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A CRITICAL REVIEW OF DEEP LEARNING ALGORITHM IN ASSOCIATION RULE MINING

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ABSTRACT

Data mining, an urging requirement within the current era and whose scope of research is predicted to be for upcoming decades. Among the competent techniques of data mining association rule mining plays an amazing role. This technique indicates on curious association, correlations and frequent patterns from the given data sources to be mined. The primary goal of association mining is to find common patterns and investigate association rules. There are a variety of association rule mining algorithms available, each with its own set of performance factors. Advanced of the association rules data structure format based on horizontal or vertical. Both structure formats are extensively applied in several association rule algorithm to attain the least execution time and minimum memory consumption. One of the established algorithms for association is Equivalence Class Transformation (Eclat). Deep learning (DL) has exploded as the current technology for mining of large amount of data from sources such as social media, internet, e-commerce, and online movie theatres. This massive volume of information is easily accessible and can share via cloud computing. In response to big data mining issues, the DL algorithm is recognized to be the most potential techniques when it reaches to association rule pattern generation. In this paper, we reviewed and analyzed the fundamental Eclat algorithm in DL. These reviews would determine some alternative approaches of deep learning techniques may be adopted in Eclat to boost the least execution time and reduce memory.

Keywords: *Association Rule Mining; Deep learning (DL), Eclat algorithm, Frequent itemset*

1. INTRODUCTION

Deep learning especially useful when dealing with unstructured data because of its capability to process enormous amounts of data. Deep learning algorithms, on the other hand, may be excessive for simpler problems because they require massive amounts of data to be effective. ImageNet, for example, has over 14 million images to train for complete image recognition. A deep learning model can easily fail as a result of being overfit for generalise to new data in case data is incomplete. For many practical business problems, deep learning models do not appear to be as effective as other techniques. In some cases, deep learning might operate with lesser and organised datasets, such as multiclass classification. A deep learning example can be created by combining the deception detection system mentioned above. Layers of a social network layer add to each other in a way that would take years to process by a human. Open-source platform, image recognition apps and medical research infrastructure are just a few examples of how deep learning is making its way into our daily lives.

2. RELATED WORKS

Equivalence Class Transformation (ECLAT) [1, 2] is an acronym for Equivalence Class Clustering and bottom up Lattice Traversal [3], which uses depth-first search and a vertical layout, with every item represented by a set of transaction ID, tidset, whose transactions contain item. Intersect

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the tidsets of its items will create itemset's tidset. It's rough to use the Apriori's downward closure attribute because of the depth-first search. Using tidsets, there will be benefit of eliminating needs for counting support because an itemset's support is determined by the sizes of the tidset that represents it and the sizes of tidset is really important because Eclat's major objective want to intersect tidset. There will influencing the program's execution time and the usage of memory. Larger datasets necessitate more time and memory.

As [5] proposes a new vertical data structure called Diffset. Also introduces dEclat, an Eclat-based algorithm using diffset, building on the work of [4]. The use of diffsets has lessened considerably the size of the set, making set processes much quicker. dEclat has demonstrated significant performance and the usage of the memory improvements above Eclat, particularly on compact databases. Diffset mislays its benefit over tidset when dataset is sparse. As a result, the researchers recommend that sparse databases start with tidset format, then switch to diffset format once a substituting condition is encountered. Vertical Itemset Partitioning for Efficient Rule Extraction (VIPER) [6] has been proven to surpass an optimum horizontal algorithm. Apriori algorithm of the characteristics of all frequent item sets has been complete by VIPER and just needs to find the frequency for association rule mining.

Following up from the work done in [4, 5], the authors developed a new method for vertical representation in which they cast-off a mixture of tidset and diffset. To represent databases, the diffset was sorted in decreasing order. [7]. It is claimed that the approach removes the requirement to check the exchanging condition and convert tidset to diffset format nonetheless of database condition (sparse or dense). Furthermore, the mixture can completely leverage the benefits of both the tidset and diffset formats, with preliminary findings indicating a decrease in regular diffset size and database processing pace. Despite confronting support in frequent item mining, [3] proposes an enhanced research in which a support count conjecture and traditional Eclat improvement are obtainable. Introduced the new-fangled Bi-Eclat algorithm classified according to support. Items in transaction cache are in decreasing order based on frequency, whereas during the support count, itemsets go in ascending order of support. When tested on a number of publicly available datasets, it outperformed traditional Eclat.

Inspired by vertical format to gain quicker support (frequency) of itemset, the author in [8] introduces Postdiffset algorithm that mines in tidsets format for the first level while mining in diffset format the next level onwards. The performance (in execution time) of mining itemsets are compared between traditional Eclat (tidset) [4], dEclat [5], sortdiffset [7] and Postdiffset, and yet, Postdiffset turns to be the third after dEclat and sortdiffset [7]. The performance results vary depending upon the occurrences of each itemsets either in dense or sparse datasets. For optimization purposes, author in [9] has summarized few alternatives such as item reordering [10], partitioning [11], sampling [12] and FP-Tree (frequent pattern tree) [13], are yet to be justified.

In this paper, the objective is to find the discrepancies in traditional Eclat-based algorithm, and the initiative is to offer the opportunity on the improvement specially in the filtering itemset criteria with the use of deep learning (DL) algorithms. Among the DL algorithm reviewed are Deep Convolutional Neural Network (DCNN) and Deep Non-Nested Generalized Exemplars (NNGE), Partial Tree (PART), Modified Decrease Support of LHS Item Using ECLAT (MDSLE) and Frequent Vertical Compressed Transaction Database Algorithm (FREQVCTDB). These efforts are focusing on improving the matching accuracy and execution time complexity through the memory space reduction and minimizing transaction modification.

3. DEEP LEARNING ALGORITHM

3.1 Deep Convolutional Neural Network (CNN)

The traditional concept of CNN [14] for classification has transformed to a modern approach for feature selection. Handling lots of data with multiple class identities can only be classified with a multi layers network. Learning large array of features has implementation problems which result in computation cost and lack of efficiency. Decomposing large feature arrays is significant method to address the above issue. Detecting the code word and data point, those are highly correlated in a typical scenario. All data points and code works represented by a feature set can be normalized ‖ xj ‖2= ‖ bi ‖2= 1 I≤ j ≤ n, 1 ≤ i ≤ m, x1 and x2 are two points in the region X. An optimal solution for reducing the dictionary size is done with the code word formation. A code word collectively represents multiple data points. The approach data is represented has a big influence on how well deep

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learning algorithms work. Every piece of data must be regarded as a feature. This depends on representation in a general phenomenon that appears throughout deep learning. When designing features or algorithms for machine learning, our goal is usually to identify and separate the factors that make variations in feature classifications [14]. These factors mainly depend upon the sources of data and the methods used to generate data also.

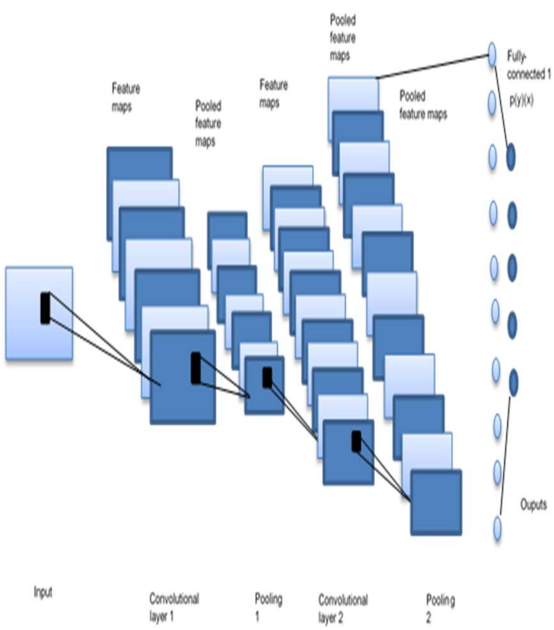

Figure 1: The Basic Functionality of CNN

Based on Fig.1, The convolutional layer's main purpose to be identify local conjunctions of preceding layer features and a feature map of their appearance. Convolution in neural networks splits the image into perceptions, which creates local receptive fields before compressing the perceptions into $m2 \times m3$ feature maps. Hence, this map keeps track of wherever the feature appears within image and how far it fits the filter. Thus, each filter is spatially prepared in relation to the location within the capacity in which it is used, and each layer has a store of m1 filters. The depth of the volume of output feature maps corresponds to the amount of filters used in single phase. Five convolutional layers, three filters, and three fully connected layers made up a successful deep learning model. With drop out values, the learning rate was observed. A higher level of accuracy was achieved, and the proportionality of build time in relation to the number of features was studied [14]. The proposed work can face many challenges in the medical field because it is an excellent classification and attribute selection method. With the chosen data set, the outstanding performance and results establish the proposed concepts experimentally and theoretically.

3.2 Deep Non-Nested Generalized Exemplars (NNGE)

NNGE [15] is a learner that is based on instances and hybrid technique that joins the Nearest Neighbor classifier concept with the rule-based classifier. A group of generalised exemplar or hyper-rectangles is generated. Generalised exemplar is an example's collection those may regarded in the role of a classification rule [16]. Considering the purpose of producing a generalised exemplar, it borrows the closest neighbor's distance function element and calculates the correlation among the generalised instance and a training set instance. The resemblance amid a hyper-rectangle and an instance does not have to be identical, and it might be partial based on a distance function. Nonetheless, the NNGE's distance function for computing similarity is stated in equation. (1) to equation (4) as denoted by [17].

$$E = -\sum_{I=1}^{20} p_i \times \log_2 p_i \tag{1}$$

$$D(E,H) = W_h \sqrt{\sum_{j=1}^{n} \left(W_j \times \frac{E_j - H_j}{maxval_j - maxval_j} \right)^2} \tag{2}$$

$$(E_j - H_j) = \begin{cases} E_j - H_{upper} & E_j > H_{upper} \\ H_{lower} - E_j & E_j - H_{lower} \\ 0 & otherwise \end{cases} \text{In case} \tag{3}$$

of numerical attributes

When it comes to nominal characteristics,

$$(E_j - H_j) = \begin{cases} 0 & E_j \in H_j \\ 1 & E_j! \in H_j \end{cases} \tag{4}$$

Based on equation above, P_i is the porbabiliity, E_j is the j^{th} example's feature value, W_j stand for the weight of hyper-rectangle j^{th} feature, W_h goes for the mass of hyper-rectangle and H_j will be j^{th} feature value of hyper-rectangle. The $maxval_j$ and $minval_j$ are the maximum and minimum boundaries for the

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j^{th} feature value of instance and H_{lower} and H_{upper} are the minimum and maximum boundaries for the j^{th} feature value of hyper-rectangle. Nevertheless, IB4 is the features system for calculating weights that applied [15]. NNGE is a straightforward and dominating predictor that can help accelerate the classification process, which is why it was proposed for protein complex prediction. [17]. As a result, it does not create overlapping hyper-rectangles during the model modification and generalisation phases, which enhances accuracy and augments the classification process. Thus, in terms of precision and complexity of time, the findings prove NNGE surpasses the current schemes (i.e., Random Forest and Probabalistic Bayesian Network). Because of NNGE's capability to handle sequential data, it is well-suited with datasets in which each situation is represented as a set of circumstances in chronological direction [18].

3.3 Partial Tree (PART)

Few methods for generating predictions using a rule set have been investigated. C4.5 [15, 19] and RIPPER [15, 20] are two of the most popular approaches. These methods produce a generalised set of classification rules. Furthermore, they both imply double phases in making generalised set of rules. They generate an initial rule set in the first phase, and then use a comprehensive elevating policy to adapt or abandon these rules in the second [15]. C4.5, for instance, generates an upruned decision tree before converting to a set of rules. For each parent-to-child connector path, a rule is generated. Then, to make each rule more simples individually, a rule-ranking method is used. Finally, until the rule set's error rate on training instances decreases, rules are remove. For rule generation, RIPPER employs a divide-and-conquer method. It merely generates single rule at a time, and remove the occurrences from the training set that this rule covers. It will keep generating fresh rules until the training set contains no more instances. To build a rule, PART [15, 21] creates a limited decision tree based on the provided collection of instances. To prevent global optimization, the leaf with the highest coverage is usually induced, and the generated partial decision tree is deleted. The induced rule-covered occurrences from the training set are also removed. This process is repeated until the training set is depleted of instances. The simplicity of PART as a prediction method is the driving force behind it. It does not require global optimization, which reduces the time complexity and improves the efficiency of the performance [21]. Furthermore, the literature [14, 22] shows that tree-based approaches to prediction are becoming more popular. As a result, higher prediction results may be obtained when PART, a hybrid method that infers a rule set from a decision tree, is used. PART, however, surpasses other current methods in relations of time complexity and accuracy, such as Random Forest, a tree-based approach, and Probabilistic Bayesian Network.

3.4 Modified Decrease Support of LHS Item Using ECLAT (MDSLE)

A hybrid method that uses the ECLAT algorithm with a heuristic technique to obscure sensitive rules. MDSLE is the name given to this hybrid algorithm (Modified Decrease Support of LHS item using ECLAT) [23]. To accelerate the association rule hiding processes, this algorithm is applied [24]. The following are the stages of the MDSLE algorithm. The very first stage involves preprocessing a decentralized database in which only non-private items are submitted to the method for producing frequent item sets. The ECLAT method is utilised to generate frequent item sets in this case [25]. ECLAT algorithm is given minimum confidence and minimum support as input in the second stage. For generating frequent item sets, a depth first search approach is used [26, 27]. Frequent item sets is generated [28] in the third stage, using the minimum confidence, minimum support and distributed database that has been processed as input. As a result, the generated item sets have more or equivalent support than the minimum support. The frequent item sets generate association rules in the fourth stage. The primary objective of the fifth stage is to find the rules that contains the item that frequency in the actual database must be decreased. A sensitive item is one of these, and such rules that contains referred to as a sensitive rule. The sensitive rule, ($A \rightarrow B$), from generated rules is selected. Additionally, the LHS [23] item is investigated as a sensitive item. 'A' is a sensitive item in this case. In the sixth step, select ‘A' from the LHS. Next stage, a sanitized database is obtained from the use of technique for hiding heuristic association rules, lowers ‘A' and ‘B' support through lowering the left side support of item ‘A', then lowering the rules confident whereas ‘A' and ‘B' occur below its minimum confidence. As a result, changing the LHS value in transaction can lower its support. The number of transactions that need to be changed that contain sensitive items is determined. The sensitive item's support count is reduced by removing A from the transactions. The sanitised database could be

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obtained in the last stage with removing the sensitive item or changing the item value with "*" in the selected transactions. Other transactions will have no effect on the value of the items involved [23]. The generation of the sensitive rule will be prevented if association rule mining is performed with sanitised database that minimum support and confidence are equal. As a result, when the database is processed using the association rule mining technique, the MDSLE algorithm protects the user's personal information from being revealed. MDSLE algorithm was tested on a distributed medical database, with the goal to reduce the value of modified transactions when using a heuristic association rule hiding algorithm [23]. The MDSLE algorithm also discovered to be extensible as the transactions value increased. Therefore, MDSLE framework concentrates on reducing the time to execute and minimising transaction through efficient hiding of sensitive rules of a single item [23].

3.5 Frequent Vertical Compressed Transaction Database Algorithm (FREQVCTDB)

The main purpose is to conserve memory space while compressing frequently used items. Run-length encoding [29] is primarily applied in image compression, however the aim here is on implementing frequent pattern mining by constricting frequent items in a dense and effective style. When compared to horizontal compression, vertical compression is superior. The vertical data layout, referring to several writers, outperforms the horizontal data layout by a significant margin. When executing RLE in the algorithm, the vertical data layout has been considered. In the sense that their contraction is minimal, the finish set of original frequent patterns can be improved. To compress the original transactional data, the CT-Apriori [22] algorithm employs a compact tree structure known as CT-tree. The CT-Apriori algorithm, which is developed from the Apriori algorithm, may create common patterns rapidly by avoiding the initial database scan and saving a considerable amount of I/O time every database scan. The FREQVCTDB Algorithm is developed in three stages. Stage 1 is Transaction Database Recompression, which involves transposing vertical data layout from a horizontal data layout. Stage 2 involves Determining the Transaction's Statistical Properties, one of which is the database's density. Maximum density and Minimum density are two types of density. Stage 3 is database compression using RLE, which compresses all of the columns in TDB and stores each column in its own output file. Merge all columns in the output file recursively to create a single compressed dataset. Using the FREQVCTDB algorithm, calculate the amount of compression in order to determine how much space is saved. It is calculated using the Space Savings Ratio (SSR) as in equation (5), which is defined as the ratio between the sizes of the original transaction database (So) and the compressed transaction database (Sc) [29].

$$\text{Space Savings Ratio} = 1 - \frac{\text{size of the Compressed database (S}}{\text{size of the Original database (So)}} \quad (5)$$

It can also be used to calculate the cost savings from a smaller database. Prior to optimization, a statistical examination of the features of the input data was carried out. The analysis was carried out using three methods: Density, Distance, and Entropy [29]. The efficiency of runtime performance of the suggested algorithms was estimated using a best-case and worst-case analysis. The obtained results may be more subjective rather than fully complete insights, which would be incompatible with the aforementioned caveats. As to recapitulate, the review and analysis of deep learning algorithms is summarized in Table 1.

For our next research, we would discover on having deep convolutional neural network (DCNN) in Eclat by introducing few layers in multi-filtering algorithm of true candidate itemsets. This could be conducted via the implementation of Keras framework in Tensorflow with our database integration of breast cancer dataset, a benchmark dataset which is publicly available. This future-to-be experimentation is vital in diagnosing the feasibility of our proposed algorithm in deep learning environment.

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Table 1: Reviews Summary of the Mining Strategies

Approach	Mining Strategy	Data source	Techniques	Advantages	Disadvantages
Deep Convolutional Neural Network (CNN)	Deep Learning	Transaction data	Applying a filter to an input results in the creation of a feature map, which summarises the presence of detected features in the input.	Better accuracy and proportionality of build time with regard to the number of features	Requires a large Dataset to process and train the neural network
Non-Nested Generalized Exemplars (NNGE)	Deep Learning	Transaction data	The distance between a new instance and a collection of exemplars is used to classify the new example.	Improve the accuracy and reduce time complexity	Large volumes of data create problems to the scalability of any detection system.
Partial Tree (PART)	Deep Learning	Transaction data	RIPPER's separate-and-conquer strategy is implemented and combined with C4.5.	Improve the accuracy and reduce time complexity	A minor adjustment in the data can result in a significant adjustment in the structure, resulting in instability.
Modified Decrease Support of LHS item using ECLAT (MDSLE)	Deep Learning	Transaction data	Remove the sensitive item value to sanitise the database from selected transactions.	The efficient hiding of sensitive rules for a single item, may improve execution time and minimize transaction modification.	Cannot select multiple items to hide.
Frequent Vertical Compressed Transaction Database Algorithm (FREQVCTDB)	Deep Learning	Transaction data	With Run-length Encoding in vertical data layout, save memory space while compressing frequently used items.	Reduce the original database's size.	Not suitable with sparse dataset

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4. CONCLUSION

Association rule mining relies heavily on the frequent item sets to generate from a dataset. The most often used algorithm is the Apriori algorithm for generating frequent item sets. However, as the database grows, the value of database scans that must be performed grows as well, lengthening the execution time. From this critical review, combining deep learning and the Eclat algorithm to generate frequent item sets is a good idea because it requires fewer database scans, giving a great result in performance and reducing execution time. This inspires the future work of applying deep learning with Eclat algorithm. As for the accuracy, filtering technique has the advantage as deep convolutional neural network (CNN) provided. In term of time reduction, mostly deep learning approach give a great result by suppressing the dataset. Those result gave us huge indication in choosing the convenient deep learning approach in our next research with Keras framework in Tensorflow. One machine learning open-source software library called XGBoost, that provides a gradient boosting framework for several scripting such as C++, Java, Python, R, Julia, Perl, and Scala. Operable in Windows, it offers a scalability, portability and provides for a Distributed Gradient Boosting library. We hope to give some improvement result as deep learning contributes to a significant future study with our database integration of breast cancer dataset.

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REFERENCES

[1] M. J. Zaki. “Scalable algorithms for association mining”. IEEE Transactions on Knowledge and Data Engineering, 12(3), 372–390, 2000.

[2] J. Han, H. Cheng, D. Xin, and X. Yan. Frequent pattern mining: current status and future directions. Data Mining and Knowledge Discovery, 15(1), 55–86, 2007.

[3] X. Yu and H. Wang. “Improvement of eclat algorithm based on support in frequent itemset mining”. *Journal of Computers*, 9(9), 2116–2123, 2014.

[4] M. J. Zaki, S. Parthasarathy, M. Ogihara, W. Li et al. “New algorithms for fast discovery of association rules”. *In Proceedings of the ACM SIGKDD international conference on Knowledge Discovery and Data Mining (KDD'97)*, 283–286, 1997.

[5] M. J. Zaki and K. Gouda. “Fast vertical mining using diffsets”. *In Proceedings of the ninth ACM SIGKDD international conference on Knowledge Discovery and Data Mining*. 326–335, 2003.

[6] P. Shenoy, J. R. Haritsa, S. Sudarshan, G. Bhalotia, M. Bawa, and D. Shah. Turbo-charging vertical mining of large databases. ACM SIGMOD Record, 29(2), 22–33, 2000.

[7] T. A. Trieu and Y. Kunieda. “An improvement for declat algorithm”. In *Proceedings of the 6th International Conference on Ubiquitous Information Management and Communication* (ICUIMC'12), 54, 1–6, 2012.

[8] WA. Bakar, MA. Jalil, M. Man, Z. Abdullah, F. Mohd. “Postdiffset: an Eclat-like algorithm for frequent itemset mining”. International Journal of Engineering & Technology. 2018;7(2.28):197-9.

[9] B. Goethals. Frequent set mining. In Data Mining and Knowledge Discovery Handbook, Springer, 321–338, 2010.

[10] C. Borgelt and R. Kruse. Induction of association rules: Apriori implementation. In Compstat, Springer, 395–400, 2002.

[11] A. Savasere, E. R. Omiecinski, and S. B. Navathe. An efficient algorithm for mining association rules in large databases. In Proceeding of the 21th International Conference on Very Large Data Bases (VLDB '95), 432–444, 1995.

[12] H. Toivonen. Sampling large databases for association rules. In Proceeding of the 22nd International Conference on Very Large Data Bases (VLDB '96), 134–145, 1996.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

[13] J. Han, J. Pei, Y. Yin, and R. Mao. "Mining frequent patterns without candidate generation: A frequent-pattern tree approach". *Data Mining and Knowledge Discovery*, 8(1), 53–87, 2004.

[14] Anil K.R, Gladston Raj S. "A Deep Learning based Feature Selection Method with Multi Level Feature Identification and Extraction using Convolutional Neural Network". IAETSD Journal For Advanced Research In Applied Sciences, ISSN NO: 2394-8442, 2017.

[15] Misba Sikarndar, Waqas Anwar, Ahmad Almogren, (Senior Member, IEEE), Ikram Ud Din, (Senior Member, IEEE), and Nadra Guizani. "IoMT-Based Association Rule Mining for the Prediction of Human Protein Complexes". IEEE Transactions on Knowledge and Data Engineering, 2020.

[16] H. A. Kholidy et al., "Attacks detection in SCADA systems using an improved non-nested generalized exemplars algorithm," 2017 12th International Conference on Computer Engineering and Systems (ICCES), 2017, pp. 607-612, doi: 10.1109/ICCES.2017.8275377.

[17] B. Martin, ''Instance-based learning: Nearest neighbour with generalization,'' Dept. Comput. Sci., Univ. Waikato, Hamilton, New Zealand, Tech. Rep. No.95/18, 1995.

[18] U. Adhikari, T. H. Morris and S. Pan, "Applying Non-Nested Generalized Exemplars Classification for Cyber-Power Event and Intrusion Detection," in IEEE Transactions on Smart Grid, vol. 9, no. 5, pp. 3928-3941, Sept. 2018, doi: 10.1109/TSG.2016.2642787.

[19] S. L. Salzberg, ''C4.5: Programs for machine learning by J. Ross Quinlan. Morgan Kaufmann Publishers, Inc., 1993,'' Mach. Learn., vol. 16, no. 3, pp. 235–240, Sep. 1994.

[20] W. W. Cohen, ''Fast effective rule induction,'' in Machine Learning Proceedings 1995. Amsterdam, The Netherlands: Elsevier, 1995, pp. 115–123.

[21] E. Frank and I. H. Witten, ''Generating accurate rule sets without global optimization,'' in Proc. 15th Int. Conf. Mach. Learn., Morgan Kaufmann Publishers, San Francisco, CA, USA, 1998, pp. 144–151.

[22] Kalpana.B. et. al., A Study on the Performance of CTAPRIORI and CT-PROAlgorithms using Compressed Structures for Pattern Mining, Journal of Global Research in Computer Science Volume 1, No. 2, September 2010.

[23] Melissa Fernandes and Joanne Gomes. "Heuristic Approach for Association Rule Hiding using ECLAT". 2nd International Conference on Communication Systems, Computing and IT Applications (CSCITA), 2017.

[24] Marathe Shashank S, Manjusha Yeola, "Generating and Hiding Sensitive Association Rules," International journal of Advance Foundation and Research in Computer (IJAFRC), Volume 2, Issue 5, May - 2015.

[25] Manjit Kaur, Urvashi Garg, Sarbjit Kaur, "Advanced Eclat Algorithm for Frequent Itemsets Generation," International Journal of Applied Engineering Research, ISSN 0973-4562 Volume 10, Number 9, pp. 23263-23279, 2015.

[26] Man, Mustafa & Wan Abu Bakar, Wan Aezwani & Jalil, Masita & Jusoh, Julaily. (2018). Postdiffset algorithm in rare pattern: An implementation via benchmark case study. International Journal of Electrical and Computer Engineering. 8. 4477-4485. 10.11591/ijece.v8i6.pp.4477-4485.

[27] Garg, Kanwal & Kumar, Deepak. (2013). Comparing the Performance of Frequent Pattern Mining Algorithms. International Journal of Computer Applications. 69. 21-28. 10.5120/12129-8502.

[28] Pramod S.,O.P. Vyas, "Survey on Frequent Item set Mining Algorithms", International Journal of Computer Applications (0975 - 8887) Volume 1 – No. 15, 2010.

[29] A. MEENAKSHI. "A Novelty Approach to Compression of Frequent Transaction Items by using Statistical Methods in Vertical Data Layout". 2nd IEEE International Conference on Engineering and Technology (ICETECH), 2016.