Selection of Representative Instances using Ant Colony: A Case Study in a Database of Children and Adolescents with Attention-Deficit/Hyperactivity Disorder

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Keywords: ADHD, Attention-Deficit/Hyperactivity Disorder, Instance Selection, Ant Colony.

Abstract: Instance Selection (IS) helps select the most notable instances from the database, improving its characterization and relevance. In this context, this article applies the IS, using the Ant Colony Optimization (ACO) heuristic, to obtain more efficient classification models in the identification of school performance, in arithmetic, writing, and reading, of children and adolescents with Attention-Deficit/Hyperactivity Disorder (ADHD), characterized by excessive symptoms of inattention, hyperactivity, and impulsivity. The Random Forest, Neural Networks, KNN, and CART classifiers were used to evaluate the performance of the selection performed by the ACO method. With the ACO, it was possible to obtain a gain of 20 percentage points with the KNN ($K = 1$), in arithmetic, in the metric F-measure, referring to the upper class, the minority class. The results achieved show the excellent efficiency of the ACO in this study.

1 INTRODUCTION

Data Mining (DM) is the process of obtaining practical knowledge from a sufficiently large dataset in an automated or semi-automated manner. There are many processes in this field, mainly supervised learning, whose results are affected by the quality or size of the dataset used for knowledge extraction. Furthermore, many algorithms can become unfeasible in the face of a large data set.

The Data Reduction (DR) area defines a series of pre-processing tasks to handle the abovementioned problem. The primary function of DR techniques is to reduce the size of a dataset by selecting the most representative information (Pyle, 1999). Therefore, the main objective of DR techniques is to choose a representative subset of data that offers results with performance equal or better to the same experiments without the data reduction step (Garcia et al., 2014).

Instance Selection (IS) represents one of the main tasks in DR (Liu and Motoda, 2001). The role of IS is to select the most significant rows in the dataset. One usage of IS algorithms is to improve the characterization of instances. Consequently, it can be helpful for health-oriented databases applications such as Attention-Deficit/Hyperactivity Disorder (ADHD), creating a more representative model.

Attention-Deficit/Hyperactivity Disorder (ADHD) is a neuropsychiatric disorder characterized by the symptomatic triad: inattention, hyperactivity, and impulsivity, which is excessively manifested through behavior, and speech. In addition to these central behaviors, people with ADHD usually have difficulty organizing their daily tasks and regulating their emotions. The worldwide prevalence of ADHD is around 5.3% in children and adolescents and 2.5% in adults (da Silva et al., 2020; Retz et al., 2020). ADHD can harm the diagnosed individual's social, educational, and family life (Mattos, 2015). Decreased academic performance and success, social rejection, and relationship difficulties are often related to the disorder, which leads to considerable educational and social losses (Rangel Júnior and Loos, 2011).

Thus, the objective of this work is to apply the IS using the Ant Colony Optimization heuristic to ob-

Hott, H., Jandre, C., Xavier, P., Miloud-Aouidate, A., Miranda, D., Song, M., Zárate, L. and Nobre, C.
Selection of Representative Instances using Ant Colony: A Case Study in a Database of Children and Adolescents with Attention-Deficit/Hyperactivity Disorder.
DOI: 10.5220/0010843000003123
In *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2022) - Volume 5: HEALTHINF*, pages 103-110
ISBN: 978-989-758-552-4; ISSN: 2184-4305

tain more efficient classification models in identifying the school performance of people with ADHD - Attention-Deficit/Hyperactivity Disorder. In this context, we analyzed a database containing the performance of 266 children and adolescents in the following subjects: Arithmetic, Writing, and Reading. Furthermore, the Random Forest, Neural Networks, K-Nearest Neighbors (KNN) and Classification and Regression Trees (CART) classifiers were used to evaluate the efficiency of the selection performed by the Ant Colony method.

The article follows the following structure: in Section 2, the theoretical foundation is presented, which brings the main concepts related to work. The works related to the theme are covered in Section 3. Section 4 presents the methodology used, with a detailed description of the database and the pre-processing steps. Section 5 gives the discussions regarding the results found. Finally, in Section 6, the final considerations in this article are exposed.

2 BACKGROUND

2.1 Attention-Deficit/Hyperactivity Disorder

The characteristics of ADHD are related to a dysfunction of the brain's frontal lobe neurons, and its complex etiology stems from genetic and environmental factors. Its symptoms vary according to the stage of development of the disorder (da Silva et al., 2020; Jennum et al., 2020). Its diagnosis is made through symptomatology since there are no specific biomarkers that indicate it. Therefore, it is essential to differentiate the symptoms of the disorder with behavior characteristic of children of active age, such as excessive noise and running around, or even with symptoms of other disorders, such as anxiety and mood (da Silva et al., 2020).

ADHD individuals may have the predominantly inattentive subtype, which concerns only characteristics related to inattention. Or the predominantly hyperactive/impulsive subtype, which is characterized only by hyperactive/impulsive behaviors. Or the combination of both, which is the most prevalent of the subtypes. In this case, the individual has both inattentive and hyperactive/impulsive characteristics. It happens in about 62% of people with ADHD (APA et al., 2014; Cardoso et al., 2018). ADHD is usually noticed when the individual is of school age since it is the phase in which concentration is most necessary. However, its symptomatic signs may extend into adulthood (Santos and Vasconcelos, 2010).

The therapeutic follow-up of people with ADHD includes psychosocial and drug interventions. The symptoms of inattention, hyperactivity, and impulsivity can significantly impact academic development and the areas of neurodevelopment, psychosocial interaction, adaptive functioning, and emotional self-regulation of the individual. All of this can contribute to low self-esteem and the emergence of other difficulties in your life (Maia and Batista, 2021). Thus, the earlier diagnosis of ADHD and the implementation of therapeutic measures, the smaller the negative impact that the disorder may have on people with the disorder and its surrounding (Moreira and Barreto, 2017; Muzetti and de Luca Vinhas, 2017).

2.2 Instance Selection with Ant Colony

Instance Selection is one of the most critical preprocessing tasks that play a central role in the DR area. The main objective of IS is to find the minimum cardinality subset of the original samples whose execution of a Data Mining (DM) algorithm has a performance equal to or with less deterioration than compared with using the complete dataset (Liu and Motoda, 2001).

The IS problem is classified as an NP-hard problem, as it requires a thorough search of every possibility to find the best solution. Dealing with this high complexity requires a lot of research effort to find heuristics or approximate solutions that obtain acceptable results considering a reasonable time and computational resources.

The traditional IS approach in the literature uses neighborhood criteria to eliminate noisy or redundant instances. The traditional technics are focused on improving the performance of classifiers based on the nearest neighbors rule (Garcia et al., 2012). In this approach, an example is retained if it disagrees with the established metrics of similarity.

In addition to the classical approach, the use of constructive heuristics has also been successfully applied in IS, with emphasis on the evolutionary algorithms (EAs) (Derrac et al., 2010). However, in this work, we will use the well-known Ant Colony Optimization (ACO) (Dorigo and Stützle, 2004), another type of constructive heuristic not much explored for the IS task.

ACO is a search meta-heuristic proposed in Dorigo and Di Caro (1999), designed to tackle combinatorial problems, inspired by the foraging behavior observed in ant colonies in finding the shortest path between a food source and a nest. The main idea is that the self-organization principles that allow the highly coordinated behavior of natural ants can be exploited to coordinate groups of artificial agents that collaborate to solve computational problems. A pseudo-code of a basic ACO algorithm is described in Algorithm 1.

Algorithm 1: Basic ACO Pseudocode.

input: Any Combinatorial Problem
$InitializePheromoneValues(T)$;
$\mathfrak{s}_{bs} \leftarrow NULL$;
while *termination conditions not met* **do**
  $\mathfrak{S}_{iter} \leftarrow \emptyset$;
  for $j = 1, ..., n_a$ **do**
    $\mathfrak{s} \leftarrow ConstructSolution(T)$;
    if $\mathfrak{s}$ *is a valid solution* **then**
      if $f(\mathfrak{s}) > f(\mathfrak{s}_{bs})$ *or* $(\mathfrak{s}_{bs} = NULL)$ **then**
        $\mathfrak{s}_{bs} \leftarrow \mathfrak{s}$;
      end
      $\mathfrak{S}_{iter} \leftarrow \mathfrak{S}_{iter} \cup \{\mathfrak{s}\}$;
    end
  end
  $ApplyPheromoneUpdate(T, \mathfrak{S}_{iter}, \mathfrak{s}_{bs})$;
end
output: The best-so-far solution $\mathfrak{s}_{bs}$

ACO agents (artificial ants) represent stochastic construction procedures that incrementally generate the solution by adding opportunely defined solution components. In essence, an ACO algorithm initially transforms the search space into a graph linking the possible solution components. The colony then navigates over this graph building its candidate solution. The probability of an ant selecting the path to its next solution component is based on two properties: the heuristic advantage and the amount of pheromone present in it.

The core of an ACO algorithm is the T pheromone model used. The model defines τ_{ij} parameters for every possible path of the search space. These parameters represent the knowledge accumulated by the colony. A higher value in τ_{ij} indicates to an ant that choosing that path $\{i, j\}$ will lead to a high-quality region.

An ant increments the value of the pheromone parameters belonging to its current route. Consequently, a path that more agents choose has its pheromone values reinforced, increasing the probability that more ants will choose it in future iterations. This behavior implicitly deduces that good solutions are made with good solution components.

At the end of each iteration of an ACO algorithm occurs a simulation of pheromones evaporation by the environment. In this step, the amount of pheromones deposited in previous iterations reduces at a defined rate. Such a process helps to reduce the chance that the algorithm will early converge on local maxima.

As mentioned at the beginning of the section, IS is an NP-Hard problem that requires an exhaustive search to find the best set. In this way, we can also classify an IS as a combinatorial problem.

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Because of this property, we can easily define an ACO algorithm for the IS task. The input set instances can create the search graph that combines the decision components that represent adding a sample to the reduced set. In this way, the colony navigates the graph creating subsets of examples. A DM algorithm or another specified metric evaluates the subsets by the performance obtained.

3 RELATED WORKS

The IS approach with an ACO metaheuristic remains less explored in the literature than other constructive heuristics. Among the studies, two stand out for providing us with new ACO models for the IS task (ACO-IS).

Anwar et al. (2015) proposed a new ACO algorithm for the IS task called ADR-Miner. The new approach aims to improve the accuracy of the classification model provided as a parameter by selecting the most representative samples. The ADR-Miner has been validated in 20 public databases offering promising results that surpass classical IS approaches. Furthermore, in (Salama et al., 2016) the ADR-Miner was enhanced to perform the attribute selection task together.

The Ant-IS algorithm used in this work is an ACO-IS algorithm of the condenser type proposed in Miloud-Aouidate and Baba-Ali (2015) that uses ant colony principles to perform the IS. In addition, the technique uses a nearest neighbor classifier to assess the similarity between subsets generated by the colony. In experiments carried out with public databases, Ant-IS surpassed results obtained for classification models without IS.

On the educational theme, Li (2019) proposes an adaptive online learning model based on the ant colony algorithm, which seeks to better respond to people's demands for multimedia learning. Appropriate learning paths must match users' personalized information, including personal education background and learning style, catering to different student preferences, tastes, and knowledge levels, without the need for them to be aware of it. According to the author, the adaptive learning system based on an ant colony algorithm can help teachers develop personalized courses for different students and provide suitable learning objects, helping to improve students' academic performance and learning efficiency.

In the health area, the ant colony can help in the diagnosis of diseases. Selcuk and Alkan (2019) used the ant colony algorithm to aid in the accurate, effective, and automatic detection of microaneurysms, which are difficult to detect in color fundus images in the early stages of diabetic retinopathy. Accurate detection of these lesions is critical in the early diagnosis of this disease. The same procedure was also applied to five different image processing and clustering algorithms for performance comparison. The results show that the ant colony-based method proposed in this work successfully detects microaneurysms even in low-quality images, facilitating early diagnosis by specialists.

The related works help prove the effectiveness of using the ant colony, validating its application in work. However, the differential of this article is the use of the ant colony on a database focused on the school performance of students with ADHD.

4 MATERIALS AND METHODS

4.1 Description of the Database

The database was made available by a Brazilian University based on individual and family responses present in questionnaires. The sample is composed of students aged between 6 and 18 years old, with and without a diagnosis of ADHD. There are data related to health, financial conditions, parental care and education amongst others, in addition to the grades for each student's arithmetic, writing, and reading tests.

As the objective is to identify, from a posterior perspective, the academic profile of students in each discipline. The original database was divided into three, in which each class is represented by a discipline. After the split, there were some pre-processing steps:

- Exclusion of instances that had no value in the respective class. Table 1 presents the total number of instances in each discipline and also the number of instances distributed in High and Low.

Table 1: Number of instances.

Discipline	**Total instances by performance**		**Total instances**
	High	Low	
Arithmetic	70	189	259
Writing	59	203	262
Reading	47	177	224

- Filling in the missing data by the average, in numerical data, or by mode, in categorical features.
- Binarization of non-ordinal nominal features, that is, they were coded as the presence or absence of the characteristic.
- Attribute selection through the Genetic Algorithm (GA). In this step, the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) algorithm was chosen to find the best subset of features maximizing its fitness, in this case, the F-measure. To measure the F-measure, the classifier KNN was used, varying the value of the K in the range of [1-10]. The number of GA generations was the stopping criterion in analyzing the values that best fit the algorithm parameters. For each set of parameters, 10 different random seeds were used. The GA was implemented in the Python language, using the DEAP library, available from Université Laval (Fortin et al., 2012). Figure 1 shows which features will remain in each discipline after selecting the GA.

4.2 Ant Colony Description

The Ant-IS algorithm proposed in Miloud-Aouidate and Baba-Ali (2015) was used in the present work. This technique aims to condense as many instances as possible with a minimal negative impact on the performance of classification models. This method uses the ACO principles (Dorigo and Stützle, 2004) to perform the instance selection. In addition, the algorithm internally uses a nearest neighbor classifier (Cover and Hart, 1967) to validate the subsets selected by the colony.

In this way, each ant in the colony performs a parallel search in its neighborhood for nearby instances, which are also as close as possible to the initial search point. The IS was performed during neighborhood analysis, in which an ant randomly decides to include or not an instance in its reduced set.

There is a particularity between Ant-IS and other ACO methods. The number of ants used by the colony

Arithmetic
01. Is the student Catholic?
02. Does the student have/already had a food allergy?
03. Has the student had an accident?
04. Does the student undergo neurological monitoring?
05. Mother's schooling.
06. Is the father married?
07. Does the father live together with anyone?
08. Is there a family history of the mother's disorders?
09. Socioeconomic class.
10. Was there use of contraceptives during pregnancy?
11. Type of delivery.
12. Student performance on the IQ test.
13. Student performance at TDE in writing.
14. Mother's hyperactivity level.
15. The mother has some functional impairment.
16. Father's level of inattention.

Reading
01. Has the student gain/gained a lot of weight?
02. Is the student afraid to sleep alone?
03. Is the mother married?
04. Family history of disorders in second-degree relatives?
05. Length at birth.
06. Student performance at TDE in writing.
07. Parental level of indulgence.

Writing
01. Gender of the student.
02. Age of the student.
03. Is the student Protestant/evangelical?
04. Is the student Catholic?
05. School year.
06. Does the student have/already had a hearing problem?
07. Has the student gain/gained little weight?
08. Does the student have/had seizures or epilepsy?
09. Does the student have/had asthma or bronchitis?
10. Does the student do psychological counseling?
11. Does the student have frequent nightmares?
12. Does the student talk in his sleep?
13. Does the student live with his parents?
14. Does the student live with his mother and her partner?
15. Number of brothers.
16. Number of mother's partners.
17. Mother's age.
18. Is the mother single?
19. APGAR 5 minutes.
20. Did the student cry at birth?
21. Student performance on the IQ test.
22. Student performance at TDE in reading.
23. Student performance at TDE in arithmetic.
24. Parental level of indulgence.
25. Level of punishment.
26. Mother's level of inattention.
27. Symptoms of ADHD in the mother before 12?
28. Father's level of hyperactivity.
29. The mother's state of anxiety.

Figure 1: Features selected by the GA in each discipline.

is not defined as a user parameter, but rather one ant per instance is created. According to the algorithm's authors, given each instance as initial points, all path probabilities are explored without restricting the search to an initial condition.

The Ant-IS implementation provides the following parameters for the user: the parameter τ_{init} defines the initial amount of pheromone in each search path; the Q parameter that controls the amount of pheromone deposited by an agent; and parameter $\rho \in [0,1]$ which represents an evaporation rate of pheromones at the end of an iteration.

The Euclidean distance was used as a similarity metric to calculate the distance between the set information. We define the remaining parameters in our experiments as follows: $\tau_{init} = 1$, $Q = 1$ and $\rho = 0.1$.

4.3 Machine Learning Methods Used

Four classification algorithms were used to evaluate the performance of Ant-IS: 1NN; the CART Decision Tree algorithm; the Neural Network Backpropagation algorithm; and Random Forest (RF), a set of methods that uses a set of decision trees to perform its classification.

For the algorithms mentioned above, the implementations provided by Scikit-learn (Pedregosa et al., 2011) were used. It is worth emphasizing that Scikit-learn uses a more performing version of the CART algorithm called by the *DecisionTreeClassifier* library.

4.4 Model Quality Assessment Metrics

Precision, Recall, and $F-measure$ metrics were used to determine the quality of the models. The Precision[1] metric concerns the percentage of instances classified correctly in a class out of all those that were classified in the class. The Recall[2] refers to the percentage of instances of a class that were correctly predicted to belong to the class. Already the metric F-measure [3] represents the harmonic mean between Precision and Recall.

[1] $Precision = \frac{VP}{VP+FP}$
[2] $Recall = \frac{VP}{VP+FN}$
[3] $F-Measure = \frac{2 \times Recall \times Precision}{Recall+Precision}$

Given the stochastic nature of the ACO algorithms, the experiments were performed differently for the Ant-IS collected sets. In this case, the experiment was done using the 10-fold stratified cross-validation proposed in Salama et al. (2016). In this process, the cross-validation procedure is repeated ten times. In addition, a new subset of instances is generated on each model run, and the test result is the average result of all runs.

5 RESULTS AND DISCUSSIONS

Figure 2 presents the graph of the results obtained in experiments. Each column referred to the experiments performed with whole datasets and applied the instance selection with ANT-IS. Furthermore, the results for each metric are presented by discipline.

Analyzing the results, it is possible to observe an improvement in most metrics evaluated in the Ant-IS sets. In general, this enhances the ability of Ant-IS to select the most representative from the database. In few cases, like the 1NN algorithm for the high class, a reduction in the evaluation metrics was observed with the selected subsets. In this case, there was a reduction of 5 percentage points with the application of Ant-IS. An important observation is about the neural network, which obtained much lower results than other classifiers. We believe that a better adjustment of hyperparameters can improve the performance of the algorithms.

The most significant contribution of this work can be seen in the improvement under the minority class (high). Overall, the performance of the 'high' class with Ant-IS increased significantly, with a gain of up to 24.06 percentage points considering the *F-measure* metric, using the 1NN in the writing database. Thus, the experiment results indicate that Ant-IS made it possible to represent the database better.

The CART and RF models that use decision trees to carry out the classification were obtained on the' high' class learning. CART gained around 23 percentage points of accuracy in the arithmetic discipline and 10 in the writing discipline. Similarly, the RF algorithm increased all its high class metrics for all subjects, with a gain ranging from 11.1 to 18.44 percentage points.

Regarding the low class, only in the 1NN algorithm was there a loss of 9 percentage points in the F-measure metric in the arithmetic prediction topic. However, in writing and reading subjects, using the 1NN, and in all other algorithms, in all disciplines, the result was either very close to that achieved without the use of Ant-IS or better. In the CART algorithm, for example, in arithmetic prediction, there was a gain of 7.41 percentage points in the F-measure metric of this class.

Besides, we can note that the application of Ant-IS in the database contributed to a more effective prediction of student performance, especially regarding high performance, which is represented by the minority class. This makes the knowledge acquired through the most selected instance groups valid.

6 FINAL CONSIDERATIONS

The objective of this work, as presented, was to carry out the selection of instances using Ant Colony to obtain more efficient classification models in identifying the school performance of children and adolescents with ADHD.

The early identification of possible school difficulties of students with ADHD can positively help the prognosis of educational and social interventions. In addition, finding both the characteristics that lead to low and high performance supports the creation of more effective mediations that minimize the effects of elements (be they family, social, among others) that can lead to low performance and enhance those that help in achieving high performance.

Thus, the results presented effectively contribute to achieving this early identification. Furthermore, Ant-IS was essential in improving high and low-performance prediction, making it possible to later extract reliable rules from this database. Through these rules, the standard that governs the low or high performance in arithmetic, writing, and reading, of students with ADHD can be evaluated, and, with this, more targeted actions can be taken.

As a proposal for future work, we intend to analyze the most selected instances by class and validate these characteristics with an expert. Furthermore, evaluating other pheromone models for Ant-IS can improve the results obtained.

ACKNOWLEDGEMENTS

The authors thank the National Council for Scientific and Technological Development of Brazil (CNPq), the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES), the Foundation for Research Support of Minas Gerais State (FAPEMIG) and Pontifical Catholic University of Minas Gerais (PUC Minas).

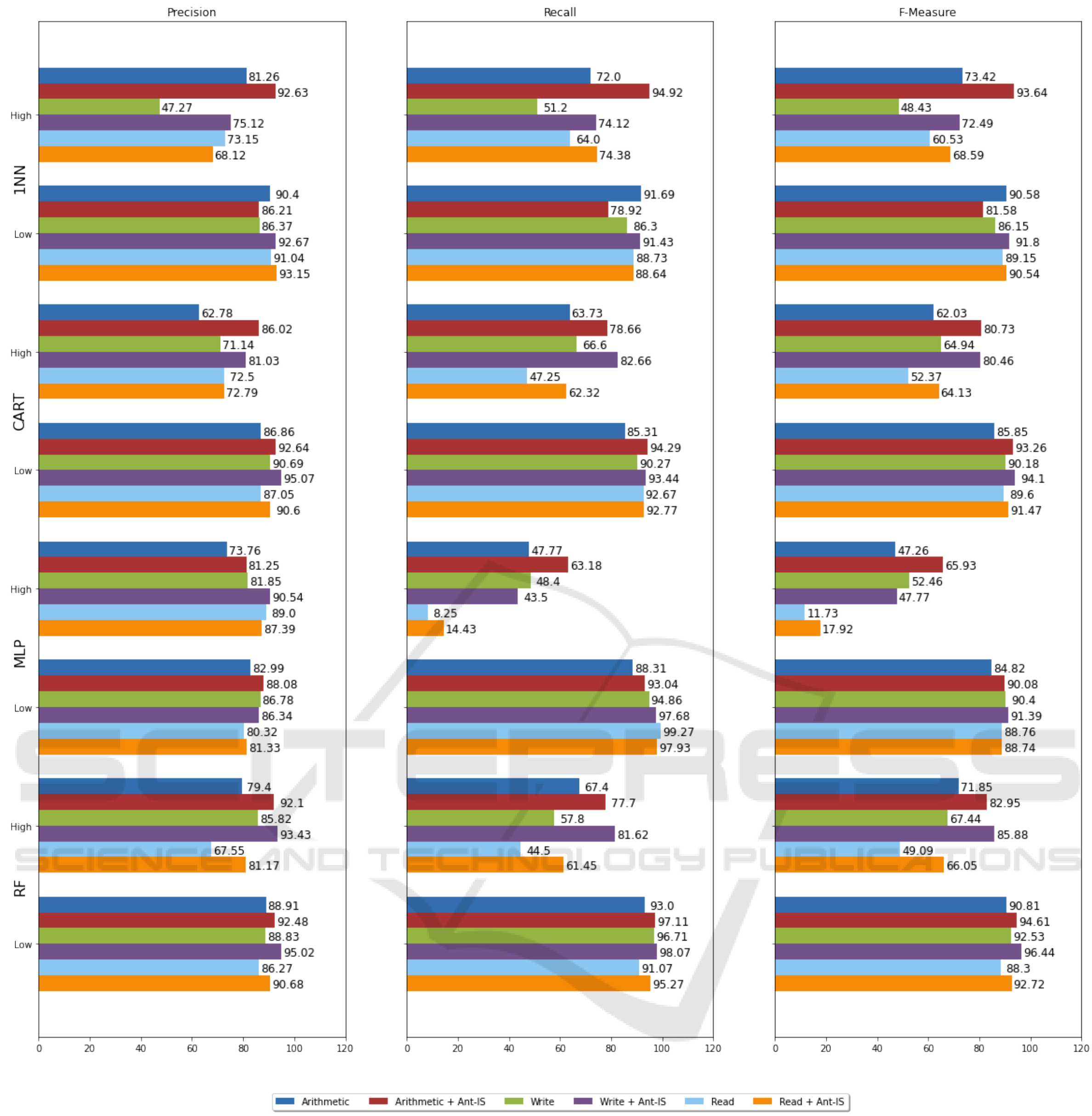

Figure 2: Performance obtained in each experiment per metric.

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