Volume: 3 Issue: IV Month of publication: April 2015

DOI:

Volume 3 Issue IV, April 2015
ISSN: 2321-9653

International Journal for Research in Applied Science & Engineering Technology (IJRASET)

Worm Attack Classification Using Ensemble Classifier and DAG

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Abstract—the growth of internet technology spread a large amount of data communication. The communication of data compromised network threats and security issues. The network threats and security issues raised a problem of data integrity and loss of data. For the purpose of data integrity and loss of data before 20 year Anderson developed a model of Malware Classification technique. Initially Malware Classification technique work on process of satirical frequency of audit technique logs. Latter on this technique improved by various researchers and apply some other approach such as data mining technique, neural network and expert technique. Now in current research trend of Malware Classification technique used soft computing approach such as fuzzy logic, genetic algorithm and machine learning. For malware classification feature selection is important. The selection of feature in attack attributes and normal traffic attribute is challenging task. The selection of known and unknown attack is also faced a problem of classification. DAG is graph based technique used for the process of feature selection in classification. The acyclic nature of DAG select attribute on selection of entropy. The attribute entropy is high the feature value of DAG network is selected and the attribute value is low the DAG feature selector reduces the value of feature selection. After selection of feature the Gaussian kernel of support vector machine is integrated for classification.

Keywords— network threats, malware classification, feature selection, DAG, support vector machine

I. INTRODUCTION

The detection of worms is very critical process due to abnormal traffic of data and unknown number of pattern of data. Automatic detection is particularly challenging because it is difficult to predict what form the next worm will take so, an automatic detection and response is rapidly becoming an imperative because a newly released worm can infect millions of hosts in a matter of seconds. Several different types of machine learning techniques were used in the field of intrusion detection in general and worm detection in particular. Malicious ways like in the form of viruses, self-propagating worms, and denial of service attacks is a brutal threat to the internet and to the infrastructures using it for communication. The catastrophe of analysing illegitimate access of computer systems on the network which is to make out individuals who are using a computer system without permission (crackers) and those who have legal access to the system but are prevail over their privileges (insider threat) is known as intrusion detection. There is traditional detection approach known as "misuse detection" using worm’s signatures to detect the worms, but this method failed to reach the state zero-day attacks. The important step in malware analysis is a collection of specific attributes by which a malware can be characterized. Mobile malware reverse engineering provides comprehensive view on malware functionality instead of only deep analysis. However, this process is mainly manual and based purely on knowledge of the analyst in contrast to Anti-Virus (AV) software. Anti-Virus (AV) software uses signatures databases, which are hardly interpretable by average person or by court of law. Furthermore, signatures contain single measurements (or features) of parameters in time, which are discrete and targeted only on specific malware. This means that there should be used security metrics instead of pure discrete features. Some study has shown that security metrics are more suitable for human representation and abstraction of features. This is because features are mainly collected through statistical analysis while metrics are mapped by analyst.

A. Intrusion Detection Model

The intrusion detection model based on the attribute-weighted clustering, as shown in below figure .The model first pre-treats collection of data, chooses training samples, reduces attributes in decision tables, produces reduced output rules to construct rule base of safe system and intrusion detection detector. The initial intrusion model needs gradually perfect and improvement in subsequent studies to reach the best detection effect.

IDS are one of the key technologies to guarantee the systems security. IDS make a real time response to intrusion actions and intrusion processes. The goal of Intrusion Detection is to identify all the proper attacks and negatively identify all the non-attacks. The datasets (KDD’99CUP, NSL-KDD, and TCP Dump) are used. And the various techniques for detection of vulnerabilities that improve the performance of the detection of known and unknown vulnerabilities, and use a dataset which is efficient means without redundancy.

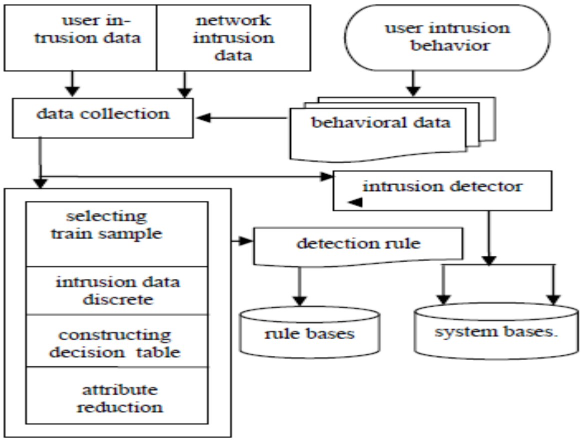

Fig 1: Intrusion Detection Model

B. Malware Detection Technique:

Malware includes viruses, worms, Trojan horses, spy-ware, and adware. A virus is a computer program that attaches itself to a host (e.g., a program file or a hard disk boot record) and spreads when the infected host is moved to a different computer. A worm is a computer program that can replicate itself and spread across a network. A Trojan horse appears to be a legitimate computer program but has malicious code hiding inside which runs when activated. Spy-ware is malware that collects and sends data copied from the victim's computer, such as financial data, personal data, passwords, etc. Adware, or advertising- supported software, is a computer program that automatically displays ads. Soft computing embraces several computational intelligence methodologies, including artificial neural networks, fuzzy logic, evolutionary computation, probabilistic computing, and recently it is extended towards artificial immune systems, belief networks, etc. These members neither are independent of one another nor compete with one another. Rather, they work in a cooperative and complementary way. There are various soft computing and machine learning techniques which are used in malware detection. Malware is a program that has malicious intention. Whereas has defined it as a generic term that encompasses viruses, Trojans, spywares and other intrusive codes. Malware is not a "bug" or a defect in a legitimate software program, even if it has destructive consequences. The malware implies malice of forethought by malware inventor and its intention is to disrupt or damage a system.

II. RELATED WORK

A. Adaptive Worm Detection Model Based On Multi Classifiers

In this paper [1] author proposed a detection model for worm based on multi classifier and the details are, A "WDMAC" model for worm's detection using data mining techniques by combination of classifiers (Naive Bayes, Decision Tree, and Artificial Neural Network) in multi classifiers to be adaptive for detecting known/ unknown worms depending on behaviour anomaly detection approach, to achieve higher accuracies and detection rate, and lower classification error rate. Our results show that the proposed model has achieved higher accuracies and detection rates of classification, where detection known worms are at least 98.30%, with classification error rate 1.70%, while the unknown worm detection rate is about 97.99%, with classification error rate 2.01%.

B. MAP Reduce IDS Based on Particle Swarm Optimization Clustering Algorithm

In this paper [2] author proposed an intrusion detection system based on a PSO and clustering algorithm and the details are, an intrusion detection system based on a parallel particle swarm optimization clustering algorithm using the Map Reduce methodology. The use of particle swarm optimization for the clustering task is a very efficient way since particle swarm optimization avoids the sensitivity problem of initial cluster centroids as well as premature convergence. The proposed intrusion detection system processes large data sets on commodity hardware. The experimental results on a real intrusion data set demonstrate that the proposed intrusion detection system scales very well with increasing data set sizes. Moreover, it achieves close to the linear speedup by improving the intrusion detection and false alarm rates.

C. ISMCS: An Intelligent Intrusion Sequence Based on Malware Categorization System

In this paper [3] author proposed a Malware categorization system and the description are, develop an intelligent instruction sequence based malware categorization system (ISMCS) using a novel weighted subspace clustering method. ISMCS is an integrated system consisting of three major modules: feature exactor, malware categorizer using weighted subspace clustering method and malware signature generator. ISMCS can not only effectively categorize malwares to different families, but also automatically generate the unify signature for every family. Promising experimental results demonstrate that the effectiveness of our ISMCS system outperform other existing malware categorization methods, such as K-Means and hierarchical clustering algorithms.

D. Bingraph: Discovering Mutant Malware Using Hierarchical Semantic Signature

In this paper [4] author proposes Bin Graph, a new mechanism that accurately discovers metamorphic malware. Bin Graph leverages the semantics of malware, since the mutant malware is able to manipulate their syntax only. To this end, we first extract API calls from malware and convert to a hierarchical behaviour graph that represents with identical 128 nodes based on the semantics. Later, we extract unique sub graphs from the hierarchical behaviour graphs as semantic signatures representing common behaviour of a specific malware family. To evaluate Bin Graph, we analyzed a total of 827 malware samples that consist of 10 malware families with 1,202 benign binaries. Among the malware, 20%samples randomly chosen from each malware family were used for extracting semantic signatures, and rest of them were used for assessing detection accuracy. Finally, only 32 sub graphs were selected as the semantic signatures. Bin Graph discovered malware variants with 98% of detection accuracy.

III.PROPOSED METHOD

A. Feature Extraction

Malware classification can either have single variable approach or a multi-variable approach to detect Malware depending on the algorithm used. In the single variable approach a single variable of the system is analyzed. This can be, for example, port number, CPU usage of a local machine etc. In multi-variable approach a combination of several features and their inter-correlations are analysed. In addition based on the method the way in which features are chosen for the IDS can be divided into two groups; into feature selection and feature reduction.

1) *Feature Selection:* In the feature selection method the features are either picked manually from the data monitored or by using a specific feature selection tool. The most suitable features are selected by handpicking from the feature spectrum based on the prior knowledge about the environment that the IDS are monitoring. For example features that can distinguish certain type of traffic from the traffic flows are picked for the network traffic model training. The idea behind the feature selection tools is to reduce the amount of features into a feasible subset of features that do not correlate with each other. Examples of feature selection tools are Bayesian networks (BN) and classification and regression tree (CART). Bayesian network is a probabilistic graphical model that represents the probabilistic relationships between features. CART is a technique that uses tree-building algorithms to construct a tree-like if-then prediction patterns that can be used to determine different classes from the dataset. Feature selection process is illustrated in Fig 2 On the left there are the features (F0…FN) that are available from the data monitored, which is, for example, from network traffic. On the right side is the output (F0...FM) of the selection tool. The number of features in the output varies based on the selection tool used and the inter-correlation of features in the input. Following the basic principles of feature analysis the number of features in the output (M in Fig 2) is in most of the cases less than the number of features in the input (N in Fig 2). However, it is possible that the output is equal to the input.

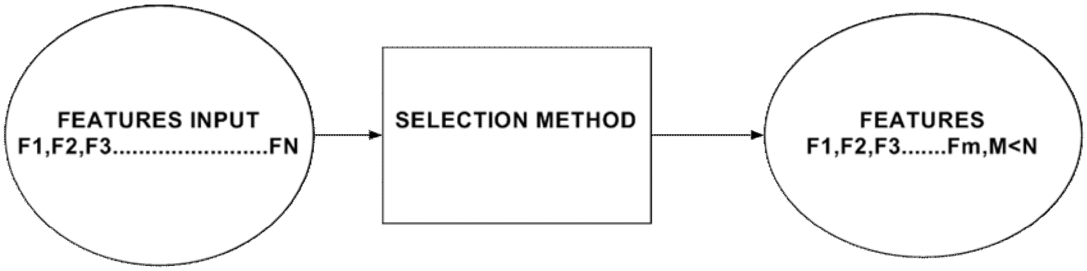

Fig 2: Feature selection process in feature variable

B. Support Vector Machine (SVM)

Support Vector Machine (SVM) is a novel machine learning method based on statistical learning theory developed by V.N.Vapnik, and it has been successfully applied to numerous classification and pattern recognition problems such as text categorization, image recognition and bioinformatics. It is still in the development stage now SVM can be used for pattern recognition, regression analysis and principal component analysis. The achievements of SVM in training have Platt's the sequential minimal optimization method, Osuna's the method of Chunking, Joachims' SVM light method and so on. These methods are directed at the training process, and not related to classification process. In the process of SVM training, all the samples are used. So it has no effect on the speed of the classification. Lee and others propose a method of reduction SVM training time and adding the speed of training, reduced support vector machines. The method in the training process is not used in all the samples but by randomly selecting one of the subsets to train, which is through reducing the scale of training to achieve the objective of speeding up the training pace. At the same time, because of the reduction of the support vector quantity, the speed of classification is improved to some degree. However, due to the loss of some support vector classification, precision has declined, especially when the number of support vector is so many that the accuracy of its classification will decline. Burges put forward a way of increasing the speed of Classification ,which does not use the support vector in the category function but use a reduction of vector set, which is different from the standard vector set .That is neither training samples nor support vector but it is the transformation of the special vector. The method achieved certain results, but in the process of looking for the reduction of the vector collection, the cost of calculation paid is too large to widely use in practice. The concept of SVM is to transform the input vectors to a higher dimensional space Z by a nonlinear transform, and then an optical hyper plane which separates the data can be found. This hyper plane should have the best generalization capability. As shown in Figure 4.1, the black dots and the white dots are the training dataset which belong to two classes. The Plane H series are the hyper planes to separate the two classes. The optical plane H is found by maximizing the margin value $2/\|w\|$. Hyper planes H_1 and H_2 are the planes on the border of each class and also parallel to the optical hyper plane H. The data located on H_1 and H_2 are called support vectors.

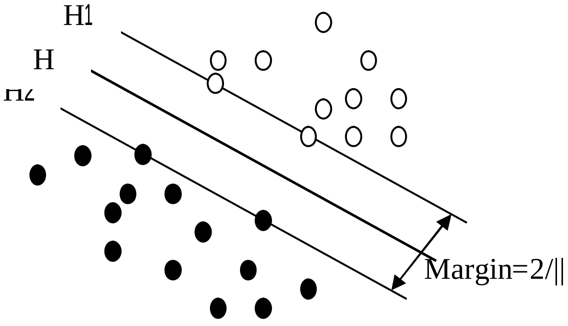

Fig 3: The SVM binary classifications

C. Directed Acyclic Graph (DAG):

A DAG is a graph based multi-classification technique in this technique pair-wise SVMs used, let the decision function for class *i* against class *j*, with the maximal margin, be:

$$Dij(x) = wijT\emptyset(x) + bij$$

Where Wij is the d-dimensional vector, Ø(x) is a mapping function that maps x into the d-dimensional feature space bij is the bias term and Dij(x)= --Dji(x) The regions Ri are shown in figure 4.4 .1 with labels of class I, II and III.

$$Ri = \{x|Dij(x) > 0, j = 1,2, \dots \dots . n, j \neq i\}$$

If x is in Ri, we classify x into class i. if x is not in Ri(i=1,2,……,n), x is classified by voting. Namely, for the input vector x,Di(x) is calculate at follow:

$$Di(x) = \sum_{i\neq j, j=1}^{n} sign(Dij(x))$$

Where $sign(x) = \begin{cases} 1\ for\ x \geq 0, \\ -1\ for\ x < 0, \end{cases}$

And x is classified into class

$$\arg \max_{i\,=\,1,2,\,\dots\,,\,n} Di(x)$$

If xϵRiDi(x)=n-1 and $D_k(x)$<n-1 for k≠i thus x is classified into i but if any of Di(x) is not n-1,may be satisfied for plural i's. In this case x is unclassified. In the shaded region in figure 1,Di(x)=0(i=1,2 and 3). Therefore, this region is unclassified, although the unclassified region is much smaller than that for the one-against-all support vector machine.

In pair wise SVMs, classification reduces the unclassifiable regions that occur for one-against-all support vector machines but it still exists. To resolve this problem DAG SVM uses a decision tree in the testing stage. Training of a DAG is the same as conventional pair wise SVMs.

Classification by DAGs is faster than by conventional pair wise SVMs or air wise fuzzy SVMs. Fig 4 shows the decision tree for the three classes shown in Figure 1. In the figure, i show that x does not belong to class i.

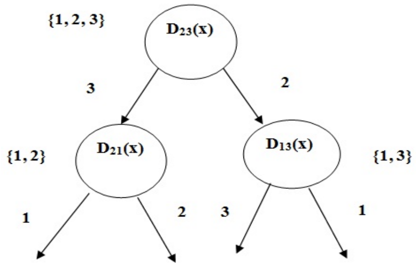

Fig 4: DAG classification

IV. PROPOSED MODEL

Step1: Initially input Malware data passes through pre-processing function and extracted feature part of Malware data in form of traffic type.

Step2: the extracted traffic feature data converted into feature vector.

Step 3: In phase of feature mapping in feature space of DAG create a fixed class according to the group of data.

Step 4: steps of processing of DAG.

A. Initialize Gaussian hyper plane margin.

B. Choose a random vector from training data and present it to the DAG.

C. The weight of the plane support vector is estimated. The size of the vector decreases with each iteration.

D. Each vector in the SV's neighborhood has its weights adjusted to become more like the SV. Vector closest to the SV are altered more than the vector furthest away in the neighborhood.

E. Repeat from step 2 for enough iteration for convergence.

F. Calculating the SV is done according to the Euclidean distance among the node's weights (W_1, W_2, … , W_n) and the input vector's values (V_1, V_2, … , V_n).

G. The new weight for a node is the old weight, plus a fraction (L) of the difference between the old weight and the input vector… adjusted (theta) based on distance from the SV.

Step 5: After processing of support vector finally malware data are classified.

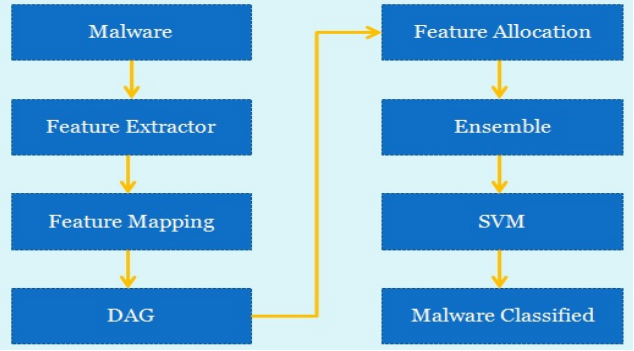

Fig 5: Proposed Model

V. RESULTS

The results are calculated by using KDD99 DATASET. It includes 4 attacks description with their classes as shown in Table 1.

TABLE 1: KDD99 Dataset

Sr. No.	4 Main Attack Classes	22 Attacks Classes
1	Probing	ipsweep, nmap, portsweep, satan
2	Denial of Service (DOS)	Back, lend, option, pod, smart, teardrop
3	User to Root (U2R)	buffer_overflow,perl,loadmodule,rootkit
4	Remote to User (R2L)	ftp_write,guess_passwd,imap,multihop,phf,spy, warezclient, warezmaster

We are showing the consequence for the following parameters i.e. - Accuracy, Precision, Recall for data sets.

Precision- Precision measures the proportion of predicted positives/negatives which are actually positive/negative.

Recall -It is the proportion of actual positives/negatives which are predicted positive/negative.

Accuracy-It is the proportion of the total number of predictions that were correct or it is the percentage of correctly classified instances.

TABLE 2: Evaluation of TPR, TNR, FPR, FNR, Detection rate, Precision rate and Recall rate for Improved Ensemble method and the input value is 0.1.

Value	Types of Attacks	TPR			TNR			FPR			FNR		
		EN	HE	PM	EN	HE	PM	EN	HE	IE	EN	HE	PM
0.1	NORMAL	4.27	3.70	3.70	0.70	0.74	0.84	1.56	1.70	1.74	0.69	0.70	0.75
	DOS	4.37	3.51	3.51	0.29	1.74	1.84	0.56	1.70	1.73	0.30	0.63	0.74
	PROBE	4.48	2.31	2.31	1.70	1.74	1.85	0.19	0.60	0.73	0.35	0.13	1.13
	U2R	5.27	3.51	3.31	0.40	0.85	0.85	1.43	0.84	0.85	0.30	1.73	1.85
	R2L	3.47	3.09	3.09	1.59	0.69	0.69	0.56	0.40	0.40	0.16	1.85	1.85

TABLE 3: Evaluation of TPR, TNR, FPR, FNR, Detection rate, Precision rate and Recall rate for Improved Ensemble method and the input value is 0.1.

Value	Types of Attack	Detection Rate			Precision Rate			Recall Rate		
		EN	HE	PM	EN	HE	PM	EN	HE	PM
0.1	NORMAL	89.79	95.30	95.80	81.93	84.01	85.02	80.93	82.97	83.97
	DOS	88.79	92.83	93.83	80.93	79.97	81.97	78.93	77.97	80.97
	PROBE	86.79	93.83	94.83	79.93	83.97	84.97	81.93	80.97	81.97
	U2R	85.79	93.85	94.85	82.93	84.97	85.97	81.93	83.97	84.97
	R2L	86.79	91.83	92.83	84.43	85.97	86.97	79.93	81.97	82.97

EN-Ensemble Method, HE-Hybrid Ensemble Method, PM- Proposed Method (Improved Ensemble Method)

VI. CONCLUSION

In this paper, we have proposed a novel hybrid method, based on DAG and Gaussian Support Vector Machines, for malware classification. Experiments with the KDD Cup 1999 Data show that SVM-DAG can provide good generalization ability and effectively classified malware data. Moreover, the modified algorithms proposed in this desecration outperform conventional CIMDS and ISMCS in terms of precision and recall. Specifically, accuracy of the modified algorithms can be increase due to feature allocation of DAG, and reduces feature sub set increase the accuracy of classification. From our experiments, the DAG-

SVM can detect known attack types with high accuracy and low false positive rate which is less than 1%.

The proposed method classified attack and normal data of KDDCUP99 is very accurately. The proposed method work in process of making group of attack very accurately, the learning process SVM training process makes very efficient classification rate of Malware data. Our empirical result shows better performance in compression of ISMCS and another data mining technique for malware detection.

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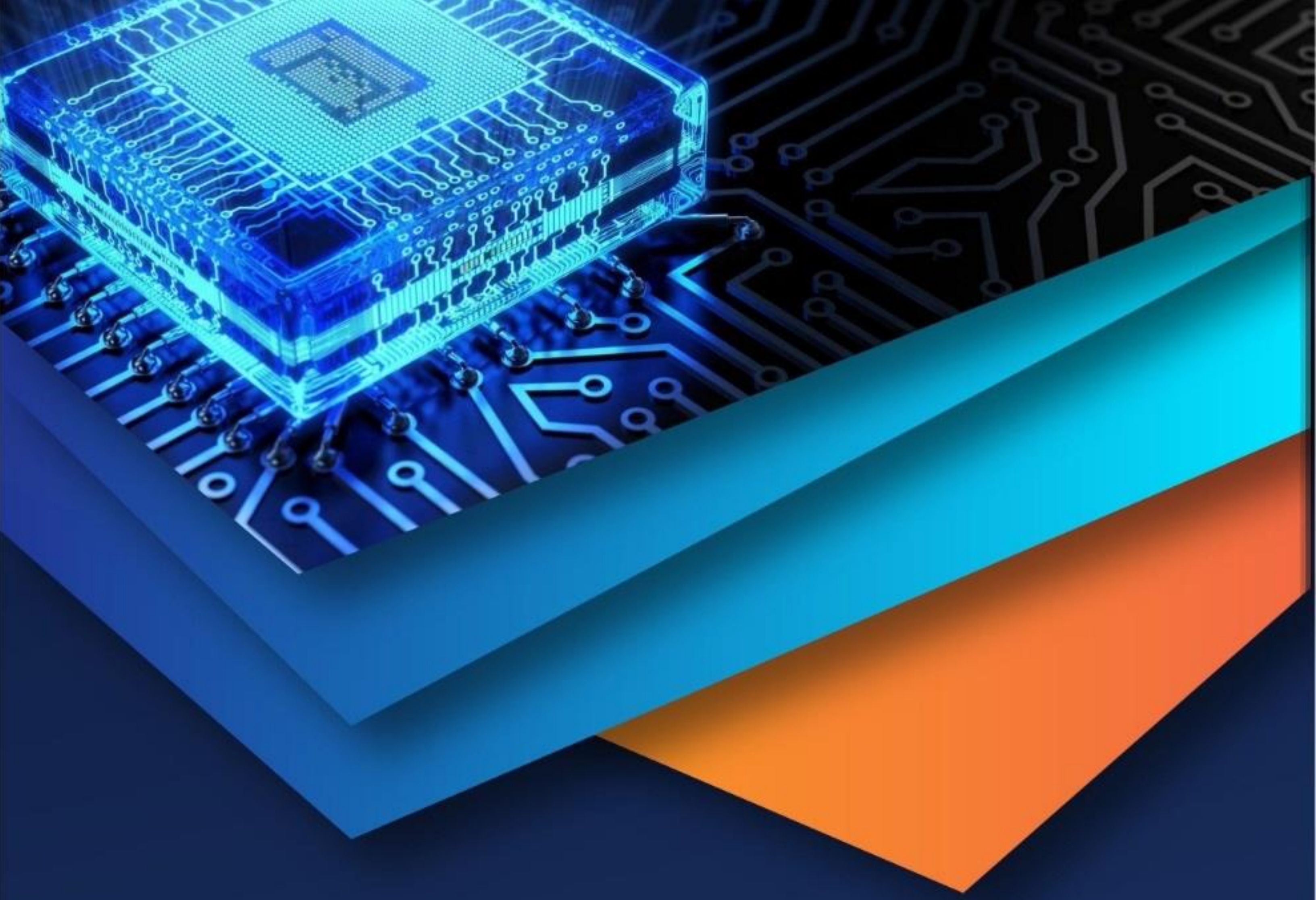

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