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REGULAR PAPER

Application of rough set classifiers for determining hemodialysis adequacy in ESRD patients

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Abstract The incidence and the prevalence of end-stage renal disease (ESRD) in Taiwan are the highest in the world. Therefore, hemodialysis (HD) therapy is a major concern and an important challenge due to the shortage of donated organs for transplantation. Previous researchers developed various forecasting models based on statistical methods and artificial intelligence techniques to address the real-world problems of HD therapy that are faced by ESRD patients and their doctors in the healthcare services. Because the performance of these forecasting models is highly dependent on the context and the data used, it would be valuable to develop more suitable methods for applications in this field. This study presents an integrated procedure that is based on rough set classifiers and aims to provide an alternate method for predicting the urea reduction ratio for assessing HD adequacy for ESRD patients and their doctors. The proposed procedure is illustrated in practice by examining a dataset from a specific medical center in Taiwan. The experimental results reveal that the proposed procedure has better accuracy with a low standard deviation than the listed methods. The output created by the rough set LEM2 algorithm is a comprehensible decision rule set that can be applied in knowledge-based healthcare services as desired. The analytical results provide useful information for both academics and practitioners.

Keywords Rough set theory · Global method · End-stage renal disease (ESRD) · Hemodialysis (HD) adequacy · Urea reduction ratio (URR)

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1 Introduction

With a prevalence rate of 11.5 % in Taiwan, there are approximately two and a half million people that are within stages 1–5 of chronic kidney disease (CKD, also known as chronic renal disease, CRD). These patients progressively lose renal function over a period of months or years. It almost takes many years to progress from CKD to renal failure, that is, CKD will eventually lead to uremia, which is also called end-stage renal disease (ESRD) [42]. When serum creatinine, which is an indicator of uremia, is above 8.0 mg/dl, a special treatment is required to treat this serious condition. In the healthcare industry, patients with ESRD are initially managed with conservative therapy, but eventually, they require dialysis or renal transplantation. Not all patients with ESRD are suitable candidates for transplantation, and for those who are, there is often a long waiting period because of the shortage of donated organs. In contrast, dialysis is a safe method for removing waste materials, such as potassium and urea, and free water from the blood. Therefore, dialysis treatment has become a widely performed, relatively safe procedure and represents a reliable method to achieve a good quality of life (QOL) and quality of service (QOS) for the ESRD patients and their doctors, respectively. There are two types of dialysis treatments: hemodialysis (HD) and peritoneal dialysis (PD). Although they both alleviate potential kidney trauma and damage, the HD replacement therapy is the most commonly used method in treatment centers (e.g., hospitals or clinics) and at home. The prevalence of ESRD patients on HD therapy is still increasing at an alarming rate [4] and corresponds to an overall increase in patients undergoing HD. Hence, it would be valuable to analyze the performance of HD treatment to address the associated problems in the ESRD patients.

The most effective way to analyze HD performance in the healthcare services is to evaluate HD adequacy (or sufficiency), which is required to assess the effectiveness of HD. Based on the literature [53], the urea reduction ratio (URR), the clearance rate per volume (named Kt/V), albumin levels, and the hematocrit are related HD adequacy. Specifically, Szczech et al. [80] indicated that the URR is a principal measure for HD treatment and is commonly used to assess the HD dose. Using URR as a determinant of HD dose, determining the amount of HD that is necessary has substantially improved in recent years. Therefore, this study considers the URR as an indicator of HD adequacy. The URR has been used to measure HD adequacy in different types of disease in numerous previous studies [12,13,53,80]. However, the conventional methods of classifying URR measurements rely on the restrictive assumptions of linear separability, multivariate normality, and independence of the predictive variables [62]. Unfortunately, many of the common models violate these assumptions, and these models become more complex if the relationships in the input/output dataset are nonlinear [84]. Therefore, it has recently been recommended that more efficient methods of classification be employed [5,89] based on artificial intelligence (AI) techniques, which have emerged as alternatives to the conventional statistical methods for addressing real-world problems. The use of AI techniques for classification, such as rough set theory (RST), has become a significant research trend for both practitioners and researchers [7,63], and these tools have been used in various domains, such as energy [8], finance [7], and medicine [38]. Furthermore, upon reviewing the literature [6,52,63], it was observed that an important direct method of building knowledge is to build a rule-based model [58,88] that explains the given dataset and that provides a reasonable and powerful explanation. Many previous studies have concluded that the performance of various classification models was highly dependent on the context and the data used [39]. Therefore, it is of interest to develop more reliable tools to forecast classification problems in the context of the healthcare industry.

The four reasons for employing rough sets in this study are the following: (1) rough sets require no preliminary or additional information about the given data; (2) rough sets can provide a valuable analysis even with missing values; (3) rough sets enable the interpretation of large amounts of both quantitative and qualitative data; and (4) rough sets can model highly nonlinear or discontinuous functional relationships to provide powerful methods for characterizing complex and multidimensional patterns [54,82]. Unfortunately, one of the main limitations of "traditional" rough sets is the large number of generated decision rules if the data are not first discretized [82]. Therefore, before the data can be inputted into rough set models, they must first be discretized to reduce the number of decision rules and to further improve the classification accuracy. Importantly, the generality of the data will be increased [82]. However, there is a new approach of generalizations of RST such as dominance-based rough set approach (DRSA), which does not need any prior discretization of continuous-valued attributes [24]. Rough set classifiers support some data discretization methods to identify the cutoff points that are concurrently used for attributes. As for discretization methods, there are two types of groups. When a domain expert follows his judgment, knowledge, or intuition or uses norms established in the subject domain to specify the subintervals for the discretization, the method is called expert discretization [78,82]. When the subintervals for the discretization were defined automatically, it is called automatic discretization [78,82]. Certainly, the experience of experts yields more reasonable cutoff points than the automatic discretization method. Nevertheless, sometimes due to the lack of an expert's supervision or to other attributes being involved in the proposed models, it is necessary to utilize automatic discretization methods [82]. Moreover, rule-filtering algorithms can be used to reduce the large number of redundant or poor-quality rules. Although the RST proposed by Pawlak [54] has inspired many researchers and has made great progress, using RST to define problems in URR classification is a newer approach for determining HD adequacy in the healthcare services.

This study aims to construct an integrated procedure based on rough set classifiers to address HD adequacy measurements to aid ESRD patients and their doctors. The three objectives of this study are as follows: (1) to construct a suitable model for assessing the performance of rough set classifiers in effectively predicting HD adequacy in the healthcare industry; (2) to examine the determinants that influence HD adequacy and classify the URR; and (3) to generate comprehensible decision rules to be applied in knowledge-based healthcare services for ESRD patients, their family members, and their doctors to improve doctor–patient relationships and communication.

The study is organized as follows: Sect. 2 describes the related studies; Sect. 3 presents the proposed procedure and summarizes the experimental results; and Sect. 4 includes the discussion. Finally, Sect. 5 includes the conclusions and recommendations for future work.

2 Related works

This section reviews the related issues of HD adequacy for uremia patients in the healthcare industry and the prediction of the urea reduction ratio. The topics covered include HD adequacy and the urea reduction ratio, rough set theory and its generalization, related rule induction methods, rule filter and rule evaluation, related rough set-based rule approaches using medical data, and related AI algorithms of classification.

2.1 Hemodialysis adequacy and urea reduction ratio

In humans, the kidneys are paired organs that are located in the space behind the abdominal cavity (called the retroperitoneum). The kidneys produce the liquid waste product (the urine) of the body by filtering it from the blood. In medicine, the indicators that monitor kidney function roughly comprise the glomerular filtration rate (GFR), the creatinine clearance rate (CCR), and blood urea nitrogen (BUN) [66]. The GFR represents the flow rate of filtered fluid through the kidneys and is one of the most useful indicators of kidney function and kidney disease. Based on the degree of decrease in the GFR, CKD is separated into five stages that are associated with corresponding treatment plans. Qualitatively, Stages 1 and 2 represent kidney damage, Stage 3 is moderately decreased kidney function, Stage 4 is severely decreased kidney function, and Stage 5 is kidney failure, usually with signs and symptoms of uremia that require kidney replacement therapies such as dialysis or transplantation [21]. Stage 5 is called uremia or ESRD. In this stage, dialysis is the only method of filtering out toxins that can affect the body and eventually cause death and prolonging of life other than receiving a renal transplant. HD treatment is one of the major concerns and the most widely used renal replacement technology for ESRD patients. Evaluating the outcomes that measure the HD adequacy is a good approach for understanding the success of HD treatment, and many initiatives have been taken to measure and compare the adequacy of HD treatment.

Some professional nephrology groups have established therapeutic levels for HD adequacy in the form of clinical practice guidelines. In terms of measuring the HD adequacy, there are four criteria, including URR, Kt/V, albumin, and hematocrit [13]. For the URR, the relative reduction in the BUN concentration caused by dialysis treatment is a specific indicator of HD adequacy [13,51]. The efficiency of the dialysis membrane must be altered to adequately remove waste products from the ESRD patients [14]. The goal of HD therapy is to attain a URR greater than or equal to 65 % or to lower the BUN to at least 35 % of the pre-dialysis BUN level [13]. Two professional organizations, the Renal Physicians Association and the National Kidney Foundation, recommend that the minimum level of HD adequacy for dialysis patients consists of a Kt/V value of 1.2 or a URR equal to 65 % [13]. In practice, using the URR alone could be appropriate for both academics and practitioners. Moreover, Szczech et al. [80] stated that the URR is the main determinant of HD dose in the United States. Hence, the URR was used as an evaluation criterion in this study. The equation for URR is as follows: $\text{URR} = (1 - \text{the post-dialysis BUN}/\text{the pre-dialysis BUN})$.

2.2 Rough set theory and its generalization

Rough set theory, which was first proposed by Pawlak [54], employs mathematical modeling to address class data classification problems and has turned out to be a very useful tool for decision support systems, especially in cases in which hybrid data, vague concepts, and uncertain data are involved in the decision process. To use the rough set process, one begins with a relational database, a table of objects with attributes, and attributes values for each object. One attribute is chosen as the decision attribute, and the rest of the attributes are the condition attributes [54,81]. Rough sets address the continuing problem of vagueness, uncertainty, and incompletion by applying the concept of equivalence classes to partition training instances according to specified criteria. Two partitions are formed in the mining process. The members of the partition can be formally described as unary set-theoretic operators or as successor functions for the lower approximation and upper approximation spaces from which both possible and definite rules can be easily derived. Vague and imprecise data sets have no clear-cut boundaries. Rough sets are based on refusing certain set boundaries, implying that every set will be roughly defined using a lower and an upper approximation.

Let $B \subseteq A$ and $X \subseteq U$ be an information system (also called an attribute-value system) that is a basic knowledge representation framework comprising an information table with the columns "attributes" and the rows "objects." ***A*** is a non-empty, finite set of attributes, ***B*** is a reduced set of attributes, ***U*** is a non-empty set of finite objects (i.e., the universe), and ***X*** is subset of objects in the approximation space. For $B \subseteq A$, there is an associated equivalence relation denoted ***IND***(***B***), which is called a ***B***-indiscernibility relation, and the equivalence classes of the ***B***-indiscernibility relation are denoted $[x]_B$. The set ***X*** is approximated using information contained in ***B*** by constructing the ***B***-lower and ***B***-upper approximation sets:

$$\underline{B}X = \{x|[x]_B \subseteq X\} \quad \text{(lower approximation), and}$$
$$\bar{B}X = \{x|[x]_B \cap X \neq \emptyset\} \quad \text{(upper approximation),}$$

where x is an object in the universe ***U***. The ***B***-lower approximation is the union of all of the equivalence classes in $[x]_B$ that are contained by the target set. The objects in $\underline{B}X$ can be classified as positive members of ***X*** by the knowledge that they are in ***B***. However, the ***B***-upper approximation is the union of all the equivalence classes in $[x]_B$ that have non-empty intersections with the target set. The objects in $\bar{B}X$ can be classified as possible members of ***X*** by the knowledge that they are in ***B***. The set $BN_B(x) = \bar{B}X - \underline{B}X$ is called the ***B***-boundary region of ***X***, and it consists of the objects that cannot be classified with certainty as members of ***X*** with the knowledge that they are in ***B***. The set ***X*** is called "rough" or "roughly definable" with respect to the knowledge of ***B*** if the boundary region is non-empty. The details of rough sets can be referenced by the studies of Pawlak [54,55].

Following RST, many subsequent extension methods have been proposed. Here, (1) the generalization of RST as tolerance-based RST and (2) the DRSA are introduced, which allow numerical attributes with missing values and do not require pre-discretization. Subsequently, (3) the so-called action rule method on related RST is discussed. (1) The tolerance-based RST methods include approximation spacing according to tolerance relations [69] to address real-valued data based on the similarity measure and the non-symmetrical similarity relation [72]. This approach is based on the concept that the similarity relation is not necessarily symmetrical and can enhance the indiscernibility relation and fuzzy-valued relation [76] to probabilistically handle attributes with missing values. (2) DRSA, which was introduced by Greco et al. [23], is an extension of RST to handle the semantic correlation of criteria for a multiple criteria decision analysis (MCDA) or for problems that include background knowledge about the ordinal evaluations of objects from a universe and about the monotonic relationships between these evaluations [3]. The main difference in this method compared to classical RST is the substitution of a dominance relation for the indiscernibility relation to address inconsistencies in the consideration of the criteria and the preference-ordered decision classes. There are many potential applications for DRSA in practical problems [3]: decision support in medicine [44,45], customer satisfaction surveys [25], bankruptcy risk evaluation [22], and operational research problems, such as location [20], finance [26], and ecology [17]. (3) A new class of rules called action rules, which are constructed from certain pairs of association rules from a given database, has been proposed by Ras and Wieczorkowska [60] and Im et al. [37]. An action rule is a rule that is extracted from a decision system that describes a possible transition of objects from one state to another with respect to a distinguished attribute, which is called the decision attribute [60]. It is assumed that the attributes used to describe the objects in a decision system are partitioned into two groups, stable and flexible, and that the values of flexible attributes can be changed. Action rule mining was initially based on comparing the profiles of two groups of targeted objects: those that are desirable and those that are undesirable [60,61].

2.3 Rule induction methods

It is worthwhile to review some of the literature regarding rough set-based rule induction algorithms. Three good examples in this domain are from Grzymala-Busse's works. (1) In RST, decision rules are frequently induced from a given decision table, which is transformed into a minimal set of rules. Rough set rule induction algorithms were first implemented using a LERS (learning from examples based on rough sets) [29] system. The learning system LERS induces a set of rules from examples and classifies new examples using the previously induced set of rules. A local covering is created by exploring the search space of blocks of attribute–value pairs, which are then converted into the rule set. (2) The LEM2 (Learning from Examples Module, version 2) algorithm is correctly applied for symbolic attributes and is a part of the LERS data mining system [30]. The LEM2 algorithm is based on calculating a single local covering for each concept from a decision table to generate decision rules. The quality index of each rule is computed using a specific rule quality function based on the measure of support, consistency, and coverage to determine the strength of the rules. The decision as to which concept a case belongs is made based on three factors: strength, specificity, and support [31]. (3) The MLEM2, a modified version of the existing LEM2 algorithm, is a rule induction algorithm that is based on simple machine learning trick, which processing numerical attributes with a special threshold operations and in which rule induction, discretization, and handling missing attribute values are all conducted simultaneously [35]. MLEM2 includes numerical attributes and symbolic attributes, and it induces rules from raw data with numerical attributes without any prior discretization. However, MLEM2 provides the same results as LEM2 for symbolic attributes.

In addition to Grzymala-Busse's works, other inspired rule induction methods that are closer to a rough approximation have been performed. (1) The MODLEM rule induction algorithm was introduced by Stefanowski [75] as a generalization of the LEM2 for generating a minimal set of rules given a set of positive examples and a set of negative examples. The minimal set of rules is the smallest set of rules that covers all of the positive examples but not any of the negative examples. MODLEM induces rules directly from the numerical data of conditional attributes, and no prior discretization is required for the rule induction. (2) Tsumoto and Tanaka [85] proposed the rule induction algorithm PRIMEROSE (probabilistic rule induction method based on rough sets) for medical diagnostic procedures from databases. PRIMEROSE first analyzes the statistical characteristics of attribute–value pairs from training examples. Subsequently, the type of diagnosing model that should be applied to the training examples is determined, and the algorithm extracts domain knowledge based on a selected diagnosing model. (3) Bazan [2] presented a lazy rule induction algorithm that constructs a local rule that contains the conditions that are common for the testing, and the training object then checks whether the training objects that support the constructed local rule are in the same decision class. The algorithm then selects the decision that is most frequent in the support set to induce a minimal rule set that covers a test object. (4) Nguyen [47] defined the discretization problem using "soft cuts" and based the reasoning scheme on rough sets and fuzzy sets to obtain suitable discretization methods, such as cuts, for decision rule induction. Any set of cuts defines a partition of real values into intervals in which the values are not discernible. For more details related to this method, please refer to Nguyen [47].

Based on the information above, there are two approaches for processing the numerical data of attributes: (1) to conduct the discretization process before rule induction (e.g., LEM2) and (2) to implement both the discretization and the rule induction at the same time (e.g., MLEM2 and MODLEM). Generally, the former approach is more frequently used in the practice of data mining, and the LEM2 algorithm is the most frequently used rule induction option of the LERS data mining system [35]. Therefore, this study adopts LEM2 as the rule induction algorithm. A comparison of LEM2 and the other rule induction algorithms will be explored in the future.

2.4 Rule filter and rule evaluation

Regarding rule filters, rough set-generated rule sets usually contain large numbers of distinct rules [67], and the large number of rules limits the classification capabilities of the rule set because some rules are redundant or of "poor quality;" therefore, some rule-filtering algorithms can be used to reduce the number of rules [48]. For example, a rule-filtering solution could be based on the calculated quality indices of the rules in a rule set. The quality index of each rule is calculated using a specific rule quality function, which determines the strength of the rule based on measurements of the support, consistency, and coverage. The heuristic is based on the assumption that the strongest rules are preferred to form the minimal coverage set. The heuristic algorithm proposed here does not seek the minimal solution for efficiency reasons. In the initialization step, all rules are marked as "unused." For each object, the strongest rules that cover it are identified and are flagged for inclusion in the resulting set. The remaining rules that are not used in the covering process are filtered out.

A rule quality measurement is required for both rule induction and classification processes, and this measure can be used as an evaluation heuristic to select attribute–value pairs in the rule specification process [1]. Some of the latest studies regarding the evaluation of rules are discussed here. Yao and Zhong [91] analyzed quantitative measures that were associated with if-then type rules to examining multi-faceted concepts representing the confidence, uncertainty, applicability, quality, accuracy, and interestingness of rules. An and Cercone [1] experimented with various statistical and empirical formulas for defining rule quality measurements. They presented a meta-learning method for generating a set of so-called formula-behavior rules that were combined into formula-selection rules to select a rule quality formula before rule induction. Additionally, these authors reported the effects of formula selection on the predictive performance in a rule induction system. Greco et al. [27] proposed an evaluation method for the contribution of elementary conditions that was based on previous results concerning the importance and interactions of elementary conditions for the confidence of a single rule in a given set of rules. Their method was demonstrated for two rule-discovery problems in the set of discovered rules. Szczech [79] presented an Apriori-like algorithm for the generation of rules with respect to attractiveness possessing valuable properties and evaluated the rules using a multicriteria approach to analyze such a desirable property in terms of the property (M), the property of confirmation, and the hypothesis symmetry of the popular interestingness measures of the decision and association rules. Greco et al. [28] concentrated on measuring the relevance and utility of induced rules according to three popular interestingness measures, including Piatetsky-Shapiro's rule interest function, Fukada et al.'s gain measure, and Pawlak's dependency factor. They demonstrated that the rule interest function and gain measure are characterized by satisfying both valuable properties (M) and hypothesis symmetry (HS), while the dependency factor does not satisfy any of these properties. Additionally, Greco et al. [28] showed that the rules that maximize the rule interest function or gain are included on the rule support-anti-support Pareto-optimal border.

2.5 Rough sets-based rule approaches to medical data

A wide range of methods based on rough set theory alone or in combination with other approaches [56] and other rule induction-based approaches from the machine learning community have been discovered to have applications in medicine as discussed in Grzymala-Busse and Grzymala-Busse [31], Grzymała-Busse and Stefanowski [32], Grzymala-Busse et al. [33], Grzymala-Busse and Hippe [34], Slowinski et al. [71,73,74], Kononenko et al. [41], Tsumoto [86], and Michalowski et al. [43]. Some of the research that has been performed since the 1990s using rough sets-based rule approaches for medical data is discussed here. Tsumoto [86] introduced the new rule induction algorithm PRIMEROSE-REX (Probabilistic Rule Induction Method based on Rough Sets and Resampling methods for Expert Systems) to examine three medical databases, which regarded headache, meningitis, and cerebrovascular diseases (CVD); the experimental results showed that their proposed method correctly induces diagnostic rules and estimates the statistical measures of rules. Slowinski et al. [74] discussed a process of analyzing medical diagnostic data by a combined rule induction and rough set approach. Their approach was illustrated on a medical problem concerning the arthroscopy of patients with anterior cruciate ligament (ACL) rupture of the knee. Michalowski et al. [43] applied rough set theory and fuzzy measures to identify the most relevant clinical symptoms for evaluating abdominal pain in the emergency room (ER) of a hospital. The information was used to develop a multilevel clinical algorithm that forms a reasoning module for a clinical support system that can be installed on Palm handheld and that can be used to triage a child irrespective of the available information. Tsumoto [87] used the rule induction algorithm PRIMEROSE4.5 (Probabilistic Rule Induction Method based on Rough Sets Version 4.5) to evaluate the three medical databases mentioned above, and the induced rules correctly represented experts' decision processes. Michalowski et al. [45] proposed a "Scrotal Pain Decision" method to support early the emergency department (ED) triage of acute pediatric conditions using rough set theory, which resulted in good triage accuracy. The triage decision-making model was created using knowledge discovery techniques that were based on rough set theory [70] and that were implemented as rule-based models. Following that, Farion et al. [15], Michalowski et al. [44], and Michalowski et al. [46] designed and developed a related clinical decision support system (CDSS) on mobile emergency triage (MET), which is a computer-based clinical support system for supporting the triage decisions regarding the abdominal pain of children in the ED. Wilk et al. [90] used a scenario-based design methodology to model the user's mental representations of tasks to accomplish and an object-action-interface model combined with the Eight Golden Rules of Interface Design to design the input and output components of an interaction framework of the MET system, which facilitates the emergency triage of patients with various acute pain conditions at the point of care. Farion et al. [16] constructed a decision tree model to predict the severity of pediatric asthma exacerbations in children in the emergency department 2 h following triage. They demonstrated a high performance with an area under the ROC curve (AUC) of 0.83, a sensitivity of 84 %, a specificity of 71 %, and a Brier score of 0.18. O'Sullivan et al. [50] proposed a methodological framework that used the ontologies of diagnosis-, treatment-, and patient-related concepts to guide the indexing and retrieval of empirical research evidence in pediatric asthma to support evidence-based decision making at the point of care. Table 1 summarizes the above literatures.

As stated above, this study focuses on the application of rough sets to provide an alternative method of predicting the urea reduction ratio as a measure of HD adequacy for ESRD patients and their doctors. The method, which is based on rough set classifiers, offers analytical results to both academics and practitioners. Particularly, the application of such a

Table 1 The summary of earlier studies to medical data based on rough sets

Earlier study	Methodology	Object	Number of rule	Example	Accuracy (%)
Tsumoto [86]	PRIMEROSE-REX	1. Headache,	–	1. 1,477	1. 95.0
		2. Meningitis,		2. 213	2. 88.9
		3. CVD		3. 620	3. 91.0
Slowinski et al. [74]	Rough set theory and attribute discretization	Arthroscopy patients	1. 20 (MI)	140	1. 88.86
			2. 16 (ME)		2. 92.86
			3. 20 (MD)		3. 90.00
Michalowski et al. [43]	Rough set theory Fuzzy measures	1. No management class patient	–	647	1. 91.0
		2. Surgical consult patients			2. 75.0
		3. NYD class patient			3. 13.0
Tsumoto [87]	PRIMEROSE4.5	1. Headache	–	1. 52,119	1. 95.2
		2. Meningitis,		2. 141	2. 82.0
		3. CVD		3. 7,620	3. 74.3
Michalowski et al. [45]	Scrotal pain decision algorithm (rough sets)	Acute scrotal pain in ED patient	123	171	72.5
Farion et al. [15]; Michalowski et al. [44]; Michalowski et al. [46]	MET CDSS	Pediatric abdominal pain in children	–	574 [44]	67.2 [44]
Wilk et al. [90]	Scenario-based design and object-action-interface (OAI) model	Abdominal pain in triaging patients	–	574	72.0
O'Sullivan et al. [50]	Methodological framework	Pediatric asthma	–	–	–
Farion et al. [16]	Decision trees	Asthma exacerbations in children	7	362	77.24 (M4)

The "–" denotes no given answer in this field method to HD adequacy measurement problems has been very limited in the literature until now.

2.6 AI algorithms of classification

Three classification methods are used in this study to verify the proposed procedure. First, the ID3 is a decision tree algorithm that is based on information theory, and C4.5 is a software extension of the basic ID3 algorithm that was designed by Quinlan [59] to address some issues that are not addressed by ID3. Second, multilayer perceptron is one of the most widely used types of neural network, and it is both simple and definitive based on mathematical computation [36]. Finally, naive Bayes is a well-known and well-studied algorithm in both statistics and machine learning; it is an efficient classification model that is easy to learn and has high accuracy in many application domains [92]. Specifically, Noh et al. [49] used decision trees C4.5, multilayer perceptron, and naive Bayes to compile a threat into a rule set and obtained high performance. These methods are chosen as performance comparisons for the present study.

A common machine learning solution to process classification problems is rule induction [9,10], of which the goal is to induce a set of rules from data. Three typical machine learning rule induction algorithms can prune rules and are discussed here. (1) A popular method called RIPPER was developed by Cohen [10] and is a fast rule induction algorithm that is based on the incremental reduced error pruning method, which divides the training data into a growing two-thirds of the data set and a pruning one-third of the set. RIPPER uses the so-called description-length criterion to decide when to stop adding and pruning rules. (2) The learning algorithm PART (partial decision trees), which was introduced by Frank and Witten [19], is a rule-based learning method that produces rules from pruned partial decision trees. Its primary advantage is not performance, but simplicity. PART functions by building a rule to select the branch with the largest coverage and repeats the process until all of the examples are covered. (3) The rule induction algorithm CN2 [9], which was designed to work even if the training data are imperfect, is a learning algorithm and induces an ordered set of if-then classification rules from examples using entropy. CN2 uses the covering approach to construct a set of rules for each possible class, which correctly classifies some examples, and then removes the corrected classified examples from the training dataset. The process is repeated until no more examples remain. This study presents an empirical evaluation of these rule induction algorithms that are compared for medical classification tasks.

3 The proposed procedure

This section introduces the research framework of the proposed procedure. Subsequently, the algorithm with an actual dataset is used, and classification performance is assessed. Finally, the empirical results and the implications for the management of health care are discussed.

3.1 Research framework of the proposed procedure

Although renal transplantation may greatly alleviate the expense of dialysis, seeking a kidney from a living donor is considerably difficult. For ESRD patients, dialysis represents a secure treatment option. HD is the most common dialysis treatment performed in clinics or medical centers; therefore, evaluating HD adequacy is very crucial in understanding the HD outcome. This paper follows Szczech et al.'s study and adopts the URR as a measure of HD adequacy.

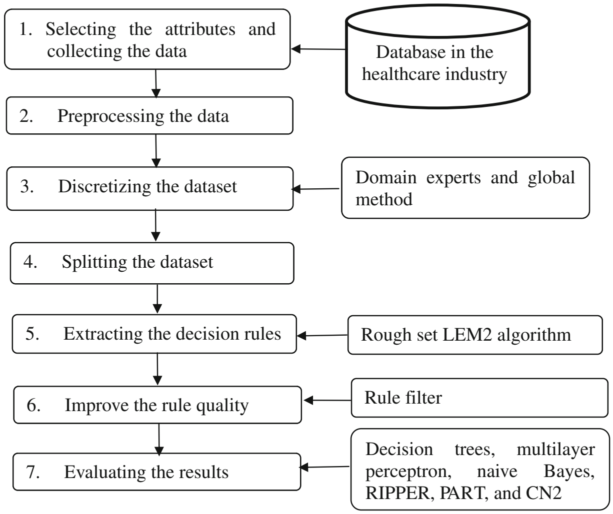

Fig. 1 Flowchart of the proposed procedure

This study offers an integrated procedure that is based on rough set classifiers as an informed alternative for classifying the HD adequacy measurements for ESRD patients and their doctors in the healthcare industry. Generally, the proposed procedure comprises seven parts. First, all of the conditions and decision attributes are selected and collected from a specific database. Second, data preprocessing is performed. Third, the decision attributes are partitioned into different classes based on the professional knowledge of domain experts, and the global cut method is employed to discretize the continuous data of selected condition attributes to improve the classification accuracy. Fourth, the experimental dataset is randomized and split into both training and test sub-datasets. Fifth, the rough set LEM2 algorithm measures the important attributes that influence HD adequacy and generates decision rules as knowledge-based systems. Sixth, a rule-filtering process is used to remove rules with low support. Finally, the performance of the seven different AI methods is evaluated. Figure 1 illustrates a flowchart of the proposed procedure.

3.2 Algorithm of the proposed procedure using a practical HDA dataset

The computational processes of the proposed procedure using an empirical case dataset are discussed step-by-step as follows:

Step 1: Selecting the attributes and collecting the data
Initially, an actual dataset was analyzed by physicians from a branch of a medical center in Taiwan to identify the related background for HD adequacy. Consequently, 27 essential (including condition and decision) attributes were selected as the target dataset from the database of healthcare records on the HD adequacy of uremia patients based on the expert recommendations. This dataset was labeled the HDA dataset. The data were collected from Jul 2008–Dec 2008.

Step 2: Preprocessing the data
Change the format of HDA dataset into an EXCEL file for the convenience of experimental operations. To effectively improve the accuracy of classifying HD adequacy, specific fields are normalized. For example, the birth date of ESRD

Table 2 The attribute information in the HDA dataset

No.	Attribute name	Attribute unit	Attribute information	Number of values	Note
1	AGE	Years	Numeric	Continuous	Min: 26–Max: 92
2	GNR	–	Symbolic	2	'M' and 'F' refer to male and female, respectively
3	ICD	–	Symbolic	4	'C,' 'D,' 'H,' and 'O'
4	WBC	$10^3/\mu$l	Numeric	Continuous	Min: 2.0–Max: 20.27
5	RBC	$10^6/\mu$l	Numeric	Continuous	Min: 1.61–Max: 5.59
6	HBC	gm/dl	Numeric	Continuous	Min: 4.8–Max: 15.3
7	HCT	%	Numeric	Continuous	Min: 14.5–Max: 45.9
8	MCV	μm^3	Numeric	Continuous	Min: 44.7–Max: 110.0
9	PLT	$10^3/\mu$l	Numeric	Continuous	Min: 22–Max: 547
10	ALB	g/dl	Numeric	Continuous	Min: 2.4–Max: 5.3
11	GOT	U/l	Numeric	Continuous	Min: 3–Max: 151
12	GPT	U/l	Numeric	Continuous	Min: 1–Max: 436
13	GLU	mg/dl	Numeric	Continuous	Min: 29–Max: 841
14	PWW	kg	Numeric	Continuous	Min: 28.3–Max: 118.2
15	AWW	kg	Numeric	Continuous	Min: 0–Max: 111.3
16	DUV	kg	Numeric	Continuous	Min: 0–Max: 300
17	TDT	min	Numeric	Continuous	Min: 25.9–Max: 300.0
18	TPB	mg/dl	Numeric	Continuous	Min: 4.2–Max: 129.1
19	TAB	mg/dl	Numeric	Continuous	Min: 3.5–Max: 10,000.0
20	TID	min	Numeric	Continuous	Min: 4.0–Max: 10,000.0
21	SCR	mg/dl	Numeric	Continuous	Min: 2.4–Max: 18.2
22	NA	meq/l	Numeric	Continuous	Min: 100–Max: 159
23	K	meq/l	Numeric	Continuous	Min: 2.4–Max: 9.8
24	CL	meq/l	Numeric	Continuous	Min: 80–Max: 139
25	CA	mg/dl	Numeric	Continuous	Min: 5.3–Max: 13.8
26	P	mg/dl	Numeric	Continuous	Min: 0.6–Max: 12.7
27	URR (class)	–	Symbolic	–	Decision attribute

The "–" denotes no given answer in this field

patients is changed to the age of the patients. As a result, a total of 1,235 instances are characterized by the 27 attributes in the HDA dataset. Table 2 shows all the attribute information.

Table 3 presents the partial data of the HDA dataset after the data preprocessing. Except for the GNR and ICD, all of the attributes are continuous data. The 26 conditional attributes are listed as follows: age, gender, international classification of diseases, white blood cell count, red blood cell count, hemoglobin check, hematocrit, mean corpuscular volume, platelet or thrombocyte count, albumin, glutamate oxaloacetate transaminase, glutamic pyruvic transaminase, glucose for ante cibum (AC), pre-wash weight, after-wash weight, dehydration ultrafiltration volume on KG, the dialysis time, the pre-dialysis BUN in mg/dl, the post-dialysis BUN in mg/dl, the time between dialysis events, serum creatinine, sodium,

Table 3 The partial data of the HDA dataset following data preprocessing

No.	AGE	GNR	ICD	WBC	...	CL	CA	P	URR
1	68	M	D	6.98	...	103	8.8	3.5	0.75
2	27	M	C	6.12	...	95	8.8	9.5	0.76
3	66	M	D	12.55	...	99	9.6	1.5	0.82
⋮	⋮	⋮	⋮	⋮	...	⋮	⋮	⋮	⋮
1233	59	M	O	7.99	...	100	9.0	6.7	0.72
1234	69	F	O	5.84	...	96	9.6	5.3	0.81
1235	65	F	D	10.49	...	106	9.5	3.2	0.68

potassium, chlorine, calcium, and phosphorus. The urea reduction ratio (URR, renamed Class) was the decisional attribute.

Step 3: Discretizing the dataset by the advice of domain experts and the RST global method
The decisional attribute Class is discretized into three classes based on the professional knowledge of the three domain experts: A (URR > 0.7, abnormal); B (URR $= 0.65$–0.70, normal); and C (URR < 0.65, abnormal). Consequently, the cardinality for classes A, B, and C is 632, 527, and 76, respectively. The 24 conditional attributes except for the GNR and ICD attributes are discretized using the RST global method, which is based on a Boolean reasoning approach [57], to automatically partition the continuous data. Table 4 shows the results of the expert discretization and the automatic global discretization procedures for the HDA dataset.

Step 4: Cutting the dataset by a 66/34 % random split
The 1,235 instances of the discretized HDA dataset are randomly split into two sub-datasets: the 66 % training set (815 records) and the 34 % testing set (420 records).

Step 5: Extracting decision rules by the rough set algorithm LEM2
LEM2 is commonly used amongst learning algorithms because it describes a minimal set of discriminant rules [30]. As such, the experiment is performed using the rough set LEM2 algorithm, which is based on the rule induction system LERS [30], with a 66/34 % random split to generate the decision rules. As a result, a total of 208 rules are produced. Table 5 shows the partial rules in the HDA dataset. 'Decision rules' refers to the decision rules that are generated by the LEM2 algorithm to predict the URR, and 'Supports' refers to the real examples that coincide with the generated decision rules.

Step 6: Improve the rule quality
To decrease the complexity of the prediction, a filter technique is employed to reduce the number of rules. From the rule set extracted in Step 5, a filtering process improves the rule quality. That is, a support threshold is used to eliminate the rules with support equal to 1. After filtering, 30 rules (14.42 %) remain from the original 208 rules.

Step 7: Evaluating the results using seven different methods
To compare methods of classification, the experiments are repeated 10 times for each of the seven different methods using the same process of a 66/34 % random split. The seven different methods are as follows: decision trees-C4.5 [59],

Table 4 The results of domain expert and automatic discretization in the HDA dataset

Attribute	Threshold	Interval
AGE	54.5, 65.5	3
WBC	6.5*	2
RBC	3.5	2
HBC	–	0
HCT	31.5	2
MCV	92.5	2
PLT	212.5	2
ALB	3.5	2
GOT	19.5	2
GPT	17.5	2
GLU	84.5	2
PWW	–	0
AWW	57.5	2
DUV	2.5	2
TDT	–	0
TPB	–	0
TAB	18.5	2
TID	–	0
SCR	8.5	2
NA	137.5	2
K	4.5	2
CL	–	0
CA	8.5	2
P	4.5	2
URR (by experts)	0.65, 0.7	3

* Values < 6.5 are considered low, and those > 6.5 are high

multilayer perceptron [36], naive Bayes [92], the RIPPER algorithm [10], the PART algorithm [19], the CN2 algorithm [9], and the proposed procedure. Except for the proposed procedure, which uses a discretized dataset, the other classification methods use the original dataset. Moreover, except for the CN2 algorithm, which is implemented in TANAGRA package, the other methods are implemented by WEKA package. The RIPPER algorithm uses the minimum total weight of 2 examples in a rule and the number of optimization runs is 2. The PART algorithm is experimented with a confidence factor used for pruning the tree of 0.25 and a minimum number of examples of 2 for per rule. The CN2 algorithm adopts the default settings. The average accuracy of each method with its standard deviation is calculated. Table 6 compares the average accuracy and its standard deviation of the 10 tests for the seven different methods.

3.3 Classification rules and performance of the proposed procedure

Four directions discuss the performance of the proposed procedure:

(1) Regarding Table 5, the generated rules are classified into three classes of rules, A, B, and C, that compose a knowledge-based system that can be used by ESRD patients and their doctors. The three classes of rules are based on the 1,235 real examples

Table 5 The partial rule set extracted by the LEM2 algorithm from the HDA dataset example

Decision rules		Supports
1	If (CA = "(8.5,∞)") & (ALB = "(3.5,∞)") & (TAB = "(18.5,∞)") & (NA = "(−∞,137.5)") & (GLU = "(84.5,∞)") & (MCV = "(−∞,92.5)") & (WBC = "(6.5,∞)") & (GOT = "(19.5,∞)") & (AGE = "(54.5,65.5)") => Then Class = B	20
2	If (CA = "(8.5,∞)") & (GLU = "(84.5,∞)") & (DUV = "(−∞,2.5)") & (K = "(−∞,4.5)") & (TAB = "(−∞,18.5)") & (GNR = F) & (GOT = "(19.5,∞)") & (GPT = "(17.5,∞)") & (AGE = "(65.5, ∞)") => Then Class = A	18
3	If (CA = "(8.5,∞)") & (TAB = "(−∞,18.5)") & (DUV = "(−∞,2.5)") & (ALB = "(3.5,∞)") & (K = "(4.5,∞)") & (GNR = F) & (MCV = "(92.5,∞)") & (GOT = "(19.5,∞)") & (HCT = "(31.5,∞)") => Then Class = A	15
4	If (CA = "(8.5,∞)") & (AWW = "(−∞,57.5)") & (PLT = "(−∞,212.5)") & (GNR = F) & (MCV = "(92.5,∞)") & (ALB = "(3.5,∞)") & (WBC = "(−∞, 6.5)") & (HCT = "(−∞,31.5)") & (TAB = "(−∞,18.5)") => Then Class = A	14
5	If (GPT = "(−∞, 17.5)") & (TAB = "(−∞,18.5)") & (K = "(−∞,4.5)") & (MCV = "(92.5,∞)") & (DUV = "(−∞,2.5)") & (NA = "(137.5,∞)") & (ALB = "(3.5,∞)") & (WBC = "(6.5,∞)") => Then Class = A	14
6	If (CA = "(8.5,∞)") & (AWW = "(−∞,57.5)") & (GNR = F) & (ALB = "(3.5,∞)") & (K = "(4.5,∞)") & (GPT = "(17.5,∞)") & (HCT = "(−∞,31.5)") & (AGE = "(65.5, ∞)") => Then Class = A	13
7	If (CA = "(8.5,∞)") & (TAB = "(−∞,18.5)") & (DUV = "(−∞,2.5)") & (GNR = F) & (GLU = "(84.5,∞)") & (MCV = "(92.5,∞)") & (AWW = "(−∞,57.5)") & (GOT = "(19.5,∞)") & (K = "(−∞,4.5)") & (PLT = "(−∞,212.5)") & (WBC = "(−∞, 6.5)") & (NA = "(137.5,∞)") & (AGE = "(65.5, ∞)") => Then Class = A	12
8	If (CA = "(8.5,∞)") & (ALB = "(3.5,∞)") & (RBC = "(3.5,∞)") & (NA = "(137.5, ∞)") & (GOT = "(−∞, 19.5)") & (MCV = "(−∞,92.5)") & (WBC = "(−∞, 6.5)") & (GLU = "(84.5,∞)")& (AGE = "(54.5,65.5)") => Then Class = B	11
9	If (CA = "(8.5,∞)") & (GPT = "(−∞, 17.5)") & (PLT = "(−∞,212.5)") & (WBC = "(−∞, 6.5)") & (HCT = "(−∞,31.5)") & (NA = "(137.5,∞)") & (MCV = "(−∞,92.5)") & (GNR = F) & (K = "(4.5,∞)") => Then Class = B	10
10	If (CA = "(−∞,8.5)") & (ALB = "(−∞,3.5)") & (TAB = "(18.5,∞)") & (GLU = "(84.5,∞)") & (MCV = "(−∞,92.5)") & (WBC = "(−∞,6.5)") & (AWW = "(57.5,∞)") & (HCT = "(−∞,31.5)") & (K = "(−∞,4.5)") & (PLT = "(−∞,212.5)") & (P = "(−∞,4.5)") & (GNR = M) & (AGE = "(65.5, ∞)") => Then Class = C	6

Table 6 Comparison of the experimental results of the 10 tests for the seven different methods

Method	Decision trees	Multilayer perceptron	Naive Bayes	RIPPER algorithm	PART algorithm	CN2 algorithm	Proposed procedure
Accuracy	0.8357	0.6688	0.5914	0.8276	0.8288	0.7398	*0.8880*
Standard deviation	0.0229	0.0276	0.0258	0.0365	0.0218	0.0138	*0.0102*
Number of rules	69.0	–	–	*8.7*	104.3	15.1	30.0

The "–" denotes no given answer in this field and the italics values refer to a better outcome in rows

Table 7 An example for rule A from the HDA dataset

Attribute	Observed value	Measure result	
CA (calcium)	≥8.5	Higher values	↑
GLU (glucose AC)	≥84.5	Higher values	↑
DUV (dehydration ultrafiltration volume)	≤2.5	Lower values	↓
K (potassium)	≤4.5	Lower values	↓
TAB (the post-dialysis BUN)	≤18.5	Lower values	↓
GNR (gender)	F	Female	
GOT (glutamate oxaloacetate transaminase)	≥19.5	Higher values	↑
GPT (glutamic pyruvic transaminase)	≥17.5	Higher values	↑
AGE (age)	≥65.5	The elderly	↑

Table 8 An example for rule B from the HDA dataset

Attribute	Observed value	Measure result	
CA (calcium)	≥8.5	Higher values	↑
ALB (albumin)	≥3.5	Higher values	↑
TAB (the post-dialysis BUN)	≥18.5	Higher values	↑
NA (natrium)	≤137.5	Lower values	↓
GLU (glucose AC)	≥84.5	Higher values	↑
MCV (mean corpuscular volume)	≤92.5	Lower values	↓
WBC (white blood cell count)	≥6.5	Higher values	↑
GOT (glutamate oxaloacetate transaminase)	≥19.5	Higher values	↑
AGE (age)	54.5 ∼ 65.5	The older	

that coincide with the generated decision rules. An example of each class is presented below:

(a) **Rule A (abnormal condition):**

Table 7 depicts an example for rule A from the HDA dataset to demonstrate the indications of the rules derived from the clinical laboratory data in Table 5.
For example, the attribute CA receives a higher inspection value if its value is equal to or exceeds 8.5. Conclusively, the result for the HD adequacy measurements of ESRD patients is the abnormal conditions that are included in rule A.

(b) **Rule B (normal condition):**

Similarly, Table 8 depicts an example for rule B from the HDA dataset to demonstrate the indications of the rules derived from the clinical laboratory data in Table 5.
For example, the attribute NA receives a lower inspection value if its value is less than or equal to 137.5. Conclusively, the result for the HD adequacy measurements of ESRD patients is the normal conditions that are included in rule B.

Table 9 An example for rule C from the HDA dataset

Attribute	Observed value	Measure result	
CA (calcium)	≤8.5	Lower values	↓
ALB (albumin)	≤3.5	Lower values	↓
TAB (the post-dialysis BUN)	≥18.5	Higher values	↑
GLU (glucose AC)	≥84.5	Higher values	↑
MCV (mean corpuscular volume)	≤92.5	Lower values	↓
WBC (white blood cell count)	≤6.5	Lower values	↓
AWW (after wash weight)	≥57.5	Higher values	↑
HCT (hematocrit)	≤31.5	Lower values	↓
K (potassium)	≤4.5	Lower values	↓
PLT (platelet count)	≤212.5	Lower values	↓
P (phosphorus)	≤4.5	Lower values	↓
GNR (gender)	M	Male	
AGE (age)	≥65.5	The elderly	

(c) **Rule C (abnormal condition):**

Table 9 depicts an example for rule C from the HDA dataset to demonstrate the indications of the rules derived from the clinical laboratory data in Table 5.
For example, the attribute AGE receives a higher inspection value if its value is equal to or exceeds 65.5, which refers to an elderly people. Conclusively, the result for the HD adequacy measurements of ESRD patients is the abnormal conditions that are included in rule C.

(2) As Table 6 shows, the proposed procedure has better accuracy (0.8880) with a low standard deviation (0.0102) for predicting HD adequacy. The analytical results demonstrate that the proposed procedure outperforms the listed methods not only in accuracy, but also in standard deviation. Regarding the number of generated rules, it is indicated that the RIPPER algorithm has achieved the fewest rules (8.7), followed by CN2 algorithm (15.1), the proposed procedure (30.0), decision trees-C4.5 (69.0), and PART algorithm (104.3), respectively.

(3) Typically, because the one-way ANOVA (analysis of variance) method is used to test the 'statistically significant differences' phenomenon between three or more independent variables, this study applies it to further verify the accuracy of our method among the AI methods listed in Table 6. To assess the seven methods, each method is run 10 times, and 10 example populations are obtained. The results of a one-way ANOVA of the accuracy are shown in Table 10. Table 10 shows that decision trees-C4.5, multilayer perceptron, naive Bayes, RIPPER, PART, CN2, and the proposed procedure differed significantly at a confidence level of 0.95. This finding indicates that significant differences exist in the accuracy of these methods.

(4) The goal of Scheffe's test is to determine significant differences between group means in an analysis of variance setting as a post hoc test; thus, it is considered one of the most conservative post hoc tests. To validate the significance ANOVA of the seven AI methods listed in Table 6, Scheffe's test is used as a post hoc test. For ease of presentation, the methods (decision trees-C4.5, multilayer perceptron, naive Bayes, RIPPER, PART, CN2, and the proposed procedure) are indicated by the numbers 1–7, respectively, and the results of Scheffe's test are presented in Table 10. Table 10 indicates that

Table 10 The validation results of a one-way ANOVA and Scheffe's test in the HDA dataset

Statistical test	One-way ANOVA		Scheffe's test
	F-statistic	P value	
Accuracy	175.414	0.000**	7 > 1, 4, 5 > 6 > 2 > 3

** $P < 0.05$

five groups can be identified: the proposed procedure > decision trees-C4.5, RIPPER, and PART > CN2 > multilayer perceptron > naive Bayes. No significant difference was indicated between decision trees-C4.5, RIPPER, and PART. Based on the results in Table 10, the proposed procedure outperforms other groups in accuracy. Particularly, the proposed procedure is a combined method of several steps, such as attribute reduction, rule induction, and rule filtering, while the compared classifiers are just used as an alternative of one step (rule induction) of the authors' approach.

3.4 Empirical results and the implications for the management of health care

This study explores and analyzes the experimental results and the extracted rule set to develop statistical tables to mine hidden information from a hospital information system dataset. The results and the implications for the management of health care are compiled, and they are of value to the academics and practitioners who focus on the healthcare fields.

3.4.1 An effective method for the use of the HDA dataset

The methods listed above are cataloged into two groups based on Tables 6 and 10. One group includes decision trees-C4.5, RIPPER, PART, and the proposed procedure, and the group includes CN2, multilayer perceptron, and naive Bayes. The former can be selected as an effective tool for predicting the URR in the hospital context because the accuracy of the methods of this group exceeds 80 %, which is an accepted threshold in forecasting outcomes. However, the methods of the latter group can be considered insufficient because of their lower accuracy. More importantly, the proposed procedure surpasses the listed methods not only in accuracy, but also in standard deviation. Moreover, the proposed procedure generates comprehensible decision rules as a knowledge-based system that can provide ESRD patients and their doctors with an important tool for healthcare services to improve the emotional well-being and QOL for the patients and their family members.

3.4.2 A key determinant for predicting URR

As shown in Table 2, a total of 27 attributes were pre-selected from an empirical case database to measure the HD adequacy. Regarding the ESRD patients, the safety of healthcare treatments and attaining a better QOL are a major issue; therefore, an important need exists for identifying the critical determinants of HD adequacy. The critical variables are significant factors that supporting a better outcome and determine a good QOL for ESRD patients undergoing HD therapy. Table 11, which was based on the 208 rules that were extracted by the LEM2 algorithm, shows the top 10 attributes based on the frequency (presented in the 208 rules) of attribute in the HDA dataset. The ranking of these attributes, in order of importance, is GNR(198) $\rightarrow$ AGE(189) $\rightarrow$ WBC(184) $\rightarrow$ HCT(178) $\rightarrow$ PLT(174) $\rightarrow$ GPT(174) $\rightarrow$

Table 11 The top 10 attributes based on the statistical analysis of the rule set for the HDA dataset

Attribute	Presentation frequency/Total rules
GNR (gender)	198/208
AGE (age)	189/208
WBC (white blood cell count)	184/208
HCT (hematocrit)	178/208
PLT (platelet count)	174/208
GPT (glutamic pyruvic transaminase)	174/208
TAB (total post-dialysis BUN)	172/208
MCV (mean corpuscular volume)	172/208
GLU (glucose AC)	171/208
ALB (albumin)	170/208

Table 12 The statistical results for the gender attribute in the HDA dataset

Class (Post-dialysis)	Male (%)	Female (%)
A	34.7	65.3
B	65.7	34.3
C	89.5	10.5
Total population (pre-dialysis)	51.3	48.7

TAB(172) → MCV(172) → GLU(171) → ALB(170). The analytical results indicate that the 10 attributes are key determinants for predicting the URR; concurrently, the attributes were all validated by an expert physician (please see the Acknowledgments section).

3.4.3 Redundant attributes in predicting URR

Six redundant attributes, including HBC, PWW, TDT, TPB, TID, and CL, are found in the HDA dataset that is based on the discretized results in Table 4 and the extracted rule set in Table 5 because they were calculated to have intervals of zero (see Table 4). These attributes were not used to predict the URR in the decision rules set (see Table 5) after the automatic discretization was performed, and they can thus be removed from the empirical analysis. The above hidden information implies that the global discretization that is used in rough set methods has a similar function to the feature screening tools and is based on evaluating attributes based on rule syntax and the discretization results.

3.4.4 An interpretation of key determinants

For a more in-depth analysis of the 10 key determinants, the characteristics of these attributes were analyzed using interviews with three experts in the Division of Nephrology.

1. **The gender attribute GNR** is familiarly coded ‘M’ and ‘F,’ which correspond to male and female, respectively. For examining the impact of gender, Table 12 shows the gender for the different classes according to the statistical results in the HDA dataset. For class A, 34.7 % (over one-third) of the patients are male, and 65.3 % (approximately two-thirds)

are female. However, 89.5 % of class C is male; conversely, only 10.5 % is female. That is, males are the absolute majority of patients with the abnormal condition of class C, in which the URR values are less than 0.65. It will be worthwhile to explore this meaningful issue in subsequent research. Furthermore, the percentages of males and females pre-dialysis are 51.3 and 48.7 %, respectively, which is nearly half and half and is consistent with the results of earlier reports (53 % vs. 47 %) [77]. Two-thirds of the ESRD patients with normal HD adequacy conditions are male, and only one-third is female. This information implies that male ESRD patients are more suitable for receiving HD therapy in the final stage of CKD, and this implication will be further discussed in Sect. 4. Similarly, this observation matches that of earlier literature [83]. The identification of gender as a potential determinant in HD treatments could be further explained by the fact that the genders have different concerns regarding different diseases, which potentially affects the self-administrated healthcare of males and females differently [65,68].

2. **The age attribute AGE** refers to the age of the ESRD patient. In the analysis of the descriptive statistics, 13.9 % of the patients are less than or equal to age 49. In other words, 86.1 % are age 50 or above (an age of 50 years is meaningful for the Taiwanese people because it is considered to be slightly elderly in Taiwanese society). This phenomenon implies that the higher age of the ESRD patients indicates a larger probability for implementing HD treatment. The average age of the ESRD patients in the HDA dataset is 64 (the elderly), which shows that CKD takes many years to finally progress to renal failure and, eventually, lead to uremia. This result is consistent with the study of McClellan et al. [42]. The high-risk group of the elderly suffers more from uremia. The method presented here provides sufficiently new information and is of fundamental importance for advancing the knowledge regarding human aging and the social aspects of geriatrics. Therefore, the attribute of age is a key factor in uremia. This result matches that of a previous study [83] and the professional knowledge of an expert physician.
3. **The white blood cell count (WBC)** is the number of white blood cells, which in a healthy person are an important part of the immune response in defending the body against both infectious diseases and foreign substances. The WBC in the blood is often an indicator of disease. Regarding the WBC reference range, the normal value of a healthy adult is between 1.1×10^3 and 4.0×10^3 cells per μl of blood. A number above the upper limits of the WBC reference range is abnormal and likely indicates that an infection is present somewhere in the body. Likewise, a number much lower than the lower limit is also abnormal and indicates an infection or disease that requires the production of new white blood cells. In the dataset of this study, 6.7, 86.0, and 7.3 % of the ESRD patients fell within the ranges less than $1.1 \times 10^3/\mu$l (microlitre), equal to $1.1 - 4.0 \times 10^3/\mu$l, and greater than $4.0 \times 10^3/\mu$l, respectively. This finding indicates that the WBC for a majority of the ESRD patients in the HDA dataset is within the normal range. In class B, 4.9, 88.3, and 6.8 % of the ESRD patients are below, equal to, or above the reference range ($1.1 - 4.0 \times 10^3/\mu$l), respectively. This finding indicates that most of the ESRD patients that are classified under the normal have the normal WBC value. Generally, the WBC attribute is regarded as a predictive factor for HD adequacy. Our result matches both that of the previous literature [64] and the professional knowledge of an expert physician.
4. **The hematocrit (HCT)** refers to the percentage of red blood cells found in a whole blood example. The hematocrit is an important evaluator of a person's health. Although the reference range of the hematocrit varies with the gender and age of the patients, it

is approximately 40–53 %. However, only approximately 3 % of the ESRD patients in the HDA dataset are greater than the lower limit (40 %) and within the normal range, and the remaining (97 %) are lower than the lower limit (40 %). More specifically, no patient's value is greater than the upper limits (53 %), and the maximum value is 45.9 %. This phenomenon implies that the ESRD patients have a lower hematocrit value than that of a normal person. This result matches both that of a previous study [11] and the professional knowledge of an expert physician.

5. **The platelet count (PLT)** is the fifth important determinant of the URR. Platelets have a major role in hemostasis by helping the formation of blood clots following injuries, such as car accidents, a scrape, or a cut, and they are produced by the bone marrow. The PLT refers to a measure of how many platelets are in the blood. Blood is composed of red blood cells, white blood cells, and platelets; however, platelets are smaller than the other two cell types. The reference range of platelet counts in a healthy individual that is clinically stable with no bleeding symptoms is between 150 and 450×10^3 per μl of blood. An abnormality or disease state regarding platelets is either a lower or higher number of platelets. According to experts, a level below $50 \times 10^3/\mu$l is associated with abnormal surgical bleeding in patients undergoing surgery. In the HDA dataset, only 1 % of the ESRD patients are below this threshold, and 0.2 % exceed the upper limits (450). Most of the ESRD patients have normal platelet numbers after dialysis.
6. **The glutamic pyruvic transaminase (GPT)** is an indicator that is used to clinically measure the relationship between alanine aminotransferase (ALT) levels and metabolic syndrome (MS) in non-alcoholic fatty liver disease (NAFLD) as a part of liver function diagnostics to determine liver problems. This measurement is most commonly associated with the liver, is measured in units/liter (U/l) and is called ALT. For diagnostic purposes, significantly elevated levels of GPT often suggest the existence of other medical problems, such as viral hepatitis, which often occurs in the Taiwanese; liver damage; or congestive heart failure. Based on the opinion of the experts who were consulted, when elevated levels of GPT are found in the blood, the possible underlying causes can be narrowed down by measuring other enzymes. The GPT level alone cannot yield a diagnosis. Its reference range is 10–35 U/l. In the HDA dataset, the GPT values of 18.0, 72.1, and 9.9 % of individuals are below, equal to, or above the reference range, respectively. This result emphasizes that the GPT value of most ESRD patients is within the normal range. Only approximately one-tenth of the GPT values exceeds the normal value, and the maximum value is 436 U/l.
7. **The total post-dialysis BUN (TAB)** refers to the sum of the BUN levels after successive HD sessions for an ESRD patient. In the BUN test, TAB measures the amount of urea nitrogen, which is a waste product of protein metabolism, that remains in the blood, and it is used as a major indicator for renal function [40]. The reference values for BUN are 7–20 mg/dl, and both an increase and a decrease in the BUN level are considered abnormal conditions. Intrinsically diseased or damaged kidneys can cause an increase in BUN because the kidneys are less able to clear urea from the bloodstream. However, a decrease in BUN has little influence and can be observed with liver problems or excessive alcohol consumption. An elevated BUN indicates poor kidney function (i.e., azotemia), but a greatly elevated BUN (exceeding 60 mg/dl) indicates a moderate-to-severe degree of renal failure. Importantly, an accurate measure of renal function is required to assess urea nitrogen clearance for medical dosing. In the HDA dataset, 1.5, 56.1, and 42.4 % of the ESRD patients had BUN levels below, equal to, or above the reference range, respectively, after HD treatments. However, 0.3, 10.2, and 89.5 % of patients had BUN levels in these categories before HD treatment.

Specifically, the rate of BUN levels within the normal range pre-dialysis versus post-dialysis is 10.2 % versus 56.1 %. This finding proves that HD therapy is an effective way to improve the BUN of ESRD patients, and an expert physician validated the analytical result.

8. **The mean corpuscular volume (MCV)** is a measure of the average volume (i.e., size) of red blood cells, which help carry oxygen in the blood. The normal range of MCV measurements in people above age 18 is between 78 and 98 μm^3 (cubic micrometer). Similar to the attribute PLT, measurements either below or above the normal range for the attribute MCV are considered abnormal. A level below the normal range is called microcytic anemia, and a level above the normal range is called macrocytic anemia. For microcytic anemia patients, the MCV is as low as 60–70 μm^3, whereas it can range up to 150 μm^3 in macrocytic anemia patients. In the HDA dataset, 7.2, 73.1, and 19.7 % of the ESRD patients have an MCV below, equal to, or above the normal range, respectively. These results demonstrate that most ESRD patients are within the normal range for MCV after HD treatments.
9. **Glucose AC (GLU)** represents a measure of glucose levels ante cibum (AC) in the blood and is called the fasting blood glucose. A common disease involving the irregular control of glucose is diabetes, so the GLU measurement can be used as an essential method to screen for diabetes. Glucose is one of the simplest forms of sugar and comes from digesting carbohydrates, which are changed into a chemical substance that can be easily converted to energy. Accordingly, glucose is the main energy source in the human body. However, too high glucose levels (called hyperglycemia) and too low glucose levels (called hypoglycemia) can cause dangerous health problems; thus, maintaining glucose within normal ranges is important. The normal ranges for GLU are 70–105 mg/dl. Levels of 105–126 mg/dl are diagnosed as pre-diabetes. Values above 126 mg/dl are considered true diabetes. In the HDA dataset, 17.1, 44.9, 11.0, and 27.0 % of individuals are below the normal range, equal to the normal range, within the pre-diabetes range, or within the diabetes range, respectively. Regarding glucose as an attribute in this study, a higher inspection value is associated with a higher probability of being classified under 'severe' diabetic conditions. Likewise, a lower inspection value is also associated with a higher probability of being classified under 'dangerous' conditions. One exception to this trend is within the normal ranges for GLU. Based on the knowledge of an expert physician, nearly half of the ESRD patients are within normal ranges after HD therapy.
10. **Albumin (ALB)** is the tenth important factor for classifying URR and is used as a tool to evaluate nutrition status, specifically protein nutrition. In the human body, albumin is an important component, and it is vital to the health and well-being of many organisms. Albumin is an important class of protein that has water solubility. Both an albumin deficiency and an oversufficiency lead to medical issues. High levels of albumin are always caused by dehydration. In contrast, low albumin may be caused by liver disease, nephrotic syndrome, and malignancy (e.g., cancer). A doctor may conduct a blood albumin test to further understand a patient's medical condition. As to the normal range of albumin levels, the reference interval in adults is 3.5–5 g/dl. In the HDA dataset, 8.7, 91.2, and 0.1 % of individuals had albumin levels below, equal to, or above the reference intervals, respectively. Similar to the previous item (9), both higher and lower values are associated with a higher probability of being classified under abnormal conditions. One exception to this trend is within the normal ranges for ALB value. The analytical results were confirmed by the knowledge of an expert physician.

3.4.5 A best practice using expert and automatic discretization methods

Previous literature [82] suggested that before data can be inputted into rough set models, they must first be discretized. In the present study, an automatic discretization method of conditional attributes and an expert discretization method of the decisional attribute are applied to construct a threshold for improving the classification accuracy in the rough set analysis. This study is a good example of how the information in the literature can be used.

3.4.6 A guide for ESRD patients and their doctors

It is well worth mentioning that the proposed procedure applies the RST LEM2 algorithm to generate comprehensible decision rules, which directly support an "if…then" rule set, known as a knowledge-based system, to guide treatment strategy and offers an intelligent explanation for ESRD patients and their doctors. The advantages of the generated rule set are that it is easy to interpret, easy to use, easy to understand, and easy to manipulate.

4 Discussions and findings

Below, three problems that stem from the experimental results are presented and discussed.

1. **Error costs:** In the real world, a manual mistake occasionally occurs, and errors in judgment and treatment incur error costs. Particularly in the healthcare services, medical malpractice in the doctor-patient relationship (doctor-patient confidentiality) also occurs occasionally. Well-known errors in healthcare treatments are known as Type I (also known as α errors or false positives) and Type II (β errors or false negatives) errors and are characterized as an incorrect judgment in a clinical-pathological analysis, for example a positive result when the patient is actually negative or vice versa. Error costs represent something that patients possibly pay, including tangible values (e.g., money) and intangible values (e.g., pain or QOL), due to a mistake in their healthcare treatments, but these costs are not considered in the procedure proposed here. There is evidence that the error costs for Type I and II errors may not be equal for all patients. Incorporating error costs into forecasting systems can lead to better and more desirable results and will help in applying these systems to practical situations. Error costs, which are a problematic issue, may eventually result in possibly unbearable losses to patients. Therefore, the evaluation criteria of other types of forecasting models in subsequent research should minimize the total error costs, including tangible and intangible values, rather than roughly minimize the accuracy rate. After all, life is invaluable and unique for patients.
2. **Differentiation between nightly home HD and in-center HD:** HD can be performed at a center or at home. ESRD patients generally receive regular HD 3 times per week, usually 3–5 h per session, at the HD units of general district hospitals or university medical centers, which provides a comprehensive and high-quality dialysis therapy and a safe healthcare environment. In other cases, ESRD patients were generally treated at home with regular HD three to 7 times per week, taking 3–10 h per session, which has the benefits of home care. When home healthcare is compared to the in-center care service, the former provides substantially more benefits than the latter, such as convenience, having more frequent or longer dialysis treatments and, thus, likely having improved survival outcomes, a significant improvement in well being, reducing symptoms during

and between dialyses, having an uninterrupted work schedule, remaining in the comfort of home during treatment, and improving QOL. It is good to examine the differences between undergoing HD at a center and at home. Although various problems could potentially arise, adding home HD data into the proposed procedure to predict the URR for measuring HD adequacy should be considered in future works.

3. **A decisional attribute for the QOL:** For ESRD patients, a good QOL is potentially more important than HD adequacy. QOL is being used increasingly as an important evaluator of healthcare services and patient well-being in assessing the HD outcome. Using the QOL attribute as decisional attribute in the proposed procedure instead of the URR is advisable. The practical data for the QOL of the ESRD patients can be gathered by a questionnaire so that this vital issue can be addressed in subsequent research and to compare the determinants that influence the URR and the QOL.

Meanwhile, the five examined findings that emerged are as follows:

1. **Male patients are a high-risk group:** Based on the literature [80], numerous studies have demonstrated an association between the amount of HD and mortality among ESRD patients. That is, mortality is higher when the HD dose is low, while mortality is lower when the HD dose is high. In the HDA dataset, the 89.5 % of male patients that fall into class C (URR < 0.65) are the high-risk group for mortality according to Table 12 because their URR value is lower than that of other patients. This information is useful for ESRD patients and their doctors to aid them in selecting a suitably preventive treatment in advance. Correspondingly, female patients are at a lower risk.
2. **The suitable group for receiving HD therapy:** Table 12 shows that a higher percentage of male patients (65.7 %) than female patients (34.3 %) are classified in class B; however, the percentages of males and females in the HDA dataset are 51.3 and 48.3 %, respectively. This phenomenon implies that male ESRD patients are more suitable for receiving HD therapy in the final stage of CKD than female patients because better outcomes are observed for male patients after HD treatment. Together with the observations above, these data suggest that male ESRD patients achieve better performance with respect to HD adequacy, but they are the higher mortality group if their URR value is not decreased after the HD therapy.
3. **Lower hematocrits in ESRD patients:** According to the statistical data, only 3 % of the ESRD patients have hematocrit values in the normal range (40–53 %). In addition, 97 % are under the lower limit (40 %), and none are above the upper limit (53 %). Thus, the ESRD patients have characteristically low hematocrits, and this characteristic could be used as an indicator for measuring HD adequacy. Simultaneously, this observation matches that of previous studies [13,53] and that of an experienced physician. To use this generalization in future applications, it is necessary to validate the phenomenon with more datasets.
4. **The superiority of the proposed procedure:** According to Table 6, the experimental results support the conclusion that the proposed procedure has superior performance to the other methods tested for the HDA dataset because it not only has better accuracy but also has a lower standard deviation. This finding confirms the requirement for the discretization of the conditional and decisional attributes in a rough set analysis, which can increase the classification performance of the rough set analysis and enhance the stability of the standard deviations.
5. **An example of using discretization methods:** This study offers an example of using the appropriate discretization methods for attributes, including automatic attribute dis-

cretization and expert attribute discretization, and this combined method is capable of improving classification accuracy.

5 Conclusions

Given the increase in the elderly population and the high incidence of chronic disease diagnoses in Taiwan, ESRD patients receive much attention. With regard to medical technology, the main treatment for ESRD patients is HD, which can support the patient's life and prevent death. However, HD is an expensive procedure, and it composes a relatively large proportion of medical expenditures, even though the expense is contingent upon a higher survival rate. In other words, the higher survival rate means that prolonged and regular medical treatment is required for ESRD patients, which results in higher costs for the HD treatment. The statistical data of the National Health Insurance Research Database (NHIRD) in Taiwan indicate that over fifty thousand people were diagnosed with ongoing ESRD and were treated with HD, and this occurs at an annual cost of approximately \$0.9 billion. The motivation for this study was to integrate existing methods to support medical "applications" that prevent healthcare squandering and to properly couple HD treatment with increasing QOS and QOL [18]. Introducing a novel method was not the primary objective in this study. Rather, the "applications" of the major advanced classification approaches and the techniques that were used were emphasized to improve classification accuracy. Although the methodology in this study had not a new or impressive method, the proposed procedure reflected a new trial in the healthcare field for ESRD patients and obtained a satisfied result. Therefore, the main contribution of this study was conducted to organize well-known techniques to mine hidden knowledge from the HDA dataset when compared to the most related works in Sect. 2.

This study presented an integrated procedure to identify the determinants of HD adequacy and objectively classify the URR, which is used to evaluate the adequate HD treatment by ESRD patients and their doctors in the healthcare industry. The HDA dataset is used to verify the proposed procedure. Conclusively, the 10 key attributes are identified from the hidden information of data. Furthermore, the experimental results reveal that the proposed procedure outperforms the listed methods in accuracy and standard deviation. By contrast, the proposed procedure is a hybrid model of several steps and the listed methods are only used as an alternative of one step (such as rule induction). This information offers that the hybrid models surpass stand-alone models, because the hybrid models can amplify the advantages of the individual models and minimize their limitations [62,63]. The generated output is a comprehensible decision rule set (a knowledge-based healthcare system) that offers explanations to ESRD patients and their doctors. The proposed model will be a useful tool and will serve as guiding rules to assist them in determining treatment strategies and in managing HD adequacy to achieve an excellent medical–patient relationship and to promote medical quality satisfaction.

The proposed procedure is suitable for those in the healthcare field who intend to use intelligent systems. This study provides useful insight into the key characteristics that classifying HD adequacy in the healthcare industry and is critical with respect to responding to the rapidly changing healthcare conditions of ESRD patients. Generally, the analytical results have important implications that are worthwhile for both practitioners and academics that focus on HD adequacy in the healthcare field. Moreover, future research can be done in five directions. (1) Various decisional attributes could be addressed to measure HD adequacy. (2) Other types of datasets could be used to further assess the proposed procedure. (3) Other models could be used to examine the HDA dataset. (4) Other evaluation criteria could focus on accuracy in each class instead of using total accuracy rate. (5) Important statistical differences could be justified between repeated hold-out method of data (which had been implemented in the proposed procedure) and cross-validation method.

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