An improve unsupervised discretization using optimization algorithms for classification problems

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Article Info

ABSTRACT

This paper addresses the classification problem in machine learning, focusing on predicting class labels for datasets with continuous features. Recognizing the critical role of discretization in enhancing classification performance, the study integrates equal width binning (EWB) with two optimization algorithms: the bat algorithm (BA), referred to as EB, and the whale optimization algorithm (WOA), denoted as EW. The primary objective is to determine the optimal technique for predicting relevant class labels. The paper emphasizes the significance of discretization in data preprocessing, offering a comprehensive approach that combines discretization techniques with optimization algorithms. An investigative study was undertaken to assess the efficiency of EB and EW by evaluating their classification performance using Naive Bayes and K-nearest neighbor algorithms on four continuous datasets sourced from the UCI datasets. According to the experimental findings, the suggested EB has a major effect on the accuracy, recall, and F-measure of data classification. The classification performance using EB outperforms other existing approaches for all datasets.

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1. INTRODUCTION

In machine learning, a classification problem involves predicting a class label for a given example of input data. It requires that examples be classified into one of two or more classes, and it can have real-valued or discrete outputs [1]. Classification predictive modeling is used to categorize new observations based on the training dataset. Classification problems can be found in various real-world examples [2], such as spam detection in emails, handwritten character recognition, disease diagnosis, and image classification. There is no one classifier that is optimal for every situation; rather, a classifier's performance is contingent upon the properties of the data [3].

Mohamed and Azah [4], discretization processes conducted during the pre-processing phase can enhance classification performance. Discretization involves the process of converting continuous data into discrete intervals or categories, thereby simplifying the representation of complex numerical information. Further, discretization is a crucial step in various data analysis and machine learning tasks, significantly influencing downstream tasks like classification. The discretization process can be done for both unsupervised and supervised [5] learning tasks, and the approach may vary based on the context. There are various unsupervised discretization methods, including equal-width binning and discretization with k-means [6].

Optimization algorithms are crucial in discretization, helping identify optimal thresholds for transforming continuous data into discrete intervals. Optimization algorithms are used to find the best possible solution to a given problem, often involving maximizing or minimizing a real function. There are many different types of optimization algorithms such as the bat algorithm (BA) and whale optimization algorithm (WOA).

This paper, focusing on solving the classification problem [7] involves predicting a class label where the dataset is composed of continuous features. Further, the integration discretization techniques and optimization algorithm used to solve that problem. Their two techniques have been proposed in this paper, first equal width binning (EWB) is integrated with BA namely EB, and second, EWB with WOA namely as EW. In addition, the main objective to find the best combination techniques to predict the relevant class label. The experimental result is compared using two classifiers: Naïve Bayes and K-nearest neighbors (KNN). This paper starts with brief review of previous research on EWB and the two optimisation techniques selected is given in section 2. The suggested approach's technical specifics are presented in section 3. Extensive experimental results and comparative analyses across several benchmark data sets are reported in section 4. This paper is finally concluded in section 5.

2.   PRELIMINARIES
2.1. Discretization overview
Discretization techniques are diverse, with classifications including dynamic versus static, local versus global considerations, splitting versus merging strategies, and supervised versus unsupervised methods [8], [9]. The process involves grouping continuous variable values into intervals, with equal-width binning being a method that divides the range into equally sized intervals, transforming the variable into ordinal labels. In classification contexts, the impact of feature discretization has been explored on synthetic datasets, revealing that while EWB [10] simplifies complex features, it can occasionally lead to decreased classification accuracy [8]. Other researchers, like Kaya and Tekin [11], extensively analyze eight discretization methods along with classification algorithms, emphasizing the importance of discretization in enhancing algorithm performance.

Studies by Gao *et al.* [12] on clustering-based discretization shows substantial improvement in logistic regression accuracy for predicting heart-related deaths. Elhilbawi *et al.* [13] investigate the effects of discretization methods like MDLP, class-attribute interdependence maximization (CAIM), and ID3 on mortality prediction in intensive care unit (ICU), demonstrating significant enhancements in classification accuracy with support vector machine (SVM), random forest, and KNN models. Toulabinejad *et al.* [5] explore the impact of discretization methods on classification performance, finding that discretization enhances both interpretability and classification accuracy, supporting its potential to improve model performance in various contexts.

2.2. Basic equal width binning
By dividing the limit of values by the required number of bins, EWB divides the feature limit into equal-width intervals, or bins. The existing EWB method randomly determines the number of bins, calculates interval values, k for each bin (1), sorts them, and assigns data points to bins based on their values. The ultimate goal is to improve classification task performance through the effective discretization of continuous features. Let w represent the width.

$$w = \frac{mx - mn}{n} \tag{1}$$

where, n is the number of bins, mx and mn are the maximum and minimum values in the dataset, respectively. Interval for each bin is denoted as $k_n(n = 1,2 \cdots, n-1)$. The interval for bin $1st$ is determined by (2), and the interval for bin $2nd$ is determined by (3), and so forth for nth as (4).

$$k_1 = mn + w \tag{2}$$

$$k_2 = mn + 2w \tag{3}$$

$$k_n = mn + (n-1)w \tag{4}$$

2.3. Bat algorithm
In 2010, Yang [14] was introducing BA. The algorithm simulates the behavior of bats as they search for prey in the dark, using echolocation and adjusting their flight paths based on feedback from their environment. The BA involves moving "bats" through the solution space by iteratively altering their

placements. Each "bat" represents a possible solution to an optimization issue. The algorithm uses various parameters like frequency, loudness, and pulse rate to control the exploration and exploitation of the search space.

Souza *et al.* [15] presents the BA-LDA algorithm, a bat-inspired technique created to replace linear discriminant analysis (LDA) in multivariate classification for variable selection. This approach was examined and contrasted with the genetic algorithm (GA-LDA) and successive projection algorithm (SPA-LDA), taking inspiration from the echolocation behavior of bats during prey search. The results show that BA-LDA outperformed GA-LDA and SPA-LDA in terms of classification performance.

The relationship between discretization and the BA arises when dealing with optimization problems that involve continuous variables [4]. In some cases, the BA can be adapted to work with discrete variables by introducing a discretization process. The first concept is a continuous optimization with BA. The original BA is designed to work with continuous variables. It operates by adjusting the continuous parameters of potential solutions to the optimization problem [16]. This means that if the problem involves continuous variables and using the BA, there is no inherent need for discretization. The second concept is discrete optimization using the BA. If the optimization problem involves discrete variables (e.g., integer variables), the BA is adapted to handle these discrete values. One approach is to introduce a discretization step to map the continuous search space of the BA to a discrete space that corresponds to a problem [14], [15]. This can involve rounding or mapping continuous parameter values to the nearest discrete values.

The application of optimization algorithms like the BA for discretization has been explored in the context of classification problems [7], [17], [18]. The BA is primarily designed for continuous optimization. This algorithm is potentially being adapted for feature discretization by considering certain adaptations or combining it with other techniques. BA could be used for feature discretization in classification tasks such as problem formulation, encoding, adaptations, fitness function, exploration, and exploitation.

2.4. Whale optimization algorithm

The WOA is a groundbreaking metaheuristic that draws inspiration from the social dynamics of whales to effectively address intricate optimization challenges. It belongs to the swarm intelligence family, akin to BA and particle swarm optimization. Initially introduced in reference [19], recent research emphasizes the synergy between WOA and discretization, a crucial aspect of algorithmic adaptability.

Discrete optimization often involves variables with non-continuous values, transformed into discrete levels through discretization. In discrete scenarios, where WOA operates on continuous representations, discretization becomes a key preprocessing step. The integration of discretization with WOA proves influential in solving diverse optimization challenges in domains such as classification [20]. This approach harnesses the power of discretization techniques to convert continuous variables into discrete states, optimizing them efficiently with WOA in applications across various domains [21]–[23].

3.　METHODOLOGY FOR PROPOSED DISCRETIZATION METHOD

The research proposes two integrated optimization methods, namely EB (EWB integrated with BA) and EW (EWB integrated with WOA), based on four main phases: data acquisition, optimum discretization, class, label classification, and performance measurement as visualized in Figure 1. The unsupervised discretization method, EWB, is utilized and combined with optimization algorithms (BA and WOA) to transform continuous feature data into discrete features, aiming to enhance classification performance. The integration aims to identify optimal cut-points in the continuous feature space, dividing data points into discrete intervals or bins. These methods prioritize the distribution of data values over class labels.

The abbreviations used in this research as following.
- Original-refer to continuous datasets that have not been discretized.
- EWB-equal width binning is an existing discretization method.
- EB-(first proposed method) the integration method between EWB with BA.
- EW-(second proposed method) the integration method between EWB with WOA.

3.1. Phase 1: parameter setting

Dataset obtained from the UCI machine learning repository [24] (http://archive.ics.uci.edu/ml) as shown in Table 1. To more understanding the pseudocode in Figure 2 can be referred. In this research the parameter setting for BA and WOA is same where number of bats/whales in population is refer to number of instances in datasets and become the number of bins. Pulse rate and loudness is set to 0.5, the maximum frequency refer to maximum value in dataset and minimum frequency refer to minimum value in datasets. The number of iterations is 100.
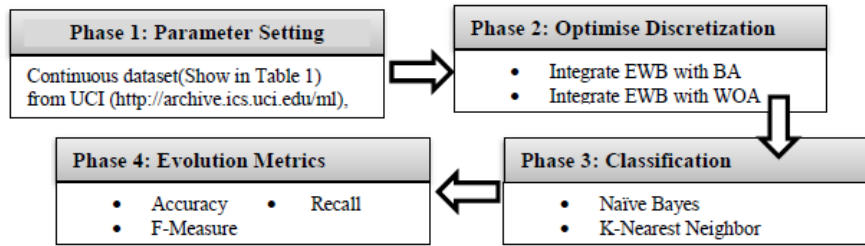
Figure 1. Research framework

Table 1. Continuous dataset information

Dataset	No. of intances	No. of attributes
Credit approval (DS1)	690	15
Image segment (DS2)	2310	19
Spambase (DS3)	4597	57
Wdbc (DS4)	569	30

3.2. Phase 2: optimize discretization

During this phase, discrete datasets are generated using EB and EW. The first step to find the number of bins, K is determined by optimization algorithm and select the minimum fitness function. Table 2 presents each position consists of k length, where k is the total number of attributes in the dataset. The information about instances is given by $S = \{s_1, s_2, \cdots, s_n\}$ where n is the number of populations known as a solution. For each solution, $S_i = \{a_{i1}, a_{i2}, \cdots, a_{ik}\}$, where k is the number of attributes for the S_i solution in the dataset.

Now let consider the example in Table 3. Table 3 shows the results of after optimization algorithm is applied for dataset consists of 6 attributes and 2 instances. Fitness function for 2nd instance or solution is the minimum value, 0.864. Thus, the best population is S_2 and optimal solution is $S_2 = \{0.19, 0.96, 1.23, 2.33, 0.13, 1.21\}$ and known as optimal values.

Table 2. The format of dataset

Instances	Attributes					Fitness function
	a_1	a_2	a_3	$\cdots$	a_k	
S_1	a_{11}	a_{12}	a_{13}	a_{14}	a_{1k}	Fitness function S_1
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
S_n	a_{n1}	a_{n2}	a_{n3}	a_{n4}	a_{nk}	Fitness function S_n

Table 3. The dataset representation matrix before discretization

Instances	Attributes						Fitness function
	a_1	a_2	a_3	a_4	a_5	a_6	
S_1	0.810	0.360	1.530	0.130	0.910	1.730	0.899
S_2	0.190	0.960	1.230	2.330	0.130	1.210	0.864

The next step to convert from continuous into discrete. Introduce b_k is bin that represent kth bin. Before conversion, the optimal values are sorted in ascending order as show in (5) know as interval value, k_n. Let d is the dataset consists of m instances, $d_m = \{d_1, d_2\}$. m is the number of instances and become the number of populations in an optimization algorithm. The instances of d_m define as (6) for first population and (7) for second population.

$$b_k = \{0.13, 0.19, 0.96, 1.21, 1.23, 2.33\} \tag{5}$$

$$d_1 = \{0.05, 0.20, 0.15, 3.00, 1.22, 1.05) \tag{6}$$

$$d_2 = \{0.15, 0.12, 0.25, 2.53, 1.12, 0.55) \tag{7}$$

Now, we will convert a continuous value in (6) and (7) into discrete values. For more understanding, let consider this example, first value from (6) is 0.05 and compare to b_1 from (5). If $0.05 \leq b_1$, the feature

will be assigned to bin number 1, and the feature value will be converted into 1. Thus, after discretization process the set of discrete value, d_m are obtain as shown in Table 4. So now, all the continuous features for all datasets, DS1, DS2, DS3 and DS4 are converted into discrete features.

Table 4. The dataset representation matrix after discretization

Instance	Attributes					
	a_1	a_2	a_3	a_4	a_5	a_6
ds_1	1	4	2	6	5	4
ds_2	2	1	4	6	5	3

Two experiments were conducted involving EBW and WOA. In the EB experiment, the algorithm used the number of dataset instances as the bat population x. The detailed algorithm is presented in Figure 2(a). In the second experiment, Figure 2(b) outlines the framework of EB integrating with WOA, where the whale population x corresponds to the number of dataset instances.
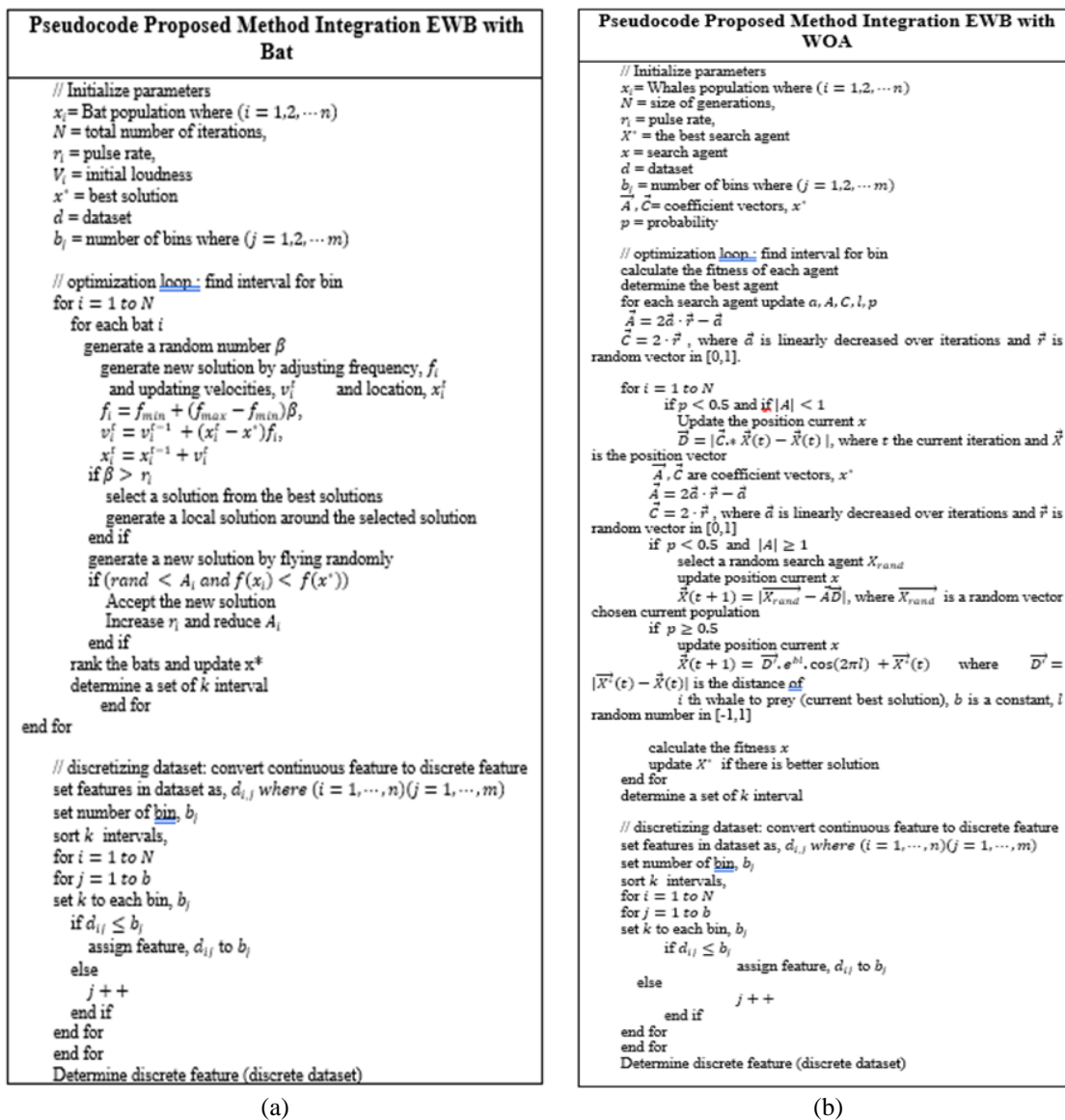

Figure 2. The proposed algorithms (a) EB and (b) integration EW

3.3. Phase 3: classification

After the discretization process, the next step is evaluating the efficiency of the proposed methods. Two classification methods are used: Naïve Bayes and KNNs. The classifier as a benchmark classifier and usually uses in classifying [25]. These classifiers used to classify the datasets DS1, DS2, DS3 and DS4 before and after discretization. Before discretization is refer to original dataset without discretization (continuous features). After discrezation refer to discretization with EWB and discretization with proposed method, EB and EW. This phase is important to verify the effectiveness of the proposed method based on the performance metrics that will be explained in the next section.

3.4. Phase 4: performance measurement

The evaluation of a classification method using metrics; accuracy, recall, and f-measure derived from confusion matrices. The proposed approach aims for high performance, with a target value of 1. It also seeks to outperform other comparison methods in achieving accuracy, recall, and f-measure values closer to 1.

4. RESULTS AND DISCUSSION

This research assesses the classification performance of EB and EW compared to the original dataset, as well as discrete data derived from the original EWB. Two classifiers, Naïve Bayes and KNN, were employed for the analysis. Four datasets were utilized in this investigation, as outlined in Table 1. Figures 3 and 4 depict the classification performance results using Naïve Bayes and KNN involving four evolution metrics. Figures 3(a) to 3(d) represent the outcomes for DS1, DS2, DS3, and DS4, respectively, using Naïve Bayes. Figures 4(a) to 4(d) represent the outcomes for DS1, DS2, DS3, and DS4, respectively, using KNN.

From Figure 3(a), EB method outperforms with the highest accuracy of 0.859, strong recall (0.858), and an impressive F-measure of 0.859. The original follows closely, showing respectable performance with an accuracy of 0.781, recall of 0.762, and an F-measure of 0.753. In contrast, the EWB and EW methods exhibit lower performance across all metrics. Figure 3(b) shows the EB method exceptional performance with the highest accuracy of 0.904, coupled with high recall (0.897) and F-measure (0.898). The original also performs well with an accuracy of 0.816, while the EWB and EW methods show lower scores across all metrics. In Figure 3(c), the EB method stands out again with an accuracy of 0.898, high recall (0.893), and an impressive F-measure of 0.940. The original dataset performs commendably with an accuracy of 0.846, recall of 0.799, and a remarkable F-measure of 0.939. EWB and EW methods, while showing lower scores, still maintain respectable performance. Figure 3(d) demonstrates the superiority of the EB method, achieving the highest accuracy of 0.960, along with high recall (0.960) and F-measure (0.960). The original dataset also performs exceptionally well with an accuracy of 0.930 and consistent recall and F-measure scores. EWB shows slightly lower scores, while EW exhibits the lowest performance across all metrics.

In Figure 4(a), the original dataset achieves an accuracy, recall, and F-measure of 0.807, demonstrating a balanced performance. The EWB dataset lags slightly behind in accuracy (0.779), recall (0.633), and F-measure (0.550). The EB method excels with the highest accuracy of 0.833, along with superior recall (0.833) and F-measure (0.833). The EW dataset performs reasonably well but is outperformed by the EB method. From Figure 4(b) exhibits remarkable accuracy across all methods. The original dataset achieves a high accuracy of 0.972, and the EB method again stands out with the highest accuracy of 0.976. The EWB and EW datasets show lower accuracy but are still respectable at 0.770 and 0.769, respectively. The recall and F-measure metrics follow similar trends, with the EB method consistently leading in performance. Figure 4(c) shows the original dataset achieves an accuracy of 0.882, with a recall of 0.871 and an F-measure of 0.820. The EB method excels with the highest accuracy of 0.941, demonstrating superior recall (0.941) and F-measure (0.941). The EWB and EW datasets again trail behind in performance. Further, Figure 4(d) indicates high overall performance across all methods. The original dataset achieves an accuracy of 0.960, and the EB method maintains its excellence with the highest accuracy of 0.965. Both EWB and EW methods also perform well, but they exhibit slightly lower accuracy, recall, and F-measure compared to the EB method.

In summary, the EB method consistently showcases superior performance across all datasets, surpassing other methods in terms of accuracy, recall, and F-measure in both classifiers. The original dataset also maintains commendable performance, highlighting its reliability. However, the expert-witness base (EWB) and EW methods exhibit slightly lower scores, though they still demonstrate respectable performance. Overall, the findings underscore the effectiveness of the EB classification in achieving robust results across diverse datasets and classifiers.
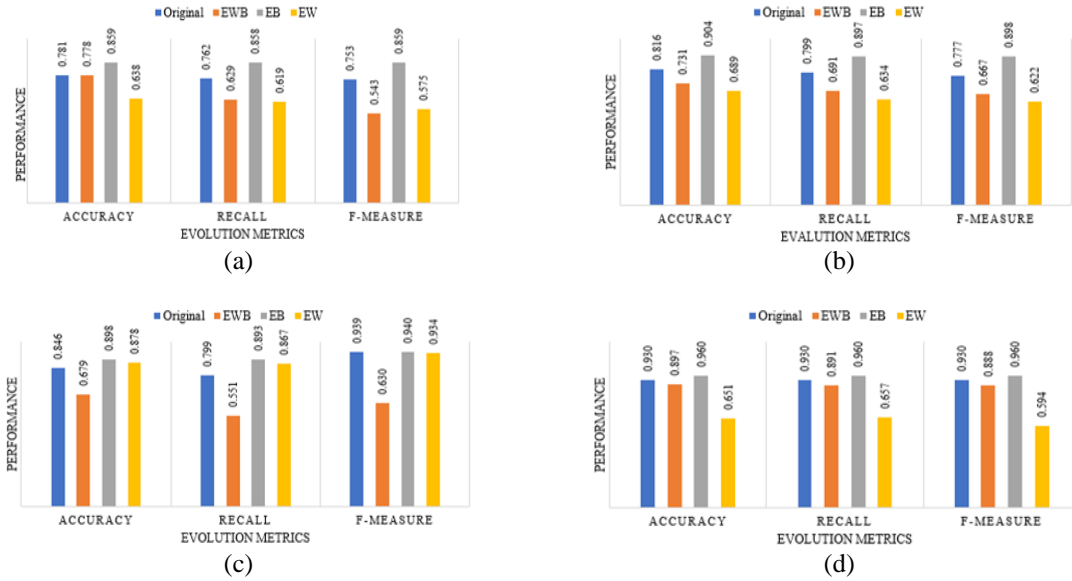
(a)

(b)

(c)

(d)

Figure 3. The comparison of performance measurement using Naïve Bayes classifier between dataset without discretization (original) with dataset with discretization method (EWB, EB, EW) for dataset (a) DS1, (b) DS2, (c) DS3, and (d) DS4
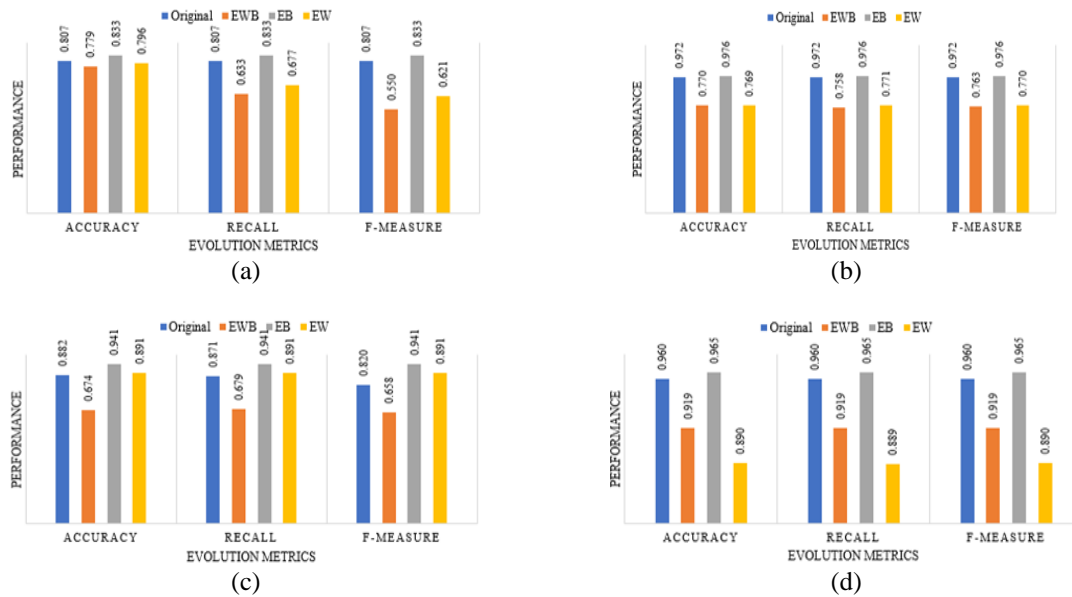

(a)

(b)

(c)

(d)

Figure 4. The comparison of performance measurement using KNN between dataset without discretization (original) with dataset with discretization method (EWB, EB, EW) for dataset (a) DS1, (b) DS2, (c) DS3, and (d) DS4

5.   CONCLUSION

Optimizing the discretization process stands as a pivotal task in data preprocessing, and the selection of a suitable optimization algorithm is paramount for unleashing the full potential of machine learning models. The optimal algorithm choice hinges on the nature of the problem and the data characteristics. Furthermore, fine-tuning the parameters of these algorithms is essential to achieve optimal performance. A comprehensive understanding of the nuances and applications of the BA empowers practitioners to navigate the intricacies of data transformation, ultimately facilitating more precise and reliable predictions.

Within the classification domain, discretization plays a pivotal role as a preprocessing step, transforming continuous features into discrete categories. The incorporation of EWB with the BA

demonstrates effectiveness in improving model performance. This integration is particularly impactful as it considers the specific feature characteristics of the dataset and aligns with the unique requirements of the employed classification algorithm.

In future work, it is imperative to delve into a comprehensive comparative analysis of various discretization algorithms, with a particular focus on the EWB. Investigate the robustness of the BA and EWB in the presence of noise or imperfect data. Develop strategies to handle noisy data effectively during the discretization process and assess the impact on classification model performance.

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