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A Data Classification Method in Machine Learning Based on Normalised Hamming Pseudo-Similarity of Fuzzy Parameterized Fuzzy Soft Matrices

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Abstract: In this study, we propose a classification method based on normalised Hamming pseudo-similarity of fuzzy parameterized fuzzy soft matrices (*fpfs*-matrices). We then compare the proposed method with Fuzzy Soft Set Classifier (FSSC), FussCyier, Fuzzy Soft Set Classification Using Hamming Distance (HDFSSC), and Fuzzy k-Nearest Neighbor (Fuzzy kNN) in terms of the performance criterions (accuracy, precision, recall, and F-measure) and running time by using four medical data sets in the UCI machine learning repository. The results show that the proposed method performs better than FSSC, FussCyier, HDFSSC, and Fuzzy kNN for "Breast Cancer Wisconsin (Diagnostic)", "Immunotherapy", "Pima Indian Diabetes", and "Statlog Heart".

Keywords: Fuzzy sets, soft sets, *fpfs*-matrices, similarity measure, data classification.

1. Introduction

Soft sets (Molodtsov, 1999), a standard and practical mathematical tool, are often used for modelling uncertainties, and a great variety of studies have been conducted on this concept (Çağman and Deli, 2012a, b; Deli and Çağman, 2015; Enginoğlu et al., 2015; Şenel, 2016; Zorlutuna and Atmaca, 2016; Atmaca, 2017; Çıtak and Çağman, 2017; Riaz and Hashmi, 2017; Atmaca, 2019; Çıtak, 2018; Riaz and Hashmi, 2018; Riaz et al., 2018; Şenel 2018a, b; Jana et al., 2019; Karaaslan, 2019a, b; Sezgin et al., 2019a, b). Fuzzy soft sets (Maji et al., 2001; Çağman et al., 2011b), fuzzy parameterized soft sets (Çağman et al., 2011a), and fuzzy parameterized fuzzy soft sets (*fpfs*-sets) (Çağman et al., 2010) are among known general forms of soft sets. Also, studies on the matrix representations of these sets have been increasingly continued such as soft matrices (Çağman and Enginoğlu, 2010), fuzzy soft matrices (Çağman and Enginoğlu, 2012), and fuzzy parameterized fuzzy soft matrices (*fpfs*-matrices) (Enginoğlu, 2012; Enginoğlu and Çağman, In Press). Even if parameters and objects have uncertainties, *fpfs*-matrices can successfully model such problems.

The rest of the paper is organised as follows: In Section 2, we present definitions of *fpfs*-sets (Çağman et al., 2010; Enginoğlu, 2012), *fpfs*-matrices (Enginoğlu, 2012; Enginoğlu and Çağman, In Press), and normalised Hamming pseudo-similarity of *fpfs*-matrices. In Section 3, we propose Fuzzy Parameterized Fuzzy Soft Normalized Hamming Classifier (FPFSNHC) using normalised Hamming pseudo-similarity of *fpfs*-matrices. In Section 4, we compare FPFSNHC with Fuzzy Soft Set Classifier (FSSC) (Handaga et al., 2012), FussCyier (Lashari et al., 2017), Fuzzy Soft Set Classification Using Hamming Distance (HDFSSC) (Yanto et al., 2018), and Fuzzy k-

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Nearest Neighbor (Fuzzy kNN) (Keller et al., 1985) in terms of the performance criterions (accuracy, precision, recall, and F-measure) and running time by using four medical data sets in the UCI machine learning repository (Dua and Graff, 2019). The results show that proposed method performs better than FSSC, FussCyier, HDFSSC, and Fuzzy kNN for "Breast Cancer Wisconsin (Diagnostic)", "Immunotherapy", "Pima Indian Diabetes", and "Statlog Heart". Finally, we discuss the need for further research. This study is a part of the first author's PhD dissertation.

2. Preliminaries

In this section, firstly, we present the concept of *fpfs*-matrices (Enginoğlu, 2012; Enginoğlu and Çağman, In Press). Throughout this paper, let E be a parameter set, $F(E)$ be the set of all fuzzy sets over E, and $\mu \in F(E)$. Here, a fuzzy set is denoted by $\left\{{}^{\mu(x)}x : x \in E\right\}$ instead of $\{(x, \mu(x)) : x \in E\}$.

Definition 2.1. (Çağman et al., 2010; Enginoğlu, 2012) *Let U be a universal set, $\mu \in F(E)$, and α be a function from μ to $F(U)$. Then, the set $\{({}^{\mu(x)}x, \alpha({}^{\mu(x)}x)) : x \in E\}$ being the graphic of α is called a fuzzy parameterized fuzzy soft set (fpfs-set) parameterized via E over U (or briefly over U).*

In the present paper, the set of all *fpfs*-sets over U is denoted by $FPFS_E(U)$. In $FPFS_E(U)$, since the $graph(\alpha)$ and α generated each other uniquely, the notations are interchangeable. Therefore, as long as it does not cause any confusion, we denote an *fpfs*-set $graph(\alpha)$ by α.

Example 2.1. *Let* $E = \{x_1, x_2, x_3, x_4\}$ *and* $U = \{u_1, u_2, u_3, u_4, u_5\}$. *Then,*

$\alpha = \{({}^{0.5}x_1, \{{}^{0.7}u_1, {}^{0.3}u_4\}), ({}^{0}x_2, \{{}^{0.1}u_1, {}^{0.8}u_3, {}^{1}u_5\}), ({}^{0.9}x_3, \{{}^{0.4}u_1, {}^{0.2}u_2, {}^{0.7}u_4\}), ({}^{1}x_4, \{{}^{0.6}u_1, {}^{0.9}u_5\})\}$

is an fpfs-set over U.

Definition 2.2. (Enginoğlu, 2012; Enginoğlu and Çağman, In Press) *Let $\alpha \in FPFS_E(U)$. Then, $[a_{ij}]$ is called the matrix representation of α (or briefly fpfs-matrix of α) and is defined by*

$$[a_{ij}] \coloneqq \begin{bmatrix} a_{01} & a_{02} & a_{03} & \dots & a_{0n} & \dots \\ a_{11} & a_{12} & a_{13} & \dots & a_{1n} & \dots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ a_{m1} & a_{m2} & a_{m3} & \dots & a_{mn} & \dots \\ \vdots & \vdots & \vdots & \ddots & \vdots & \ddots \end{bmatrix}$$

such that for $i \in \{0,1,2,\cdots\}$ and $j \in \{1,2,\cdots\}$,

$$a_{ij} \coloneqq \begin{cases} \mu(x_j), & i = 0 \\ \alpha({}^{\mu(x_j)}x_j)(u_i), & i \neq 0 \end{cases}$$

Here, if $|U| = m - 1$ and $|E| = n$, then $[a_{ij}]$ has order $m \times n$.

Throughout this paper, the set of all *fpfs*-matrices parameterized via E over U is denoted by $FPFS_E[U]$.

Example 2.2. *The fpfs-matrix of the fpfs-set α provided in Example 2.1 is as follows:*

$$[a_{ij}] = \begin{bmatrix} 0.5 & 0 & 0.9 & 1 \\ 0.7 & 0.1 & 0.4 & 0.6 \\ 0 & 0 & 0.2 & 0 \\ 0 & 0.8 & 0 & 0 \\ 0.3 & 0 & 0.7 & 0 \\ 0 & 1 & 0 & 0.9 \end{bmatrix}$$

Secondly, we present the normalised Hamming pseudo-similarity of *fpfs*-matrices.

Definition 2.3. *Let $[a_{ij}], [b_{ij}] \in FPFS_E[U]$. The normalised Hamming pseudo-similarity of $[a_{ij}]$ and $[b_{ij}]$ is defined by*

$$s([a_{ij}], [b_{ij}]) \coloneqq 1 - \frac{\sum_{i=1}^{m-1}\sum_{j=1}^{n}|a_{0j}a_{ij} - b_{0j}b_{ij}|}{(m-1)n}$$

3. Fuzzy Parameterized Fuzzy Soft Normalized Hamming Classifier (FPFSNHC)

In this section, firstly, we give some necessary notations. Let $u, v \in \mathbb{R}^n$. Then, the Pearson correlation coefficient between u and v is defined by

$$P(u,v) \coloneqq \frac{n\sum_{i=1}^{n}u_iv_i - (\sum_{i=1}^{n}u_i)(\sum_{i=1}^{n}v_i)}{\sqrt{[n\sum_{i=1}^{n}u_i^2 - (\sum_{i=1}^{n}u_i)^2][n\sum_{i=1}^{n}v_i^2 - (\sum_{i=1}^{n}v_i)^2]}}$$

Throughout this paper, let $[dm]$ be a data matrix having order $m \times n$, $[\widetilde{dm}]$ be the feature fuzzification of $[dm]$, the last column of $[\widetilde{dm}]$ be the class column, $[tm]$ be a training matrix which is a submatrix of $[dm]$, $[tm^r]$ be a submatrix of $[tm]$ whose values of the last column are equal to r, and $[tm]^j$ be j^{th} column of $[tm]$.

Secondly, we propose FPFSNHC classification algorithm. FPFSNHC's steps are as follows:

FPFSNHC's Algorithm Steps

Step 1. Read a nonempty $[dm]$

Step 2. Calculate the feature weight vector $[fw_{1j}]$ based on the Pearson correlation coefficient between feature vectors and class vector defined by

$$fw_{1j} \coloneqq P([dm]^j, [dm]^n), for\ j \in \{1,2,\dots,n-1\}$$

Step 3. Obtain $[\widetilde{dm}]$ such that for $i \in \{1,2,\dots,m\}$ and $j \in \{1,2,\dots,n\}$,

$$\widetilde{dm}_{ij} \coloneqq \begin{cases} \dfrac{dm_{ij}}{\max\limits_{k} dm_{kj}}, j \neq n \\ dm_{ij}, \quad j = n \end{cases}$$

Step 4. Obtain $[tm]$ from the $[\widetilde{dm}]$

Step 5. Obtain $[tm^r]$ for all r

Step 6. Calculate the cluster centre matrix $[e_{rj}]$ such that for $i \in \{1,2,\dots,k_r\}$ and $j \in \{1,2,\dots,n-1\}$,

$$e_{rj} \coloneqq \frac{1}{k_r}\sum_{i=1}^{k_r} tm_{ij}^r$$

Here, k_r is row number of $[tm^r]$.

Step 7. Obtain the train *fpfs*-matrices $[a_{ij}^r]$ such that for all r, $a_{0j}^r = fw_{1j}$ and $a_{1j}^r = e_{rj}$

Step 8. Obtain the unknown class data $[u_{1j}]$ from the test data

Step 9. Obtain the test *fpfs*-matrix $[b_{ij}]$ such that $b_{0j} = fw_{1j}$ and $b_{1j} = u_{1j}$

Step 10. Compute S_r for all r defined by

$$S_r \coloneqq s([a_{ij}^r],[b_{ij}]) = 1 - \frac{\sum_{i=1}^{m-1}\sum_{j=1}^{n}|a_{0j}^r a_{ij}^r - b_{0j}b_{ij}|}{(m-1)n}$$

Step 11. Obtain c such that $c = \arg\max\limits_{r} S_r$

Step 12. Assign the data $[u_{1j}]$ without class to class c

Step 13. Repeat Step 9-12 for all data $[u_{1j}]$ without class in test data

4. Simulation Results

In this section, we first simulate the algorithms using "Breast Cancer Wisconsin (Diagnostic)", "Immunotherapy", "Pima Indian Diabetes", and "Statlog Heart" datasets provided in UCI Machine Learning Repository (Dua and Graff, 2019) and detailed in Table 1. We then compare the performance of the algorithms by using four performance criterions: accuracy, precision, recall, and F-measure, defined by

$$Accuracy \coloneqq \frac{TP+TN}{TP+TN+FP+FN}$$

$$Recall \coloneqq \frac{TP}{TP+FN}$$

$$Precision \coloneqq \frac{TP}{TP+FP}$$

$$F-Measure \coloneqq \frac{2(Precision \times Recall)}{Precision + Recall} = \frac{2TP}{2TP+FP+FN}$$

where TP: True positive, FP: False positive, TN: True negative, and FN: False negative.

Here, the accuracy of a classifier is calculated by dividing the total correctly classified positives and negatives by the total number of samples, the precision of a classifier is calculated by dividing correctly classified positives by the total positive count, the recall of a classifier is calculated by dividing correctly classified positives by total true positive class, and the F-measure of a classifier is harmonic mean of precision and recall values.

Table 1. Description of The UCI data sets.

No.	Name	Instances	Attributes	Class
1	Breast Cancer	569	30	2
2	Immunotherapy	90	7	2
3	Pima Diabetes	768	8	2
4	Statlog Heart	270	13	2

Secondly, we present the performance results of the algorithms in Table 2 for "Breast Cancer Wisconsin (Diagnostic)", in Table 3 "Immunotherapy" data sets, in Table 4 for "Pima Indian Diabetes", and in Table 5 "Statlog Heart" data sets. In Figures 1-4, we give the figures of Table 2-5. In Table 6 and Figure 5, we give the running times of algorithms for all of four medical data sets. We use MATLAB R2019a and a workstation with I(R) Xeon(R) CPU E5-1620 v4@3.5 GHz and 64 GB RAM for simulation. All simulation results are obtained at random 100 independent runs. A split of data 80 per cent is a training set, and 20 per cent is a testing set. The performance results are obtained by averaging the performance values of each class.

Table 2. The average accuracy, precision, recall, and F-measure results (%) of algorithms for "Breast Cancer Wisconsin (Diagnostic)" data set.

	Breast Cancer Wisconsin (Diagnostic)			
Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**
FSSC	93.54	93.16	**92.98**	93.00
FussCyier	93.77	94.40	92.27	93.11
HDFSSC	92.90	92.90	91.79	92.23
Fuzzy kNN	91.35	91.05	90.30	90.56
FPFSNHC	**94.10**	**94.64**	92.70	**93.48**

Table 3. The average accuracy, precision, recall, and F-measure results (%) of algorithms for "Immunotherapy" data set.

	Immunotherapy			
Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**
FSSC	62.28	61.15	65.84	56.69
FussCyier	68.00	63.48	68.12	60.99
HDFSSC	67.89	62.98	68.09	60.78
Fuzzy kNN	61.33	45.04	45.60	43.18
FPFSNHC	**70.67**	**66.68**	**73.16**	**64.63**

Table 4. The average accuracy, precision, recall, and F-measure results (%) of algorithms for "Pima Indian Diabetes" data set.

	Pima Indian Diabetes			
Classifier	**Accuracy**	**Precision**	**Recall**	**F-Measure**
FSSC	70.69	69.97	71.70	69.62
FussCyier	73.01	70.62	70.91	70.58
HDFSSC	73.24	71.23	**72.28**	71.41
Fuzzy kNN	67.27	64.25	64.22	64.03
FPFSNHC	**73.94**	**71.51**	71.61	**71.43**

Table 5. The average accuracy, precision, recall, and F-measure results (%) of algorithms for "Statlog Heart" data set.

	Statlog Heart			
Classifier	**Accuracy**	**Precision**	**Recal**	**F-Measure**
FSSC	80.78	81.30	81.61	80.49
FussCyier	82.46	82.54	81.69	81.73
HDFSSC	79.81	79.50	79.36	79.18
Fuzzy kNN	58.22	57.84	57.70	57.01
FPFSNHC	**83.39**	**83.79**	**82.50**	**82.62**

Table 6. The mean running times of the algorithms for the data sets (In Seconds).

Classifier	**Breast Cancer**	**Immunotherapy**	**Pima Indian Diabetes**	**Statlog Heart**
FSSC	0.00113	0.00039	0.00125	0.00063
FussCyier	0.00077	0.00041	0.00074	0.00050
HDFSSC	0.00085	0.00036	0.00089	0.00050
Fuzzy kNN	0.00681	0.00041	0.00557	0.00114
FPFSNHC	0.00157	0.00053	0.00157	0.00084

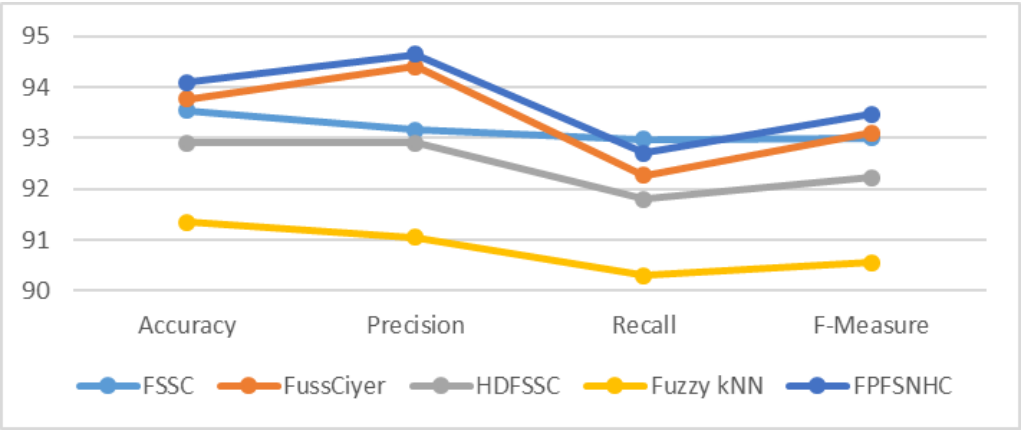

Figure 1. The Figure of the average accuracy, precision, recall, and F-measure results (%) of algorithms for "Breast Cancer Wisconsin (Diagnostic)" dataset in Table 2

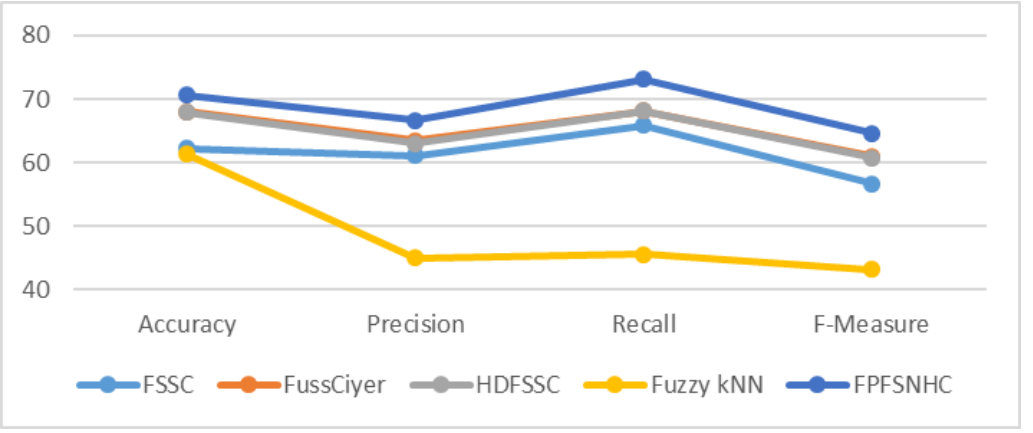

Figure 2. The Figure of the average accuracy, precision, recall, and F-measure results (%) of algorithms for "Immunotherapy" dataset in Table 3

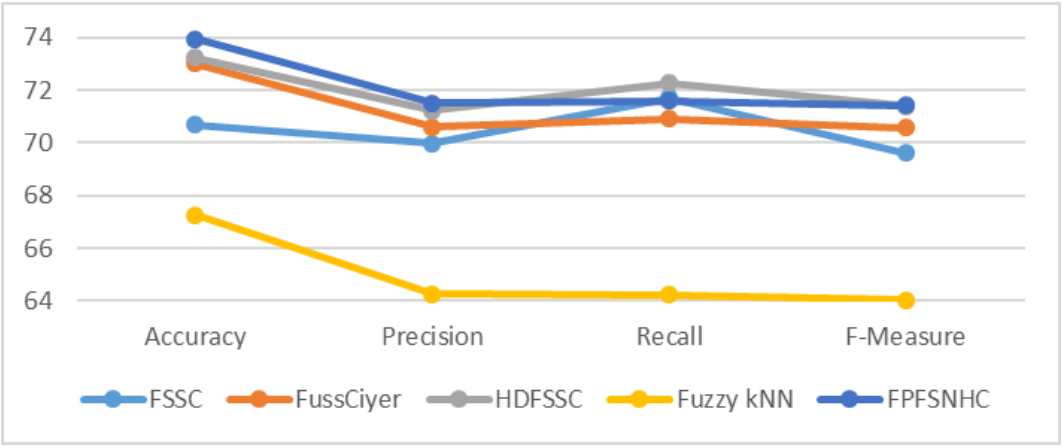

Figure 3. The Figure of the average accuracy, precision, recall, and F-measure results (%) of algorithms for "Pima Indian Diabetes" dataset in Table 4

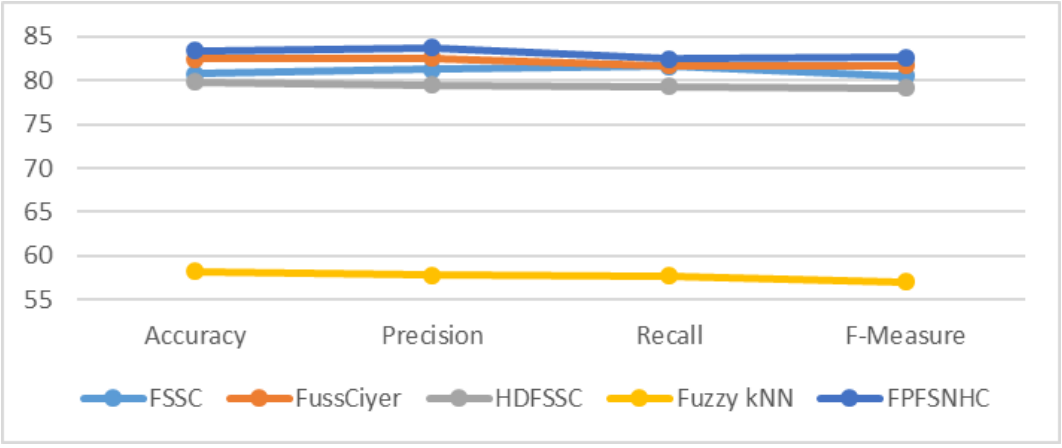

Figure 4. The Figure of the average accuracy, precision, recall, and F-measure results (%) of algorithms for "Statlog Heart" dataset in Table 5

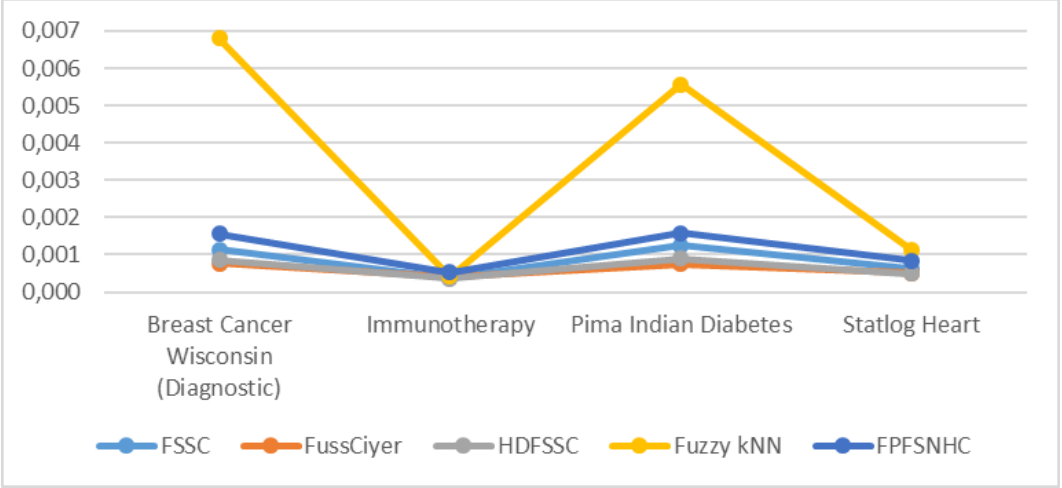

Figure 5. The Figure of the mean running times of the algorithms for the data sets in Table 6

5. Conclusion

In this paper, we have proposed the classification method FPFSNHC based on normalised Hamming pseudo-similarity of *fpfs*-matrices. We then compare proposed method with FSSC (Handaga et al. 2012), FussCyier (Lashari et al. 2017), HDFSSC (Yanto et al., 2018), and Fuzzy kNN (Keller et al. 1985) in terms of the performance criterions (accuracy, precision, recall, and F-measure) and running times by using four medical data sets in the UCI machine learning repository (Dua and Graff, 2019). In Immunotherapy data set, FPFSNHC (70.67, 66.68, 73.16, 64.63) has advantage over FSSC (62.28, 61.15, 65.84, 56.69), FussCyier (68.00, 63.48, 68.12, 60.99), HDFSSC (67.89, 62.98, 68.09, 60.78), and Fuzzy kNN (61.33, 45.04, 45.60, 43.18) and in Statlog Heart data set, FPFSNHC (83.39, 83.79, 82.50, 82.62) has advantage over FSSC (80.78, 81.30, 81.61, 80.49), FussCyier (82.46, 82.54, 81.69, 81.73), HDFSSC (79.81, 79.50, 79.36, 79.18), and Fuzzy kNN (58.22, 57.84, 57.70, 57.01), concerning accuracy, precision, recall, and F-measure results, respectively. The results show that the proposed method performs better than FSSC, FussCyier, HDFSSC, and Fuzzy kNN for the data sets. Moreover, *fpfs*-matrices can model classification problems containing uncertainty about which parameters being more effective to classify data. Therefore, it is worthwhile to study developing different classification algorithms by using different similarity measures of *fpfs*-matrices because success can be increased by using different data sets and membership functions.

Moreover, different classification algorithms also can be developed by using soft decision-making methods via *fpfs*-matrices such as (Enginoğlu and Memiş, 2018a, b, c, d; Enginoğlu et al., 2018a, b, c, d; Enginoğlu and Çağman, In Press). Additionally, this study also gives an inspiration about how to construct *fpfs*-matrices for real-life problems such as data classification.

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