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Modified Multi-Criteria Decision Making Methods to Assess Classification Methods

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Abstract

During the last few decades, many academic and professional groups gave attention to adopting the multi-criteria decision-making methods in a variety of contexts for decision-making that are given to the diversity and sophistication of their selections. Five different classification methods are tested and assessed in this paper. Each has its own set of five attribute selection approaches. By using the multi-criteria decision-making procedures, these data can be used to rate options. Technique for order of preference by similarity to ideal solution (TOPSIS) is designed utilizing a modified fuzzy analytic hierarchy process (MFAHP) to compute the weight alternatives for TOPSIS in order to obtain the confidence value of each classifier for each feature selection approach individually. Defuzzification of the fuzzy values to obtain the final criteria weights, the rank function is used. The modification of TOPSIS is assessed in tests using five prediction models (alternatives) and six performance measurements (criteria) to analyze the German credit data sets. Overall the results of the experiment show that the proposed strategies are successful in credit approval data.

Keywords: Multi-criteria decision-making techniques, financial decision domains, Shannon entropy, TOPSIS.

استخدام طريقة صنع القرار المعدلة متعددة المعايير لتقييم طرق التصنيف

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الخلاصة

لقد أولت المجموعات الأكاديمية والمهنية أهمية كبيرة لاعتماد أساليب صنع القرار متعددة المعايير في مجموعة متنوعة من السياقات لصنع القرار نظرًا لتنوع اختياراتهم وتعقيدها خلال العقود القليلة الماضية. تم اختبار وتقييم خمس طرق تصنيف مختلفة في هذه البحث ، ولكل منها مجموعتها الخاصة من خمسة مناهج لاختيار السمات. باستخدام إجراءات صنع القرار متعددة المعايير ، يمكن استخدام هذه البيانات لتقييم الخيارات. تم تصميم TOPSIS باستخدام (MFAHP) لحساب الوزن لكل طريقة من أجل الحصول على قيمة الثقة لكل مصنف . تم استخدام دالة الرانك للحصول على أوزان المعايير النهائية. تم تقييم تعديل TOPSIS في الاختبارات باستخدام خمسة نماذج تنبؤ (بدائل) وستة قياسات أداء (معايير) لتحليل مجموعات بيانات الائتمان الألمانية. أظهرت النتائج الإجمالية للتجربة أن الاستراتيجيات المقترحة كانت ناجحة في بيانات الموافقة الائتمانية.

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1. Introduction

The unpredictability and complication of diagnostic decision-making has lately increased. This state foresees new issues that must be met in light of current financial constraints. Statistical methods, for example, discriminate analysis, multivariate adaptive regression splines and logistic regression that are utilized to make the majority of the selections[1]. Moreover, these methodologies have a number of flaws which makes incorporating qualitative elements into the decision-making procedure impossible[2]. New technologies are available that are influenced by the principles of operations research (for example, the multi-criteria decision-making techniques, the mathematical programming) and the intelligent systems (for example, the fuzzy logic, the evolutionary computing,the neural networks and the support vector machines). These methods were introduced as potential substitute for traditional approaches to solve these limitations[3]. Because these operations research and management tools have several aspects that make them especially ideal for assessing sophisticated real-life problems[4]. In recent years, the multiple-criteria decision-making (MCDM) models have been garnered considerable attention in several sectors of finance. One of the most distinguishing features of MCDM approaches is that they can handle both quantitative and qualitative data[5].The ultimate goal of the MCDM model structure is to give a mechanism for someone taking part in a decision procedure to create and change their choices or make a decision based on the purposes rather than the best solution to a problem. A ($M \times N$) decision matrix can be used to define a general MCDM problem, where M denotes the list of alternatives and the decision criteria number is indicated by the N[1].The analytical hierarchy process (AHP) is some of the furthermost common and generally applied MCDM techniques. It is successfully used to a diversity of practical decision-making problems. Zadeh was the first to introduce the fuzzy set theory, it is well designed to handling to data ambiguity and imprecision[6][7].

The fuzzy analytic hierarchy process (FAHP) approach is used to determine the weights of the criteria due to its computational ease and efficiency[8].Because more computations are required to evaluate a large number of features, the high detection time increases. Feature selection can be used to reduce the number of features while keeping accuracy within acceptable bounds. With feature selection, there is a whole range of algorithms is suggested. Different sorts of datasets may cause algorithms to respond differently. As a result, research is essential to find the superlative algorithm for financial data sets.

In this paper, the number of features, precision, false positive rate, F-measure, true positive rate and receiver operating characteristics (ROC) area of numerous feature selection techniques are compared. In some cases, making a decision focused on a particular criterion may be difficult. If one classification method has to be elected from a set of possibilities, for example, the selection cannot be made solely on the basis of a single criterion such as accuracy, despite the fact that this may lengthen time consumption. In these cases, the technique for ordering preferences by similarity to the ideal solution is a procedure that can be applied. When there are multiple classification algorithms to select from, within each set of criteria including such accuracy, a quantity of features, and so on. The rest of the paper is organized as follows. The first section introduces the topic. Section II discusses relevant work on classification and multi-criteria decision-making for financial problems. Section III discusses methodology. Section IV depicts the experiment setup and dataset utilized. Section V contains the results and discussion Finally, section VI concludes the study.

2. The related works.

Much study is done for classification problems in this section, and they compared classification strategies based on many factors such as accuracy. A new method is proposed to investigate credit scoring performance by combining the back propagation of neural networks with the traditional discriminate analysis strategy[9]. A genetic algorithm strategy for feature selection and parameter optimization by support vector machine [10].

The particle swarm optimization and support vector machine techniques are created in [11], which incorporate particle swarm optimization (PSO) to determine support vector machine parameters and feature selection. A wide range of classifiers and feature selection methods were tested and assessed in [12]. To assess the effectiveness of five methods that is widely used feature selection procedures in forecasting: the t-test, correlation matrix, stepwise regression, principle component analysis (PCA) and factor analysis (FA) were applied. The neural networks used during the classification algorithm include multi-layer perceptron (MLP) [13].

A comparison of the performance of major ensemble techniques, such as bagging, boosting and stacking is done using four foundation modules, namely decision tree (DT), artificial neural network (ANN), logistic regression analysis (LRA), and support vector machine (SVM)[14].The study in [15] suggested an ensemble classifier is built by combining numerous data mining approaches including optimum association binning to discrete continuous values; neural networks, support vector machines, and the Bayesian networks. The Markov blanket concept of the Bayesian networks, in particular, allows for a natural kind of feature selection, which can be used to mine association rules [16].

The credit decision-making problem was studied by [17], the author invented a multi-kernel multi-criteria programming methods based on evolving techniques. It has been introduced a novel feature subset selection method depends on tabu search and rough sets that includes conditional entropy as a criterion function[14]. Multiple strategies for analyzing credit rating data sets with imbalances were compared. Two credit data sets were employed in the experiments: one from Australia and the other from Germany [18]. Hybrid the Genetic Algorithm and Neural Networks (HGA-NN)" for selecting ideal attributes set for improving credit risk classification accuracy [19]. A systematic literature assessment of binary classification approaches for credit scoring and financial analysis was conducted [20]. A novel classifier was proposed in [21]. Credit rating difficulties are solved using fuzzy clustering analysis and a modified Kohonen network technique [22]. Using soft probability, a novel dynamic ensemble cataloguing technique for credit scoring was proposed [23]. This technique chooses a subset of classifiers based on the ability of the base classifiers and the comparative costs for Type I and Type II errors completed in the validation set. Clustering is used through a fuzzy assignment process in the model to make better use of the data pattern and increase performance. This research presents a new way for selecting classifiers after they have been trained using evolutionary algorithms [24].

A proposed method depends on K-means clustering algorithm used for feature selection with five classifiers . The ensemble classification system is based on Radial Basis Function Neural Network (RBFN), Decision Tree (DT), Multi-layer Feed Forward Neural Networks (MLFN), Naive Bayes (NB) and Probabilistic Neural Networks (PNN) [25]. The Hybrid technique where Multivariate Adaptive Regression Splines (MARS) were applied for features selection while ensemble classifier for classification with German credit data [26]. A proposed modification of the Gustafson-Kessel algorithm of credit risk valuation was combined with a binary particle swarm optimization technique. Anew algorithm was used to calculate the optimal number of clusters and identify the feature subset automatically [27]. From a pool of features, Bolasso (Bootstrap-Lasso) identifies consistent and relevant features. The robustness of selected features with respect to changes in the dataset is termed as consistent feature selection. They then put it to the test using classification techniques with K-Nearest Neighbors (K-NN),Support Vector Machine (SVM),Random Forest (RF) and Nave Bayes (NB) to see how accurate it is at predicting. The Bolasso enabled Random Forest Algorithm (BS-RF) is determined to provide the best results for credit risk assessment [28]. A survey was conducted, as well as a comparison of data from literature using machine learning approaches to forecast credit scores. Then four machine learning algorithms (Random Forest, Support Vector Machine, Bagged Decision Trees and Multilayer Preceptor) were implemented [29]. To deal with unbalanced credit scoring data, Shen et al. 2020, created a novel deep learning ensemble credit risk assessment technique. To overcome known SMOTE flaws, a developed synthetic minority over sampling technique was created first[30]. Extreme Learning Machine (ELM) was utilized such as a cataloguing technique with new activation function for credit scoring risk evaluation model[31]. A new method for imputing missing data that could be useful for intelligent credit scoring systems was suggested and had two stages. In the first stage, the entire dataset was used to build a Bayesian network containing all of the attributes from the original dataset [32] . A study was conducted of existing credit risk appraisal research methods and machine learning (ML) approaches [33]. A novel technique based on modified binary teaching–learning based optimization was developed for the execution of the attribute selection problem in binary recognition, and this new algorithm was linked with a supervised data mining technique (support vector machine) [34].A model was proposed in [35] that integrated two methods the Synthetic Minority oversampling Technique (SMOTE) and Extreme Gradient Boosting entitled SMOTEXGBoost . It has the maximum AUC value among the other models.

The test sample classification results were reviewed using six performance metrics and analyzed using two MCDM methods [36]. The performance of many systems for bankruptcy forecast and credit scoring depends on ensembles of classifiers were investigated. Three financial datasets were chosen for the trials in this study: Creditworthiness in Australia, Germany and Japan [37].

A varied integer of linear programming designs is based on delays of support vector machines that was suggested to solve the inadequacies of features selection, which is an NP-hard issue that has received a lot of attention in the literature[38]. The study two well-known multiple-criteria decision-making approaches (MCDM) combined to contribute decision makers process and analysts a valuable tool for selecting a prediction (s)[39]. The TOPSIS combined with rapid descriptive techniques can improve PREFMAP [40]. A strategy was used to explain why customers preferred or rejected certain products. The project's objective is to use a participative method to create an artificial risk index to assist smaller banks and small and medium-sized businesses (SMEs) with debt restructuring by analyzing realty credit risk[41]. A multi-SCSS that takes into account environmental as well as financial and management issues to analyze applications, a credit scoring system was constructed utilizing a combination of the Best-Worst Method (BWM) and the fuzzy-TOPSIS, with the BWM being used to calculate the weight of criterion[42].

3. Research methodology

3.1 Ranking function

In a fuzzy environment, ranking fuzzy numbers is a crucial part of decision making. Before a decision maker may take action in a fuzzy decision making dilemma, fuzzy numbers must be rated. Fuzzy quantities are used in fuzzy decision analysis to explain the performance of options in modeling an actual situation[1]. For rank fuzzy quantities, each one will be transferred to a real number and evaluated using a ranking function that provides a real number to every fuzzy number when a natural order obtains. Assume that the triangular fuzzy number has a membership degree and is denoted as $\tilde{A}$= (a; b; c), where b is the middle, a is the left width, and c is the right width. A new technique was suggested for determining a ranking function for trapezoidal and triangular membership [43].The ranking function is as follows:

$$R(\tilde{A}) = \frac{1}{4}(a + 2b + c) \quad (1)$$

3.2 The Shannon entropy weight method

The Shannon Entropy technique was not only used to calculate data quantity numerically but also to estimate the weight of data practically [44]. Entropy was initially meant to denote a physical phenomenon such as numerator disorder amount or the probability measure below a definite situation. Lower entropy values outcome in more proportionate numerator degrees, signifying as nearby to the best entropy as feasible [45]. In contrast, as entropy levels increase, the numerator degrees have a more inconsistent inflection [46]. As a result, the entropy weight technique was developed to determine the relative weight for every feature. The entropy weight method's computation approach is as follows. Consider D is the decision matrix, which consists m choices or alternatives (A_1,…,Am) and n characteristics or criteria (X_1,…,Xn):

$$D= \begin{array}{c c} & \begin{array}{cccc} X_1 & X_2 & \dots & X_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \vdots \\ A_m \end{array} & \begin{bmatrix} X_{11} & X_{12} & \dots & X_{1n} \\ X_{21} & X_{22} & \dots & X_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ X_{m1} & X_{m2} & \cdots & X_{mn} \end{bmatrix} \end{array} \quad (2)$$

The decision matrix is normalized as:

$$P_{ij}=\frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}, \forall i,j \quad (3)$$

Where (P_{ij}) is standardized the decision matrix

Ej is the entropy of the set of pattern effects of characteristic j.

$$E_j = -K\sum_{i=1}^{m} P_{ij} \ln P_{ij} \ \forall\ j \quad (4)$$

Furthermore, the entropy values should be between 0 and 1, and k is a positive constant, 0≤Ej ≤1, k= $\frac{1}{\ln m}$ (where m is decision alternatives) diversification $d_j$of the data supplied by attribute j's outcomes could be defined::d_j=1−Ej , ∀j.

and the weight obtained from information entropy is expressed as follows:

$$w_j = \frac{d_j}{\left(n-\sum_{j=1}^{n} E_j\right)} \quad (5)$$

Where $0 \le w_j \le 1$ *and* $\sum_{j=1}^{n} w_j$=1

3.3 The Fuzzy analytic hierarchy process (FAHP)

In real-world contexts, when dealing with multi-attribute decision-making issues, the analytic hierarchy process (AHP) was widely used [47]. Saaty devised this approach, which establishes a hierarchical framework for complex challenges. Even though the traditional (AHP) may accommodate expert opinions and generate an evaluation based on a variety of factors, it is not totally capable of representing human judgment since pair-wise comparison matrices require exact numerical values[48].

To solve the limitations, the fuzzy analytic hierarchy process (FAHP) was developed as an alternative to the classical AHP and to facilitate adaption to real-world issues. The many techniques employed in FAHP are systematic methodologies established for alternative selection depending on hierarchical organization analysis and fuzzy theory.

3.4 Determining the weights of the criteria by (FAHP)

FAHP's technique for establishing evaluation criterion weights is presented and shown as follows:

Step 1: Create pair-wise comparison matrices for every element and criterion in the hierarchical system's dimensions. Identify linguistic phrases to pairwise comparisons by asking which of the two parts or criteria seems to be more important, for example,

$$\tilde{X} = \begin{bmatrix} 1 & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & 1 & \cdots & \tilde{x}_{2n} \\ \vdots & \vdots & & \vdots \\ \tilde{x}_{n1} & \tilde{x}_{n2} & \cdots & 1 \end{bmatrix} \qquad (6)$$

Where

$$\tilde{x}_{ij} = \begin{Bmatrix} \tilde{1}, \tilde{2}, \tilde{3}, \tilde{4}, \tilde{5}, \tilde{6}, \tilde{7} \text{ the criterion j is relative less import for criterion i} \\ 1 \qquad j = i \\ \tilde{1}^{-1}, \tilde{2}^{-1}, \tilde{3}^{-1}, \tilde{4}^{-1}, \tilde{5}^{-1}, \tilde{6}^{-1}, \tilde{7}^{-1} \text{ the criterion j is relative import for criterion i} \end{Bmatrix} \qquad (7)$$

Step 2: Through using fuzzy geometric mean, find the fuzzy weights for every criteria [49] as follows:

$$\tilde{r}_i = (\tilde{x}_{i1} \otimes \tilde{x}_{i2} \otimes \ldots \otimes \tilde{x}_{in})^{\frac{1}{n}} \qquad (8)$$

$$\widetilde{w}_i = (\tilde{r}_i \otimes (\tilde{r}_2 \otimes \ldots \otimes \tilde{r}_n)^{-1} \qquad (9)$$

Where

The compared result of the fuzzy criteria i with criterion n is $\tilde{x}_{ij}$. Consequently, for every criterion, the geometric mean of the fuzzy comparison score of the criterion was computed $\widetilde{w}_i$.

The fuzzy weights of the i[th] criterion were expressed as a triangular fuzzy number (TFN), $\widetilde{w}_i$= (L$\widetilde{w}_i$; M$\widetilde{w}_i$; U$\widetilde{w}_i$), L$\widetilde{w}_i$; M $\widetilde{w}_i$ and U $\widetilde{w}_i$ denote the lower, middle, and highest values of the criteria fuzzy weight, respectively. Hsieh defuzzification approach yielded the Best Non-fuzzy Performance score (BNP)[49].

$$BNP_i = ((U_i - L_i) + (M_i + L_i))/(3 + L_i) \ \forall i \qquad (10)$$

3.5 Modified fuzzy analytic hierarchy process (MFAHP)

The traditional FAHP system involves the decision-maker to providing relative weights to the criteria and can handle expert opinions when making an evaluation based on numerous criteria. However, because it uses exact numerical values in the pair-wise comparison matrices, it is not fully capable of capturing human judgment. FAHP modification was suggested as a way to resolve the ambiguity that usually arises from human judgments and preferences. The Shannon entropy technique was used to compute the entropy of all criteria to give the important of the criteria. The method is to determine the assessment criteria weights by MFAHP can be illustrated as follows:

Step 1.Compute entropy values of each criterion by using Eq. 2, 3 and 4
Step 2. Arrange the values from minimum to maximum and the lower the information entropy, the higher is the value of importance for the criterion. That means criterion with low entropy has more important.
Step 3.The scores were assigned to classification validity measures by given the linguistic factors for the seven categorization validity measures that are (very less important, less important, equally important, important, more important, very more important and completely more important).
Step 4. Construct a fuzzy pair-wise comparing matrix for the hierarchical system's criteria in the variables. Provide linguistic labels to the pairwise comparisons by determining which of the two elements/criteria is much more significant using Eq. (6)
Step 5. All column elements were divided by the sum of the column Eq (7).
Step 6.Compute the mean for each matrix entry.
Step 7. To obtain the final weights of each classification validity measure, we can use the ranking function for triangular numbers Eq. (1).

3.6 Technique for Order Preference by Similarity to Ideal Solution (TOPSIS)

TOPSIS is a suitable method for dealing with multi-criteria decision-making[50]. Hwang suggested this method to rank alternatives over multiple criteria[51]. It determines the optimal options by reducing the length of the Positive-Ideal Solution (PIS) and increasing the distance to the nadir, or Negative-Ideal Solution (NIS) [8]. TOPSIS evaluates the distances to both PIS and NIS at the same time and a preferred ordering is rated based on its relative distance and a combination of two distance metrics[52]. TOPSIS appears to offer four advantages: (i) A sound logic that represents human choice justification; (ii) A clear value that accounts for both the best and worst alternatives at the same time; (iii) A simple data processing process that can be easily destined into a spreadsheet and (iv) All alternative evaluation metrics on attributes can be viewed on a polyhedron, at least for any two dimensions.[48]. TOPSIS is an important MCDM approach when is comparing to other existing like AHP and ELECTRE because of these features[1].
The TOPSIS approach is divided into the following steps:
Step 1. Standardize the decision matrix (r_{ij}) using Eq. (2):

$$r_{ij}=\frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}{}^{2}}} \quad i=1,2,...,m; j=1,2,...,n. \tag{11}$$

Where (r_{ij}) is standardize the decision matrix
Step 2. Applying w_j, to calculate the criteria weights by MFAHP.

Step 3. Multiplying each column of the normalized decision matrix Eq. (2) by its associated weight w_j, the resulting matrix may be derived. The sum of the weights is equal to one.

$$v_{ij} = w_j \times r_{ij} \quad i=1,2,...,m; \quad j=1,2,...,n \tag{12}$$

Step4. Determining the two ideal solutions A^{+}(the positive ideal) and A^{-}(the negative ideal) where
A^{+}= { $\max_i(v_{ij})$; i = 1,.., m} ,A^{+}= {$v_1^{+}, v_2^{+},...,v_n^{+}$}

A^-= { min$_i$ (v_{ij}); i = 1,… , m},A^-={$v_1^-, v_2^-, \dots, v_n^-$}

Step5. Computing the distance from point v_{ij} to positive and negative ideal points v_j^+ and v_j^- , for j = 1,2,.., n as follows:

$$d_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \ , i = 1,2, \dots, m \qquad (13)$$

$$d_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \ , i = 1,2, \dots, m \qquad (14)$$

As a result of this stage, each option has two values $d_i^+$and d_i^-, which illustrates the distance between every alternative and both the positive and negative ideals

Step 6.Determine how close an alternative would be for the ideal solution. The nearness of A_i for the ideal solution A^+ (larger is preferable) is specified in this phase as:

$$c_i = \frac{d_i^-}{d_i^+ + d_i^-} \qquad (15)$$

Clearly, c_i= 1 only if and only if A_i= A^+. Likewise, if and only if A_i= A^-, c_i= 0.

Step 7. Evaluating the alternatives based on how near they are to the ideal solution. The alternative's set can be graded, with the highest value indicating the alternative's best performance.

4-Experiment Setup and Data Set

In order to avoid risks from the bank's standpoint, the bank requires a determination rule for who receives a loan approval and who does not. Loan managers consider the applicant's socioeconomic aspects before making a judgment on a loan application. The German Credit Data provides data on 20 criteria and classification of whether an application is considered a good or terrible credit risk, as well as 20 input variables, seven of which are numerical (integer), for 1000 loan applicants and thirteen of which are categorical. There are two types of customers: good customers and bad customers. Bad customers are the default or negative class, whereas good customers are the exception or positive type. The good customers account for 70% of the cases, whereas the bad customers account for 30% of the total.

The German credit data can be found here[53]. A bank manager must be able to construct a forecasting models depending on this data to determine whether or not to accept a loan to a potential applicant based on their profiles. The performance of several classification approaches is evaluated using this dataset as a benchmark. The accuracy of categorization techniques is evaluated in this experiment using nine factors itemized in Table 1.

Table 1: Desired values of various parameters

No.	Parameter name	Desired Values
1	Number of features	Minimum
2	Precision	Maximum
3	False positive rate	Minimum
4	F-Measure	Maximum
5	Receiver operating characteristics	Maximum
6	True positive rate	Maximum

Maximum values should be set for some criteria, such as accuracy and true positive rate in an optimal condition, while others, such as a number of features and false positive rate, should have minimal values. Each parameter is given a unit weight because they are all regarded an equivalent importance. In other circumstances, however, some criteria may be more important than others, and the weighting must be updated accordingly. On the basis of features, the various available classification techniques can be compared, although it is impossible to recommend a single technique for every dataset. Five classification strategies and five feature selection processes (full feature and four feature selection techniques) are used in this experiment, as shown in Table 2.

Table 2: Classification method and features techniques used for Experimentation

Classification method No.	Features selection techniques
Native Bayes	all features
Logistic	Gain Ratio Attribute Eval
SVM	One Ra Attribute Eval
KNN	Info Gain Ratio Attribute Eval
J48	CFS Subset Eval

The feature selection technique number corresponds to the classification method No. in Table 2. Each classifier is used in five experiments (one full feature plus four different approaches), for a total of 50 experiments. These trials were carried out with the help of the Weka data mining tool[54]. Weka is a Java-based machine learning framework that may be used for data pre-processing, classification, clustering, and other data mining activities. TOPSIS is then applied in the Matlab technical computing program[55] that is used for numerical computations, visualization, and programming. Each classifier's output is subjected to this algorithm. A confidence value set by TOPSIS was ranging from 0 to 1. Based on the confidence value, a classification strategy might be suggested. The desired technique is indicated by a greater confidence value. Various approaches were ranked in this experiment based on the confidence levels obtained after applying each classifier. The methods used in this experiment are shown in Table 1. Five classification methods (Nave ayes, J48, Logistic, SVM, and KNN) and five feature selection strategies (all features, Gain Ratio Attribute Eval, One Ra Attribute Eval, Info Gain Ratio Attribute Eval, and Info Gain Ratio Attribute Eval) were employed.

5 The Results and Discussion

The results of five classifiers were illustrated in Table 3. This table shows the results of every feature selection for each classifier during experiments. These are the values for the parameters that were used in this investigation. A comparative study of several classifiers can be performed using specific criteria. Alternatives can be easily chosen relying on a single parameter, but selecting an alternative when there are numerous criteria is complicated.

Table 3: Performance of Classification method with all features

Classification method No.	Precision	TP Rate	FP Rate	Roc Area	Recall	F-measure
Native Bayes	0.385	0.797	0.787	0.395	0.740	0.750
Logistic	0.379	0.798	0.785	0.398	0.744	0.752
SVM	0.371	0.681	0.671	0.410	0.741	0.751
KNN	0.241	0.721	0.689	0.464	0.687	0.694
J48	0.270	0.673	0.605	0.475	0.721	0.726

In the instance of CFS subset eval selection features, Table 4 illustrates the values of various criteria for each classifier technique. This table can be used to perform a comparative analysis. In the instance of gain ratio attribute eval selection features, Table 5 illustrates the values of various criteria for each classifier technique.

Table 4: Performance of Classification method with CFS Subset Eval selection features.

Classification method No.	Precision	TP Rate	FP Rate	Roc Area	Recall	F-measure
Native Bayes	0.375	0.797	0.787	0.393	0.746	0.753
Logistic	0.379	0.798	0.785	0.410	0.744	0.752
SVM	0.371	0.681	0.671	0.410	0.741	0.751
KNN	0.241	0.721	0.689	0.464	0.684	0.694
J48	0.251	0.657	0.639	0.475	0.692	0.705

Table 5: Performance of Classification method with Gain Ratio Attribute Eval selection features.

Classification method No.	Precision	TP Rate	FP Rate	Roc Area	Recall	F-measure
Native Bayes	0.385	0.797	0.787	0.393	0.746	0.754
Logistic	0.379	0.798	0.785	0.398	0.744	0.752
SVM	0.396	0.808	0.792	0.389	0.751	0.759
KNN	0.241	0.721	0.689	0.464	0.687	0.694
J48	0.251	0.657	0.639	0.475	0.692	0.705

In the case of the one Ra attribute eval selection feature, Table 6 illustrates the values of various parameters for each classifier technique. In the instance of info gain ratio attribute eval selection characteristics, the values of various parameters for each classifier technique were also shown in Table 7.As it is shown in Table 8, the TOPSIS approach uses these inputs to rank feature selection techniques.

Table 6: Performance of Classification method with One Ra Attribute Eval selection features.

Classification method No.	Precision	TP Rate	FP Rate	Roc Area	Recall	F-measure
Native Bayes	0.385	0.797	0.787	0.393	0.746	0.754
Logistic	0.379	0.798	0.785	0.398	0.744	0.751
SVM	0.371	0.6810	0.671	0.410	0.741	0.751
KNN	0.241	0.721	0.689	0.464	0.687	0.694
J48	0.251	0.657	0.639	0.475	0.692	0.705

Table 7: Performance of Classification method with Info Gain Ratio Attribute Eval selection features.

Classification method No.	Precision	TP Rate	FP Rate	Roc Area	Recall	F-measure
Native Bayes	0.385	0.797	0.787	0.393	0.746	0.754
Logistic	0.379	0.798	0.785	0.398	0.744	0.702
SVM	0.371	0.681	0.671	0.410	0.741	0.751
KNN	0.241	0.721	0.689	0.464	0.687	0.694
J48	0.251	0.757	0.639	0.475	0.692	0.705

There are five distinct classification methods, each with its own set of five attribute section approaches. These numbers can be used to rank options using multi-criteria decision-making techniques. To acquire the confidence value of each classifier for each feature selection strategy separately, TOPSIS is developed using the MATLAB technical computing program. For each classifier, Table 8 displays the confidence values of several feature selection strategies.

Table 8: Confidence Level Based on TOPSIS Method of Classification methods

Classification method No.	All features	CFS Subset Eval	Gain Ratio Attribute Eval	One Ra Attribute Eval	Info Gain Ratio Attribute Eval
Native Bayes	0.8886	0.8786	0.8116	0.8857	0.8856
Logistic	0.8832	0.9055	0.8028	0.8826	0.8814
SVM	0.7840	0.7986	0.8233	0.7856	0.7859
KNN	0.1526	0.1280	0.1713	0.1258	0.1237
J48	0.2192	0.1374	0.1923	0.1347	0.1393

Ranks for various approaches have been determined based on these confidence ratings. Techniques with the same level of confidence are ranked the same. The strategy with the lowest rank value is the most preferred, hence rank 1 is the most chosen way. Table 9 shows how rank is calculated from confidence values. The final rank is determined by averaging the ranking values of five separate classifiers produced through the use of five different feature section approaches.

Table 9: Final Ranking of Classification methods

Classification method No.	All features	CFS Subset Eval	Gain Ratio Attribute Eval	One Ra Attribute Eval	Info Gain Ratio Attribute Eval	Final Rank
Native Bayes	1	2	2	1	1	1
Logistic	2	1	3	2	2	2
SVM	3	3	1	3	3	3
KNN	5	5	5	5	5	5
J48	4	4	4	4	4	4

Because it achieves rank one for an average of five feature selections, Native Bayes is ranked first. The logistic technique comes in second, followed by SVM. Individual rankings of distinct five-feature selections are aggregated to offer final ranks to all other techniques.

6- Conclusions

In this study, the use of MCDM approaches to evaluate the performance of credit risk prediction models is recommended. It has been demonstrated that relying on a single efficiency validation set might lead to inaccurate findings about the best-performing algorithm. As a result, determining the most appropriate model for tackling a certain financial problem is difficult. Using a modified fuzzy analytic hierarchy process (MFAHP) to compute the weight alternatives for TOPSIS, the popular MCDM approach, a modification of TOPSIS has been suggested. The rank function is also utilized to defuzzify the fuzzy values and get the final alternative weights. Over the German credit data sets, in tests, the TOPSIS modification is assessed with five classification models (alternatives) and five measurements (criteria). When single evaluation metrics is used to analyze models, the results are inconclusive in the fact that different evaluations suggested various algorithms as the correct solution. This demonstrates that credit predicting is a serious challenge for which MCDM techniques should be utilized to consistently evaluate a group of models. When a combination of measures is used to evaluate performance, TOPSIS has found that Naive Bayes and support vector machines are the best prediction models for German credit data sets.

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