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Efficient Framework for Extracting Desired EEG Signals using Robust Filtering Mechanism

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Abstract: A robust architecture based on quantum mechanics is proposed for processing neural information with the help of Schrodinger Wave Equation (SWE). Non-stationary stochastic signal is represented as a time varying wave packets that is characterized by Recurrent quantum neural network (RQNN).Statistical behavior of the input signal is effectively captured and signal embedded noise is estimated by RQNN algorithm. In order to increase the signal separability, Motor Imagery (MI) based Brain Computer Interface (BCI) is used to filter the Electroencephalogram (EEG) signals before feature extraction and classification. Brain Computer Interface performance is improved by RQNN EEG filtering.
Keywords: recurrent quantum neural network, electroencephalogram, brain computer interface

I. INTRODUCTION

In general a Brain Computer Interface (BCI) is a technology that allows a person with external devices using the Electroencephalogram (EEG).The BCI is designed to recognize pattern in data extracted from the brain and associate the patterns with commands. Those patterns are referred accordingly on the systems that relay on BCI techniques for input . Motor Imagery(MI) based BCI are obtained from control signals coming from human brain. The Motor Imagery classifies the specific EEG pattern that is subjected to imagined task,(moment of hand, legs). The EEG signals are the graphical representation of electrical activity of the brain. The raw EEG signals which come from human brain tends to have low signal to noise ratio(SNR)and these EEG signals consists of many unwanted components with in the EEG signal which increase the signal quality resulting better feature reparability. Preprocessing is carried out to remove unwanted signals from raw EEG. Schrodinger Wave Equation (SWE) is used to measure the distance between two peak signals which comes from EEG.

The RQNN filtering procedure is applied in a two-class Motor Imagery(MI)-based Brain Computer Interface(BCI) where the objective is to filter electroencephalogram(EEG) signals before feature extraction and classification to increase signal separbility.RQNN EEG filtering significantly improves BCI performance compared to raw EEG or Savitzky-Golay filtered EEG across multiple sessions.

II. LITERATURE SURVEY

Recently robust spatial filtering algorithms based on Kullback-Leibler Common Spatial Pattern(KLCSP) integrated with feature extraction and Bayesian learning were adopted to obtain very low SNR **.**The performance of the proposed KLCSP algorithm is against two existing algorithms**,** CSP and stationary CSP**.** The Common Spatial Pattern(CSP) algorithm is an effective and popular method for classifying motor imagery electroencephalogram(EEG) data.When compared to CSP and stationary CSP, KLCSP improves the performance in motor imagery BCIs signal separability is enhanced by self-organizing fuzzy neural network for obtaining further more enhanced performance related to BCI system Savitzky-Golay(SG) and Kaman filter are Used.
RQNN model parameters usinga two-step inner-outer fivefold cross-validation and a Particle Swarm Optimization (PSO) techniques are used for the selection of RQNN model parameters.
Savitzky-Golay (SG) and Kaman filter are some of the existing filtering techniques to produce a stable filter EEG which results in a statistically significant enhancement in performance of BCI system .Using the concept of time varying pdf proposed by Buy which was again improved by Behead which uses the maximum likelihood estimation (MLE) instead of inverse filter in the feedback loop. Further particular application analytical analysis of nonlinear Schrodinger Wav Equation (SWE) and use the close form solution.For purpose of smooth data to increase the signal-to-noise ratio without distortion the signal. Try to smooth a series of data in order to obtain a continuous function that could represent a given data it came out of Savitzky-Golay method could be a good way. Parametric avalanche stochastic filters were used for increasing the performance with the help of time varying probability density function which was in term improved using maximum likelihood equation estimation (MLE) instead of inverse filter in feedback loop. Maximum Likely hood Equation the estimating of the parameters of a statistical models of the given

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observations ,by finding parameters values are find out by Maximum Likelihood Estimation.MLE can be seen as a special case of the maximum a posterior estimation (MAP) that assumes a uniform prior distribution of the parameters, or as a variant of the MAP that includes the prior and which therefore is a unregulaized .The method of Maximum Likely hood corresponds to many well-known estimation methods in statistics.

III. PROPOSED METHODS

The conceptual frame work of RQNN model is shown below

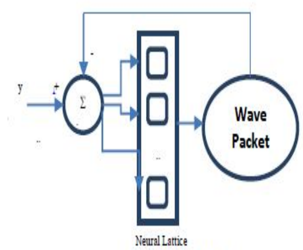

Fig.3.1 RQNN Model

Signal quality and separability of synchronous MI-based BCI can be improved by preprocessing of EEG signal in filtering mechanism. In presence of potential field dynamics of wave packets are described by partial differential equation which is in turn time dependent single dimension non-linear SWE .Neural lattice collective response is represented by quantum object which is robust concept determined by RQNN model .By using Habana learning rule EEG signal filtering errors that simulates neurons and weights of the network were updated.

Below figure3.2 shows the signal estimation using RQNN model.RQNN filter is used for stochastic filtering, due its stability of being sensitive to model parameters, due to imperfect tuning the system gets failed to track the signal and its output gets saturated and this filter is also able to reduce noise. In this figure the spatial neurons are excited by input signal Y(t). The weight factor w(x) is used in order to weight the difference between the output of spatial neuronal network and the pdf feedback to get the potential energy V(x). In the Gaussian mixture model estimator of potential energy ,the weights are varied and also these weights are trained using learning rule . Here the parameters are selected using two step inner outer fivefold cross validation and also particle swarm optimization techniques are used to filter the EEG data sets.

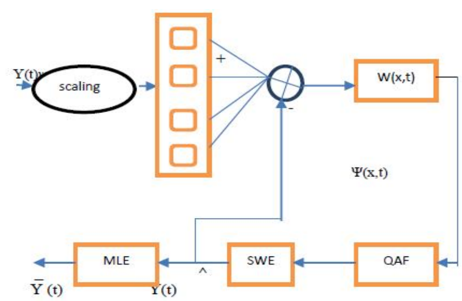

Fig.3.2 RQNN model using signal estimation

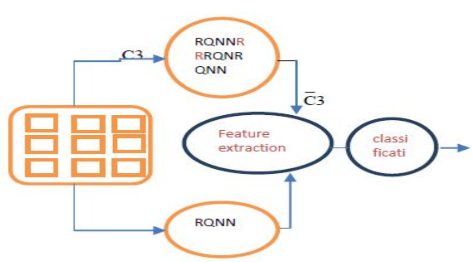

Fig.3.3 RQNN model framework for EEG signal enhancement

There are also different optimization techniques used for EEG filtering which can be time consuming which leads to under filtering

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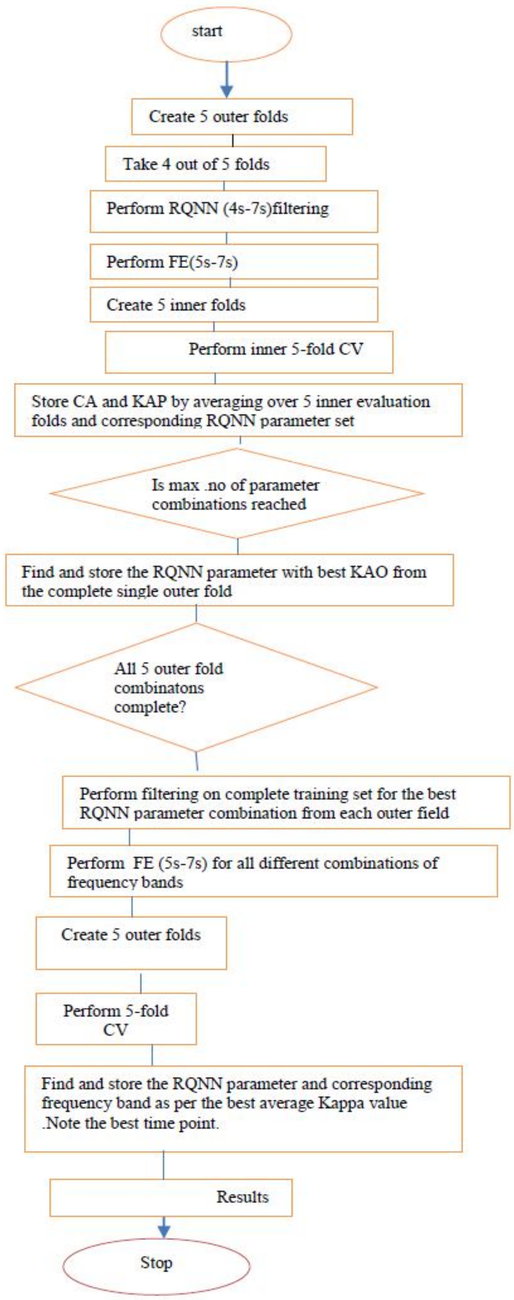
or over filtering without making the system unstable. Fig3.3 shows the position of RQNN model within BCI system. The results of filtering process are obtained by feeding one sample of raw eeg signal at a time and get enhanced signal. The range to scale an EEG signal is 0-2 and again this signal fed to RQNN model. In offline classifier training process only particular channel of EEG signal is available, and the EEG signal is scaled at maximum amplitude. During online training process the EEG signal scaled in the range of 0-2 with maximum amplitude. The input signal is fed to the two RQNN models through channels c3 and c4,again the signal gets filtered using feature extraction and classification ,at the end we obtain the noise free signal. In feature extraction and classification, the obtain signal is fed as an input to train the offline classifier in which LDA classifier is used. The weight factors are stored to identify the EEG data during online process. In offline stages the classifier parameters are tuned off and parameters kept fixed in online stages. Various feature extraction methods are used in order to filter the signal and extract its features.



Flow chart for extracting desired EEG signal

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IV. SIMULATION RESULTS

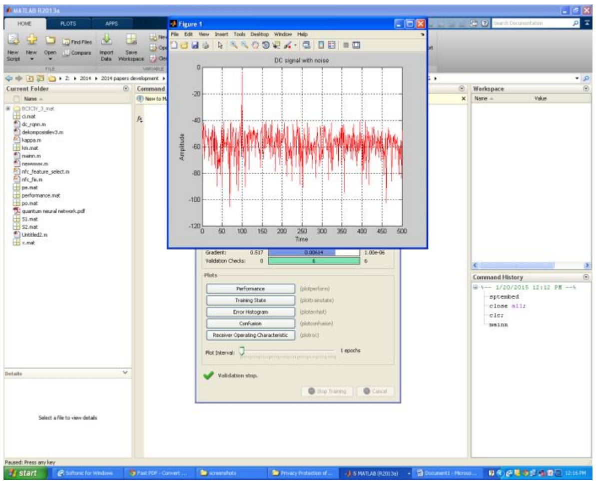

Fig 4.1: dc signal with noise

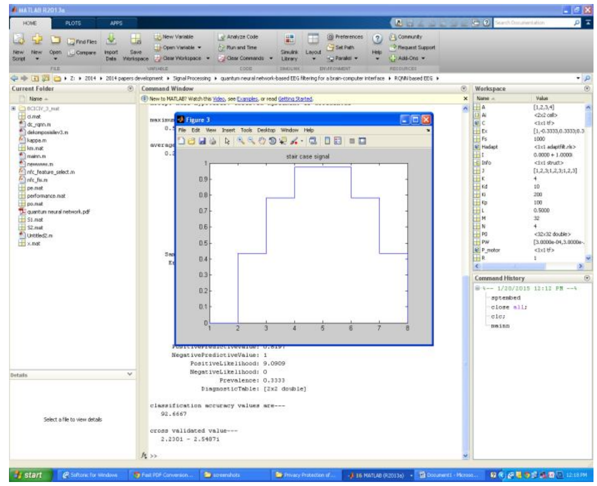

Fig 4.2: staircase signal

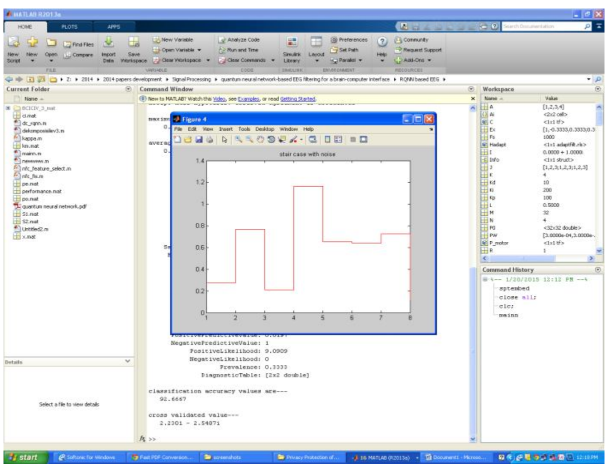

Fig 4.3: staircase with noise

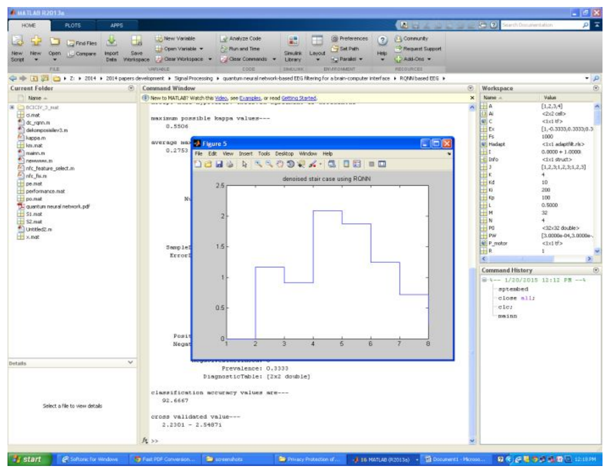

Fig 4.4: denoised staircase signal using RQNN

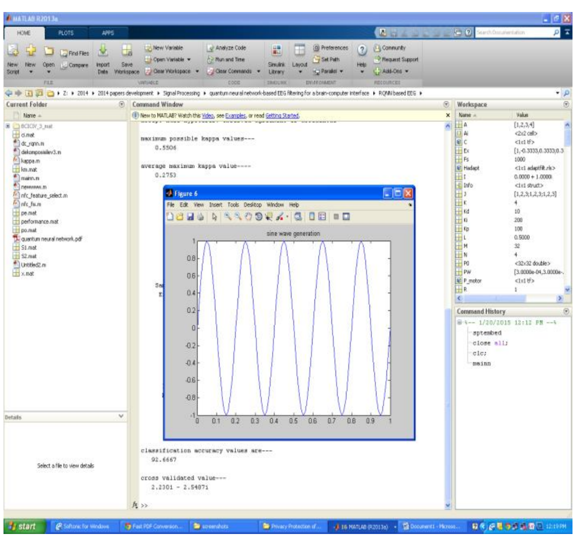

Fig 4.5: sine wave generation

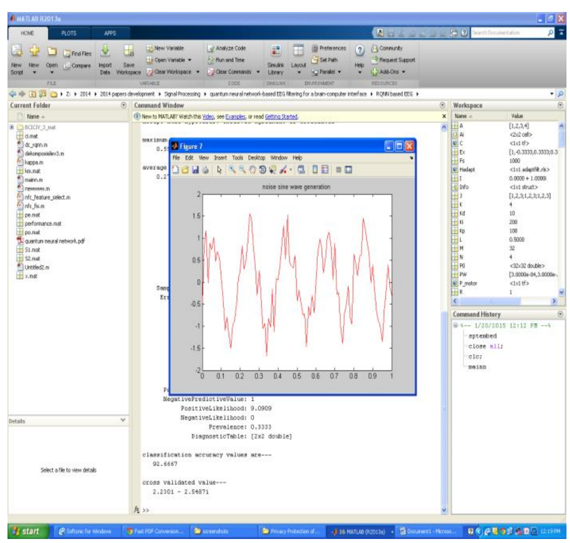

Fig 4.6: noise sine wave generation

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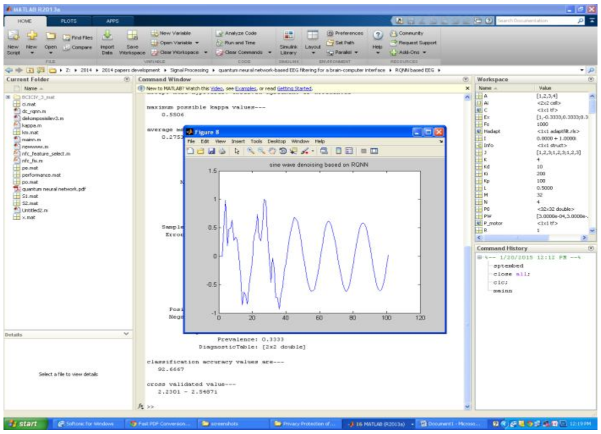

Fig 4.7: sine wave denoising based on RQNN

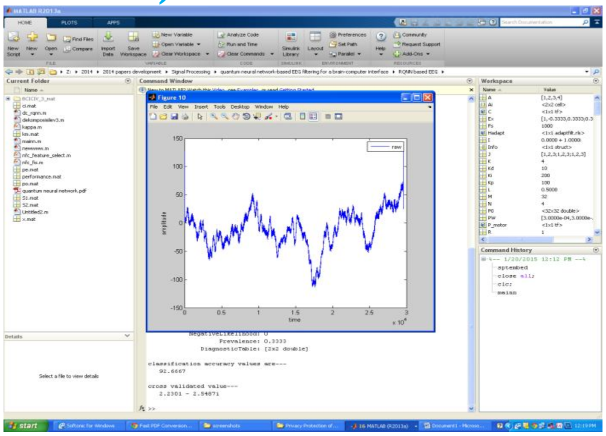

Fig4.8: A raw EEG signal

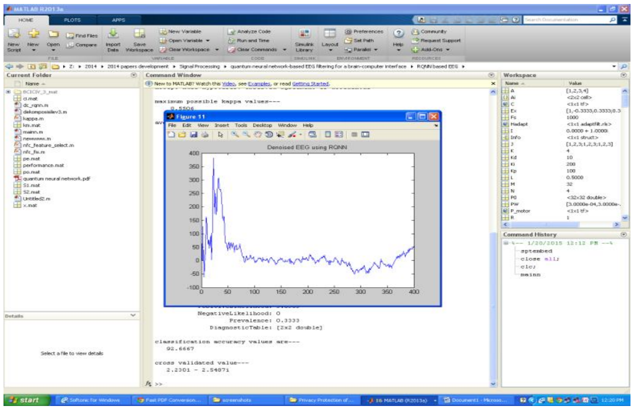

Fig 4.9 Denoised EEG using RQN

V. CONCLUSION

The RQNN was evaluated with case studies of simple signals and the results of RQNN are significantly better than Kalman filter. While filtering of dc signal consists of three different noise levels the architecture of RQNN associated with learning algorithm which is the complex nature of EEG signal. The statistical behaviour of input signal is converted to Wave Packet by using the response of quantum dynamics of the network. EEG signal is encoded as Wave Packet which is of the form of pdf of the signal.

The two step inner outer five fold cross validation technique is used to enhance the EEG signal that signal is used further for feature extraction and classification process. The CA and KAPPA values obtained from RQNN enhanced EEG signal shows the significant improvement during both the training process.

The performance of RQNN model is better when compared to the raw EEG model with the PSD or the BSP based features.Future work involves developing automated computational techniques such as GA or PSO for selecting RQNN model parameters which improves signal processing frame work which will also increase online performance of BCA for applications in stroke rehabilitation.

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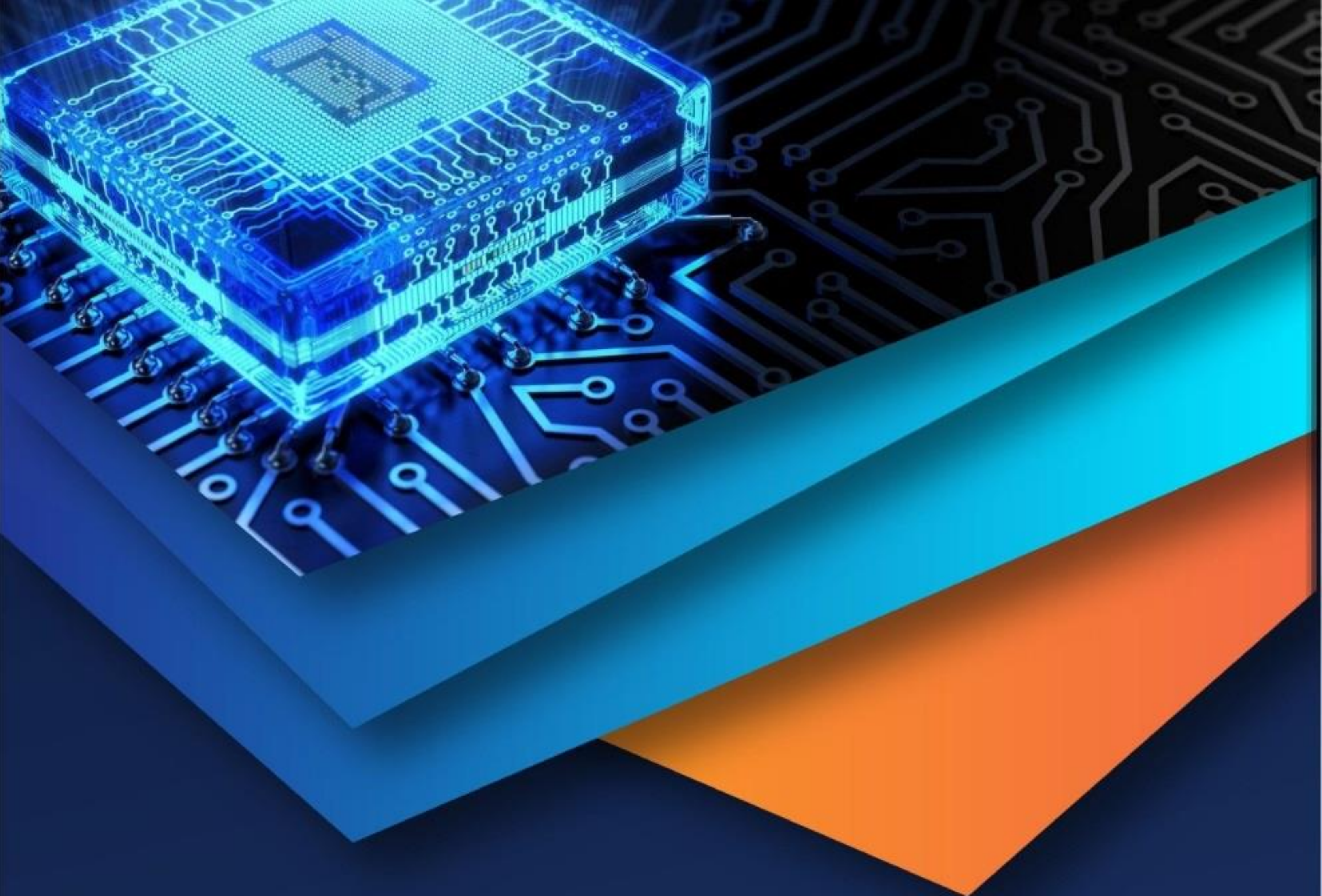

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