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Frequent Items Mining in Data Streams

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Abstract - The main goal of this research is to mine frequent items in data streams using ECLAT and Dynamic Itemset Mining algorithms and finding the performance and drawbacks of these two algorithms. Most commonly used traditional association rule mining algorithms are APRIORI algorithms, Partitioning algorithms, Pincer-Search algorithms, FP-Growth Algorithms and Dynamic Item Set Mining Algorithms, Eclat algorithms and so on. The performance factors used are number of frequent items generated using different thresholds and execution time. From the experimental results we come know that the performance of Éclat algorithm is better than the Dynamic Item Set Counting Algorithm.
Keywords - Data streams, Association rules, Frequent Items, Éclat algorithm, Dynamic Item Set Counting Algorithms.

I. INTRODUCTION

Advanced developments in the hardware industry have provided the organizations to store and process huge flow of transactional data. These types of data sets which endlessly and quickly grow over time are known as data streams. Nowadays, real time events are monitored with the help of sensor technology which creates a platform to store this information in the databases. In order to handle these databases, i.e. to mine or knowledge extraction is not possible by using the traditional data mining algorithms. In many cases, these large volumes of data can be mined for interesting and relevant data stream information in a wide variety of applications [1]-[2].

This research work mainly concentrated on generating frequent items which is the first and essential step of association rule generation. From these frequent items only, the association rules are generated. This work helps to generate the frequent items in data streams using existing association rule data mining algorithms. Popular association rule generation algorithms, ECLAT and DIC are used and its performances are compared by using the factors number of rules generated and execution time

The paper is organized as follows. Section 2 provides the related works. Proposed methodology and the traditional association rule mining algorithms are given in Section 3. Section 4 described the experimental results. Conclusion is given in Section 5.

II. REVIEW OF LITERATURE

Vijayarani S et al., [17] described frequent item-set mining in data streams. Authors have used ECLAT and RARM algorithms for generating the frequent item-sets. The dataset was divided into number of windows with different threshold values. The performance factors used are number of frequent items generated and execution time. From the results, the authors observed that the performance of ECLAT is more efficient than RARM.

Vijayarani S et al., [18] performed a comparative analysis of traditional association rule mining algorithms for data streams. The algorithms considered for analysis are APRIORI, APRIORI PT (Prefix Tree) and APRIORI MR (Map/Reduce). Different sizes of windows and threshold values are used and it is concluded that APRIORI MR has produced good results than other algorithms.

Charu C. Aggarwal, [4] presented the complete information about data streams. He discussed how to relate variant data mining technologies to data streams for supportive and unknown data extraction. He also discussed data stream clustering, data stream classification, association rule mining algorithm in data stream and frequent pattern mining.

Preeti Paranjape-Voditel et al., [11]-[8] discussed the distributed algorithm based on DIC algorithm for frequent item generation. It is based on APRIORI algorithms in the number of single pass of the databases and which is used to represent the different methods in distributed association rule mining algorithms. From the performance evaluation, the distributed DIC algorithm is efficient in dense data set and reduced the execution time.

Bin et al., [4]-[14] described the DIC algorithms in association rule mining. Author explained the real time number of passes of the databases in certain computations and which is used to represent the different methods in association rule mining algorithms. Author used different types of structures and this structure can be associated from single passes.

Rakesh Agrawal et al., [12] analyzed the association rule mining algorithms. Authors described how to find the large item-sets from the dynamic databases. It can be used from different methods and techniques. In this methods are derived from two different processes, candidate item sets and pruning item sets. Candidate item sets are generated from the single scan passes of the database. In pruning item sets are falls from predefined threshold values.

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III. PROPOSED METHODOLOGY

The system Architecture of this work is given in Figure 1.

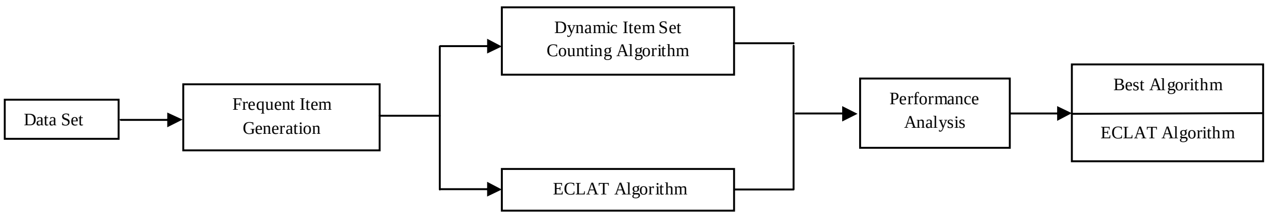

Fig. 1 System architecture

A. Dataset

The connect data set is used in this work. It is taken from http://fimi.ua.ac.be/data/connect.dat. It consists of 67,558 instances and 48 attributes. From this 1K, 2K and 5K transactions are used in this work. In data streams, we have assumed that the nonstop arrival of data is divided into many windows with permanent size, i.e. $W_1, W_2, W_3 \ldots\ldots W_n$. In this work, we have created five windows W_1, W_2, W_3, W_4, W_5 with the static data set size of 1K, 2K and 5K.

B. Association Rule using Frequent Items Generation

The frequent item generation is used in association rule mining algorithms. Let, the sample data set D be a number of transactional item, i.e. $D = \{I_1, I_2, \ldots\ldots I_{(D)}\}$. Let X be the set of all frequent interesting patterns occurring in database D, g be a counting function like g: X * D -> N, Where I is the number of transactions, and N is the set of non-negative integers. Given parameters p ∪ X and i ∪ I, g(p,i) returns the amount of transactional time occurs in i.

The support of a pattern p ∪ X in the data set D is defined by,

$$Support\ (X) = \sum_{k=0}^{k=D} Y\,(g\,(p, I_k\,))$$

The frequent item is an item generation which frequently occurred in a transaction. Frequent item set mining is used to discover the patterns in customer transaction databases. These types of transactional databases are used in business organizations and supermarkets for taking important decisions. The algorithms used here are,

1. ECLAT Algorithm.
2. DIC Algorithm.

C. ECLAT Algorithm.

Equivalence Class Clustering and Bottom up Lattice Traversal is an acronym for ECLAT algorithm. The name implies that the algorithm uses the bottom up searching method like as horizontal and vertical layouts to find out the frequent item set. This algorithm also performed the item set mining. It uses the t_{id} set of intersection to compute the support of the candidate item set and it is compared with other algorithms like Apriori , FP-growth, Partitioning algorithm, Apriori Map/Reduce, Apriori PT, frequent items, Supervised Association rules and Association outliers algorithm, etc., It required the candidate generation phases and pruning phases.

There are two important steps in ECLAT algorithm. First one is, candidate generation and the second one is pruning. In the candidate generation step, each *k-item sets* candidate is produced from two frequent *(k-1) – item sets* and then its support is calculated, if it considered as supported value is lesser than the threshold values, then it will be discarded, otherwise it is frequent item-sets and used to *(k+1) – item sets*. Because, the ECLAT algorithm uses the vertical layout, counting support is unimportant. Candidate generation is really a search in the search tree. This search is a depth-first search and it begins with frequent items in the item base and then *2 – item sets* are reached from *1- item sets, 3 – item sets* are reached from *2 – item sets* and so on.

1) *Candidate Generation :* A k- item set is generated by taking the union of two *(k-1) – item sets* which have *(k-2) item sets* at frequent, the two *(k-1) –item sets* are called parent item sets of the *k-item set*. For example, *{{abc} = {ab} {ac}}*, {ab} and {ac} are parent of {abc}. To avoid generating duplicate item sets, *(k-1) – item sets* are sorted in some order. For example, we have a set of *1 – item sets {a,b,c,d,e}*, which share 0 items and sort items in the alphabet order; to generate all *2 – item sets*, union of *{a}* with *{b,c,d,e}*to result 2-itemsets *{ab,ac,ad,ae}*, then it take union of *{b}* with *{c,d,e}* to have *{bc,bd,be}*, similarly, for *{c}* and *{d}*; lastly, get all possible, *2- item sets {ab,ac,ad,ae,bc,bd,be,cd,ce,de};* generate all feasible *3-itemsets* from these *2-itemsets*. Initially have divided these item sets into groups, anywhere each group has a common item; in each group, to generate feasible *3-itemsets* from that group, then collecting all *3-itemsets* generated from groups, all possible *3-itemsets* from the item base *{a,b,c,d,e}*.The search tree of an item base *{a, b, c, d, e}* is represented by the tree as below:

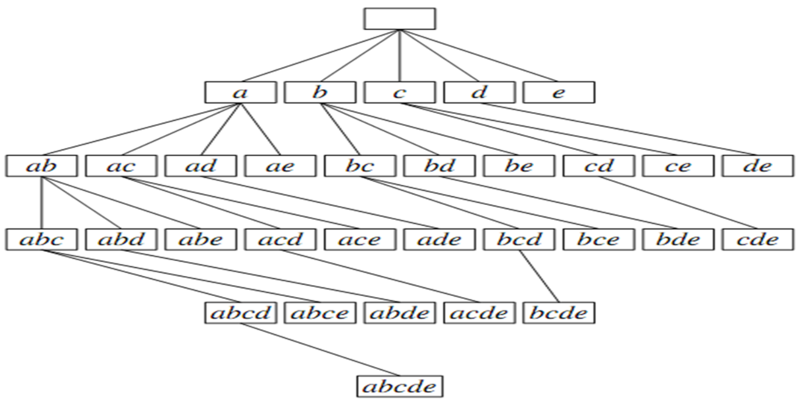

Fig. 1 Searching tree for frequent item based

2) *Pseudo Code for ECLAT Algorithm*

```
Input: E((i_1,t_1), ... (i_n,t_n))|P), s_min
Output: F(E, s_min)
for all i_j occuring in E do
P := P ∪ i_j // add i_j to create a new prefix
init(E') // initialize a new equivalence class with the new prefix P
     for all i_k occuring in E such that k > j do
          t_tmp = t_j ∩ t_k
          if |t_tmp| ≥ s_min then
               E' := E ∪ (i_k, t_tmp)
               F = F ∪ (i_k ∪ P)
          end if
     end for
     if E' ≠ {} then
     Eclat(E', s_min)
     end if
end for
```

Fig. 3 Pseudo code for ECLAT algorithm

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D. DIC Algorithm

Dynamic Item Set Counting Algorithm is proposed by Bin et al. in 1997. The validation behind DIC works like a train running over the data, with stops at intervals N between Numbers of transactions. When the train arrives at the end of the transaction file, it has made one pass over the data, and it starts all over again from the starting for the next pass. The passengers on the train are item sets. While an item set is on the train, count its occurrence in the transactions that are interpreted. When an APRIORI algorithm is considered in all item sets get on at the start of a pass and get off at the end. The *1 – item sets* obtained the first pass, the *2 – item sets* obtain the second pass, and so on. In DIC, there is the added flexibility of allowing item sets to get on at any stop as long as they get off at the same stop the next time the train goes around. Therefore, the item set has seen all the transactions in the file.

Consider the DIC example, imagine 40,000 transactions and N = 10,000. It will count all the *1 – item sets* in the first 40,000 transactions. Though, begin counting *2 – item sets* after the first 10,000 transactions have been interpreted. It will begin counting *3 item sets* after 20,000 transactions. To assume that *4 – item sets* need to count. It will be getting to the end of the file and top counting the *1 – items sets* and go back to the start of the file to count the *2 – and 3 – item sets*. After the first 10,000 transactions and finish counting the *2 – item sets* and after 20,000 transactions, finally finish counting the *3 – item sets*. In total, have made 1.5 passes over the data in its place of the 3 passes a level – wise algorithm would build.

1) *Structure of DIC:* Dynamic Item Set Counting Algorithm has defined by four different structures like as, Dashed Box, Dashed Circle, Solid Box, and Solid Circle. Each of these structures maintains a list of item sets. It gives a two important factors are used, that is Dashed and Solid Categories.

This item sets in the **"dashed"** category of structures has a counter and discontinue number with them.

a) The counter is to maintain track of the support value of the corresponding item set.
b) The stop number is to maintain track whether an item set has fulfilled one full pass over a database.
c) The item sets in the **"solid"** category structures are not subjected to any counting.
d) The item set in the solid box is an established set of frequent sets.
e) The item sets in the solid circle are the established set of infrequent sets.
f) The algorithm counts the supported values of the item sets in the dashed structure as it moves along from one stop point to another.

2) *Pseudo Code for DIC Algorithm:*

```
1.  Solid box contains the empty itemset;
2.  Solid circle is empty;
3.  Dashed box is empty;
4.  Dashed circle contains all 1 – itemsets with the respective stop – number as 0;
5.  Current stop – number := 0;
6.  do until the dashed circle is empty read the database till the next stop point and increase the counters of the itemsets in
    the dashed box and in the dashed circle as we go along, record by record, to reach the next stop.
7.  increase the current – stop – number by 1;
8.  for each itemset in the dashed circle
9.  if count > item set
10. {
11. then move the itemset to the dashed box generate a new itemset to be put into the dashed circle with,
12. counter value = 0
13. stop number = current stop number.
14. }
15. Else if its stop number = current stop number{
16. then move this itemset to solid circle.
17. for each itemset in the dashed box{
18. if its stop_number = current stop number{
19. then move this itemset to the solid box }}}
20. return the itemsets in solid box
```

Fig. 4 Pseudo code for DIC algorithm

During the execution of the DIC algorithm, at any stop point, the following events take place,

1) Certain item sets in the dashed circle move into the dashed box. These are the item sets whose support – counts reach value during this iteration (reading records between two consecutive stops).
2) Certain item sets enter the system and get into the dashed circle. These are essentially the supersets of the item sets that move from the dashed circle to the dashed box.
3) Item sets that have completed one full pass move from the dashed structure to a solid structure. That is, if the utmost is in a dashed circle while completing a full pass, it moves into the solid circle. If it is in the dashed box, then it moves into a solid box after completing a full pass.

IV. EXPERIMENTAL RESULTS

The experimental results of **ECLAT** and **DIC** algorithms are described in this section. The work is implemented in MySQL Query Browser and Java IDE Environments. Totally, five windows W_1, W_2, W_3, W_4 ,W_5 are used in this research work. Thereare four different sizes of datasets; 1K, 2K, 5K, 10K is tested and their results are obtained. Different threshold values are applied for analyzing the results. The performance factors used for analysis are number of rules generated and execution time.

TABLE I ECLAT ALGORITHM FOR FREQUENT ITEM GENERATION

Window Size	**Threshold (σ) - %**	**1000 Ds**	**2000 Ds**	**5000 Ds**	**10,000 Ds**
		Items			
W1	20	75774	77589	89345	89904
	40	75265	73986	87234	89245
	60	75563	69239	79345	93890
W2	20	73734	77012	88121	90678
	40	74907	71209	87345	87123
	60	74026	68910	79678	90319
W3	20	78934	77239	89456	81307
	40	78342	72900	86563	85510
	60	76345	63921	73456	90456
W4	20	72057	77921	82901	94512
	40	73901	75454	89456	87745
	60	71902	69320	72723	79345
W5	20	76003	77320	88841	79412
	40	71945	74393	85890	95120
	60	73678	69921	73121	96433

Table 1 provided the number of frequent items generated using ECLAT algorithm for different threshold values i.e. $\sigma = 20,40,60$. This is represented in Fig. 5

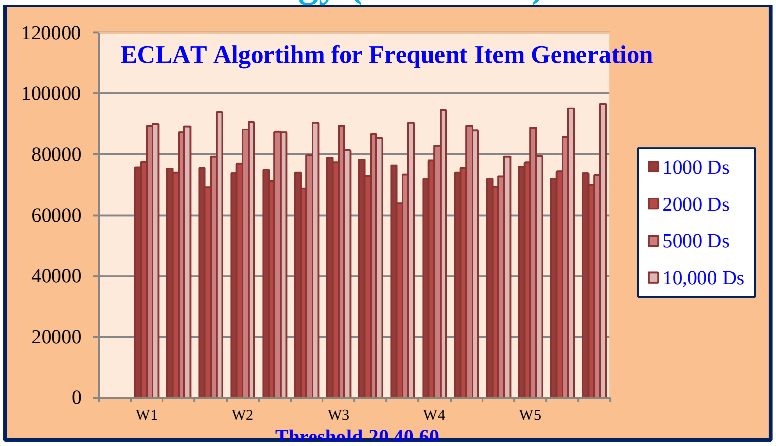

Fig. 5 ECLAT algorithm for frequent item generation

TABLE II EXECUTION TIME FOR ECLAT ALGORITHM

Window Size	**Threshold (σ) - %**	**1000 Ds**	**2000 Ds**	**5000 Ds**	**10,000 Ds**
		Time (ms)			
W1	20	459	454	860	899
	40	420	523	861	903
	60	531	489	845	923
W2	20	459	520	855	826
	40	421	425	869	945
	60	530	588	851	833
W3	20	433	429	874	952
	40	491	398	891	849
	60	587	476	901	866
W4	20	412	519	845	890
	40	487	430	867	941
	60	491	501	843	820
W5	20	482	462	821	913
	40	534	497	841	821
	60	491	433	832	802

Table 2 represented the execution time required for generating frequent items by using ECLAT algorithm.

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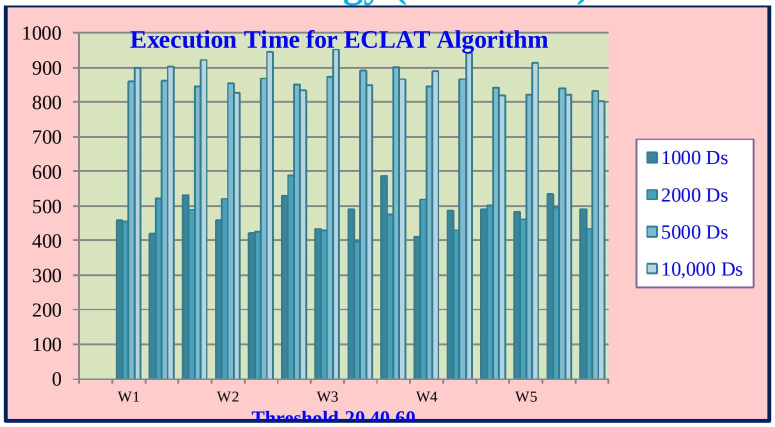

Fig. 6 Execution time for ECLAT algorithm

Fig. 6 illustrated the execution time required for generating frequent items by using ECLAT algorithm.

TABLE III EXECUTION TIME FOR DIC ALGORITHM

Window Size	Threshold (σ) - %	1000 Ds	2000 Ds	5000 Ds	10,000 Ds
		Items			
W1	20	40210	44992	64322	79944
	40	59198	44827	69451	79823
	60	55069	57867	60812	65290
W2	20	58161	60418	59345	76120
	40	29944	62902	61998	79345
	60	57898	47550	60569	72901
W3	20	44519	43120	51816	53234
	40	45221	55780	62010	72938
	60	61665	62439	64756	55902
W4	20	65211	54832	65443	78432
	40	47551	45121	52983	73965
	60	41229	47672	68344	69091
W5	20	62819	43892	60528	84589
	40	59320	59320	51290	79943
	60	49413	60475	58320	77120

Table 3 represented the frequent item generation using DIC algorithm for different threshold values i.e. σ = 20,40,60.

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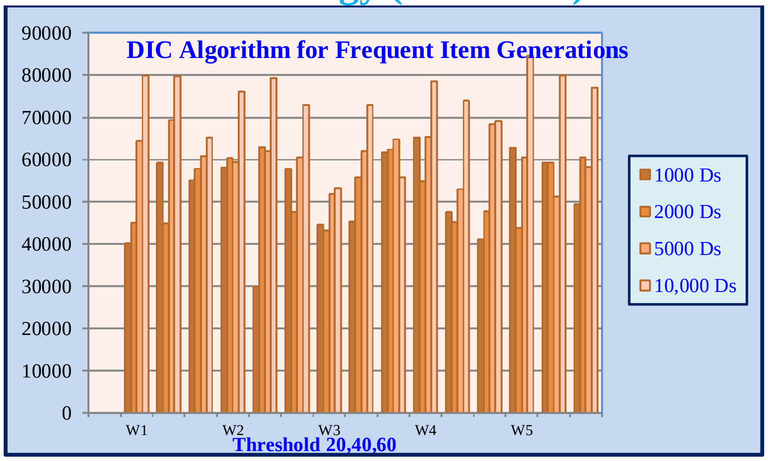

Fig. 7 DIC algorithm for frequent item generations

Fig. 7 represented the frequent item generation using DIC algorithm.

TABLE IV EXECUTION TIME FOR DIC ALGORITHM

Window Size	Threshold (σ) - %	1000 Ds	2000 Ds	5000 Ds	10,000 Ds
		Time (ms)			
W1	20	1691	1564	1956	2096
	40	967	1694	1969	2101
	60	619	1573	1938	2387
W2	20	1000	1623	1822	1980
	40	1691	1565	1934	1992
	60	988	1699	1561	1965
W3	20	723	1897	1832	2014
	40	1989	1958	1976	1995
	60	1625	1687	2038	2289
W4	20	954	1938	2014	2332
	40	670	793	1983	2591
	60	1990	1654	1594	1997
W5	20	991	1732	1494	2115
	40	754	1322	2048	2389
	60	1902	1357	2032	1991

Table 4 shows the execution time required for generating items by using DIC algorithm for different threshold values

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i.e. σ = 20,40,60.

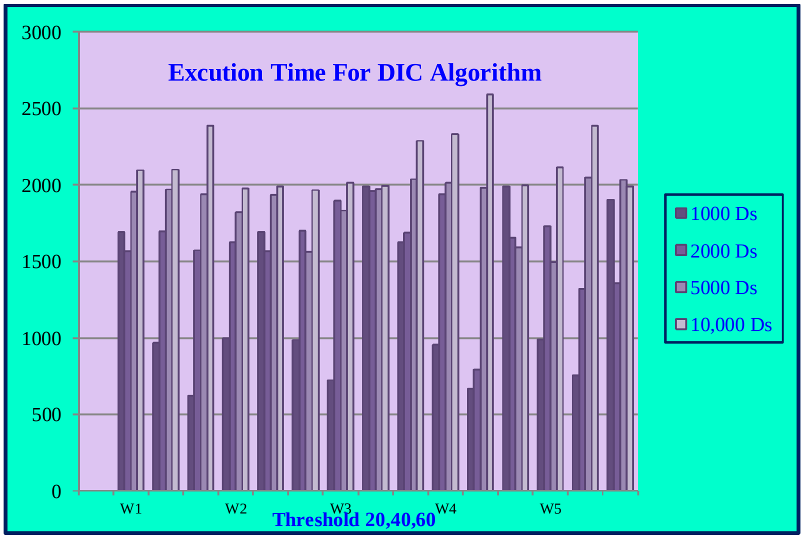

Fig. 8 Execution time for DIC algorithm

Figure 8 shows the execution time required for generating items by using DIC algorithm

V. CONCLUSION AND FUTURE WORK

From this work, it is concluded that the performance of ECLAT algorithm is better than DIC algorithm. ECLAT algorithm has generated more number of frequent items with different thresholds and different sizes of data sets. The execution time required to generate frequent items by ECLAT is also less than DIC algorithm. In future, association rules are generated by using the enhanced versions of these algorithms.

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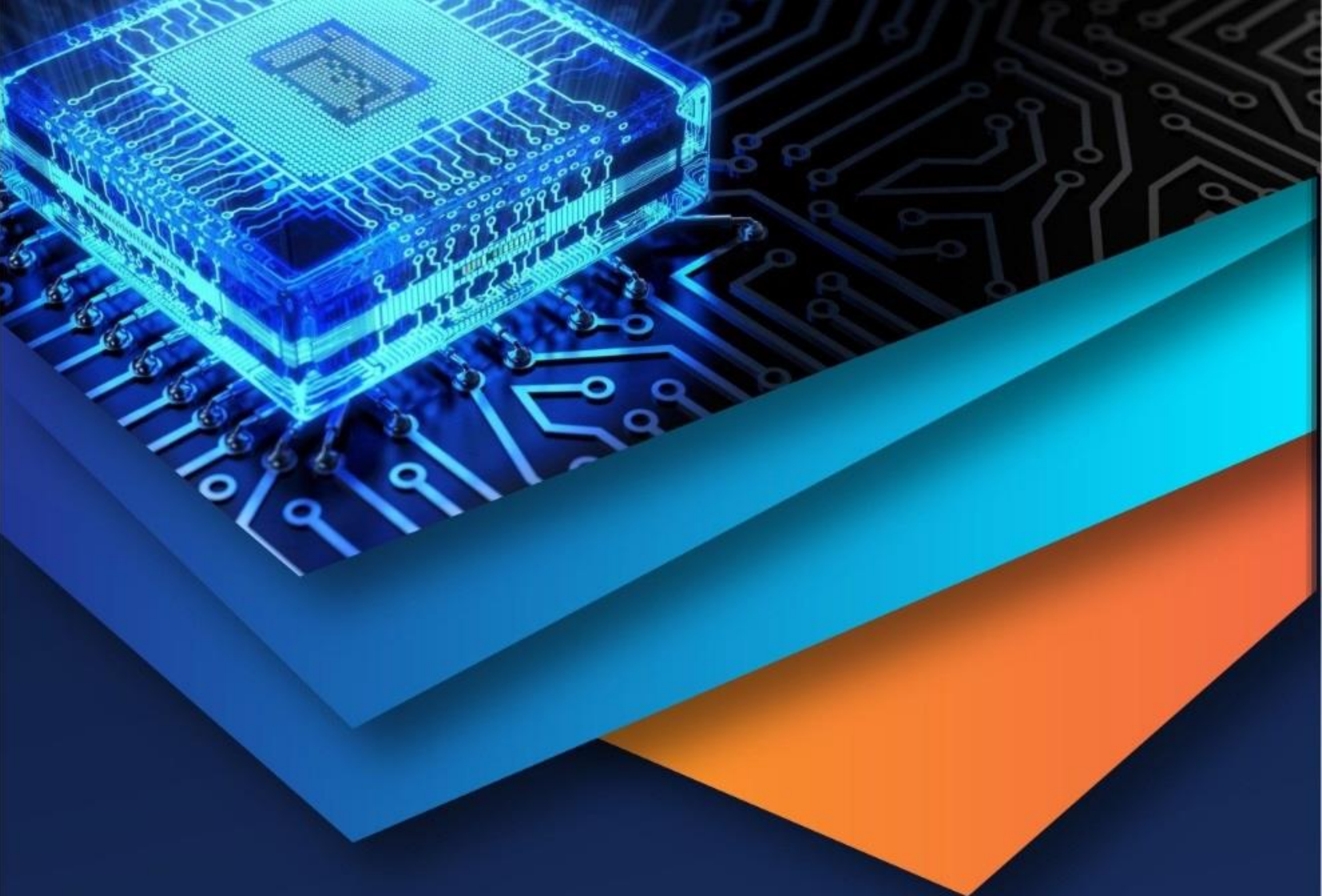

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