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Predicting Autism Spectrum Disorder using Machine Learning Technique

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Abstract: Autism Spectrum Disorder (ASD) is a psychiatric disorder that puts constraints on the ability to use of cognitive, linguistic, communicative, and social skills. Recently, many data mining techniques employed to serve this domain by determining the main features of the condition and the correlation between them. In this article, we investigate the Association Classification (AC) technique as a data mining technique in predicting whether an individual has autism or not. Accordingly, seven well-known algorithms are selected to conduct analysis and evaluation of the performance of the AC technique in term of identifying correlations between the features to help decide early on whether an individual has autism; this is particularly significant for children. The evaluation for the behavior and the performance in the prediction tasks for the AC algorithms was conducted for the common metrics of including Precision, Accuracy F-Measure as well as Recall. Finally, a comparative performance analysis among the algorithms was used as final result for the study. The results show better performance for the WCBA algorithm in most test scenarios with accuracy of 97 % although, the majority of algorithms exhibited excellent accuracy when applied in this domain.

Keywords: Association Classification, Autism Spectrum Disorder, Association Rules, Classification.

I. INTRODUCTION

Data Mining is considered one of the most prominent fields in computer science, it aims to discover hitherto unseen insights or patterns in small, moderate and big datasets thus leading to enhanced decision making processes in many fields (Alwedyan *et al* 2011). Several modelling techniques exist in Data Mining including regression, classification, association rules, clustering, as well as Association Classification (AC) (Abdelhamid et al., 2014; Ma et al., 2014; Taware et al., 2015; Srinivas et al., 2018). In the proposed here, the authors will analyze the impact of the AC technique on enhancing the decision-making process in the Autism Spectrum Disorder (ASD).

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The AC technique generates simple and more understandable rules that have positive effects on the accuracy of the classifier or on enhancing the decision-making process inside the organization; this makes this technique more attractive for researchers. However, the AC technique has a disadvantage due to the large number of association rules it normally generates hence requiring additional time and storage than other, traditional data-mining techniques.

Furthermore, most of the AC algorithms tend to be affected by the content of the datasets such that it makes most of these algorithms behave in an unstable way once applied to different datasets or domains (Tan et al., 2006; Hadi, 2013; Abdelhamid et al., 2015; Wadhawan, 2018).

It is worth mentioning that the AC technique has been deployed in different regions or domains; one of the most critical domains that has not yet been investigated sufficiently by researchers is Autism Spectrum Disorder (ASD) which is a “brain development disorder that limits communication and social behaviors” (Bolton et al., 1994; Thabtah, 2017). Examples of clinical diagnosis approaches are “Autism Diagnostic Interview” (ADI) (Lord et al., 1994) and “Autism Diagnostic Observation Schedule-Revised” (ADOS-R) (Lord et al., 2000). On the other hand, and to enhance the accuracy of ASD diagnosis, researchers recently adopted machine-learning approaches (Bone et al., 2014; Duda et al., 2016; Wall et al., 2012a; Wall et al., 2012b), approaches in which the following goals can be achieved dramatically:

- Improving classification accuracy.
- Reducing the screening time.
- Identifying the minimal number of ASD codes that reduce the complexity of the problem.

Furthermore, data mining offers automated classification models for ASD that are effective and efficient. These models combine several search algorithms from computer science (Thabtah, 2007; Thabtah, 2011)]. Researchers have recently developed a number of data mining techniques for the ASD issue, e.g. support vector machines (Platt, 1998), decision trees (Quinlan, 1993), rule neural network (Mohammad et al., 2014), and classifiers (Abdelhamid and Thabtah, 2014). ASD diagnosis is regarded as a typical data mining classification task because we can build a model from previously classified instances. The diagnosis of a new instance (ASD, No-ASD) can then be predicted using this technique. The main aim of this article is to compare seven AC algorithms and apply them to an adult autism dataset. A comprehensive experimental study using adult autism UCI dataset will be presented to compare and evaluate well-known association classification algorithms based on their precision, recall, accuracy and F1 measures, this will in turn show the overall performance for such algorithms in the autism domain.

Relevant work to this area is presented in Sections 2, meanwhile section 3 covers experimental results in detail and finally, section 4 is about conclusions as well as any proposed future work.

1. Background: Data Gathering and Mining in Healthcare (Autism)

Smartphones, tablets and portable computing devices have a link to health of children in many ways: The common, prevailing perception about the impact of these devices is that frequent consumption and excessive use of such devices impact the quality of life and health of children in several, adverse ways. These tend to affect sleep quality, propensity for obesity, overall fitness, "musculoskeletal pain, ocular health, and migraine/headaches" (Domoff *et al* 2019).

(Liu *et al* 2017) analyzed the impact of mobile devices and negative emotions among Chinese adolescents by extending current research asserting links between mobile use and negativity of emotions. The authors extended current research work to investigate the "mechanisms underlying" the association as well as conducting comparative analysis of mobile effects on addict groups vs. non-addict groups. Their work concluded that adolescent groups addicted to mobile phone use a) tend to spend a lot more money on mobile phones and, b) that these groups were more susceptible to negative emotion.

According to (Davidovitch *et al* 2018): Autism Spectrum Disorder (ASD) is not only linked to children's excessive access to smartphones, rather that factors like eye contact constitute essential ingredients in the healthy growth of infants. This eye contact with parents (joint attention) is affected adversely during their preoccupation with their own mobile devices when around their children, especially if the children are already predisposed to Autism.

In contrast, another, less common effect of mobile, digital devices is as instruments used by practitioners and researchers in order to measure the daily behavior patterns in children. (Jones et al., 2018) utilized smartphones to provide caregivers with data about children's behavior including anxiety, irritability and mood variations. This enabled the efficient gathering of data with 2 weeks of data collection with smartphones showing similar quantity and quality of gathered data equivalent to 8-weeks with traditional methods.

The role of data mining in support of healthcare varies with the requirements and the available technologies and also with the availability of quality (and volume) data. Nonetheless, caretakers, medical practitioners and therapists benefit immensely from new developments in this area which provides support to help understand learning styles as well as provide a good basis for designing bespoke programs for early detection and intervention planning (Vellanki et al., 2017).

The past few years have seen the introduction of several techniques purporting to address symptoms of Autism Spectrum Disorder (ASD), including techniques that utilize technology for screening and rehabilitation. (Golestan et al., 2018) present a review and analysis of previous studies in this area and classify their findings into three categories plus sub-categories. Their work serves to provide a review reference of prominent approaches for different technology based solutions related to screening, assessing and rehabilitation of ASD.

II. LITERATURE REVIEW

Associative Classification (AC) is the 2nd generation of the association rule techniques, and it is important and essential in order to enhance the classifier performance on the mined Class Association Rules (CARs). The association rules technique help in finding the association between attributes presented in the dataset that best match the classes of the data instances, while classification process utilizes the set of generated class association rules for the purpose of predicting the class label. Furthermore, and to design a classification model with higher accuracy, all of the AC algorithms go through three primary stages of rule generation, pruning and prediction (RGPP) (Alwidian *et al*., 2018).

While adopting association rules in the classification process includes RGPP, many algorithms through the literature amend those stages into further implementations in order to gain better accuracy for the classification final results. The "Classification Based on Association Rules (CBA)" algorithm as introduced by (Liu *et al* 1998), this algorithm is built depending on the previous mentioned and it uses Apriori algorithm to generate the itemset that represent (CARs) and satisfy the rules estimation measures (Minimum Support and Minimum Confidence). However, this algorithm lacks the efficiency needed when the dataset to be processed is not resident in local, main memory; such inefficiency results due to the need to make multiple passes against the dataset during rule generation and evaluation by the algorithm.

Accordingly, researchers in the field try to solve the multiple pass issue with new, enhanced methods and techniques, authors in (Pie, 2001) introduced an efficient approach for frequent rule mining in their "Classification Based on Multiple Class-Association Rules (CMAR)" algorithm for mining large datasets by constructing a class distributed-associated FP-tree. In addition, the authors adopted a CR-tree to preserve the structure of mined association rules and to enhance the storing and the retrieving processes, alongside adopting other rules pruning measures based on correlation rates, confidence as well as database coverage. This is in order to achieve higher accuracy from the classification model when predicting new class labels. CMAR produced better accuracy when compared to C4.5 and CBA models.

(Thabtah et al., 2005) proposed the (MCAR) algorithm, which can circumvent dataset passes issue. In MCAR, a single itemset will be generated using traditional procedure from the CBA algorithm. Also, facilitating the next itemset-generation process that alleviates the need for extra scanning of the dataset implemented by storing the occurrence positions for each item. MCAR adopts rule ranking method to ensure that high confidence, detailed rules will be presented during the classification process, in order to minimize the randomization decision when selecting between two or more rules.

Finding the best frequent patterns, alongside the optimum, minimal confidence and support play a critical role in the process that evaluates rules for CBA and MCAR, while other points are also noticed through the literature, for instance,

"Fast Associative Classification Algorithm (FACA)" was proposed in (Hadi et al., 2016). The authors managed to enhance the speed of model building, and sort the rules generated, alongside considering the confidence and support for the generated rules. To increase the classification accuracy, FACA divides the matched set of rules into clusters in order to simplify selecting the class label with highest number of rules.

From another perspective, authors in (Alwidian et al., 2016), proposed the Enhanced CBA (ECBA) algorithm that showed better performance among the above mentioned algorithms in terms of accuracy, the authors adopted optimizing Apriori algorithm, alongside implementing some statistical measures for ranking the rules such that they can obtain better accuracy performance. Work by the same authors outperformed the aforementioned algorithms (CBA, CMAR, MCAR and FACA) in terms of scalability, accuracy and the time taken to build the model (Alwidian et al., 2016).

The "Weighted Classification Based on Association Rules (WCBA)" algorithm which was introduced in (Alwidian et al., 2018), adopts a new approach for rule evaluation and prioritization through implementing an efficient weighted association classification technique, also statistical measures were adopted in order present a new prediction and pruning technique for accurate association rules generation. Also, WCBA's authors discussed problematic measures estimation done by the users and its effects on the classification accuracy for the model, the proposed algorithm exhibited consistently improved performance in comparison with the other algorithms on two breast cancer datasets.

In this view and based on the aforementioned issues, a comprehensive experimental study was conducted in this paper in order to show the performance achieved by the AC algorithms (CMAR, CBA, FACA, MCAR, FCBA, ECBA, and WCBA) and to facilitate comparing them among each other's.

III. EXPERIMENTAL RESULTS

Extensive analysis was performed against experimental results for the purpose of assessing the accuracy, F-measure, recall and precision as statistical measures for seven of the well-known AC algorithms early mentioned. Also, varying values for minimum support as well as minimum confidence were used in order to evaluate the reliability of the selected algorithms on autism adult dataset.

The specification of the experimentation environment includes a 4GHz i7 PC with a 16GB random access memory (RAM). The compared algorithms were implemented by the authors using Java in combination with the WEKA tool (Hall et al., 2009). Minimum Support together with Minimum Confidence parameters for the selected algorithms used in the three experiments were as follows:

1st experiment: 0.1 and 0.5;
2nd experiment: 0.1 and 0.6;
And 3rd experiment: 0.2 and 0.4) respectively.

A. Dataset

To evaluate the behavior of the selected AC algorithms in specific domain, the autism adult dataset (UCI repository). The autism dataset described by 21 attributes to cover 704 instances, where 515 instances classified under no autism class label and 189 instances under autism class label. Furthermore, the main features that are employed to describe this dataset are reported in table 1 with number of values for each attribute.

Table 1. Autism Spectrum Dataset features

Name of attribute	Number of values
A1_Score	2
A2_Score	2
A3_Score	2
A4_Score	2
A5_Score	2
A6_Score	2
A7_Score	2
A8_Score	2
A9_Score	2
A10_Score	2
Age	4
Gender	2
Ethnicity	11
Jaundice	2
Autism	2
country_of_res	67
used_app_before	2
Result	4
age_desc	1
Relation	5
class/ASD	2

B. Evaluation and Results

Our evaluation process presents a comparison of the average accuracy of CMAR, CBA, FACA, MCAR, FCBA, ECBA and WCBA algorithms. In addition, three well-known statistical measures (F1, Precision, and Recall) are used to reflect the overall performance for all of those algorithms on the Autism Adult UCI Dataset, where F1 is calculated using equation (1) to find harmony value between Precision and Recall measures.

$$\mathrm{F-measure} = 2 * \frac{Precision * Recall}{Precision + Recall} \qquad Equation(1)$$

Furthermore, Recall and Precision measures calculated using equations 2 and 3 respectively, as shown in table 2.

$$Precision = \frac{TP}{TP + FP} \qquad Equation\ (2)$$

$$Recall = \frac{TP}{TP + FN} \qquad Equation\ (3)$$

Table 2. Confusion Matrix of Classes

Class	Predicted as	
	Actual Class	**Other Classes**
Actual Class	True Positive (TP)	False Negative (FN)
Other Classes	False Positive (FP)	True Negative (TN)

Table 3 shows the performance of the considered AC algorithms in terms of Precision, Recall, Accuracy and F-measure, with WCBA outperformed the others in terms of accuracy and F-measure with values 85.2% and 84.5 % respectively. In addition to achieve second place in the Precision and Recall measures with values 75.3 % and 96.3% respectively. ECBA algorithm was ranked first in term of Precision with value 85.5 % and FCBA placed last in terms of Recall measure with value 96.6 %.

Table 3. Evaluation of CMAR, CBA, FACA, MCAR, FCBA, ECBA and WCBA algorithms using minimum support value: (0.1) and minimum confidence value: (0.5)

Algorithm	Accuracy	F-measure	Precision	Recall
CBA	0.827	0.794	0.805	0.827
CMAR	0.784	0.750	0.733	0.784
MCAR	0.838	0.835	0.832	0.839
FACA	0.852	0.874	0.846	0.905
FCBA	0.823	0.844	0.749	0.966
ECBA	0.796	0.769	0.855	0.699
WCBA	0.852	0.845	0.753	0.963

Table 4 and 5 emphasize on the outstanding performance for the WCBA algorithm in term of accuracy. Table 4 shows the performance of all algorithms when the minimum support and minimum confidence changed to 0.1 and 0.6 respectively. Increasing the value of the minimum confidence to reach 0.6 will affect the number of association rules that will be generated at the rule generation phase and this scenario used to trace the behavior of the considered algorithms under small number of association rules in the prediction phase. Moreover, the WCBA algorithm came in the first place in terms of F-measure as well as Recall in this experiment with values 88.6% and 97.2 % and the reason beyond this performance is the harmonic mean value that features during rule generation instead of the confidence and support measures.

Table 4. Evaluation of CMAR, CBA, FACA, MCAR, FCBA, ECBA and WCBA algorithms using minimum support value of: (0.1) and minimum confidence value: (0.6)

Algorithm	Accuracy	F-measure	Precision	Recall
CBA	0.827	0.794	0.805	0.827
CMAR	0.784	0.749	0.735	0.784
MCAR	0.838	0.835	0.832	0.839
FACA	0.822	0.823	0.796	0.852
FCBA	0.802	0.823	0.796	0.852
ECBA	0.8454	0.813	0.704	0.963
WCBA	0.8784	0.886	0.814	0.972

The outperformance of the FCBA algorithm presented in table 5 in terms of all measures, where it came in the first place in this experiment. In this experiment, the minimum support and minimum confidence values assigned to 0.2 and 0.4 to monitor the behavior of all selected algorithms in the average case. The outperformance for this algorithm in this case refers to types of rules that are generated in the rule generation phase, where this algorithm depends on generating the most general rules that may have good confidence and support at the early stages without going to increase the effort in the pruning phase to select the optimal rule that should pruned.

Table 5. Evaluation of CMAR, CBA, FACA, MCAR, FCBA, ECBA and WCBA algorithms using minimum support value: (0.2) and minimum confidence value: (0.4)

Algorithm	Accuracy	F-measure	Precision	Recall
CBA	0.788	0.753	0.738	0.788
CMAR	0.748	0.711	0.712	0.748
MCAR	0.819	0.795	0.791	0.819
FACA	0.8112	0.823	0.796	0.852
FCBA	0.8436	0.874	0.846	0.905
ECBA	0.7895	0.778	0.857	0.71
WCBA	0.8436	0.822	0.850	0.796

Finally, all of the selected AC algorithms compared based on the average of accuracy for all experiments that shows the outperformance for the WCBA algorithm with average accuracy 85% while, the ECBA and CBA algorithms were second in terms of performance with average accuracy 81%. Lastly, the CMAR algorithm placed last with average accuracy 77%.

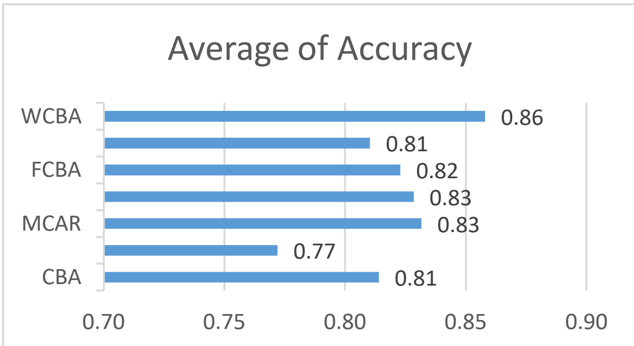

Figure 1. Evaluation of CMAR, CBA, FACA, MCAR, FCBA, ECBA and WCBA algorithms in term of average of accuracy

IV. CONCLUSIONS AND FUTURE WORK

Data mining techniques constitute essential aids in the decision-making processes in many critical areas such as the medical field, online phishing prevention, text analysis, social media, and many others. Seven well-known AC algorithms were employed to reflect the overall performance for the AC technique in the autism spectrum disorder field.

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Based on that, all of these algorithms showed good performance in serving the autism patients, in addition to enhance the prediction process that decide if the person has autism spectrum disorder or not.

The WCBA algorithm outperformed all other AC algorithms in terms of four common statistical measures: Accuracy, Recall, Precision and F Measure. While, in all the experiments the performance for these algorithms was high and gave a strong indicator about the potential power of the AC technique in serving such critical domain. As future work, we will emphasize on further studies related to the potential power of the AC technique by proposing a new AC algorithm or modifying one of the existing AC algorithms, in order to achieve high level of accuracy when applied on such related domains.

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