mostly qualitative diagnostic criteria into a more objective quantitative signal feature classification problem.

The wavelets and the scaling functions, as follows:

$$x(t) = \sum_k 2^{j_0/2} a_{j_0}(k) \varphi\left(2^{j_0} t - k\right) + \sum_{j=j_0}^{\infty} \sum_k 2^{j/2} d_j(k) \psi\left(2^j t - k\right) \quad \text{----} (1)$$

$$a_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t) \varphi\left(2^j t - k\right) dt \quad (2)$$

$$d_j(k) = \int_{-\infty}^{\infty} 2^{j/2} x(t) \psi\left(2^j t - k\right) dt \quad (3)$$

The wavelet packet (WP) transform is a generalization of the DWT in which decomposition is undertaken in both directions (lower and higher frequencies).. In the WP tree, each node is recognized by the decomposition level (scale) l with respect to the WP tree root and the frequency band f. The ability of the wavelet transform in adaptive time-scale representation and decomposition of a signal into different frequency sub-bands presents an efficient signal analysis method without introducing a calculation burden [36]. Based on wavelet coefficients obtained after the wavelet transform, the signal can be reconstructed in each of the previously derived sub-bands and its time-domain features in different sub-bands can be studied separately.

2) De-Noising

After an appropriate signal analysis (e.g. wavelet transform used in this research), as well as feature extraction, the feature vector $Y = [y_1, y_2 \ldots y_n]$ is derived.

The selection of the matrix A is a trade-off between the desired level of simplicity of the classification procedure and the inevitable loss of information due to dimension reduction.

$$P_k \approx \frac{N_k}{N}, k = 1, \ldots, c \qquad (6)$$

C. SVM Classifier

These are the steps followed for real time EEG signal processing

Acquisition of EEG signal using DAQ (data acquisition).

Filtering of the acquired signal using band pass filter set to the frequency range 4 to 40 Hz.

Differentiation of the filtered signal.

Squaring of the differentiated signal.

Integration of the squared signal.

Determination of the frequency of the integrated signal.

Time period calculation using the determined frequency which gives the R_R interval.

Time period = 1/ frequency.

Calculation of the heart rate by using the R_R interval

Diseases classification

In the first step the algorithm passes the signal through a low pass and a high pass filter in order to reduce the influence of the muscle noise, the power line interference, the baseline wander and the T-wave interference.

The low pass filter is given by,

y(n)=2*y(n-1)-y(n-2)+x(n)-2*x(n-6)+x(n-12) (1)

and the high pass filter is given by,

y(n)=y(n-1)-1/32*x(n)+x(n-16)-x(n-17) +1/32*x(n-32) (2)

After filtering the signal is differentiated using the formula below:

Y(n)=1/8*[2*(n)+x(n-1)-x(n-3)-2*x(n-4)] (3)

Then the signal is squared to make all the data points positive

y(n)=x(n)*x(n) (4)

after this the signal is integrated using sliding window integration.

Y(n)=1/N*[x(n-(N-1))+x(n-(N-2))+…+x(n)] (5)

N=size of window. This step is used to obtain waveform feature information. In the last step the peak of the signal is identified using thresholds. Thus by using this method the positions of the peak R can be identified.

Classification: Based on features extracted (RR, PR intervals and P1,P2,P3 duration) decision rules were formed. In our algorithm we take average of 8 RR, PR interval and P1,P2,P3 width.so intervals considered are averaged ones. If

(P1,P2,P3==0.11&&PR>0.2&&abnorm albeats==0&&PR<0.2) ----------

For Tachycardia

If(P1,P2,P3 == 0.11&&PR<0.2 && RR<0.85 && (abnormalbeats==0))

Using this decision rules we can detect totally **four** Arrhythmias those are Bradycardia, Tachycardia, Ventricular Tachycardia, Asystole (Complete Heart Block).

1) Support Vector Machines (SVM): Support vector learning strategy is a principled and very powerful method that has outperformed most other systems in a wide variety of applications. The learning machine is given a training set of examples (or inputs), belonging to two classes, with associated labels (or output values). If the data are not linearly separable, a set of slack variables is introduced representing the amount by which the linear constraint is violated by each data point. Kernel based SVM is used for classification in this methodology.

D. Implementation Of Svm For P1,P2,P3 Detection

Implementation of SVM for P1,P2,P3 detection in EEG signal is done by using LIBSVM software .LIBSVM is an integrated software package for support vector classification, regression and distribution estimation. The values of $\gamma > 0$ and $\nu < 0$ are more suitable for sigmoid kernel.. The first pattern vector is formed by taking twenty normalized entropy values (ten belonging to P1,P2,P3 and ten belonging to nonP1,P2,P3) from first to tenth sampling instant. In order to differentiate between trains of 1's for P1,P2,P3 complex and that for P or T waves, an average duration of all the trains of 1's is calculated. Those trains whose duration is greater than average pulse duration are picked up as P1,P2,P3 complexes by the algorithm and those whose duration is smaller than the average pulse duration are discarded. Thus, false positive detection of P1,P2,P3 complexes can be reduced.

III. RESULTS AND DISCUSSION

A. Performance: We have used three parameters for evaluating performance of our algorithm. Those are accuracy, sensitivity, positive predictive. These parameters are defined using 4 measures True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN)

1) True Positive: arrhythmia detection coincides with decision of physician

2) True Negative: both classifier and physician suggested absence of arrhythmia

3) False Positive: system labels a healthy case as an arrhythmia one

4) False Negative: system labels an arrhythmia as healthy

B. Accuracy

Accuracy is the ratio of number of correctly classified cases, and is given by

$$\text{Accuracy} = (TP+TN) / N$$

Total number of cases are N

C. Sensitivity

Sensitivity refers to the rate of correctly classified positive. Sensitivity may be referred as a True Positive Rate. Sensitivity should be high for a classifier

$$\text{Sensitivity} = TP / (TP+FN)$$

D. Positive Predictive

Positive predictive is probability that disease is present when test is positive, which is by how much amount disease is correctly predicted.

$$\text{Positive predictive} = TP / (TP+FP)$$

$$S_e = \frac{TP}{TP + FN}$$

$$S_p = \frac{TN}{TN + FP}$$

$$Acc = \frac{TP + TN}{TP + FN + TN + FP}$$

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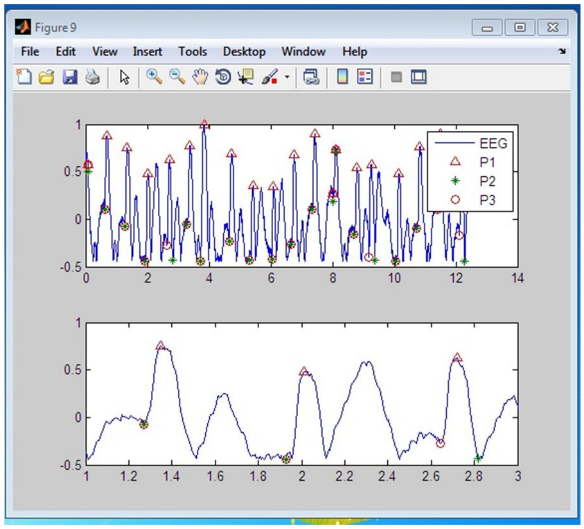
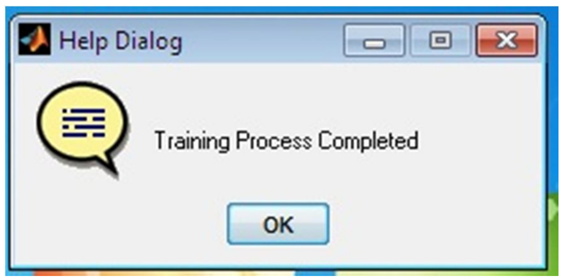
After classifying the signal it is shown as ,



By finishing the classification it indicates,



Then the disorder and the disease is detected.

IV. CONCLUSION AND FUTURE ENHANCEMENT

This paper presented an EEG data classification algorithm which, based on a large number of features extracted after wavelet transform and statistical pattern recognition, makes an objective decision about the type of the EEG data processed and thus the brain state of a patient. The main advantages of the algorithm are: (a) the ability of the algorithm to run robustly in a clinical setting with noised EEG; (b) feature extractions with highly meaningful wavelet transform because hidden EEG information can be revealed and the noise effort reduced as certain data under some scales are omitted; (c) simplicity and low computational cost guaranteeing real clinical application; (d) very good sensitivity and specificity as well as an overall classification accuracy of 99%; and (e) patient-independent algorithm that does not require any specific prior knowledge of each subject. Therefore, the conclusion is that the proposed algorithm can be used to classify EEG signals and detect seizures in a clinical setting.

In future the various methods can be used for denoising and the feature reduction can be done easily. Instead of the quadratic svm classifiers various other classifiers can be used and their performance level can be measured.

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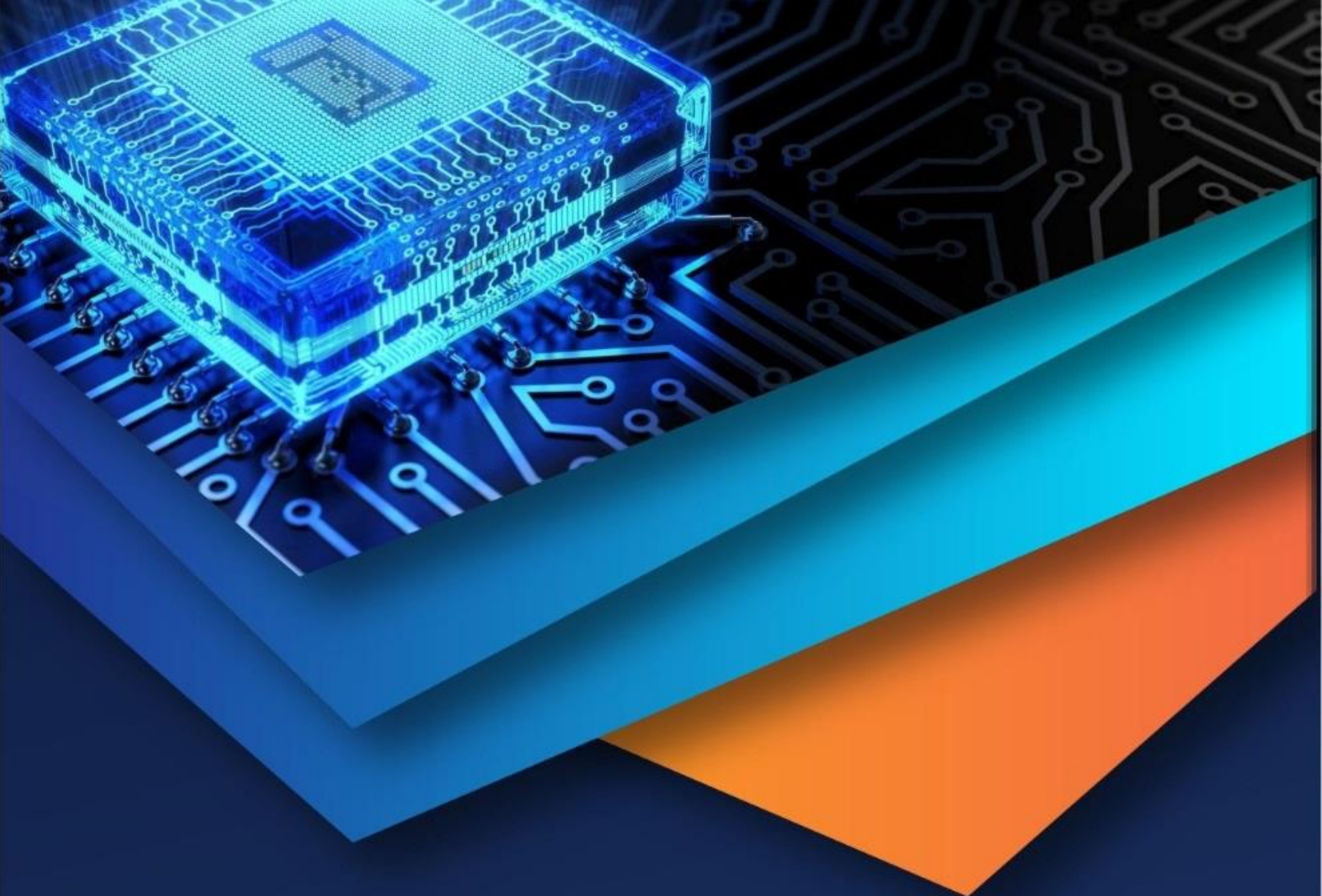

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