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A review of feature selection in gender classification

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Mohd Shahizan Othman [1,*], Nurul Liyana Hairuddin [1], Lizawati Mi Yusuf [1], Dewi Nasien [1], Hairudin Abdul Majid [1]

[1] Faculty of Computing, Universiti Teknologi Malaysia, 81310 Skudai, Johor, Malaysia

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ABSTRACT

In recent years, gender classification has been an active research area and is becoming one of the most vital tasks in real-world problems. The problem in this area becomes challenging when a big data lacks information and when the information could not help classify the data into the class of male or female. Complex classification problems are likely to present a big number of features where many of them might be redundant and irrelevant for the task of classification. Hence, in order to increase the accuracy of the classifier, there is a need to apply feature selection to select the most relevant features from the data. This paper attempts to highlight the importance of feature selection and its approaches towards classification. Based on the previous work, it showed that feature selection did help in improving the accuracy of gender classification.

1. Introduction

Gender classification problem has revolved more in current research area which has attracted the attention of many parties recently and is becoming one of the most essential tasks in the real world. We are often flooded with a large amount of data but lack information, and clearly data cannot supply information without being processed first [1-4]. The main idea of gender classification is to learn from the given data set the pattern of the classes of male and female. Complex classification problems tend to present the number of features in bulk where most of the features may be unnecessary and irrelevant in the classification process.

Hence, if the number of features is very large, the classifier will take more time to classify the data set. It is better to have a method that is competent in selecting the most relevant and informative features required to come up with a good outcome for the classification. In order to help the classifier, classify the data set correctly, feature selection is applied before the classification

* *Corresponding author.*
E-mail address: shahizan@utm.my (Mohd Shahizan Othman)

process is done. This paper provides a review of gender classification and several feature selection techniques used in gender classification.

2. Data classification

Classification is the process of recognizing which categories the data belongs to on the basis of a training set of data whose category membership is known [2-3]. There are many real-world problems that exhibit classification problem. Among them are categorizing a particular email into "spam" or "non-spam" class, categorizing categories such as "food" or "drinks" and "plants" or "flowers", and assigning a disease based on the prescription by the doctor [2,5-7]. Figure 1 shows the general process of data classification.

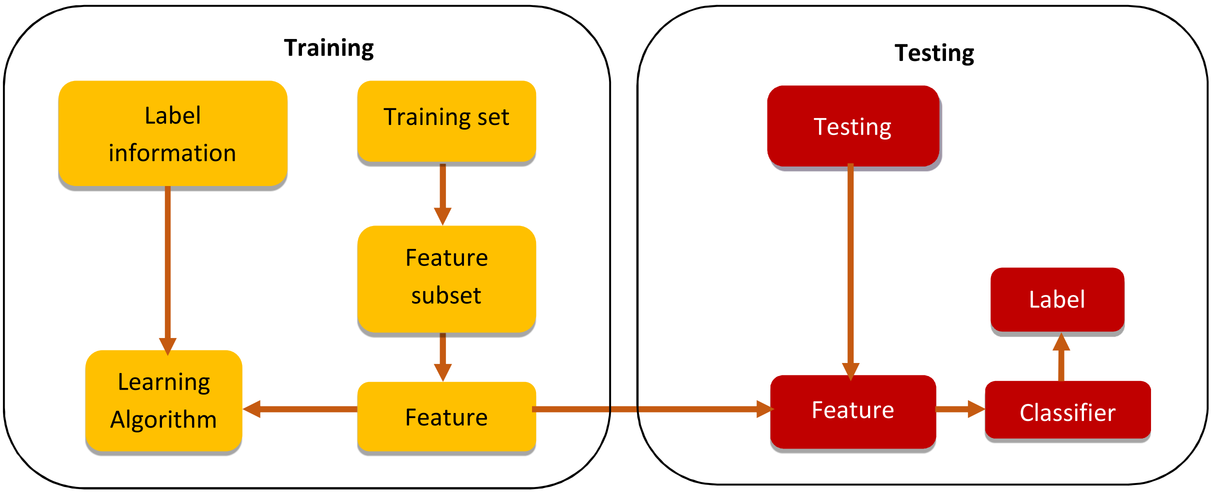

Fig. 1. General Process of Data Classification [2]

The process starts with the training phase where, based on the feature generation model, data is analysed into a set of features. The features may either be ordinal, categorical, real-valued, or integer-valued [2]. Some algorithms work only in terms of discrete data and require real-valued data to be discretized into groups. The learning algorithm will utilize the label information when the data has been represented through the extracted features, and the data itself will learn the map function f from features to label [2] such as the following:

$$f(features) \rightarrow label \quad (1)$$

In the prediction phase, the data is represented by the feature set extracted in the training process. After that, the map function learnt from the training phase is performed on the feature-represented data so that the labels can be predicted. The feature set used is the same for both the training phase and prediction phase. There are many types of classifiers that have been used as discovered in the literature. These methods can be widely categorized into linear classifiers [8-10], support vector machines [5,11-15], decision trees [16-18] and neural networks [13].

3. Gender classification

Recently, gender classification has been receiving more attention since gender carries various distinguished information regarding male and female in social activities [19-21]. Gender classification problems have become an active research area and attracted the attention of others in solving the problems. The purpose of gender classification is to determine the gender of a person based on the characteristics that appear in a person. Classifying gender is considered an important process as it boosts many potential applications in human-computer interaction (HCI) [20], security and surveillance industry [22-23], demographic research [24], commercial development [25-26], mobile application and video games [27-30], and forensic anthropology [31-32].

a) Human-Computer Interaction (HCI)
   In the HCI field, with the purpose to improve performance, robots and computers need to identify and verify human gender based on personalized information. When the gender determination is successful, the system can provide more suitable, or proper, and customized services for customers by adapting to the users according to their gender [20-23].
b) Surveillance System
   In surveillance systems for the public such as at airports, train stations, and shopping malls, classifying gender serves to improve the security such as by counting the number of females and males where it aims to restrict access of a gender to certain areas. Another application is to assist the intelligent security and surveillance system to track moving objects and detect abnormal behaviors. With this application, it can help better evaluate the threat level of an individual if the gender information can be obtained in advance [22-23].
c) Commercial Development
   Gender classification has its benefits in guiding an effective market and implementing smart shopping environment where the production can be directed to specific users through websites, electronic marketing, and advertising [25-26].
d) Demographic Research
   The process of collecting demographic information in a demographic research can be done efficiently with the help of gender classification application [27]. Automatic identification of human gender improves the demographic statistics, for example, gender, disability status, race definition, and population prediction [28]. The capability to detect gender information automatically serves as supplementary method for the existing demographic research on the web or in public places [29].
e) Mobile Application
   Supportive information can be provided from gender classification in order to improve user experiences in mobile applications and video games. In video games, different genders have different character features. Character features like gait can be analyzed using gender classification techniques so that it can increase the realism of a video game. In mobile games, by applying different gait patterns to different virtual characters according to their gender, it will apparently enhance the sense of reality to the player [30].
f) Forensic Anthropology
   In forensic anthropology, the determination of gender has become the first important step for anthropologists for a correct identification process [31-32], and this process is usually included when identifying skeletal remains. In order to identify the biological profile of unknown remains, the identity of the skeletal remains is an important part of the post-mortem. In previous work, Deoxyribose Nucleic Acid (DNA) analysis was used by forensic anthropologists in the laboratory [33] for identification of skeletal remains. Despite the well-known fact that DNA could lead to identification, its drawback is that if the skeleton is in a critical condition such as damaged or burned, the DNA cannot be extracted; thus, data on some important parameters of the biological profile cannot be acquired [34].

4. Classification approaches

In the gender classification process, there are two types of approaches which are appearance-based approach and non-appearance-based approach.

a) Appearance-based Approach

The appearance approach is a vision-based approach, and it contains three categories of features that can be extracted which are static body features, dynamic body features, and apparel features. Static body features are the static traits of the human body, including body shape, face, hand shape, eyebrows, and fingernails. Meanwhile, dynamic body features refer to the movements and activities of a human such as gait [27] and motion [34]. Apparel features can be gleaned from what the person is wearing, including footwear and clothing. The vision-based approach utilizes image processing method to conduct gender classification. The image of the human appearance can deliberately display many variations that could affect the accuracy of the computer's vision system. Consequently, gender classification based on visions is relatively fragile as these features are easily affected by illumination changes, pose, age and ethnicity, or different accessories on the face such as glasses, jewelry, and cap [19].

b) Non-Appearance-based Approach

The non-appearance approach refers to features extracted from a person's physical and biometric traits. Using this approach, features are extracted from biological information and social-network-based information. Biological information can be obtained from biometric traits such as voice [35], iris [28], fingerprint [36], and DNA information [37]. Biometric information is referred to as bio-signal, which is used for gender classification. It is also possible to conduct gender classification using features from social-network-based information. Social-network-based information is information from the daily social activities of a person, which includes emails [6], handwriting [38], and blog posts. Thus, with distinguished language and social styles among male and female, the process of conducting gender classification is possible by using these features.

Based on the discussion of two types of approaches, it can be concluded that

appearance-based approach is the feature or trait which can be identified from the appearance of human body, for example, what the person is wearing and the movement or activities of a human. While, non-appearance-based approach refers to features extracted from a person's physical and biometric traits.

5. Feature selection

Dimensionality is a crucial characteristic involved in data mining and machine learning tasks. Of late, dimensionality problems have increased highly. Existing learning methods are facing serious challenges with extremely high dimensional data [40-42]. Many unnecessary attributes presented in the data need to be reduced by removing those data [3]. A relevant feature is neither unnecessary nor redundant to the target concept. Irrelevant features, however, affect the learning process and they are also not directly associated with the target concept. Furthermore, redundant features do not contribute anything new to the target concept [4].

In order to select a subset of features that are relevant to the target concept, feature selection process can be carried out [4, 43-44] as one of the first steps before classification takes place.

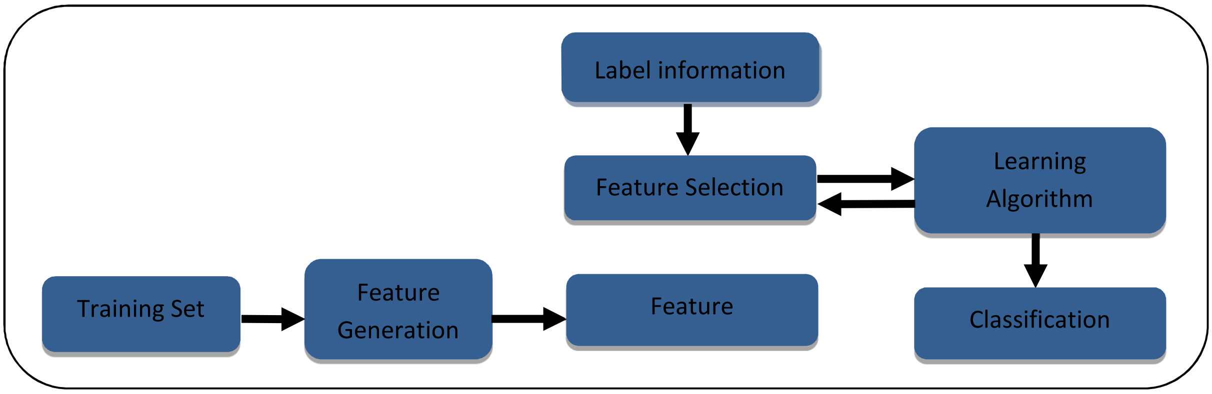

Fig. 2. General Feature Selection for Classification Framework [2]

Therefore, feature selection techniques are necessary to be applied before any kind of mining algorithm is put into application since the main objectives of feature selection are to keep the data from over fitting, give better model performance, and also come up with faster models [3-4, 43-44]. Mostly, feature selection only focuses on the training phase of the classification. Figure 2 shows the framework of the general feature selection for classification.

There are three basic approaches for feature selection: filter approach, wrapper approach, and embedded approach.

a) Filter Approach

Feature selection and classifier learning are run separately. In this process, the bias of the feature selection algorithm does not interfere with the bias of the learning algorithm [2]. In the adaptive system, there are algorithms created for data analysis [45]. An evaluation function that depends on the properties of the data is used in this approach. In many cases, low-scoring features are removed by calculating the features' relevance score. The subset of features left after feature elimination is presented as input to the classification algorithm [3]. The superiority of filter techniques is that they execute within a short time and easily scale to high-dimensional data set. Feature selection needs to be performed only once as the filter approach is independent of the mining algorithm [3, 44]. Other than that, the computational cost of a filter model is low for a large data set. The drawbacks of filter methods, though, are that each feature is considered separately and ignores the interaction with the classifier and feature dependencies which may lead to a worse classification performance [3].

b) Wrapper Approach

In wrapper approach, to decide how good a given attribute subset is, the attribute selection method uses the result of the data mining algorithm. A search procedure in the space of possible feature subsets is defined and different subsets of features are generated and evaluated [3]. The major characteristic of the wrapper approach is that the quality of an attribute subset is directly computed by the performance of the data mining algorithm applied to that attribute subset. In supervised learning problems, wrapper methods are a superior alternative and also more accurate in that they produce better recognition rates than the filter methods [44, 46]. Although they have their own advantages, wrapper methods still have drawbacks where they are prone to be much slower than the filter approach and over fitting problem is more likely to occur than in filter techniques [3]. Other than that, since the wrapper method is bound to some classifiers, there is the deficiency of generality in it [44].

c) Embedded Approach

Searching for an optimal subset of features is the main process in embedded approach, in which it is built into the classifier. It can be seen as a search in the combined space of feature subsets

[3]. It is specific to a given learning algorithm. Furthermore, this approach comprises the interaction with the classification model while being less computationally expensive than the wrapper methods [3, 7, 44]. However, in embedded approach, the classifier needs to be run many times to access the quality of features, which is actually computationally expensive [2].

6. Feature selection techniques in classification

Since most of the data comes in high dimensionality, it might contain redundant and irrelevant features. These entire unusable features will give bad effect on the classification process. So, feature selection has become a popular pre-processing step in classification process. In a recent time, feature selection has been used by many researchers for classifying many types of category such as classifying the disease, email and gender. Different type of data will produce different accuracy because physically, features and dimensionality of the data are different.

Table 1 shows feature selection techniques which have been used by other researchers in classification process. From Table 1 below, it shows that feature selection did help in the classification process as it produced better accuracy. This can be seen from paper [47] where it compares the accuracy of classification without feature selection technique and with feature selection technique. It shows that the KNN produces the accuracy of 77.16% without feature selection technique while with Improve Binary Particle Swarm Optimization, KNN produce 92.29% of accuracy. It can be concluded that it is better to do classification with feature selection technique.

Furthermore, from Table 1, it also shows that most of the researchers preferred metaheuristic strategy in feature selection such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Bat Algorithm (BA) and Artificial Bee Colony Algorithm (ABC). It shows that metaheuristic strategy has been used more times for solving many problems as it tends to move quickly towards a good solution and it provides an efficient way to deal with complicated problems. Therefore, metaheuristic strategy is much better in feature selection to produce better classification accuracy for high dimensionality data.

7. Feature selection techniques in gender classification

Right now, the usage of feature selection techniques in gender classification is still lacking as many researchers prefer to use feature extraction to perform pattern recognition. This is because in gender classification process, they tend to classify gender from face detection. Thus, feature extraction is preferred rather than feature selection in gender classification. Since feature selection has many advantages, some researchers has come out with research regarding feature selection in gender classification.

Among the techniques of feature selection that have been used by researchers in gender classification are Ant Colony algorithm, Particle Swarm Optimization, and ReliefF algorithm. Different techniques select different features and give different accuracies. Table 2 shows the accuracy of some feature selection techniques. It can be seen that Ant Colony Optimization gave the highest accuracy rate, followed by the hybrid of Particle Swarm Optimization and Genetic Algorithm. Since PSO, ACO and GA are belonging to metaheuristic algorithm, it shows that metaheuristic feature selection is better compared to statistical type of feature selection.

Table 1
Classification Rate of Various Feature Selection Techniques

Author	Feature Selection Techniques + Classifier	Data	Accuracy (%)
[47]	Improve Binary PSO + KNN	Gene Expression	92.29
[47]	KNN	Gene Expression	77.16
[48]	PSO + Naïve Bayes	Breast cancer	92.98
[49]	Bat Algorithm + Optimum Path Forest	Ionosphere	77.00
[49]	Firefly Algorithm + Optimum Path Forest	DNA	75.00
[50]	ABC + SVM	Hepatitis	94.92
[51]	GA + SVM	Leukemia	94.74
[52]	ReliefF + Naïve Bayes	Vote	91.70
[52]	Naïve Bayes	Vote	90.10
[53]	Genetic PSO + SVM	Leukemia	97.38
[53]	Bat Algorithm + Naïve Bayes	Mushroom	98.52
[54]	ANN	Spam	91.76
[54]	ACO + ANN	Spam	92.55
[55]	PSO + ANN	Spam	93.34

In a study on gender classification of web authors [56] two different experiments were conducted: one is classification with feature selection and the other is without feature selection. It was found that the accuracy rate of the classification with feature selection was higher compared to that without the feature selection process as feature selection aims to reduce the dimensionality by removing many unnecessary attributes presented in the data [3] and select a subset of features that are relevant to the target concept [43-44]. So, it is proved that feature selection did help in increasing the accuracy of gender classification.

Table 2
Classification Rate of Various Feature Selection Techniques in Gender Classification

Author	Feature Selection Techniques + Classifier	Accuracy (%)
[5]	PSO-GA + SVM	98.30
[56]	ACO + SVM	100.00
[56]	SVM	98.70
[57]	ReliefF Algorithm + SVM	70.50
[58]	AdaBoost + Karcher	86.05
[59]	t-test +SVM	92.20

8. Conclusion

This paper has provided a review of research on feature selection for gender classification. The paper had discussed the importance of feature selection in classification. It is proven that a good technique or approach for feature selection will give a positive impact on the classification accuracy rate. Furthermore, in the current situation, it was revealed that metaheuristic feature selection gives a better accuracy rate compared to the other types of feature selection. From this review paper, it can be concluded that feature selection techniques provide better alternatives for classifying gender accurately.

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