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Detection of Sleep Apnea Using Deep Learning Techniques

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Abstract: Sleep Apnea is due to a respiratory condition, which is linked to a sleep issue that often contributes to reduction in airflow and often sometimes fully prevents airflow. In addition, this issue needs the individual to be checked overnight to determine the amount of oxygen in the blood. Several experiments carried out on animals like-mice the research reveals that sleep apnea can also contribute to cancer. In this paper a deep learning algorithm for evaluating different variables including throat muscles, it usually collapses whilst a sleep, triggering both gasping and snoring as body searches for oxygen. This paper provides a description of the apnea deep learning paradigm related to dynamic cancer impermanence. Deep Learning (DL) technology, primarily the modified Fusion Convolution Neural Network (MFCNN), is used as a function detector to learn the features of the high-order association between observable data and associated marks. Preparing and segmenting the data model is a critical move toward training into deep learning. During the last stage of the MFCNN, a completely linked layer is attached to the output layer and builds the required number of outputs for sleep apnea occurrences during investigate the ECG data,
Keywords: Sleep Apnea, Deep Learning, Fusion Convolutional Neural Networks.

I. INTRODUCTION

Sleep apnea is known to be the severe sleep condition that happens when a person's breathing while sleep is disturbed. People with chronic sleep apnea avoid breathing repeatedly, often hundreds of times throughout the night, throughout their sleep. If the respiratory interruption is complete which persists for 10 seconds or longer than the condition is considered apnea. Apnea episodes can occur once or several times an hour during the course of sleep, where the length of the occurrence can be ten seconds or more Carbon dioxide (CO_2) levels rise during sleep apnea, and the level of oxygen (O_2) reduces in the blood. The increase in concentration of O_2 and CO_2 is directly related to an airflow barrier [5]. This atypical form of respiration ends in disturbance. Primary state of the sleep apnea is Obstructive sleep apnea (OSA) at the upper airway due to physical obstruction to the airflow. This type sleep apnea outcome in our weight people the ages of 35 to 65 who have broad tonsils, short neck, and a limited airway opening. Next states are Central Sleep Apnea (CSA) triggered by lack of breathing energy. When this disorder occurs, the chest and diaphragm muscles regulating the respiration do not obtain instructions from the brain for a fleeting moment. About 0.4 per cent of all patients with sleep apnea suffer from CSA This state is mixed sleep apnea owing to a transition from lengthy OSA stretches to short CSA cycles. Fifteen per cent of all sleep apnea cases are reported to suffer from complex sleep apnea Sleep apnea is not usually treated by polysomnography (PSG).

It is reasonable to assume, on the other hand, that the cancer contributes to sleep apnea," said Ludgers Grote, assistant professor and senior doctor of sleep medicine and the latter author of the current report. "The fact that both diseases have similar risk factors, such as overweight, is rational. A number of about 20,000 adult patients suffering from obstructive sleep apnea (OSA. About 2% have a history of cancer Older age was associated with a decreased risk of cancer, but the changes to body mass index (BMI), smoking and alcohol consumption revealed a potential correlation between occasional night hypoxia and a decreased prevalence of cancer Mainly women were connected and men were weaker. "Their results show a two- to three-fold risk of cancer in people with severe sleep apnea We cannot know for certain which factors are based on a sleep apnea-cancer relationship, but this suggestion indicates that it must be investigated in greater detail," said Grote Sahlgrenska Academy, University of Gothenburg, is the Assistant Professor of Respiratory Medicine Ludger Grote, specialized in sleep medicine. Sleep Medicine. "Apnea sleep is commonly known and related to snoring, daytime exhaustion and high risk of cardiovascular disorders, mostly in men. Our work paves the way for a new perspective: sleep apnea can theoretically be related to an increased risk of cancer especially in women",' says Grote. Earlier findings indicate that people with sleep apnea are more often diagnosed with cancer in their medical histories than others. There is a growing amount of work in this area, but gender implications have not been discussed. Become a major factor, especially in the relation with one type: malignant melanoma. Recently, the need for a simplified form of diagnosis has emerged for speedier and improved care.

More convenient and quicker are automatic approaches utilizing machine- learning algorithms (random forests, DBN networks, CNN- DBN) to diagnose this form of sleep disturbance that contributes to better prognosis [4]. This research allows a comparative analysis of all the common forms of classification introduced in the literature by utilizing the same characteristics and the same dataset and proposed sleep apnea detection techniques & challenges associated with complex impermanence from cancer. In addition, we were testing certain forms of classifiers that were not associated for statistical functionality. One serious psychiatric disorder is core sleep apnea. The following risks include:

1) Fatigue: The frequent sleep apnea-related awakenings make regular, restorative sleep unlikely. People with central sleep apnea often suffer extreme exhaustion.
2) Cardiovascular Problems: We are finding a lot of space to develop still. The sleep score manual was originally created for the rating of safe sleep, and is still used for sleeping under the control of medicine or medications in various kinds of patients and men. Substances may also affect the wake EEG. Therefore, we propose expanding the training data with evidence from multiple labs, diverse pathologies, age ranges, etc. We can also try utilizing data raise to improve deep learning robustness.

The remainder of our paper is structured according to this. The associated research in the literature is outlined in Section II. Section III provides an description of both the concept of the Sleep Apnea Detection CNN. In section IV Pre-processing and Features Classification using fusion FCNN we describe the tests we have performed and the findings we have obtained. Section VI concludes and future work.

II. RELATED WORK

In this segment, we would go over many study works that have been undertaken by various author to produce a high quality of performance. Because sleep apnea has adverse effect on cardiac operations In this area one has to strive to reduce their impact. In this paper author first noticed and documented the ECG shifts, along with the respiratory variations. Sleep apnea is a serious condition that is typically treated by expensive laboratory experiments [16]. A typical cyclic variability of heart rate or other shifts in the electrocardiogram (ECG) waveform is followed by a sleep apnea. When sleep apnea should be identified using just the ECG, the accurate and cheap evaluation of sleep apnea could be rendered from ECG records obtained at the patient's house. In accessible, and tests from a comparison collection of 35 separate recordings were made available in independent evaluation They contrasted 13 algorithms. The best algorithms used frequency- domain features to predict heart rate shifts and respiration impact on the ECG waveform. the author presented a bivariate autoregressive model for the measurement of HRV and R peak region beat-by- beat strength spectral density. The supervised learning classifier K- Nearest Neighbor (KNN) was utilized to categorize occurrences into regular and apnea ones OSA is a specific sleep disorder in the upper airways arising from repeated occlusions. The data is divided into two collections, each of 25 records, for training and research. The findings of the assessment demonstrated a consistency of both preparation and research greater than 85 per cent. In this paper [8] author focused on dynamic features derived from time frequency distribution, before introducing KNN Classifier to distinguish regular and pathological signals, they implemented a technique to quantify the importance of each dynamic function There were two pieces of the report. The first was to test the capacity of an ECG recorded over night to differentiate between people with and without apnea. The second was to determine how the ECG was able to identify Apnea per minute of the video [12]. A specialist, using external clinical cues, analyzed each of the apnea records. Research groups were invited to access data through the worldwide network and to apply tests of algorithms to a conference-linked international challenge. The method's accuracy hit 92.67 percent. In this paper [9] the author suggested an automatic classification algorithm focused on a supporting vector machine (SVM) utilizing statistical features derived from ECG signals for both regular and apnea patients' dependents on the amplitude of the heart rate (HRV). peak R region, provides alternate interventions for prediagnosis of sleep apnea. 50 Recordings from the Apnea for the research, the Physio net archive was used, this software is one of the 70 archives used by the Cardiology Software Challenge conducted for 2000. Yue, L.et al (2020) [12] Discuss the full scope of heterogeneous health data, characteristic and structure. their derivatives and different hybrid models, are subsequently studied and tested in a number of standard situations.

III. MODIFIED FUSION CONVOLUTION NEURAL NETWORK (MFCNN)

CNN is widely used and is considered to be focused on the study of the optical nerve, which shows considerable significance for the CNN model in finding a theory of receptive field. As a core component of DBN s, the principal organizational framework of the CNN model has various hierarchic levels. The visual brain cortex, with simplistic signals being received from visual stimuli in a particular area of the sub-regions and complex subsequent to them from the simple group to satisfy the needs of a more complicated process.

CNN imiterates the integrated movement of the brain and works for such main concepts including the multisectoral deck, geographic coordination, weight sharing and pooling as a influential deep paradigm. This deep modified Fusion Convolution Neural Network (MFCNN) model consists of several stacks shown in the figure.1 a convolutions layer and a polling layer is included in the stage basic feature. in this context, feature layers may shape regional connectivity, which reduces hyper-parameters substantially by applying the principle of weight sharing. To order to accomplish identical, however, complex features the pooling layer fuses the neighboring nodes and thus decreases the quantity of training results. Following the construction of several stacked stages, at the end of the process data are added a number of completely connected layers and graders which make nonlinear abstract representations possible. The entire CNN model is ultimately trained through supervised learning. Owing to the excellent reputation for the quality of profound bioinformatics data analyzes, CNN has made a major contribution in key and related fields of science. The straightforward applications of CNN can be accomplished, as it has the ability to retrieve the learning for the purpose of extracting the repetitive pattern, but in a two-dimensional image grid (for example mammography). The automated representation of an input data set tensor structure for all tasks is the most important benefit to CNN and. However, when measuring intermediate values of the hidden layers and creating a completely linked classifier the final stage requires plenty of memories and energy.
DBN is made up of many restricted Boltzmann (RBM) devices, since each RBM consists of a visual layer and a hidden layer, a two-way connection path between two layers, where the visible layer operates concurrently with multiplexing input and output seen. The first one DBN is trained by forming RBM layers level by level, having the characteristics. The RBM model applies to a contrasting separation algorithm, which trains undeveloped samples without high college costs. Thanks to a bidirectional feature, the end model is able to retrieve the visual layer dates from the secret layer dates, which makes it the abstract representation of the visual layer. The phase of DBN development is like SAE: Prepare with one RBM, then freeze weights and set the hidden layer as the visible layer of the next RBM, using the same preparation system to obtain the second RBM. A deep Boltzmann (DBM) computer is continuously piled into many RBMs in sequence. At the top of the DBM, a layer called the associative memory transforms the DBM. Like SAE, the output is an abstraction of multi-level input data after the layer-unchecked analysis of patterns. When classifiers are applied to highly abstract elements, good results are generally obtained. Recently, the positive test results for fusion approach for adding convolution layer prior to DBN to create a new convolution DBN. As DBN preparation consists fundamentally of simple RBM simulation of the contrast algorithm, it shows the ability to easily extract an optimal parameter set from a variety of search areas. DBN also demonstrates the potential to fix low convergence speed and local optimal concerns and quantify variables outcomes in a relatively inferior manner for each sheet. Nevertheless, the disadvantages of DBN reside in the weakness of such a method, since it is a very greedy algorithm operating once a time in any layer and there is no reactions for parameter optimization in other layers.

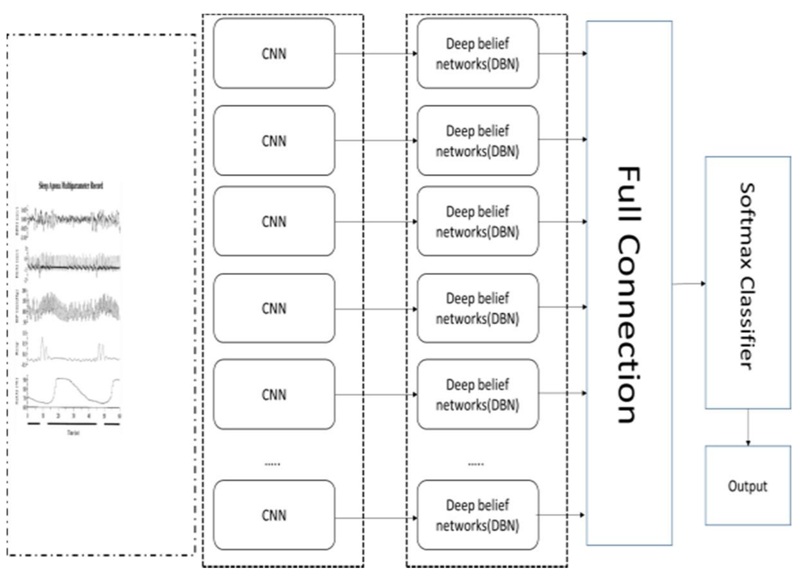

Figure 1: Fusion CNN (CNN+ DBN) for ECG signal classification SLEEP APNEA DETECTION

These network types are used in a broader model, with one or more MLP layers, as layers. These are functionally a neural architecture of a fusion kind. Perhaps the most interesting task is to combine the various network types in hybrid models. Consider a model using a CNN-pack input, DBN in the middle and MLP in output. For example, see the model for layers. Such a model can read and generate a prediction in a sequence of ECG signal.

In order to enable new capacities such as modular, which can be integrated to a modern DBN platform and used for captioning ECG signals, Network models can also be stacked in different architectures. The DBN networks of the encoder decoder can be used to provide sequences of different lengths of input and output. Deep belief networks(DBN) have many layers to deal with an ECG signals classification problem, each with the use of a cowardly layer approach. For example, to applying a Deep Network with 4 layers if my ECG signals. To show the one is input layer, two hidden layer (HL1, HL2) And last layer is output layer. The weight (W1) is between input layer and HL2, use the Auto Encoder and learning W1 from scale (this is unregulated learning) with my input layer of neurons, HL1=1000 neurons (say)=100, HL1=100 neurons and output layer=10 neurons. feed all the ECG signals through the initial hidden layers to get a set of capabilities and then use another auto encoder to get the next set and finally to classify them using a softmax layer (100 – 10). (The only thing that is tracked is learning is to know the weights of the last layer (HL2 – performance softmax layer). to create a network using just 7 x 7 patches if the same issue was resolved by FCNN than for ECG signals input. I'd have layers

To select the learning weights and taken the patches of 7 cross of 7 and select the ECG signals 50 cross of 50 feed forward approach convolutional layer after we find out the 25 feature maps the is 44 cross of 44 Then we use the 11x11 window for pooling the hand so that 25 characteristic maps of size (4 x 4) are provided as a pooling layer output. For grouping, we use these feature graphs. We don't use layer specific techniques when studying weights, as in the case of deep faith networks. But use guided studying and at the same time know the weights of both layers. Is this right, or can we know the weights otherwise? If to use DBNs to identify ECG signals, we need to resize all of ECG signals to a specific scale and have so many neurons in the input stage, while if to use CNN, only practice on a small input patch) and overlay the weights.

To determine the efficacy of approaches for evaluating sleep habits, each study team gathers its own test results utilizing time and/or financial tools. Such databases, primarily utilized as part of their own study, frequently miss some important details on acquisition and topic medical disorders (neural, cardiorespiratory, results of medication). Many of these datasets [1] still lack statistical relevance, and some of the PSG sources were only registered. Thus, an objective and comparable comparison of the efficiency of such approaches with modern techniques cannot be adequately conducted Recognizing the necessity and utility of publicly accessible sleep databases, which can be used as a standard guide for researchers, several sleep-related data sets are developed by sleep study organizations. Such databases include numerous signals from certain safe subjects and patients as seen were included in a few plays., they do not provide appropriate subjects for the purposes of generalization. is an anomaly in the PhysioBank archive, comprising 108 records, but it does consist of unique details that are important for CAP-related research? The data collection of the sleep heart health test (SHHS), which has a reasonable amount of records, is not a truly available dataset. This is only accessible upon request and consent. At the other side, owing to the availability of only the signals from two EEG channels. SHHS has drawbacks for sleep studies in general use. This is also a valuable special use resource in clinical trials concerning associations between sleep-disordered respiration and heart failure. O'Reilly et al. recently suggested Montreal Sleep Research Database (MASS), which is an open-access sleep dataset, obtained from safe participants. While the dataset is stated to include data from 200 individuals, it is a compilation of five separate data subgroups. Such subgroups were collected from eight separate testing experiments undertaken in three separate hospital-based sleep labs. Additionally, there are certain limitations on access to various kinds of data set knowledge. The subgroups of this dataset, have major variations in number of sources, to applying the filter methods on the signal processing applications, metadata, ranking criteria and epoch duration.

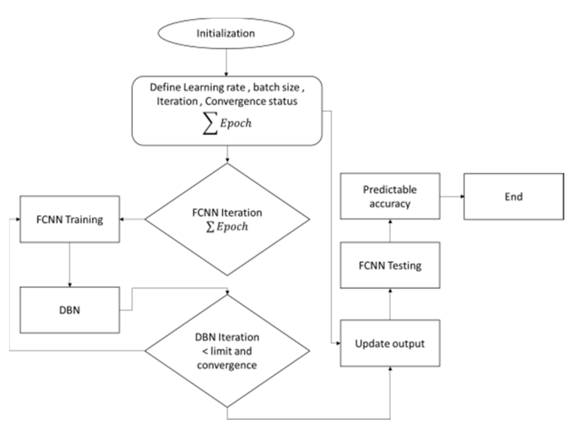

Figure 2: Flow chart of proposed approach

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IV. PRE-PROCESSING AND FEATURES CLASSIFICATION USING FUSION FCNN

Polysomnographic signals is a complicated, but indicate positive patterns that are critical used for the assessment of an expert. Waves on various frequency sites are very important for differentiating between different sleep levels: 12-14 Hz is representing as sleep spindles ,0.5-4 Hz represent as sluggish waves, 8-12 Hz is representing as alpha waves, 4-8 Hz is representing as theta oscillations. These all represent as the frequency domain. In specific when using spectrogram as functions, we have used classical specimental tests (Welch, 1967), but also a multitapering methods. Additional important sleep process measures such as fast and slow movements of the pupils, eye twitch and muscle toning can also be assessed. All observation depends on the feature and are considered characteristic engineering in their description process. The use of well-developed systems provides many advantages: it takes little training knowledge, it is simple and the tests can be interpreted. Instead of using the raw signal, we use EEG spectrogram in the first step. The key properties of the EEG sleep are well established and so we have been able to greatly the scale of our tests. The Welch method used in python for periods to measure the power density spectre. We did not preclude times and thus required a computer able to use the data with a minimum of manual pre- processing requires. Artifact epochs often provide useful information: wakefulness often matches signals of movement, and a switch to stage often accompanies a step forward. Quantitative analysis, including average power density spectrum estimation, however, involves the removal of artifacts that can be done by means. We used five segregated machine leaning methods for features extraction using classification :(RFC, KNN, SVM, DBNs networks and MFCNN). Convolution neural network with the use of VGG Face and Deep Perception Networks using Shifted Filter Responses.

Stages considered according to R&K rules: -

1) NREM1 represent the starting time of the sleeping condition at that time eye only closed.
2) NREM2 in this stage, heart rate and temperature of the body is slow down, sleeping state as the light.
3) NREM3, person going to deep sleep condition then start to body repairs and regrows tissues.
4) NREM4 (N4 or SWS)
5) REM people going to dream period considered by quicker brain action, breathing, and heart rate.

For this study, we altered the staging criteria, merging the criteria for N1 and N2 into N1 and merging N3 and N4 into a single stage (N2). The WA and REM stages are unchanged.

Highlights: - We present a novel, classic FCNN for automatic sleep stage scoring using a single channel of EEG, and then we evaluate it. The single EEG channel within the PSG signals and their spectral components for the estimation of sleep features is solely used. Four normalized power frequency spectrums are extracted from the 500 temporal data (5 seconds long acquired EEG signal), constituting both training and testing epochs.

Data set (ECG segment, ECG signals sampled, ECG data): - to perform the prepressing find out the training and testing dataset.

Table 2: Sleep Apnea data

Category	Description	Data source
ECG segment	34 324 ECG minutes were segmented	Leuven dataset.[2]
ECG signals sampled	ECG data set have a 70 single-lead ECG , and range define 7h and 10h	Physionet [15]
ECG data	16000 people ECG data sampled at 6000 sample points each and 1 or 0 representing whether person have sleep Apnea or not	ECG data

System description: - The system was divided into a training module and a deployment module:
1) FCNN Training Module: - Its used in model training module to find an accurate prediction of FCNN that can take the EEG signal as input and intelligently generate a sequence of the sleep stages.
2) Independent Inference Modules: Whenever the same pattern goes through a feature extraction process, it is mapped to a binary discretized integer or index known as a memory address (used to apply a memory module, where classification labels are stored representing the sleep stages).

In this review, we present a novel methodology for automatically inferring a qualified FCNN to detect the sleep classes WAKE, NREM1–2, NREM3–4 and REM within a single EEG log. The four sets of a FCNN model are learned and implied using a ROM framework.

Training Pattern Matrix Construction: - Sleep stage classification was focused on time segments 5s long, and the goal stages were defined by the neurologist. For this current analysis the frequency quality of PSGEEG channels recommended by the previous literature was adopted and used for classification.

Table 3: Frequency spectrum range

S.no.	Names	Frequencies Range
1.	alpha	8–12Hz
2.	delta	0.5–4Hz
3.	sigma	12–20Hz
4.	theta	4–8Hz

The main goal of this section of the data preparation process is to transform the four-spectrum bands to a 20-bit integer index used to infer class content from a memory module.

FCNN Design and Training Parameters: - The activation functions used in the input and the two secret layers are the TANH feature, while the SOFTMAX function is the one used in the output layer. For the optimization method, Adam optimizer is used.

V. RESULT

Finally, five different types of algorithms were used to get the best accuracy: -
1) RFC
2) Support Vector Machine(SVM)
3) K-Nearest Neighbors (KNN)
4) Deep belief networks(DBN)
5) MFCNN

Here best accuracy was achieved for Random Forest Classifier 65%, SVM which was 89.8%, whereas for KNN 89.2% accuracy was achieved, can also be done with the use of DBN networks 85.7, and MFCNN also 91.7. FCNN introduce additional hidden layers, Convolutional Layers (CL), in neural networks.

Table 4: Comparative study different Classification algorithm **(**RFC , **KNN,** SVM, Deep belief networks(DBN), and MFCNN**)**

Model	Predicting Time(ms)	Accuracy(ms)
RFC	11.724777698516846	65.8037326911499
KNN	11.632869467423423	84.9128237833577
SVM	7.8536545764229350	84.7128433823466
DBNs	8.6358664853246540	85.7148237835376
MFCNN	8.6336665874257370	91.7146239822378

VI. CONCLUSION AND FUTURE WORK

This work to investigate sleep apnea detection techniques & challenges associated with complex impermanence it can be assumed that it is possible to study sleep without invasive or with a minimal number of sensors based on extraction of functions, solutions and the methodology of deep learning. To create a limited size system prototype to track sleep. To add additional sensors for more precise data collection and potentially sleep apnea- related research. The proposed analysis would be done utilizing Convolutional neural network using VGG Face and Deep Belief Networks using Shifted Filter Responses by identify features in which a neuron's weighted contribution in a convolution layer is determined from the inputs and filter weight. This experiment was used to offer a method for inferring a completely qualified the classification of the sleep stage network from a single resource of ECG data set to utilize for experiment purpose a MFCNN experiment rather than the learned network. Attributes were derived from the number of sample epoch range while implementing the FFT procedure, our results based on the alpha, beta, theta, and sigma of power density. The benefit of this model, is the independent intake away from the qualified DBN network for the inference process. We think that the introduction of sophisticated deep learning algorithms will allow positive progress on technological development, while also adding to current applications by the data fusion approach and by the quality evaluation of bioinformatics results. A genius move for a deeper convergence and improved efficiency is to enter conventional deep architectures. Moreover, the expansion of conventional deep approaches, semi-controlled schooling, enhancement research, transition analysis, etc.

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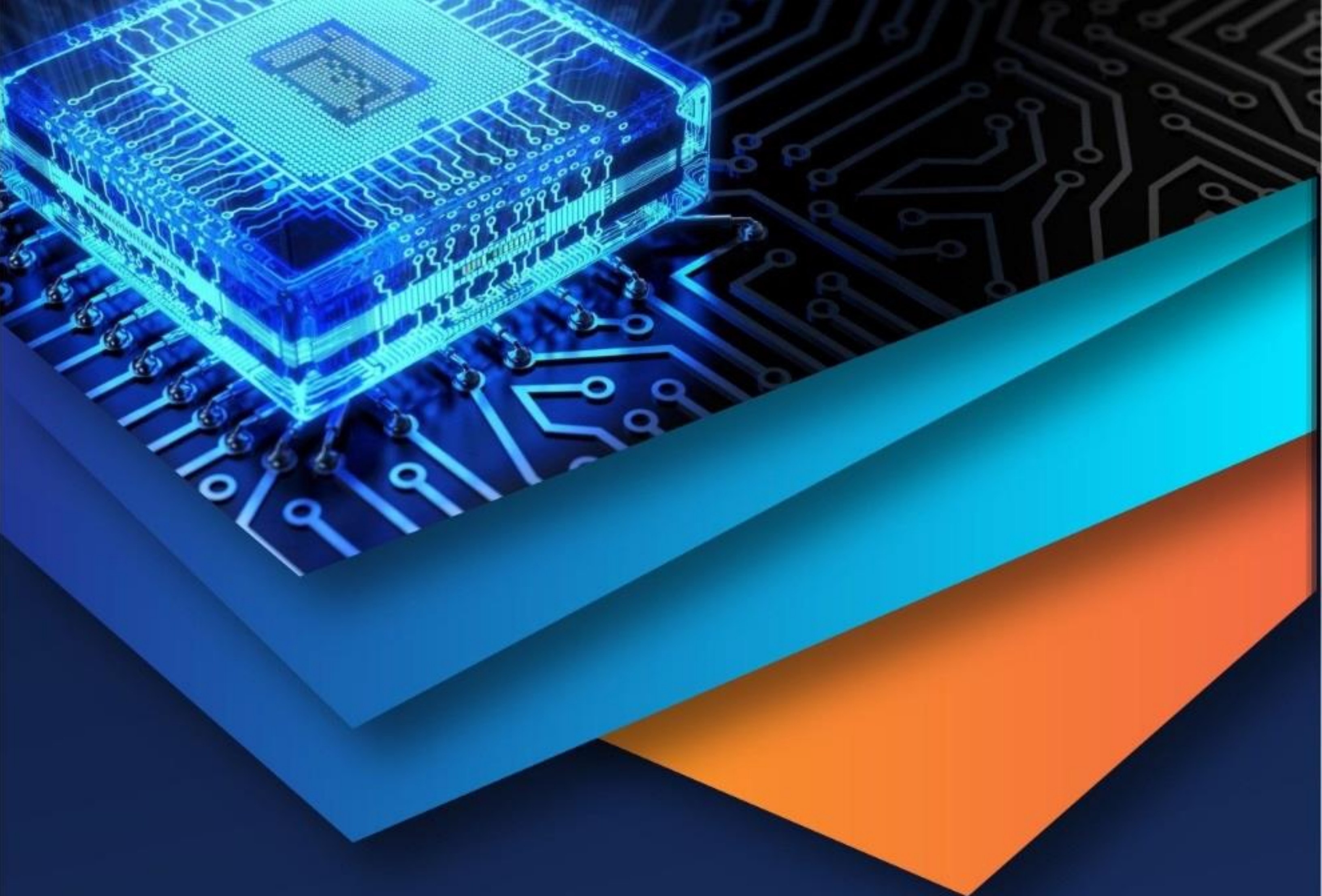

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