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Feature selection technique applied in Medical application by Supervised algorithm: A Review

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Abstract:
Feature selection is a strategy for preprocessing that determines the main features of a specific problem. Traditionally, it has been employed across a variety of topics, including biological data analysis, finance, and intrusion detection systems. In addition to minimizing dimensionality, FS was successfully used in medical systems, which often enable one to consider the causes of the disease. In this paper, a review started to describe some basic concepts related to medical applications and provide some necessary background information on feature selection and reviewed more than ten articles of the FS in the medical field that have been introduced and published in the last years.

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1. Introduction

Dimension Reduction (DR) of measurements means the transformation of data from a wide region into a limited area, which preserves some significant features of the original data via low-dimensional representation El-Bouchefry et al (2020). Feature selection is used approach to reduce high dimensions or (features, attributes) for a dataset Brank et al. (2011). Learning supervised is one of the most involved domains of machine learning. It involves the creation of a predictive model with a collection of samples that includes the target results such that the outcome of the sample not yet observed can be inferred once the model is educated. This dilemma is known as a classification or regression depending on the performance form (discrete or continuous) (Bhavsar et al., 2012; Zebari et al., 2019). Multiple methods of image processing, including classification or segmentation, are needed for medically generated photographs, such as X-rays, computed tomography (CT) scans, magnetic resonance images (MRI) Criminisi (2016), retinographies, and ultrasound images see figure1.

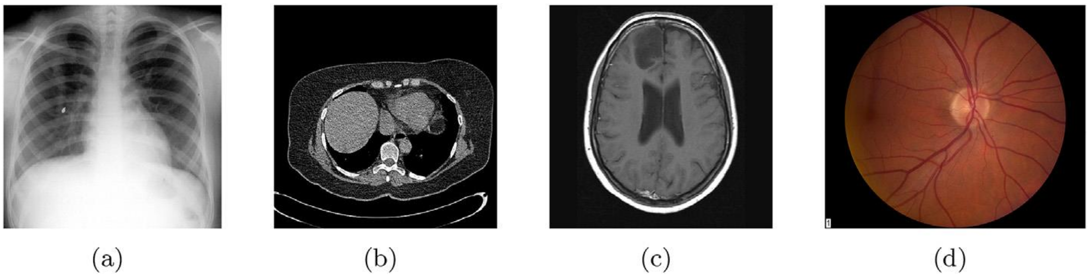

Fig. 1. Examples of different medical images: (a) chest X-ray, (b) colon CT section, (c) brain MRI section, and (d) retinographic image Criminisi (2016).

We add another way of working with picture FS to enhance the efficiency of medical imagery. The findings of tests demonstrate that our medical imagery changes are greater than other FS approaches Criminisi (2016). In this paper, a review is structured as follows. Section 2 provides the necessary background in medical imaging for machine learning. Section 3 describes basic FS concepts and the most popular techniques. Section 4 describes basic DR concepts. Section 5 related work recent medical applications that have benefited from FS. Section 6 presenting and discussing some papers related to the review paper topic. Finally, Section 7 concludes the paper review.

2. Medical Application

Many artificial intelligence methods were implemented in diverse medical problems to streamline extensive and often subjective manual procedures carried out by clinicians in various fields. In this section. So, Machine learning data may be separated into two large groups. Structured data is a matrix that stores data to complement the sample in and row. Secondly, unstructured files provide no specific performance(Ahmed et al., 2012; Zeebaree et al., 2019).

2.1 Medical Imaging

A deeply active area of the analysis of photographs and trends of medical imaging. This involves adding a range of imaging forms to medicated pictures, such as X-rays, CT scans, MRI, retinography, and ultrasound, including picture identification or segmentation (Budoff et al., 2009; Eisenberg et al., 2011; Fritscher et al., 2014; Linder et al., 2014). A deeply active area of the analysis of photographs and trends of medical imaging. This involves adding a range of imaging forms to medicated pictures, such as X-rays, CT scans, MRI, retinography, and ultrasound, including picture identification or segmentation (Ang et al., 2015; Mporas et al., 2015; Tiwari et al., 2017). However, certain features for a specific medical condition, particularly when using general-purpose procedures or a combination of techniques, maybe excessive or insignificant. In addition to the broad dimension of the data, this fact allows the use of feature selection techniques useful (high-resolution medical images). Data collection, microarray data of the DNA, or some other data set may be examined further to classify most common features and decrease the size of the final data set (Golub et al., 1999; Piatetsky-Shapiro et al., 2003).

2.2 Early initiatives

A few years back, medical problems became interested in artificial intelligence researchers. As a result, a variety of papers based on applications of the above-mentioned three medical fields (MDI), biomedical signals, and DNA data were released (Bargarai et al., 2020). In the late 1960s, medical picture detection began to be used. CT scanning has been developed and seems to be one of the most exciting fields for the analysis of medical images. Picture manipulation has been applied for many basic medical conditions such as tumors, retinal abnormalities, screening, and diagnosis. Biological messages are processed roughly from the same period. Various methods were applied in the analysis of EEG, ECG, and EMG signals. DNA microarrays started to evolve in the 1990s. Generally, to classify the outcomes, initial samples of genetic expressions are extracted and controlled education is implemented. Microarray data classification is one of the applications for classifying cancer microarray data (Almugren et al., 2019; Kumar et al., 2017; Bolon-Canedo et al., 2017; Mahmood et al., 2019; Raweh et al., 2018).

3. Feature Selection Methods

A typical approach to cope with a large number of input features is to use particular strategies to minimize the original problem's component, which often increases learning efficiency. Techniques of dimensionality reduction are typically divided into methods of FS and feature extraction FE. The biggest distinction between them is that the FE combines the original features with the current features, thus choosing a sub-set of the original features. Both tactics have advantages and drawbacks. One of the strengths of the FE is that it's discriminatory if the present range of features is usually lower than the one resulting from the collection of features (García et al., 2015; Manoj et al., 2019; Li et al., 2017; Nogueira et al., 2018; Zebari et al., 2020). To this end, the FE is more suitable for viewing and is commonly employed in fields such as image recognition, signal processing and information retrieval. However, the drawback is that variations of features may have no physical meaning and that the FE is not a good option for reading capacity, interpretability, and clarification (Dong et al., 2018; Hancer et al., 2018; Zhu et al., 2017).

The FS is a subset of the original characteristics, but it is always at the expense of compromising the accuracy when it is helpful to be able to read and to retrieve details, as it is in medicine. As our work focuses on medical matters, we concentrate on the collection of features (Hu et al., 2018; Jahwar, 2021). FS methods use person ratings (also referred to as attribute rankings) or sub-sets, based on results (Katrutsa et al., 2017; Kou et al., 2020; Pascoal et al., 2017). In the former, attributes are calculated individually and weight is given to demonstrate their value. The latter appraisal uses a certain test to pick the right feature subsets, see figure (Cai et al., 2018).

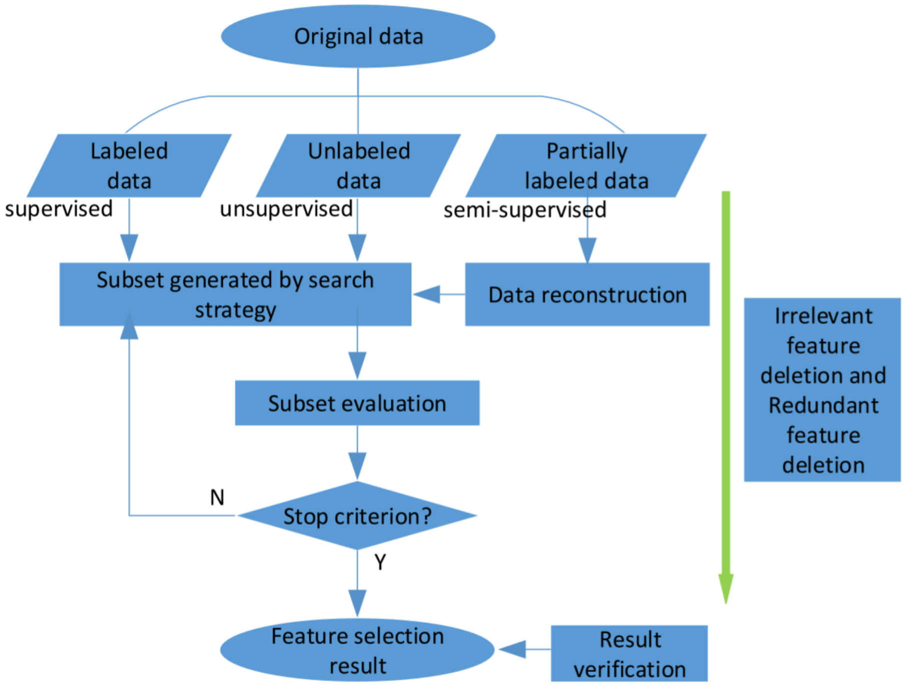

Fig. 2 A framework for feature selection Cai et al (2018).

Classification requires a careful review of the data before the data is passed to a classificator. The advice is just to take into consideration the features required to facilitate the classification process, not to incorporate several arbitrary characteristics. Therefore, Enough techniques help select the appropriate and important characteristics. Moreover, As FS is adopted in the classification, this helps find the important attribute and reduce the classification workload and often increases the precision of the classification (Kou et al., 2020; Vora et al., 2018; Wang et al., 2017).

3.1. Wrapper

Classification-dependent wrapper approaches. The "goodness" of the FS subset is directly measured on the basis of the classification precision (Paul et al., 2017). In wrapper methods, The FS method is based on an algorithm that is used by the computer to suit a particular dataset. As some research studies have demonstrated, the packaging methods can attain greater efficiency. However, the high computer sophistication involved restricted their implementations.

3.2. Filter

The key benefit of filtering approaches is that measurement costs are low because classification utilizes just a few features. However, even the "best" characteristics do not inherently guarantee high precision in the classification (Shukla et al., 2019; Zhuo et al., 2008; Shahana et al., 2016).

3.3. Recursive Feature Elimination

Recursive Feature Cutting is a common FS algorithm, or RFE, for short. RFE is popular because it is simple to modify and use and it is successful to choose certain features (columns) that are more or more important to the objective variable predictions. RFE is a wrapper-type FS algorithm. This makes the recognition and usage of a separate machine learning algorithm in the center of the process, RFE packaging, and pick features. This is in opposition to FS, which tests function and chooses those functionalities with the highest (or smallest) score. Technically, RFE is an FS-algorithm wrapper that often communicates with filter-based FS (Gupta, 2019; Sahran et al., 2018; Solorio-Fernández et al., 2016). Although we can find representative methods for all three groups, most new FS methods emerging are filters. So the option of the right approach for a given problem is complicated by a great many FS techniques now available. Below, the latest methods are listed which are common with scientists (Zaffar et al., 2018).

4. Dimensionality Reduction

DR processes transform data into metaspace with less size, according to some pre-defined criteria in a higher dimensional space, which is often found in biological and disease systems. DR Algorithm that reduces the distance between distributions of various data sets in a latent space so that efficient transfer learning is possible. Van Der Maaten et al (2009). The findings demonstrate that the data with DR are much greater than those without reduced-dimensionality for any system individually (Lin et al., 2019; Zebari et al., 2020). The small-scale data description of the original data helps to address the dimension curse dilemma and is quickly interpreted, stored, and visualized. Advantages of the methods for dimension reduction of a dataset. (i) lower the number of measurements and the capacity for data storage. (ii) Less time to measure is required. (iii) Deletion of data is meaningless, distracting, and repetitive. (iv) The accuracy of the data may well be improved. (v) increases reliability and precision of an algorithm. (vi) make data to simulate (vii) Classification is streamlined and productivity is improved (Ahmed et al., 2011; Juvonen et al., 2015; Systems, 2009). DR techniques are usually divided into two major techniques: (FS) and (FE). As FS is often generated at an ever-growing pace, certain essential dimensional problems may be reduced, for example, successful redundancies are reduced, redundant data is avoided and outcomes are better understood. FS is regarded as an important approach. Also, FE deals with identifying the most distinctive, informative, and minimized features to improve data processing and storage efficiency (figure.2) (Abd-Alsabour, 2018; Ahmed et al., 2018; Verleysen et al., 2005).

5. Related work

The FS is a fundamental mechanism in the selection data for the description of the related classification features collection. Below the paper review some of the literature on the uses of FS in the medical field and how it works. Komeili, et al. (2017) and Komeili et al. (2018) presented a novel feature selection method to address signals of Electrocardiogram (ECG) and transient evoked otoacoustic emission (TEOAE). This method's efficiency is contrasted to seven state-of-the-art algorithms for feature selection and six methods for the biometric identification of ECG and TEOAE. Data from studies suggest that the proposed approach is greatly superior to other algorithms. The incoming CXRs (chest X-ray) are processed by a fully automated tube screening method, using image preprocessing techniques to increase image quality and adaptive segmentation based on the model collection, to describe identified lung regions with a variety of image features (Vajda et al., 2018; Vajda et al., 2018). These features are then tailored by a method of feature selection that better describes the classifier, and later decides whether the picture examined is regular or abnormal. and find the best feature set in a broader pile of standardised picture characteristics – initially used for issues like object tracking, image recovery etc. Measures such as AUC and precision (ACC) were considered for performance assessments.

Using a neural network classification, the neural network classification of two (Montgomery and Shenzhen) data sets was 0.99 and 97.03% respectively, with a median curved region and precision. They contrasted their findings with current state-of-the-art programs and the decision of radiologists to find pulmonary anomalies like (TB). Pereira et al. (2016) and Pereira et al. (2018) revisited categorization and completed an exhaustive survey and new categorization of collection of features for relevant fields, such as categorization of documents, biomolecular review, landscape classification, and medical diagnoses, which have been established for a multi-label classification environment. He completed this work using basic ideas from his categorization and review for potential studies into a multi-label functional collection. Chatterjee et al. (2019) revealed that multiple forms of dissimilarity measurements have been used to find the best feature set and contrasted with each other in their proposed FDM methodology. They also used both the holdout methodology and 10-fold cross-validation in their experiments to apply the suggested algorithm on the individual datasets. The effects of the chosen sub-sets were calculated by precision using Vector Support (SVM) and Assembly Classifier variants. The empirical findings obtained from our experiments in this paper are competitive in precision and have outperformed the other common T-test, Kullback-Leibler Divergence (KLD). Our proposed holdout-based FDM-based role selection algorithm offers 80% and 78.57% accuracies for the 12 and 24 practical AAR data sets. With just 50% of the best unequal functions, the outcomes reached in the Holdout strategy are much higher than those achieved by utilizing the initial feature sets (without using any feature selection technique).

Rostami et al. (2020) and Rostami et al. (2020) suggested to eliminate uncertainty in the set of values a modern Pairwise Restriction Approach for Function Selection (PCFS). It was applied to eight datasets where he selected the smallest redundancy and greatest significance to the goal class subset of accessible characteristics. Also, the efficiency of the system presented was contrasted on eight datasets with the performance of the state-of-the-art and well-known semi-controlled pick approaches. The numerical findings revealed that the method submitted increased classification precision by around 3% and decreased the chosen characteristics by 1%. Consequently, the proposed approach, despite growing classification precision, reduced the computational sophistication of the machine learning algorithm. Additionally, Tubishat et al. (2020) suggests the Dynamic Butterfly Optimization Algorithm (DBOA), As an optimized version of the Butterfly Optimisation Algorithm (BOE) for FS questions. BOA is one of the optimization algorithms most recently suggested. Compared to other optimization algorithms, BOA has proven the ability to solve multiple forms of problems with competitive outcomes. But when optimizing high-dimensional problems, the BOA Algorithm has problems. These challenges involve local optima stagnation and no variety of options throughout the optimization process. The initial BOA proposes two major enhancements to alleviate these shortcomings: create a local mutation-based search Algorithm (LSAM) operator to prevent local optima and use LSAM to increase the variety of BOA solutions. 20 benchmark datasets from the UCI library have been used to show the reliability and supremacy of the proposed DBOA algorithm. The DBOA and its competitive algorithms announce the classification precision, health values, number of selected functions, statistical findings, and convergence curves. These findings reveal that DBOA beats comparable algorithms substantially for the majority of the efficiency measures used.

Moreover, Ghaddar and Naoum-Sawaya (2017) and Ghaddar et al. (2018) proposed an iterative adjustment method that would enable the amount of selected featuring features to converge to the optimal maximum limits by the l1-norm of a classifier vector. He studied two questions with high dimensional properties in the real-life description. The first example is the medical diagnosis of microarray data tumors, in which it proposed a genetically dependent gene expression generic cancer classification approach. In the second example, online comments from Amazon, Yelp, and IMDb were listed. The findings indicate that the proposed classification and selection method is simple, measured, and achieves low error rates which are key for the creation of advanced decision-making systems. Lee et al. (2017) and Lee et al. (2018), are working on a new invention. A modern classifier or predictor with a strong role to pick features effectively contributes to classification and prediction output. To facilitate wise clinical decision-making in the medical and healthcare regions, the latest wrapper-based C4.5 algorithm proposes. In addition to addressing the issue of data distortion, the recently introduced sampling approach S-C4.5-SMOTE increases the overall device efficiency, as the process seeks to efficiently minimize data size without distortion, retaining balanced and functionally smooth datasets. This performance promotes explicitly the Wrapper approach of productive role selection without the issue of vast volumes of data being considered. Jain and Singh (2018) and Jain et al. (2018), described the different approaches for feature selection and their underlying benefits and adversities. He then studied chronic disease prediction adaptive classification systems and concurrent classification systems. Pashaei and Aydin (2017) and Pashaei et al. (2017) suggested solving problems with the function selection in biological knowledge a Binary variant of the Black Hole Algorithm called BBHA. The BBHA is a binarization expansion of the current BHA. Besides, six prominent decision tree groups (Random Forest, Bagging, C5.0, C4.5, Boosted C5.0, and CART) are compared to the best as an assessor of the proposed algorithm in his research, C4.5 is a classification algorithm used to result in DT. This is through dominating both the continuous and the cyclic features of the missing values. DT was produced through C4.5. Which can be used for aggregation and is usually expressed as an analytical classifier. DT combines nodes and arms. Each node combines problems based on one or different properties, that is, comparing the value of an attribute to a constant or comparing more than one characteristic using some functions. A training data set is often called a results tree for the purpose of a preference tree. C4.5 is a set of algorithms for achieving classifications in machine learning and data mining (Hassan et al., 2018)

A modern, effective, global search technology focused on Black Holes behavior, the Black Hole Algorithm (BHA) is implemented to solve multiple problem optimization. However, it has not yet explored the capacity of BHA for function selection. Its findings verified that RF efficiency is higher than other algorithms on decision trees and that BBHA's proposed wrapper selection approach is superior in all metrics to BPSO, GA, SA, and CFS. In terms of Processor time, the number of model configuration parameters, and the number of selected configured functions, BBHA provides substantially better output than BPsO and GA. BBHA also performs more competitively or better than the other literature approaches. Tuba et al. (2019) Proposed an optimized algorithm for the brainstorm optimization for medical dataset function collection. The classification was carried out using a vector support machine with its parameters configured by an algorithm for brain storm optimization. The proposed approach is being tested against the other state-of-the-art approaches using traditional, readily accessible medical data sets. By evaluating the findings collected, a stronger exacting approach has been shown and the number of features needed has been decreased. Sakri et al. (2018) concentrated on the analysis of the impact of incorporating the feature selection algorithm into the breast cancer prognosis classification algorithm. They suggested that by utilizing selection strategies to reduce the number of features we would boost most classification algorithms. In contrast with other features, certain features have a stronger significance and effect on classification outcomes than others. We have provided the results of our experiments with and without the feature selection algorithm of particle swarm optimization for three common classification algorithms: naive Bays, IBK, and REPTree (PSO).

Finally, naive Bayes delivered a better performance with and without PSO, while the two remaining techniques improved with PSO.

Table 1: Review for Feature Selection Algorithms

Ref.	Year	Dataset	FS/ algorithm	problems	accuracy
(Komeili et al., 2018)	2017	ECG, TEOAE, auxiliary, synthetic	Compared with seven cutting-edge FS algorithms, EECG and TEOAE biometric identification as six alternate approaches.	Electrocardiogram (ECG) address indications and transient otoacoustic emissions evoked address (TEOAE)	75%, 85%, 95%, 99%
(Vajda et al., 2018)	2018	Montgomery Shenzhen	lung segmentation, features description, FS and classification.	Detection of pulmonary anomalies including TB (TB)	97.03%
(Chatterjee et al., 2019)	2019	• Brain Computer Interface (BCI) • Competition • III motor-imagery electroencephalogram (EEG)	FS and DM and PCA	to find the best feature subset	80% and 78.57% accuracies for the 12 and 24 features AAR datasets respectively
(Rostami et al., n.d.)	2020	SPECTF SpamBase Sonar Arrhythmia Madelon Colon	novel Pairwise Constraint FS method (PCFS)	The classifier output decreases considerably with medical applications that involve very high-dimensional datasets.	79.66%
(Tubishat et al., 2020)	2020	UCI	FS methods: filter-based methods and wrapper-based methods	Data sets usually provide irrelevant characteristics that can influence the output of the classifier	DBOA outperformed all other baseline algorithms with average accuracy (7.83% , 4.71 %, 8.09% , 3.00% , 8.94% , 7.18%) higher than(BOA, GA, GOA, POS, ALO, SCA) respectively.
(Ghaddar et al., 2018)	2017	real-world datasets	FS and SVM	Owing to the existence of several noisy properties that are not leading to the reduction of classification errors, high dimensionality microarray data is a problem.	achieves low error rates
(Lee et al.,	2017	ECG	novel bagging C4.5	How to handle the	100%

2018)			algorithm based on wrapper feature selection ((SMOTE))	multi-dimensionality and wide volume of data produced from IoT medical systems	
(Pashaei et al., 2017)	2017	8 medical-biological dataset	BBHA for solving FS	to pick a limited or substantial number of appropriate features to boost the classification efficiency.	best performance
(Tuba et al., 2019)	2019	standard publicly available medical datasets	SVM and FS	reduce the feature set.	91.46%
(Sakri et al., 2018)	2018	Wisconsin Prognosis Breast Cancer dataset	• FS with Navie Bayes. • FS with REP Tree • FS with IBK	Fear of recurrence of breast cancer and early disease prediction may help patients get early care	81.3% 80% 75%

6. Discussion

Datasets usually comprise meaningless attributes that can influence the classifier performance adversely. The number of these attributes may be minimized and an FS is better matched to the accuracy of the classification. In terms of the potential to overcome typical issues, such as similarity and redundancy, data nonlinearity, input noise, goal class noise and several features (like micro-samples) have been tested with the FS methods. The literature above shows that the FS algorithm has demonstrated its utility in reducing large data measurements and enhancing the classification work with great precision. To identify a collection of appropriate functions for classification all the previous literature deals with a simple preprocessing method in data extraction. It also helped define main features and eliminate noise from data that impaired the work's efficiency. Yet how can the dimensionality and the high number of data of large medical data sets be successfully dealt with? As demonstrated earlier, most of the above literature proposes new methods that lead to substantially better results, as in (Komeili et al., 2018; Chatterjee et al., 2019, and Rostami et al., 2020). Tubishat et al. (2020) Proposes an optimized edition of Dynamic Butterfly Optimization Algorithm (DBOA) for function selection problems as Butterfly Optimization (BOA) but the categorization of current multi-label classification approaches was revamped and the FS approaches were systematically surveyed and classified (Pereira et al., 2018).

7. Conclusion

For many factors, FS plays an important function in classification. First of all, the concept can be streamlined and computing expenses can also be minimized and therefore fewer inputs need to be inputted while a model is taken for realistic purposes. Secondly, eliminating unnecessary characteristics from the data collection will also improve the transparency and interpretation of the model to help clarify the potential diagnosis which is a crucial prerequisite in medical applications. The FS method can also minimize noise and thus increase the accuracy of classification. This research reviewed more than ten articles as shown in Table 1 of the feature selection (FS) in the medical field that has been introduced and published in the last years. The contribution of this research to describe some basic concepts related to medical applications and provide some necessary background information on feature selection within professional technique that used in feature selection and how applied in medical applications that clearly mentioned in our research compared with previous researches.

References:

Abd-Alsabour, N. (2018). On the Role of Dimensionality Reduction. *Journal of Computers*, *13*(5), 571–579. doi: 10.17706/jcp.13.5.571-579

Ahmed, Nawzat S., & Mohd Yasin, N. (2011). Towards Fractal Approach in Healthcare Information Systems: A Review. *International Journal on Advanced Science, Engineering and Information Technology*, *1*(2), 194. doi: 10.18517/ijaseit.1.2.41

Ahmed, Nawzat S., & Yasin, N. M. (2012). Improvement the cooperation feature in distributed healthcare information systems based on the fractal approach: An empirical study. *Advanced Materials Research*, *463–464*(February), 861–867. doi: 10.4028/www.scientific.net/AMR.463-464.861

Ahmed, Nawzat Sadiq, & Hikmat Sadiq, M. (2018). Clarify of the Random Forest Algorithm in an Educational Field. *ICOASE 2018 - International Conference on Advanced Science and Engineering*, *April 2020*, 179–184. doi: 10.1109/ICOASE.2018.8548804

Almugren, N., & Alshamlan, H. (2019). A survey on hybrid feature selection methods in microarray gene expression data for cancer classification. *IEEE Access*, *7*, 78533–78548. doi: 10.1109/ACCESS.2019.2922987

Ang, K. K., Chua, K. S. G., Phua, K. S., Wang, C., Chin, Z. Y., Kuah, C. W. K., Low, W., & Guan, C. (2015). A Randomized Controlled Trial of EEG-Based Motor Imagery Brain-Computer Interface Robotic Rehabilitation for Stroke. *Clinical EEG and Neuroscience*, *46*(4), 310–320. doi: 10.1177/1550059414522229

Arun Kumar, C., Sooraj, M. P., & Ramakrishnan, S. (2017). A Comparative Performance Evaluation of Supervised Feature Selection Algorithms on Microarray Datasets. *Procedia Computer Science*, *115*, 209–217. doi: 10.1016/j.procs.2017.09.127

Bargarai, F. A. M., Abdulazeez, A. M., Tiryaki, V. M., & Zeebaree, D. Q. (2020). Management of wireless communication systems using artificial intelligence-based software defined radio. *International Journal of Interactive Mobile Technologies*, *14*(13), 107–133. doi: 10.3991/ijim.v14i13.14211

Bhavsar, H., & Ganatra, A. (2012). A Comparative Study of Training Algorithms for Supervised Machine Learning. *International Journal of Soft Computing and Engineering*, *2*(4), 74–81.

Bolon-Canedo, V., Sechidis, K., Sanchez-Marono, N., Alonso-Betanzos, A., & Brown, G. (2017). Exploring the consequences of distributed feature selection in DNA microarray data. *Proceedings of the International Joint Conference on Neural Networks*, *2017-May*, 1665–1672. doi: 10.1109/IJCNN.2017.7966051

Brank, J., Mladenić, D., Grobelnik, M., Liu, H., Mladenić, D., Flach, P. A., Garriga, G. C., Toivonen, H., & Toivonen, H. (2011). Frequent Itemset. *Encyclopedia of Machine Learning*, 418–418. doi: 10.1007/978-0-387-30164-8_317

Budoff, M. J., & Taylor, A. J. (2009). Cardiac CT Imaging. In The AHA Guidelines and Scientific Statements Handbook. doi: 10.1002/9781444303476.ch20

Cai, J., Luo, J., Wang, S., & Yang, S. (2018). Feature selection in machine learning: A new perspective. *Neurocomputing*, *300*, 70–79. doi: 10.1016/j.neucom.2017.11.077

Chatterjee, R., Maitra, T., Hafizul Islam, S. K., Hassan, M. M., Alamri, A., & Fortino, G. (2019). A novel machine learning based feature selection for motor imagery EEG signal classification in Internet of medical things environment. *Future Generation Computer Systems*, *98*, 419–434. doi: 10.1016/j.future.2019.01.048

Criminisi, A. (2016). Machine learning for medical images analysis. *Medical Image Analysis*, *33*, 91–93. doi: 10.1016/j.media.2016.06.002

Dong, H., Li, T., Ding, R., & Sun, J. (2018). A novel hybrid genetic algorithm with granular information for feature selection and optimization. *Applied Soft Computing Journal*, *65*, 33–46. doi: 10.1016/j.asoc.2017.12.048

Eisenberg, R. L., & Alexander, R. (2011). *Book Reviews n BOOK REVIEWS A Patient ' s Guide to Medical Imaging Atlas of Fetal and Postnatal Brain MR*. 733.

El Bouchefry, K., & de Souza, R. S. (2020). Learning in Big Data: Introduction to Machine Learning. In Knowledge Discovery in Big Data from Astronomy and Earth Observation. Elsevier Inc. doi: 10.1016/b978-0-12-819154-5.00023-0

Fritscher, K. D., Peroni, M., Zaffino, P., Spadea, M. F., Schubert, R., & Sharp, G. (2014). Automatic segmentation of head and neck CT images for radiotherapy treatment planning using multiple atlases, statistical appearance models, and geodesic active contours. *Medical Physics*, *41*(5). doi: 10.1118/1.4871623

García, S., Luengo, J., Herrera, F., García, S., Luengo, J., & Herrera, F. (2015). Feature selection. *Intelligent Systems Reference Library*, *72*(6), 163–193. doi: 10.1007/978-3-319-10247-4_7

Ghaddar, B., & Naoum-Sawaya, J. (2018). High dimensional data classification and feature selection using support vector machines. *European Journal of Operational Research*, *265*(3), 993–1004. doi: 10.1016/j.ejor.2017.08.040

Golub, T., Slonim, D., Tamayo, P., Huard, C., Gassenbeck, M., Mesirov, J., Coller, H., Loh, M., Downing, J., Caligiuri, M., & others. (1999). Molecular Classification of Cancer: Class Discovery. *Science*, *286*(October), 531–537.

Gupta, S. (2019). *with Passphrase-Based REST API NoSQL for Big Data in Cloud* (Issue Mi). Springer Singapore. doi: 10.1007/978-981-13-7082-3

Hancer, E., Xue, B., Zhang, M., Karaboga, D., & Akay, B. (2018). Pareto front feature selection based on artificial bee colony optimization. *Information Sciences*, *422*, 462–479. doi: 10.1016/j.ins.2017.09.028

Hassan, O. M. S., Abdulazeez, A. M., & Tiryaki, V. M. (2018). Gait-Based Human Gender Classification Using Lifting 5/3 Wavelet and Principal Component Analysis. *ICOASE 2018 - International Conference on Advanced Science and Engineering*, 173–178. doi: 10.1109/ICOASE.2018.8548909

Hu, L., Gao, W., Zhao, K., Zhang, P., & Wang, F. (2018). Feature selection considering two types of feature relevancy and feature interdependency. *Expert Systems with Applications*, *93*, 423–434. doi: 10.1016/j.eswa.2017.10.016

Jahwar, A. F. (2021). *META-HEURISTIC ALGORITHMS FOR K-MEANS CLUSTERING : A REVIEW*. *17*(7), 1–20.

Jain, D., & Singh, V. (2018). Feature selection and classification systems for chronic disease prediction: A review. *Egyptian Informatics Journal*, *19*(3), 179–189. doi: 10.1016/j.eij.2018.03.002

Joseph Manoj, R., Anto Praveena, M. D., & Vijayakumar, K. (2019). An ACO–ANN based feature selection algorithm for big data. *Cluster Computing*, *22*, 3953–3960. doi: 10.1007/s10586-018-2550-z

Juvonen, A., Sipola, T., & Hämäläinen, T. (2015). Online anomaly detection using dimensionality reduction techniques for HTTP log analysis. *Computer Networks*, *91*, 46–56. doi: 10.1016/j.comnet.2015.07.019

Katrutsa, A., & Strijov, V. (2017). Comprehensive study of feature selection methods to solve multicollinearity problem according to evaluation criteria. *Expert Systems with Applications*, *76*, 1–11. doi: 10.1016/j.eswa.2017.01.048

Komeili, M., Louis, W., Armanfard, N., & Hatzinakos, D. (2018). Feature Selection for Nonstationary Data: Application to Human Recognition Using Medical Biometrics. *IEEE Transactions on Cybernetics*, *48*(5), 1446–1459. doi: 10.1109/TCYB.2017.2702059

Kou, G., Yang, P., Peng, Y., Xiao, F., Chen, Y., & Alsaadi, F. E. (2020). Evaluation of feature selection methods for text classification with small datasets using multiple criteria decision-making methods. *Applied Soft Computing Journal*, *86*, 105836. doi: 10.1016/j.asoc.2019.105836

Lee, S. J., Xu, Z., Li, T., & Yang, Y. (2018). A novel bagging C4.5 algorithm based on wrapper feature selection for supporting wise clinical decision making. *Journal of Biomedical Informatics*, *78*, 144–155. doi: 10.1016/j.jbi.2017.11.005

Li, J., & Liu, H. (2017). Challenges of Feature Selection for Big. *Ieee Intelligent Systems*, *17*(april), 9–15.

Lin, Y., Zhu, X., Zheng, Z., Dou, Z., & Zhou, R. (2019). The individual identification method of wireless device based on dimensionality reduction and machine learning. *Journal of Supercomputing*, *75*(6), 3010–3027. doi: 10.1007/s11227-017-2216-2

Linder, N., Turkki, R., Walliander, M., Mårtensson, A., Diwan, V., Rahtu, E., Pietikäinen, M., Lundin, M., & Lundin, J. (2014). A malaria diagnostic tool based on computer vision screening and visualization of Plasmodium falciparum candidate areas in digitized blood smears. *PLoS ONE*, *9*(8). doi:

10.1371/journal.pone.0104855

Mahmood, M. R., & Abdulazeez, A. M. (2019). Different Model for Hand Gesture Recognition with a Novel Line Feature Extraction. *2019 International Conference on Advanced Science and Engineering, ICOASE 2019*, *2018*, 52–57. doi: 10.1109/ICOASE.2019.8723731

Mporas, I., Tsirka, V., Zacharaki, E. I., Koutroumanidis, M., Richardson, M., & Megalooikonomou, V. (2015). Seizure detection using EEG and ECG signals for computer-based monitoring, analysis and management of epileptic patients. *Expert Systems with Applications*, *42*(6), 3227–3233. doi: 10.1016/j.eswa.2014.12.009

Nogueira, S., Sechidis, K., & Brown, G. (2018). On the stability of feature selection algorithms. *Journal of Machine Learning Research*, *18*, 1–54.

Pascoal, C., Oliveira, M. R., Pacheco, A., & Valadas, R. (2017). Theoretical evaluation of feature selection methods based on mutual information. *Neurocomputing*, *226*(October 2016), 168–181. doi: 10.1016/j.neucom.2016.11.047

Pashaei, E., & Aydin, N. (2017). Binary black hole algorithm for feature selection and classification on biological data. *Applied Soft Computing*, *56*, 94–106. doi: 10.1016/j.asoc.2017.03.002

Paul, D., Su, R., Romain, M., Sébastien, V., Pierre, V., & Isabelle, G. (2017). Feature selection for outcome prediction in oesophageal cancer using genetic algorithm and random forest classifier. *Computerized Medical Imaging and Graphics*, *60*, 42–49. doi: 10.1016/j.compmedimag.2016.12.002

Pereira, R. B., Plastino, A., Zadrozny, B., & Merschmann, L. H. C. (2018). Categorizing feature selection methods for multi-label classification. *Artificial Intelligence Review*, *49*(1), 57–78. doi: 10.1007/s10462-016-9516-4

Piatetsky-Shapiro, G., & Tamayo, P. (2003). Microarray data mining. *ACM SIGKDD Explorations Newsletter*, *5*(2), 1–5. doi: 10.1145/980972.980974

Raweh, A. A., Nassef, M., & Badr, A. (2018). A Hybridized Feature Selection and Extraction Approach for Enhancing Cancer Prediction Based on DNA Methylation. *IEEE Access*, *6*(c), 15212–15223. doi: 10.1109/ACCESS.2018.2812734

Rostami, M., Berahmand, K., & Forouzandeh, S. (n.d.). *A novel method of constrained feature selection by the measurement of pairwise constraints uncertainty*. doi: 10.1186/s40537-020-00352-3

Sahran, S., Albashish, D., Abdullah, A., Shukor, N. A., & Hayati Md Pauzi, S. (2018). Absolute cosine-based SVM-RFE feature selection method for prostate histopathological grading. *Artificial Intelligence in Medicine*, *87*, 78–90. doi: 10.1016/j.artmed.2018.04.002

Sakri, S. B., Abdul Rashid, N. B., & Muhammad Zain, Z. (2018). Particle Swarm Optimization Feature Selection for Breast Cancer Recurrence Prediction. *IEEE Access*, *6*(c), 29637–29647. doi: 10.1109/ACCESS.2018.2843443

Shahana, A. H., & Preeja, V. (2016). Survey on Feature Subset Selection for. *International Conference on Circuit, Power and Computing Technologies*, 4.

Shukla, A. K., Singh, P., & Vardhan, M. (2019). A hybrid framework for optimal feature subset selection. *Journal of Intelligent and Fuzzy Systems*, *36*(3), 2247–2259. doi: 10.3233/JIFS-169936

Solorio-Fernández, S., Carrasco-Ochoa, J. A., & Martínez-Trinidad, J. F. (2016). A new hybrid filter–wrapper feature selection method for clustering based on ranking. *Neurocomputing*, *214*, 866–880. doi: 10.1016/j.neucom.2016.07.026

Systems, D. (2009). Encyclopedia of Database Systems. In Encyclopedia of Database Systems. doi: 10.1007/978-0-387-39940-9

Tiwari, A. K., Pachori, R. B., Kanhangad, V., & Panigrahi, B. K. (2017). Automated Diagnosis of Epilepsy Using Key-Point-Based Local Binary Pattern of EEG Signals. *IEEE Journal of Biomedical and Health Informatics*, *21*(4), 888–896. doi: 10.1109/JBHI.2016.2589971

Tuba, E., Strumberger, I., Bezdan, T., Bacanin, N., & Tuba, M. (2019). Classification and Feature Selection Method for Medical Datasets by Brain Storm Optimization Algorithm and Support Vector Machine. *Procedia Computer Science*, *162*(Iii), 307–315. doi: 10.1016/j.procs.2019.11.289

Tubishat, M., Alswaitti, M., Mirjalili, S., Al-Garadi, M. A., Alrashdan, M. T., & Rana, T. A. (2020). Dynamic Butterfly Optimization Algorithm for Feature Selection. *IEEE Access*, *8*, 194303–194314. doi: 10.1109/access.2020.3033757

Vajda, S., Karargyris, A., Jaeger, S., Santosh, K. C., Candemir, S., Xue, Z., Antani, S., & Thoma, G. (2018). Feature Selection for Automatic Tuberculosis Screening in Frontal Chest Radiographs. *Journal of*

Medical Systems, *42*(8). doi: 10.1007/s10916-018-0991-9

Van Der Maaten, L. J. P., Postma, E. O., & Van Den Herik, H. J. (2009). Dimensionality Reduction: A Comparative Review. *Journal of Machine Learning Research*, *10*, 1–41. doi: 10.1080/13506280444000102

Verleysen, M., & François, D. (2005). The curse of dimensionality in data mining and time series prediction. *Lecture Notes in Computer Science*, *3512*, 758–770. doi: 10.1007/11494669_93

Vora, S., & Yang, H. (2018). A comprehensive study of eleven feature selection algorithms and their impact on text classification. *Proceedings of Computing Conference 2017*, *2018-Janua*(July), 440–449. doi: 10.1109/SAI.2017.8252136

Wang, H., Jing, X., & Niu, B. (2017). A discrete bacterial algorithm for feature selection in classification of microarray gene expression cancer data. *Knowledge-Based Systems*, *126*, 8–19. doi: 10.1016/j.knosys.2017.04.004

Zaffar, M., Hashmani, M. A., Savita, K. S., & Rizvi, S. S. H. (2018). A study of feature selection algorithms for predicting students academic performance. *International Journal of Advanced Computer Science and Applications*, *9*(5), 541–549. doi: 10.14569/IJACSA.2018.090569

Zebari, D. A., Haron, H., Zeebaree, D. Q., & Zain, A. M. (2019). A simultaneous approach for compression and encryption techniques using deoxyribonucleic acid. *2019 13th International Conference on Software, Knowledge, Information Management and Applications, SKIMA 2019*, *February 2020*. doi: 10.1109/SKIMA47702.2019.8982392

Zebari, D. A., Zeebaree, D. Q., Abdulazeez, A. M., Haron, H., & Hamed, H. N. A. (2020). Improved threshold based and trainable fully automated segmentation for breast cancer boundary and pectoral muscle in mammogram images. *IEEE Access*, *8*, 1–20. doi: 10.1109/ACCESS.2020.3036072

Zebari, R., Abdulazeez, A., Zeebaree, D., Zebari, D., & Saeed, J. (2020). A Comprehensive Review of Dimensionality Reduction Techniques for Feature Selection and Feature Extraction. *Journal of Applied Science and Technology Trends*, *1*(2), 56–70. doi: 10.38094/jastt1224

Zeebaree, D. Q., Haron, H., Abdulazeez, A. M., & Zebari, D. A. (2019). Trainable Model Based on New Uniform LBP Feature to Identify the Risk of the Breast Cancer. *2019 International Conference on Advanced Science and Engineering, ICOASE 2019*, 106–111. doi: 10.1109/ICOASE.2019.8723827

Zhu, Y., Liang, J., Chen, J., & Ming, Z. (2017). An improved NSGA-III algorithm for feature selection used in intrusion detection. *Knowledge-Based Systems*, *116*, 74–85. doi: 10.1016/j.knosys.2016.10.030

Zhuo, L., Zheng, J., Li, X., Wang, F., Ai, B., & Qian, J. (2008). A genetic algorithm based wrapper feature selection method for classification of hyperspectral images using support vector machine. *Geoinformatics 2008 and Joint Conference on GIS and Built Environment: Classification of Remote Sensing Images*, *7147*, 71471J. doi: 10.1117/12.813256

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