Bulletin of the *Transilvania* University of Braşov
Series III: Mathematics and Computer Science, Vol. 5(67), No. 1 - 2025, 259-270
https://doi.org/10.31926/but.mif.2025.5.67.1.19

A NEW APPROACH TO CONSTRUCT BASIC PROBABILITY ASSIGNMENT AND ITS APPLICATIONS IN DATA CLASSIFICATION

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Abstract

In the present work, we have proposed a classification algorithm which uses Dempster Shafer (D-S) evidence theory since it has emerged as an effective tool in handling data classification problems. As basic probability assignment (BPA) is a pre-requisite for applying D-S theory, how to generate it is a hot issue. This paper proposes a novel method for generating basic probability assignments (BPAs) from training data. Dempster Shafer's (D-S) rule of Combination is utilized for the unification of these BPAs and finally, classify each data item using these unified BPAs. Testing is carried out using some popular benchmark data sets consisting of three classes. Evaluated results show that the classification accuracy is comparatively high.

2010 *Mathematics Subject Classification:* 60A05, 15B51, 94A15.
Key words: Classification, Belief function, Dempster-Shafer (D-S) evidence theory, BPA generation.

1 Introduction

For the mathematical representation of uncertainty in real-time systems, Dempster Shafer (D-S) evidence theory has emerged as a perfect alternative to traditional probabilistic approaches. This framework allows the allocation of probability masses in the form of sets (generally known as the mass function or basic probability assignment (BPA)) or intervals instead of singletons that are mutually disjoint. Also, the probabilistic framework is highly dependent on the knowledge that is acquired independently of any particular experience and even if it is available, it fails to combine information obtained from multiple sources. Often used in various sensor fusion applications, the D-S evidence theory allows the amalgamation of evidence obtained from different sources and effectively models the conflict

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among them. In the present work, we shall investigate the D-S evidence theory as the theoretical basis for classifiers on a small data set, where classification is performed by combining pieces of evidence. Various distinct approaches have been utilized by researchers in [5], [1], [4], [12], [14], [11] for dealing with classification problems. However, how to construct BPA is still a hot issue. In the present work, we have performed the classification using the simple concept that an object will belong to a particular class if all the features/ attributes of the object are closer to the corresponding features/ attributes of that class. To classify an object, we have proposed an algorithm to compare each feature of the object to be classified with the features of each given class by constructing a BPA corresponding to each feature and then combining obtained BPAs with the weighted average approach. The construction of BPA is based on the fact that the more an object belongs to a class, the lesser will be the dissimilarity between the features.
Over the past few years, researchers have used triangular fuzzy numbers, interval numbers, gaussian numbers and various other mathematical structures and techniques for generating basic probability assignments for classifying data. Dongdong et al. [11] used the triangular fuzzy numbers to determine BPA and utilised the maximum, minimum and average values of the attributes in the training set to construct the triangular fuzzy numbers. The authors assigned a certain mass value to propositions if the test sample intersects the triangular fuzzy number model and the rest was equally assigned to the remaining propositions. However, assigning equal masses to the remaining proposition may not always generate desired results. Kang et al. [5] and Bowen et al. [14] proposed methods to determine BPA based on interval numbers. Kang et al. [5] used only maximum and minimum values of the sample as the lower and upper bound of the interval number. But the maximum and minimum values are not sufficient to describe the whole data set as the maximum and minimum values can probably be much more than or less than any other data in the same sample. Bowen et al. [14] improved this drawback by constructing interval numbers using clusters. They divided training data into two clusters and the mean values of the two clusters are taken as the lower and upper bounds of interval number. The interval number corresponding to compound propositions (say $\{A,B\}$) is taken as the intersection of the interval numbers of its components (A and B). It can be easily seen from their examples that the mass corresponding to compound propositions is mostly zero with no logical justification for it. For evaluating the distance of the test sample from training data, the maximum, minimum and average of all the values or two clusters of training data have been used so far. If the training data is large, dividing it into more than two parts to find averages can give better results as it will reduce the distance between the test sample and training data. Moreover, how to assign mass to compound propositions is still an open issue. After obtaining BPAs, the classification result depends on how the fusion of BPAs is performed. Although the D-S combination rule is a classical and well-accepted approach to fuse BPAs it may give counter-intuitive results for highly conflicting BPAs. To address this issue, many data fusion algorithms have been proposed to fuse BPAs using a weighted average approach ([15], [3], [9], [7], [13]). In the present work, we

have divided training data into more than two subparts, calculated the average of each subpart and utilized it to find the distance of the test sample from each class. The distance of the test sample from compound propositions is calculated as the average of the distances of its components from the test sample. Reciprocal of the distance obtained is taken as the supporting factor of that proposition which is then normalized to obtain BPAs. BPAs are then combined with the data fusion algorithm proposed in [6]. The paper is organized as follows. In section 2, we provide an overview of Dempster-Shafer's Evidence Theory along with some important definitions. Section 3 describes the proposed classification algorithm using BPA. In section 4, we have utilized the proposed algorithm for Iris data set classification. In section 5, a comparative analysis is shown for Iris and Seeds data sets. Section 6 concludes the paper.

2 Preliminaries

2.1 Dempster-Shafer evidence theory

Dempster-Shafer(D-S) Evidence theory [2], [8] of the combination of Basic Probability Assignment (BPA) is a generalization of probability theory. This is a classical approach for combination of evidence obtained from different sources and arriving at a degree of belief. In this theory, a degree of belief called mass is assigned to all the subsets of the evidence under consideration in the same way as we assign a probability to all the random variables of a given experiment. For fusing information, this theory combines the degree of beliefs of the evidence obtained from different sources. It has been extensively applied to decision-making, fault diagnosis, uncertain reasoning, multi-sensor data fusion, information fusion, aggregation, medical diagnosis, conflict management and other fields owing to its ability to express uncertainty.

2.1.1 Basic probability assignment

Let $X = \{X_1, X_2, \ldots, X_n\}$ be the set of all possible hypothesis under consideration known as the frame of discernment (FOD). Let $2^X = \{F_1, F_2, \ldots, F_{2^n}\}$ be the power set of X. A Basic probability assignment (BPA) is a mapping $m : 2^X \to [0, 1]$ that satisfies

$$m(\emptyset) = 0, \sum_{i=1}^{2^n} m(F_i) = 1.$$

Here, the mass $m(F_i)$ measures the belief assigned exactly to the focal element F_i and represents how strongly the evidence supports F_i.

2.1.2 Dempster-Shafer rule of combination

Consider two BPAs m_1 and m_2, the D-S rule of combination given by Dempster [2] and Shafer [8] is defined as

$$m(F_r) = m_1(F_i) \oplus m_2(F_j) = \begin{cases} 0 & F_r = \emptyset \\ \frac{\sum_{F_i \cap F_j = F_r} m_1(F_i)m_2(F_j)}{1-k} & F_r \neq \emptyset \end{cases}$$

where

$$k = \sum_{F_i \cap F_j = \emptyset} m_1(F_i)m_2(F_j)$$

is called the coefficient of conflict among the evidences.

2.2 Divergence measure

Let m_1 and m_2 be two BPAs defined on the frame of discernment $X = \{X_1, X_2, \ldots, X_n\}$. Let $2^X = \{F_1, F_2, \ldots, F_{2^n}\}$ be the power set of X. The measure of divergence [12] between m_1 and m_2 is defined as

$$\mathfrak{D}(m_1, m_2) = -\log_2 \left(\frac{1 + \sum_{i=1}^{2^n} min\{(m_1(F_i), m_2(F_i)\}}{2} \right)$$

This measure of divergence is bounded, satisfies triangle inequality and vanishes only for identical BPAs. We will utilize the above divergence measure for quantifying the dissimilarity between two BPAs. For literature on divergence measures between two BPAs, the authors can refer ([3], [9], [13]).

2.3 Data fusion algorithm

Assume that there are n alternatives $A_1, A_2, \ldots, A_n$ and k sources of evidence sending information in the form of BPAs $m_i(A_j)$, where $j = 1, 2, \ldots, n$ and $i = 1, 2, \ldots, k$.
Steps for data fusion proposed in [6] are as follows.
Step I: Evaluate divergence $\mathfrak{D}(m_i, m_j)$ between every pair of BPAs m_i and m_j

$$d_{ij} = \mathfrak{D}(m_i, m_j), i, j = 1, 2, \ldots, k$$

Step II: A degree of support $sup(m_i)$ is associated to each BPA m_i as follows.

$$sup(m_i) = \frac{1}{k} \sum_{j=1}^{k} \frac{1}{1 + \mathfrak{D}(m_i, m_j)}$$

Step III: A weight w_i is assigned to each BPA as follows.

$$w_i = \frac{sup(m_i)}{\sum_{i=1}^{k} sup(m_i)}$$

Step IV: Find the weighted average of BPAs using above-assigned weights namely

$$M(A_j) = \sum_{i=1}^{k} m_i(A_j) w_i$$

where $m_i(A_j)$ is the belief about the alternative A_j from sensor i.
Step V: Use D-S combination rule to combine the weighted averaged BPAs $k-1$ times.

3 Classification algorithm using BPA generation

Divide the data for classification into two parts: training data and test data. We will use training data for generating BPA and test data to check the effectiveness of the proposed method. Suppose we are given a data set consisting of n classes $\{C_1, C_2, \ldots, C_n\}$ and each class has k attributes $\{A_1, A_2, \ldots, A_k\}$. Let $t = \{t_1, t_2, \ldots, t_k\}$ be sample data. The problem is to identify the class to which this sample data belongs.

Step 1: Let $X = \{C_1, C_2, \ldots, C_n\}$ be FOD, the set of all possible hypothesis and $\mathfrak{P}(X) = \{H_1, H_2, \ldots, H_{2^n}\}$ be the power set of FOD. Generate BPA for each attribute as follows.

1. Calculate the deviation of the sample from all the hypotheses i.e., all the singletons of the set $\mathfrak{P}(X)$ as follows.

2. Let $a_{i1}, a_{i2}, \ldots, a_{ir}$ be the values of attribute A_i corresponding to class C_1 arranged in ascending order.

3. Find the average of these values in batches of 10 as $\mu_1 = \frac{1}{10}\sum_{j=1}^{10} a_{ij}$,$\mu_2 = \frac{1}{10}\sum_{j=11}^{20} a_{ij}, \ldots, \mu_{[r/10]} = \frac{1}{10}\sum_{j=[r/10]10+1}^{r} a_{ij}$

4. Evaluate the deviation of the sample from hypothesis C_1 as

$$d(\{C_1\}, t_i) = Min\{(\mu_1 - t_i)^2, (\mu_2 - t_i)^2, \ldots, (\mu_{[m/10]} - t_i)^2\}$$

5. Repeat steps (2) to (4) for hypothesis C_2,C_3,...,C_n to obtain $d(\{C_2\}, t_i)$, $d(\{C_3\}, t_i), \ldots, d(\{C_n\}, t_i)$.

6. The deviation of sample from other elements of $\mathfrak{P}(X)$ is calculated as

$$
\begin{aligned}
d(\{C_i, C_j\}, t_i) &= \frac{d(\{C_i\}, t_i) + d(\{C_j\}, t_i)}{2} \\
d(\{C_i, C_j, C_k\}, t_i) &= \frac{d(\{C_i\}, t_i) + d(\{C_j\}, t_i) + d(\{C_k\}, t_i)}{3} \\
&\vdots \\
d(\{C_i, C_j, \ldots, C_n\}, t_i) &= \frac{d(\{C_i\}, t_i) + d(\{C_j\}, t_i) + \ldots, d(\{C_n\}, t_i)}{n}
\end{aligned}
$$

   If the deviation from sample from any element is zero, replace it with 10^{-12}.

7. Associate a degree of support to each non-empty element of $\mathfrak{P}(X)$.

$$sup(H_j) = \frac{1}{d(H_j, t_i)} \quad \text{for} \quad j = 1, \ldots, 2^n - 1$$

8. Normalize degree of support to obtain mass m_i assigned to each non-empty element of $\mathfrak{P}(X)$.

$$m_i(H_j) = \frac{sup(H_j)}{\sum_{k=1}^{2^n-1} sup(H_k)} \quad \text{for} \quad j = 1, \ldots, 2^n - 1 \quad \text{and} \quad i = 1, \ldots, k$$

Step 2: Combine above obtained k BPAs $m_i, i = 1, \ldots, k$ using data fusion algorithm [6].
Step 3: The given sample belongs to the class with the greatest mass function value.

4 Example

The proposed algorithm is used to identify the class of the Iris plant using the Iris data set from UCI repository (https://archive.ics.uci.edu/ml/datasets/iris). This data set contains 3 classes of 50 instances each that corresponds to different types of Iris plant namely Iris Setosa (ISe), Iris Versicolor (IVe) and Iris Virginica (IVi). First class is linearly separable from the other two, the latter are linearly inseparable from each other. There are four attributes of each namely sepal length (Sl), sepal width (Sw), petal length (Pl) and petal width (Pw), all measured in centimeters.
To check the effectiveness of the proposed algorithm, firstly 20 % of instances of each class are chosen randomly to serve as the test data and the remaining 80 % as the training data.

Experiment 1:
Let's consider the first 40 instances of each class as training data and the remaining

Table 1: A sample from class Iris Setosa.

Sl	Sw	Pl	Pw
5	3.5	1.3	0.3

as test data. Take a sample from test data of class Iris Setosa as shown in **Table 1**.

Step I: Here FOD is $\{ISe, IVe, IVi\}$ and its power set is $\{\emptyset, \{ISe\}, \{IVe\}, \{IVi\}, \{ISe, IVe\}, \{ISe, IVi\}, \{IVe, IVi\}, \{ISe, IVe, IVi\}\}$. Generate the BPA for first attribute Sl as follows.

1. Arranging the values of training data of attribute Sl of class ISe in ascending order, we obtain the following averages

$$\mu_1 = 4.59, \mu_2 = 4.92, \mu_3 = 5.12, \mu_4 = 5.52$$

2. The deviation of sample value of Sl i.e., $t_1 = 5$ from hypothesis {ISe} is

$$d(\{ISe\}, t_1) = Min\{(4.59-5)^2, (4.92-5)^2, (5.12-5)^2, (5.52-5)^2\} = 0.0064$$

3. Similarly arranging the values of training data of attribute Sl of classes IVe and IVi, we obtain

$$d(\{IVe\}, t_1) = Min\{(5.37-5)^2, (5.8-5)^2, (6.18-5)^2, (6.69-5)^2\} = 0.1369$$

$$d(\{IVi\}, t_1) = Min\{(5.82-5)^2, (6.35-5)^2, (6.78-5)^2, (7.54-5)^2\} = 0.6724$$

4. The deviation of the sample from the rest of the elements are

$$d(\{ISe, IVe\}, t_1) = \frac{0.0064 + 0.1369}{2} = 0.07165$$

$$d(\{ISe, IVi\}, t_1) = \frac{0.0064 + 0.6724}{2} = 0.3394$$

$$d(\{IVe, IVi\}, t_1) = \frac{0.1369 + 0.6724}{2} = 0.40465$$

$$d(\{ISe, IVe, IVi\}, t_1) = \frac{0.0064 + 0.1369 + 0.6724}{3} = 0.2719$$

5. The results obtained after normalizing the degree of support for each hypothesis are presented in **Table 2**.

6. Proceeding as above, BPAs $m_{Sl}, m_{Sw}, m_{Pl}, m_{Pw}$ corresponding to the attributes sepal length (Sl), sepal width (Sw), petal length (Pl) and petal width (Pw) respectively are evaluated and presented in **Table 3**. It is evident from the table that the maximum mass is assigned to class Iris Setosa (ISe) by the BPAs corresponding to each attribute.

Table 2: BPA generated corresponding to attribute- Sepal length.

	{ISe}	{IVe}	{IVi}	{ISe,IVe}	{ISe,IVi}	{IVe,IVi}	{ISe, IVe, IVi}
Deviation of sample (d)	0.0064	0.1369	0.6724	0.0717	0.3394	0.4047	0.2719
Support ($1/d$)	156.25	7.3046	1.4872	13.9567	2.9464	2.4713	3.6778
Mass (m_{Sl})	0.8307	0.3888	0.0079	0.0742	0.1566	0.01314	0.1955

Table 3: BPAs generated corresponding to all the attributes.

BPAs	{ISe}	{IVe}	{IVi}	{ISe,IVe}	{ISe,IVi}	{IVe,IVi}	{ISe,IVe, IVi}
m_{Sl}	0.8307	0.03888	0.0079	0.0742	0.01566	0.01314	0.01955
m_{Sw}	0.8748	0.00303	0.0349	0.00603	0.0673	0.0056	0.0083
m_{Pl}	0.9975	0.00043	0.00019	0.00086	0.00039	0.00027	0.0004
m_{Pw}	0.9468	0.0105	0.0032	0.0208	0.0064	0.0049	0.0074

Step II: Combining above-obtained BPAs we see that the highest belief is 0.99994 which corresponds to hypothesis {ISe}. Thus overall, the attributes of the test sample are closer to class ISe. This implies that the sample belongs to the class Iris Setosa. Thus, we are able to identify the class effectively.
We applied this algorithm to the remaining 29 test samples to check its effectiveness. The results obtained are shown in **Table 4**.

Table 4: Results obtained from Experiment 1.

Actual Class	Identified Class	Actual Class	Identified Class	Actual Class	Identified Class
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVe
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi
ISe	ISe	IVe	IVe	IVi	IVi

We are able to identify the class in 29 out of 30 samples. We repeated this experiment 10 times with different random samples and the results obtained are shown in **Table 5**. To check the robustness of the proposed algorithm in the context of training data, 10 random experiments with different proportions of training data are performed. The results obtained are presented in **Table 6**. The minimum accuracy obtained in a random experiment is 86.67 % and the maximum reaches 100 %. Increasing the proportion of training data from 50 % to 100 % , the

Table 5: Results obtained from various random experiments.

Exp No.	No. of test samples	No. of correctly identified samples	Accuracy (in %)
1	30	29	96.67
2	30	29	96.67
3	30	28	93.33
4	30	29	96.67
5	30	28	93.33
6	30	29	96.67
7	30	28	93.33
8	30	30	100
9	30	29	96.67
10	30	30	100

average accuracy varies from 94.33 % to 97.67 %. The difference in classification accuracy is not large as we vary the proportion of training data.

Table 6: The classification accuracy (in %) in 10 random experiments with different proportions of training data for Iris data set.

Training data / Exp. No.	50 %	60 %	70 %	80 %	90 %	100 %
1	100.00	86.67	90.00	96.67	96.67	100.00
2	93.33	96.67	96.67	96.67	96.67	96.67
3	100.00	100.00	93.33	93.33	100.00	96.67
4	96.67	96.67	100.00	96.67	96.67	93.33
5	93.33	100.00	86.67	93.33	93.33	100.00
6	96.67	96.67	93.33	96.67	100.00	96.67
7	86.67	93.33	100.00	93.33	93.33	100.00
8	93.33	90.00	96.67	100.00	100.00	100.00
9	93.33	96.67	90.00	96.67	100.00	93.33
10	96.67	93.33	96.67	100.00	96.67	100.00
Average accuracy	95.00	95.00	94.33	96.33	97.33	97.67

5 Comparative analysis

The classification accuracy of the proposed method is compared with the methods proposed by Dongdong et al. [11], Jun et al. [12], Bowen et al. [14] and Kang et al. [5] for the Iris data as shown in **Table 4** and **Figure 1**. It is evident from **Figure 1** that accuracy obtained by the proposed algorithm is higher than the accuracy obtained by Dongdong et al., Jun et al. and Kang et al. Although the accuracy obtained by Bowen et al. is higher for 60 % and 70 % proportion of training data, their average accuracy is 95% and the average accuracy obtained by the proposed algorithm is 96 %. Thus, the results obtained are either better than others or comparative to them.

Table 7: Comparison of classification accuracy obtained by researchers for Iris data set.

Training part	50 %	60 %	70 %	80 %	90 %	100 %
Proposed Algorithm	95.00	95.00	94.33	96.33	97.33	97.67
Dongdong et. al. [11]	90.27	90.33	92.67	92.33	92.67	93.33
Jun Xia et. al. [12]	94.00	94.00	93.50	94.00	94.80	93.50
Bowen Qin et. al. [14]	95.40	94	95.40	96.00	97.40	95.40
Kang et. al. [5]	90.80	90.80	90.00	90.80	92.00	92.00

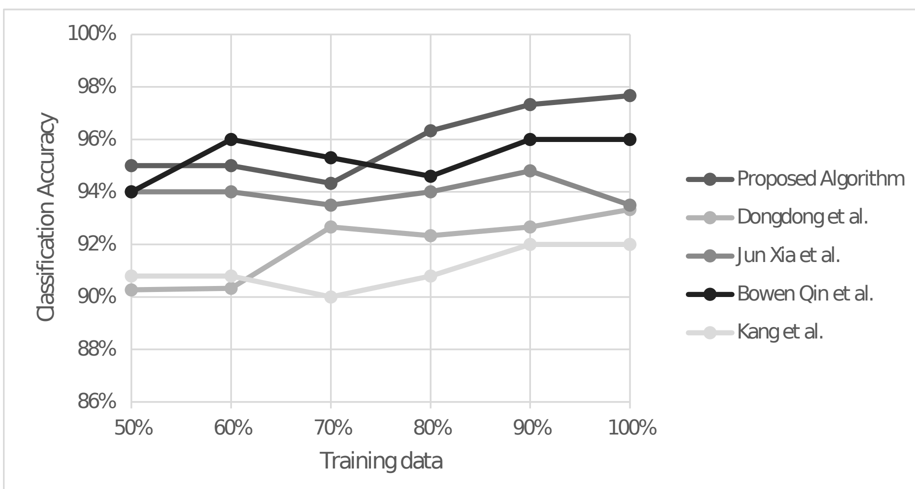

Figure 1: Graphical Comparison of classification accuracy for Iris data set.

A comparative analysis of the proposed algorithm is shown in **Figure 2** for classifying the seeds data set. Comparison is done with results obtained by Wang et al. [10], Dongdong et al. [11] and Jun et al. [12]. This data set is taken from the UCI repository (https://archive.ics.uci.edu/ml/datasets/seeds). This data set contains three varieties of wheat: Kama, Rosa and Canadian. Each class has 70 instances and 7 attributes: area, perimeter, compactness, length of kernel, width of kernel, asymmetry coefficient and length of kernel groove. The proportion of training data is taken as 80 % and test data as 20 %. The results shown are obtained after performing 10 random experiments. Each portion of bars in the figure represents the proportion of each class's accuracy. It is clear from the graph that the average accuracy obtained by the proposed algorithm is higher than all

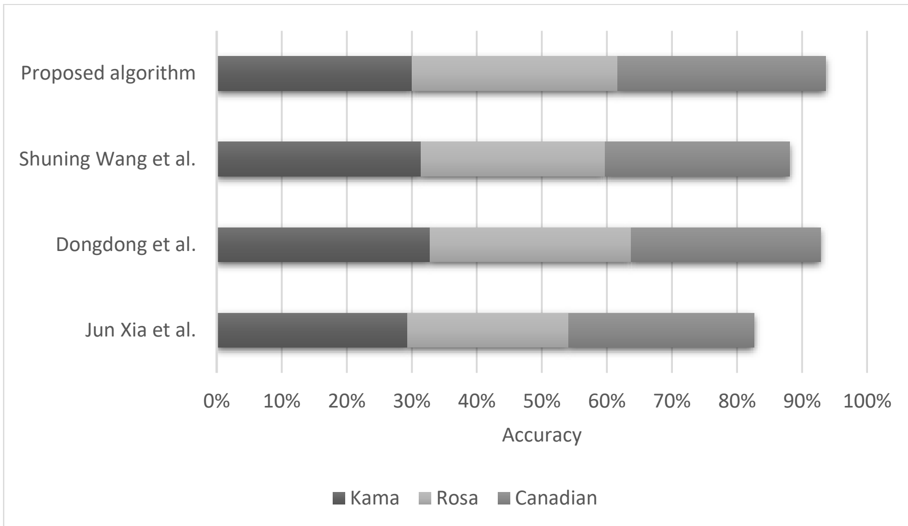

Figure 2: Graphical Comparison of classification accuracy for Seeds data set.

the other methods and quite closed to the one obtained by Dongdong et al.

6 Conclusion

In the present work, the axiomatic framework of BPAs is used for the construction of classification algorithms and then applied to the benchmark Iris data set and Seeds data set. The results show that the proposed algorithm provides comparable results as compared to other more favoured algorithms. Work on the generalization of the proposed classification algorithm is in progress and will be communicated elsewhere.

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