# A Novel Feature Selection Method Based on an Integrated Data Envelopment Analysis and Entropy Mode

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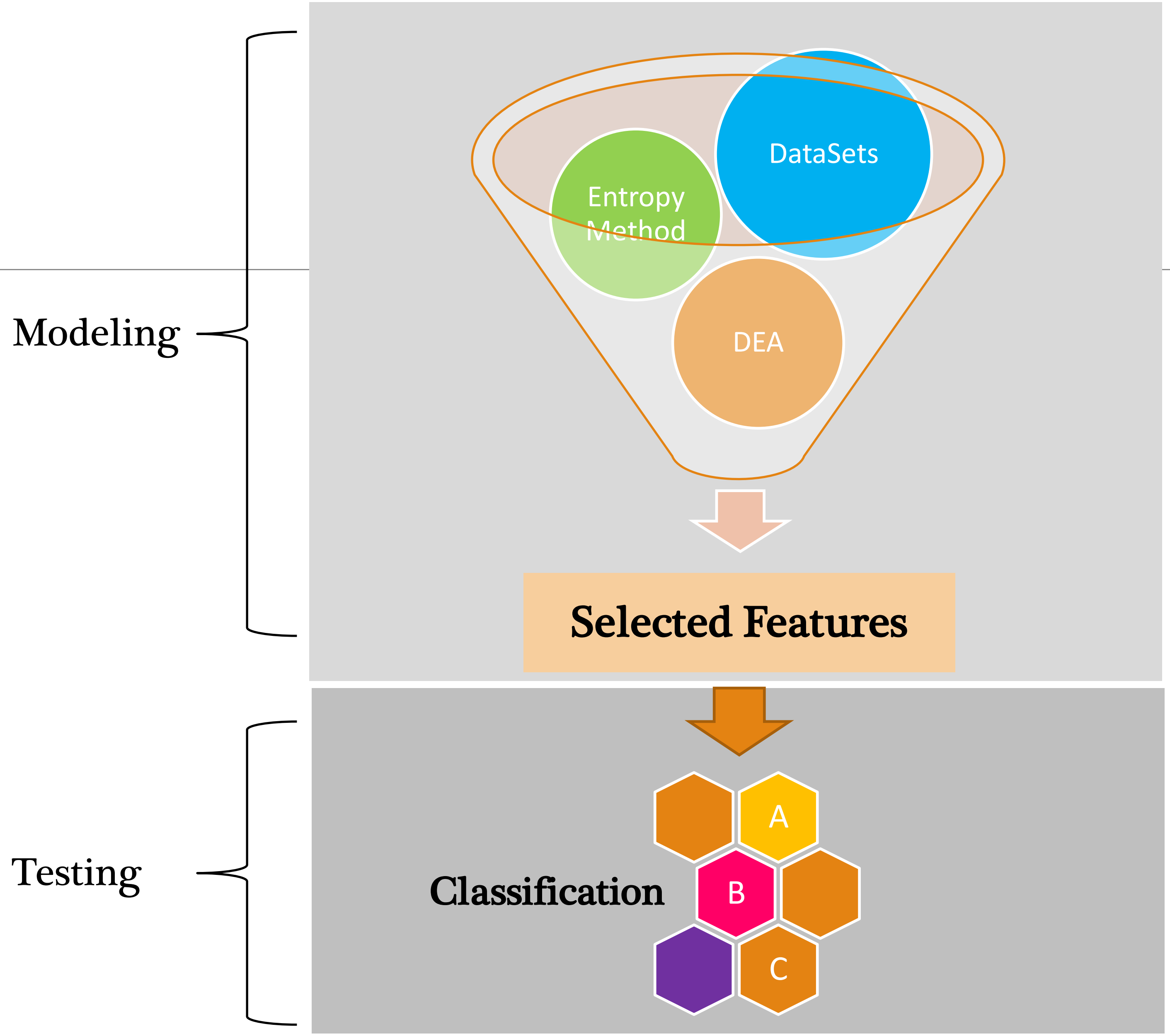
# Abstract

Data mining is a one of the growing sciences in the world that can play a competitive advantages rule in many firms. Data mining algorithms based on their functions can be divided in four categories;

- Classification
- Feature selection
- Assassination rules
- Clustering


Modeling
Testing
DataSets
Entropy Method
DEA
Selected Features
Classification
A
B
C

# Abstract

- **Feature selection algorithms** mostly used for obtaining more precise and strong machine learning algorithms along with reducing the computation time.
- **Data Envelopment Analysis** which is a useful technique for determining the efficiency of decision-making units.
- **Entropy method** which its function is weighting the criteria to selecting the appropriate features.

# Problem Definition

Classification methods are widespread and strong tools to dealing with a real problems such as firm bankruptcy prediction, credit card assessment, intrusion detection, fraud detection and ets.

Totally, a classification machine contains the following four fundamental components:

(1) a set of attribute or characteristic values

(2) a sample training data set

(3) an acceptance domain

(4) a classification function.

The **accuracy of classification** and **predictive power** are two main issues related to classification methods.

# Problem Definition

Selecting an appropriate set of features to represent the main information of original datasets is an important factor that influences the accuracy of classification methods.

**The goal of this paper is to providing a novel feature selection method based on Data envelopment analysis and Entropy to gain more classification accuracy.**

# Feature selection

- Enhancing the classification accuracy and predictability ability
- Increasing the training process speed
- Decreasing the storage demands
- Better understanding and interpretability of a domain.

# Feature selection

Different kind of methods have been proposed feature reduction. Totally they can be divided in two main groups:

- feature extraction
- feature selection.

Although a number of comprehensive studies have been done on feature selection and classification methods to select the best subset of features to improve the accuracy of classification methods, this study focus on applying new model based on MCDM methods.

# Shannon’s entropy

Shannon’s entropy is a well-known method for calculating the weights for multiple criteria decision making problem.

Step 1: Normalize the decision matrix.

$$P_{ij} = \frac{x_{ij}}{\sum_{j=1}^{m} x_{ij}}, \qquad j = 1, \ldots, m \quad , \quad i = 1, \ldots, n$$

By normalizing the decision matrix we make a free unit matrix.

Step 2: By using formula 2 calculating the entropy:

$$E_j = -k \sum_{i=1}^{m} \left[ p_{ij} \, ln_{ij} \left( p_{ij} \right) \right] \rightarrow \left\{ \begin{array}{l} \forall_j = 1, 2, \ldots, n \\ k = \dfrac{1}{\ln(m)} \end{array} \right\}$$

N : Number of attribute

M : Number of Samples

# *Shannon’s entropy*

Step 3: Calculate the degree of deviation of each criteria from its entropy’s value:

$$d_j = 1 - E_j$$

Step 3: Calculate the degree of importance or weight of each criteria:

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \rightarrow \left(\forall_j = 1, 2, \ldots, n\right)_j \quad , \sum_{j=1}^{n} w_j = 1 \rightarrow \left(\forall_j = 1, 2, \ldots, n\right)_j$$

The entropy method is based on the variance of values in each criterion, so we can conclude if criteria have more deviation, then the value of its entropy would be increased and it shows that this criterion is more important for classification.

# Data Envelopment Analysis

DEA use to calculate the efficiency of Decision-making units (DMUs). This method is a non-parametric based on linear programming and was first proposed by Charnes, Cooper & Rhodes (1978).

The basic DEA model known as CCR model:

$$E_P = Max \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}}$$

$$st: \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1$$

$$i = 1, 2, \dots, m \qquad j = 1, 2, \dots, n \qquad r = 1, 2, \dots, s$$

$$u_r, v_i \geq o$$

# Data Envelopment Analysis

There are two different methods to solve this problem, one can be output maximization or input minimization. Here, we choose the first method by placing denominator equal to 1, so in the following an output maximization CCR model presented:

$$E_P = Max \sum_{r=1}^{s} u_r y_{rp}$$

$$st: \sum_{i=1}^{m} v_i x_{ip} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq o$$

$$i = 1, 2, \ldots, m \qquad j = 1, 2, \ldots, n \qquad r = 1, 2, \ldots, s$$

$$u_r, v_i \geq o$$

# Experimental Evaluation

Table 1: Characteristics of selected datasets

| Row | Name | Number of attributes | Numbers of Instances | Numbers of Classes | Attribute Characteristics |
|---|---|---|---|---|---|
| 1 | Breast Cancer Wisconsin (Diagnostic) | 32 | 569 | 2 | Integer |
| 2 | Statlog (Landsat Satellite) Data Set | 36 | 6435 | 6 | Integer |
| 3 | Statlog (Vehicle Silhouettes) Data Set | 18 | 946 | 4 | Integer |

# Our proposed model

In the following steps we show how our model works:

Step1: compute the entropy value of each attribute in different classes by (a) at first separating the datasets according to their classes' type, (b) then calculating the Entropy of each attribute.

Step 2: considering each attribute as a Decision-Making Units (DMUs)

Step 3: placing the input of DMUs equal to 1.

Step 4: placing the output of DMUs equal to entropy value gain form step 1.

Step 5: compute the efficiency of each attribute.

Step 6: selecting the efficient attribute.

Step 7: applying other feature selection algorithms on the same datasets for selecting the features.

Step 8: comparing the result of our models with the result of step 7.

# The selected features

Table 2: The selected features from 1st dataset by different features selection algorithms and our proposed model

| Feature Selection Method | Selected Features | Number of selected features |
|---|---|---|
| CfS Subseteval | 2,7,8,14,19,21,23,24,25,27,28 | 11 |
| Consistency subset eval | 2,11,13,21,22,27,28,29 | 8 |
| Filtered Subset eval | 2,7,8,14,21,23,24,27,28 | 9 |
| Our Proposed Model | 7,8,11,13,14,16,17,20,26, 27 | 10 |

Table 3: The selected features from 2nd dataset by different features selection algorithms and our proposed model

| Feature Selection Method | Selected Features | Number of selected eatures |
|---|---|---|
| CfS Subseteval | 1,4,5,6,9,10,12,13,14,16,17,18,20,21,22,24,25,26,28,29,30,33,36 | 23 |
| Consistency subset eval | 1,2,7,10,11,17,18,24,28,29,31,33 | 12 |
| Filtered Subset eval | 1,4,5,6,9,10,12,13,14,16,17,18,20,21,22,24,25,26,28,29,30,33,36 | 23 |
| Our Proposed Model | 2,3,4,6,7,8,10,11,12,14,16,18,22,24,26,28,30,32,34,35,36 | 21 |

Table 4: The selected features from 3th dataset by different features selection algorithms and our proposed model

| Feature Selection Method | Selected Features | Number of selected features |
|---|---|---|
| CfS Subseteval | 4,5,6,7,8,9,11,12,14,15,16 | 11 |
| Consistency subset eval | 1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18 | 18 |
| Filtered Subset eval | 4,5,6,7,8,9,11,12,14,15,16 | 11 |
| Our Proposed Model | 3,4,6,7,8,11,12,13,15,16 | 10 |

# Experimental Evaluation

Furthermore, we made the new datasets based on the selected features and then try to classify these new datasets by three classifications algorithms in SPSS clementine software and compare their accuracy. We used the 75% of each dataset as training dataset and the rest as testing dataset. The result showed in table 5 to 7.

Table 5: The accuracy of classification algorithms based on the selected feature for Breast Cancer Wisconsin data set

| | The accuracy of classification algorithms | | | |
|---|---|---|---|---|
| Feature Selection Method | SVM | C5.0 | Logistic Regression | average |
| CfS Subseteval | 87.84 | 92.57 | 95.95 | 92.12 |
| Consistency subset eval | 93.24 | 92.57 | 98.65 | 94.82 |
| Filtered Subset eval | 87.84 | 91.22 | 96.62 | 91.89 |
| Our Proposed Model | 89.86 | 93.92 | 95.95 | 93.24 |

# Experimental Evaluation

Table 6: The accuracy of classification algorithms based on the selected feature for Landsat Satellite data set

| | The accuracy of classification algorithms | | | |
|---|---|---|---|---|
| Feature Selection Method | SVM | C5.0 | Logistic Regression | Average |
| CfS Subseteval | 86.84 | 85.42 | 84.98 | 85.74 |
| Consistency subset eval | 87.10 | 85.42 | 84.89 | 85.80 |
| Filtered Subset eval | 86.84 | 85.42 | 84.98 | 85.74 |
| Our Proposed Model | 88.96 | 86.04 | 85.42 | 86.80 |

Table 7: The accuracy of classification algorithms based on the selected feature for Vehicle Silhouettes Data Set

| | The accuracy of classification algorithms | | | |
|---|---|---|---|---|
| Feature Selection Method | SVM | C5.0 | Logistic Regression | Average |
| CfS Subseteval | 58.74 | 66.50 | 67.96 | 64.40 |
| Consistency subset eval | 69.42 | 68.45 | 74.27 | 70.71 |
| Filtered Subset eval | 58.74 | 66.50 | 67.96 | 64.40 |
| Our Proposed Model | 61.17 | 73.3 | 64.56 | 66.34 |

# Conclusion and future work

As shown in the last sector by applying Data Envelopment Analysis and Entropy method for selecting the features, the result is comparable with the other method and in some of the cases it has a better result.

According to the acquired result we suggest other researchers to use different MCDM methods such as TOPSIS and SAW integrated with other methods of weighting such as Expected Value method for selecting the features.

Furthermore, our proposed model can be used for ranking the features instead of selecting them.

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# Thank you