International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3s
DOI: https://doi.org/10.17762/ijritcc.v11i3s.6160
***Article Received**: 08 December 2022 **Revised**: 14 January 2023 **Accepted**: 20 January 2023*

Analysis of Rank Aggregation Techniques for Rank Based on the Feature Selection Technique

Alisha Sikri[1], N. P. Singh[2], Surjeet Dalal[3]
[1]Research Scholar, Department of Computer Science and Engineering, SRM University, Delhi-NCR, India.
Email: alisha.sikri92@gmail.com
[2]Professor, School of Business Management and Commerce, MVN University (NCR), Palwal, Haryana.
Email: dr.npsingh@mvn.edu.in
[3]Professor, Department of Computer Science and Engineering, Amity University, Gurugram, Haryana.
Email: sdalal@ggn.amity.edu

Abstract

In order to improve classification accuracy and lower future computation and data collecting costs, feature selection is the process of choosing the most crucial features from a group of attributes and removing the less crucial or redundant ones. To narrow down the features that need to be analyzed, a variety of feature selection procedures have been detailed in published publications. Chi-Square (CS), IG, Relief, GR, Symmetrical Uncertainty (SU), and MI are six alternative feature selection methods used in this study. The provided dataset is aggregated using four rank aggregation strategies: "rank aggregation," "Borda Count (BC) methodology," "score and rank combination," and "unified feature scoring" based on the outcomes of the six feature selection method (UFS). These four procedures by themselves were unable to generate a clear selection rank for the characteristic. To produce different ranks of traits, this ensemble of aggregating ranks is carried out. For this, the bagging method of majority voting was applied.

Keywords: CS, Mutual Information, Information Gain, Feature Selection, Relief from Rank Aggregation, Gain Ratio, and Symmetrical Uncertainty.

I. INTRODUCTION

An enormous amount of data has become available for numerous applications since the introduction of automated data collection techniques. The cost of analyzing and keeping data inevitably increases in direct proportion to its bulk. Therefore, it is crucial to edit these data in a cost-effective, rapid, and accurate manner while retaining the highest level of security. This is accomplished by concentrating on the data from crucial variables and eliminating the data from unimportant or pointless variables. For this purpose, feature selection, which involves evaluating significant features while ignoring ones of less importance, is a valuable technique. The focus of this research is on computing and contrasting the differences in the aggregate ranks calculated or allocated by four distinct rank aggregation algorithms, as well as the differences in the feature ranks provided by six different feature selection techniques. Researchers had not before considered the four rank aggregation strategies to be relevant to the same dataset. The goal of this research was to see how changing feature rankings affected the outputs of four distinct rank aggregation approaches used on the same dataset. Strategies such as unified feature scoring(UFS), rank aggregation, Borda count (BC), and the combining of scores and ranks were implemented. To accomplish the following objectives, a single dataset with 500 records and 12 attributes was used in this study:

- Rankings of 12 characteristics that were obtained utilizing six different feature selection techniques are compared [1-3].
- A comparison of the outcomes produced by the four distinct rank aggregation algorithms [4,5].
- The use of an appropriate ensemble approach, namely majority voting to obtain single ranks for all 12 features.

Five sections make up the article the first of which is an introduction that lists the study's goals. A comprehensive evaluation of the literature for rank aggregation procedures is presented in the second section of the literature review, which is separated into two pieces. In the first part, you'll get a synopsis of the literature on several feature selection techniques. And the goals of the research study are also mentioned, along with any research gaps in the existing literature. The third section, which also provides a description of the dataset and methods employed, describes the research methodology. The entire study's findings are

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presented in the fourth section, which is split into two parts. It provides a thorough explanation of the methods used to choose each individual attribute as well as tactics for rank aggregation. The fifth and last component is the conclusion, which provides a summary of the analysis.

II. LITERATURE REVIEW

There are two parts to this section. A review of the literature on individual feature selection strategies is presented in the first section, and a review of the literature on several rank aggregation techniques is presented in the second.

Literature Review on Individual Feature Selection Strategies

Kumar & Sree (2014) [18] reported the effectiveness of several models for the computerized assessment of descriptive answers utilizing dimensionality reduction and rank-based feature selection filters. The authors compared the results of the CS, IG, GR, relief, and SU filters. They discovered that these filters all recorded data with the same level of accuracy. This demonstrates that precision alone cannot be used to determine the optimal filter. For the purpose of conducting an automated analysis of descriptive replies, the authors propose using a rank-based feature selection technique such as symmetrical uncertainty characteristic assessment.

Rachburee & Punlumjeak (2015) [2] described the feature selection technique, a technique for reducing the number of features in a feature collection. After that, the authors looked at how well feature selection techniques predicted student progress. They proposed four feature selection methods: the greedy algorithm, IG, GR, and mRMR, all of which have been demonstrated to work with four classification models. The research findings revealed that the feature selection method was effective in categorizing and predicting student performance. The authors gave extensive information on the various feature selection strategies and the effects of those approaches on implementation.

Deepalakshmi& Velmurugan (2016) [3] defined feature selection as the act of removing redundant, unnecessary, noisy, or insignificant data to select useful features for the model's construction. They reviewed all of the text-mining feature selection methodologies in detail. The Pearson correlation, CS, SU, and MI were some of the methods that might be used to pick the optimal collection of characteristics. Additionally, the authors evaluated several filtering techniques for feature selection as well as classification techniques for performance analysis. Additionally, they applied the best set of acquired features to numerous classification algorithms.

Sulistiani & Tjahyanto (2017) [11] liked the results of the various "feature selection" techniques for gauging consumer loyalty. The researcher distinguishes between supervised and unsupervised feature selection strategies: CS, IG, GR, and MI are supervised feature selection techniques; in contrast, strategies for selecting unsupervised features include term strength, entropy-based ranking, term contribution, as well as document frequency. According to the researcher, the most popular feature selection strategies are embedding, wrapping, and filters. In their study, the CS technique assisted in extracting significant characteristics from all other available features with a threshold > 0.01 and improved the model's accuracy.

Bahassine et al. (2018) [1] explored Text miners frequently employ feature selection to narrow the focus of their analysis and boost their classification precision. The authors of this paper developed a novel method for classifying Arabic text using the CS methodology, which led to improved performance in text classification. The authors assessed the enhanced CS utilizing three classic metrics for feature selection: MI, IG, and CS. The preprocessing, feature selection, as well as learning processes are the three main components of the text classification system, according to the authors. The authors conducted an in-depth analysis of several feature selection strategies.

Review of the Literature on Rank Aggregation-Based Feature Selection Techniques

Li et al. (2017) [12] expanded the removal of repeated and pointless phrases from feature selection, a crucial technique for enhancing the effectiveness and precision of text categorization algorithms. We studied the potential for improvement of individual feature selection algorithms. For feature selection, the authors integrated various methods using combinational fusion analysis. The various feature selection tactics were evaluated using the function of rank score and a related graph called a rank score graph. The authors also made an effort to show that the grouping of numerous techniques can outperform a single strategy if every "feature selection" methodology has a distinct scoring behavior and performs exceptionally well.

Prati (2012) [17] described the six feature selection procedures in detail: the CS, IG, GR, SU, relief, and OneR. In order to create a more reliable ranking, the author looked into the issue of ensemble feature ranking. Then the author provided a basic architecture for ensemble feature ranking along with four separate implementations that each used a separate rank aggregation method. Also, three different learning methodologies and performance evaluations were

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employed to reach the conclusion that ensemble feature ranking enhances feature ranking quality. The mechanism the authors offered for combining the feature rankings was thorough and adaptable. The authors provided descriptions of various rank aggregation techniques, including the BC, Condorcet, and Schulze approaches.

Dahiya et al. (2016) [4] explored that there are various uses for feature selection, which is regarded as one way to improve a classifier's effectiveness by providing it with crucial and useful features for model construction. The authors therefore combined a variety of ranking methods to choose features for the same purpose. Five alternative feature selection techniques based on ranks were used. They suggested an improved ensemble rank modeling approach which incorporates the rankings provided by several feature selection approaches. The suggested method for rank aggregation uses the features' rank order and rank score in the ordered list of every feature selection methodology. Observations showed that models using a variety of feature selection strategies outperformed each of the five distinct rank-based feature selection techniques.

Ali et al. (2017) [5] created a solution for knowledge acquisition that includes each level of the CRISP-DM architecture and offers data mining capabilities to both experienced and novice data miners. The authors heavily utilized the DDKAT technique combined with a feature ensemble process known as UFS to analyze the feature set during the phase of data preparation for CRISP-DM. They utilized a precise multi-criteria decision-making process to identify a superior decision tree classification method. The authors demonstrated that the aesthetic, pragmatic, and hedonistic qualities of the total user experience were favorable.

Zhang & Jin (2018) [10] examined guidelines for feature selection as well as the state of the art at present. They addressed various ensemble types, as well as their composition and evaluation. They also examined the most current advancements and taught the user the foundations for assembling an ensemble for feature selection. They provided an overview of recent advances as well as the core concepts for developing an ensemble for feature selection. They also discussed feature selection approaches, which they divided into the following three groups: filters, wrappers, and embedding methods. Wrappers employ a classifier's prediction to analyse a subset of features; filters are independent of the induction technique; and embedding methods are exclusive to a particular learning machine. The authors also contrasted homogeneous and heterogeneous feature selection techniques. They then went on to demonstrate how they created an ensemble for feature selection using the software. Some of the tools discussed included the "Waikato Environment for Knowledge Analysis," "MATLAB," the "R programming language," "Knowledge Extraction Focusing on Evolutionary Learning," "Scikit-Learn," and "Apache Flink."

Ali et.al., (2018) [6] studied Feature selection, among the most crucial techniques for selecting acceptable attributes from a massive dataset, is presented in detail. According to the authors, this technique can be applied in two ways: ranking and filtering. They compiled the findings of various feature selection processes. In the ensemble-based FS technique, some of the important filter algorithms used are the IG, GR, CS, SU, OneR, and ReliefF. In order to create a final ranked list of features, we employed UFS, a cutting-edge feature ranking technique that integrates a number of filter-based algorithms. To prove that ensemble-based FS findings offer superior performance, the authors also looked at competing ensemble approaches, such as the Borda technique and univariant ensemble-based FS methodology. These metrics included accuracy, F-score, precision, and recall.

Zhao et al. (2019) [27] conducted research on the selection of optimal feature subsets for classification and the precise improvement of the classification performance. The authors claimed that ensemble learning, which is a recently established form of technology, can successfully improve feature selection classification accuracy. This study provided a full account of the research done using an environmental sound dataset. In the trials, a more effective approach focused on the constraint score and multi-model ensemble feature selection methods was used (MmEnFs). The statistics show that the revised method outperforms the current feature selection techniques when enough features are selected. The methodology of ensemble feature selection, which combines several methodologies, typically yields the best results.

III. RESEARCH METHODOLOGY

The dress dataset was subjected to six feature selection techniques (SU, CS, GR, IG, MI, and relief). The rank aggregation, BC, score and rank combination, and UFS procedures were used to combine distinct feature ranks based on diverse approaches into a single rank. Finally, majority voting was applied to create the rank ensemble.

This section is separated into two subsections: the first describes the dataset in detail, while the second discusses the data analysis algorithms.

Description of Dataset

This section contains a comprehensive explanation of the dataset, including the names, types, and measures, as well as

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descriptions of its features. The dataset included outfit characteristics and a target variable that served as a recommendation variable based on current sales. The sales in the dataset were tracked daily. The collection contained 500 examples with 13 attributes. The attribute information is summarized in Table 1.

Table 1. Description of the dataset

S.No	Feature Name	Type(Feature Name)	Measure	Description
1.	Style	Categorical	Nominal	Bohemia, brief, informal, charming, party, sensual, retro, & work are the divisions made for it.
2.	Price	Categorical	Nominal	There are five classifications: Low, Average, Medium, High, and Very High.
3.	Rating	Numeric	Scale	This ranges between 1 - 5
4.	Size	Categorical	Nominal	It is divided into the sizes S, M, L, XL, and Free Size.
5.	Season	Categorical	Nominal	There are 4 types: autumn, winter, spring, and summer.
6.	Neck Line	Categorical	Nominal	There are seven classifications: O-neck, boat-neck, bowneck, slash-neck, sweetheart, turndowncolor, and v-neck.
7.	Sleeve Length	Categorical	Nominal	It is characterized as full, half, short, sleeveless, and three-quarter sleeves.
8.	Waise line	Categorical	Nominal	It is divided into three categories: sagging, empire, and natural.
9.	Material	Categorical	Nominal	Broadcloth, Chiffon, Microfibre, Microsilk, Mix, Nylon, Ppartyyster, Rayon, and Silk are the nine categories that it falls under.
10	Fabrictype	Categorical	Nominal	It is divided into the following five categories: broadcloth, chiffon, jersey, satin, and woven.
11	Decoration	Categorical	Nominal	It is divided into ten categories, including Applique, Beading, Bow, Broadcloth, Button, hpartyLowout, Pockets, Ruffles, Sashes, and Sequined.
12	Pattern Type	Categorical	Nominal	There are six categories: Animal, Dot, Patchwork, Print, Spartyid, and Striped.
13	Recommendation	Categorical (Target Variable)	Nominal	It is the desired outcome. It is between 0 and 1.
"Source:https://archive.ics.uci.edu/ml/datasets/dresses_attribute_sales"				

Details of Approach

Individual feature selection strategies, including the SU, CS, IG, GR, relief, and MI, were investigated and contrasted in the first objective. The R programming language was used to calculate the attribute importance using six feature selection strategies. The statistics of these feature selection techniques are calculated for each attribute to define its relationship with the dependent variable. These statistics were converted into ranks from 1 to 12. 1 indicates high importance of the attribute in classifying instances into a category of dependent variable, and 12 indicates the lowest importance of the feature. Subsequently, the rank of features was combined using 4 aggregation methods, namely the rank aggregation method, the BC method, the score and rank combination method, and the UFS method, with a view to setting off variations in the rank. Moreover, the final rank is determined using the assembling majority voting method by offsetting variations in the rank obtained using the four aggregating techniques [19]. The process is presented as algorithm 1.

Algorithm 1:

Input:
Initialize the ranks
Calculate the ranks of the features "fj" using "Fi" (where i=1,2,..k) feature selection methods,
If the ranks "Rj =1,2..n" of features "fj" for feature selection techniques "Fi" are the same,
Then allocate it as the final rank,
Else if ranks "Rj =1,2..n" of features "fj"for feature selection methods "Fi" are different,
Calculate the combined ranks with rank aggregating methods RAk (k=1,..4),
If the combined ranks with rank aggregating methods RAk (k=1,..4) are the same,
Then,
Consider these ranks as the final rank
Else
Calculate the ensemble ranks using the majority vote ensemble method
End if
End if
End if

IV. RESULT DESCRIPTION

This section is split into three subsections: (i) a description and evaluation of different feature selection algorithms; (ii) a description and evaluation of rank aggregation methods;

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and (iii) a description and evaluation of the results of comparing the two approaches, i.e., the majority voting for personal feature selection techniques but also the majority voting for rank aggregation methods.

Techniques for Selecting Individual Features

Eliminating superfluous phrases from a corpus through "feature selection" is an essential method for enhancing the effectiveness and efficiency of text classification systems. Its usefulness in a variety of machine learning applications has been proven in fields such as computer vision, signal processing, and bioinformatics [7]. The training set is supervised, unsupervised, or semi-supervised depending on whether or not the data within it has been labelled [8]. The CS, GR, SU, IG MI, and relief are only some of the feature selection techniques available. Multiple feature selection processes have been shown to improve performance over a single technique [9]. This is because the dataset's lower dimensionality enables greater data comprehension, increases the efficiency of machine learning techniques, and reduces the need for storage and processing [10]. This is only possible if each feature selection approach performs well and has a distinct scoring behavior. The following feature selection methods can assist in removing extraneous data:

CS (Chi-Square): According to Sulistiani & Tjahyanto (2017) [11], CS is a supervised feature selection method that can remove many features while preserving accuracy. It is a statistical metric that establishes the connection between a feature and the class for which it is intended. This statistic is applied to evaluate the level of a word's dependence on a specific category. It is also a statistical technique for determining the connection between an "attribute A" and the "class or category Ci" to which it belongs [12]. This aids in determining whether an attribute is independent of its class. This method has been used by Zhu et al. (2019) [13], Harbil (2019) [14], and Wang et al. (2019) [15]. The formula for CS can be expressed as follows:

Chi-Square

(CS (m, 2)) = $\sum_{i=1}^{m} \left(\sum_{j=1}^{2} (Oij\text{-}E_{ij})^2\right)/E_{ij}$(1)

Where the table's core cells are all included in the sum.
If each cell's observed count O is at least 5 and the two study parameters are independent.

Then Chi-Square (CS) nearly follows a Chi-Square (CS) distribution with df=(m-1)(2-1).

IG (Information Gain): When an attribute is used to divide examples into disjoint subgroups based on its values, this measurement evaluates the increase in information entropy that results. In ID3, it served as a criterion for dividing decisions from trees [17]. It is also one of the most used criteria for selecting features, as it examines the amount of information a feature gives about the desired class [5]. A term's goodness metre for IG is the quantity of data collected for "class prediction" based on the presence or absence of the phrase in a text [16]. A "feature" with a "high IG" should typically be rated higher than another "features" because it is used to rank features and has greater data-description capability than other features. Following is the IG formula from these authors [2]:

"Gain Ratio(S,A)=Gain(S,A)/Split Information (S,A)"

$$\text{SplitInformation(S,A)} = -\sum_{i=1}^{c} \frac{|S_i|}{|S|} * \log_2 \frac{|S_i|}{|S|} \quad ..(3)$$

where |Si| is the cardinality of the subset Si in the training data as well as SplitInformation (S,A) is the entropy of the entire probability distribution subset following splitting.

Gain Ratio (GR): A discrepancy metric called the GR provides a normalized score to enhance the IG outcome [5]. After partitioning, the entropy of the probability distribution subset is accounted for by a normalization of information gain [11]. It serves as a splitting condition for decision trees in C4.5. It was created by Quinlan and is based on the IG requirement to reduce overestimation of multi-valued functions. The GR is said to function by normalizing the data stored in the split itself, according to [17]. The split information values [6] are used in this metric.

$$\text{Split}_A\text{ (D)} = -\sum_{i=1}^{v} \frac{|D_i|}{|D|} * \log_2 \frac{|D_i|}{|D|} \quad \text{...... (4)}$$

where Split_A (D) represents the structure of the v,

The GR is finally defined as follows:

Gain Ratio (A)=IG(A)/SplitInfo(A)....... (5)

SU represents symmetric uncertainty: In addition, it is a Metric based on the IG, that is normalized by multiplying the feature entropy by the class entropy. This quantity is then rescaled to the range 0 to 1 by multiplying it by two. It

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works well with feature sets that are severely unbalanced. It is an information-theoretic metric for evaluating the created solution ratings. It is a symmetric measure, as well as its expression was given by the equation given in [6]:

SU(A,B)=(2*IG(A/B))/(H(A)+H(B)) .... (6)

where the class attribute B is expressed by IG(A|B) and the independent attribute A defines the IG. H(A) & H(B) denote the entropies of traits A & B, respectively (B).

Relief: The weight of a feature is assessed using a distance-based metric called relief. The relief's original approach is restricted to two-class scenarios and can only be used with attributes that are discrete and continuous. It is inapplicable to missing data and can only be applied to discrete and continuous attributes. Relief is an extension to the relief methodology that aims to alleviate its drawbacks. It gauges a trait's usefulness by gauging how well it can distinguish between substantially identical surrounding instances belonging to different classes. This attribute assessment filter, according to [18], can be used with both discrete and continuous data. Examine a dataset with n instances and p features, where each instance and feature is assigned to one of the two groups. To ensure that the binary data remains within the range of 0 & 1, each feature utilized to gather data should be scaled to the range [0, 1]. There are M iterations of this algorithm. Start with a weight vector of p(W)-length that is empty. At each iteration, one random instance from each class that is closest to the feature vector (X) is chosen to construct the feature vectors (by Euclidean distance). A "near-hit" is used to describe the closest instance of the same class, whereas a "near-miss" is used to describe the nearest instance of a different class [19].

Wi = Wi –(xi-nearHiti)2 +(xi -nearMissi)2 …(7)

***MI ("Mutual Information")*:** When the "MI" for the term is equal to zero and the group is independent, the MI measures the degree of dependence between the variables [1]. "a tk word and a ci category." It evaluates the dependency between the features of the bits. Assume (X, Y) is a pair of random variables with values distributed across the X-Y space. Deepalakshmi & Velmurugan (2016) [3] defined it as "a method for determining the degree to which one variable depends on another." The MI is stated as follows: [20].

I(X;Y)= DKL (P(X,Y) ‖ PX PY) ….. (8)

DKL stands for the Kullback-Leibler divergence.

Table 2. Assessing the value of features using various ranking methodologies

Features	FeatureSelectionTechniques					
	Chi-Square (CS)	Information Gain (IG)	GainRatio (GR)	Symmetrical-Uncertainty (SU)	Relief	Mutual Information (MI)
Style	0.2193(2)	0.0245(2)	0.0147(4)	0.0209(4)	-0.0800(11)	0.0245(2)
Price	0.1998(4)	0.0200(4)	0.0174(3)	0.0218(3)	-0.0600(9)	0.0200(4)
Rating	0.0000(12)	0.0000(12)	0.0000(12)	0.0000(12)	0.1175(2)	0.0000(12)
Size	0.0654(11)	0.0021(11)	0.0015(11)	0.0021(11)	0.0600(5)	0.0021(11)
Season	0.2280(1)	0.0259(1)	0.0192(1)	0.0255(1)	-0.1200(12)	0.0259(1)
Neck Line	0.2136(3)	0.0236(3)	0.0187(2)	0.0243(2)	0.1000(4)	0.0236(3)
Sleeve Length	0.1582(6)	0.0128(6)	0.0094(6)	0.0126(6)	-0.0200(8)	0.0128(6)
Waiseline	0.0754(10)	0.0028(10)	0.0047(8)	0.0044(8)	0.1200(3)	0.0028(10)
Material	0.1174(8)	0.0069(8)	0.0043(9)	0.0061(9)	-0.0600(10)	0.0069(8)
Fabric Type	0.1406(7)	0.0098(7)	0.0103(5)	0.0120(5)	0.0400(6)	0.0098(7)
Decoration	0.1894(5)	0.0182(5)	0.0094(7)	0.0139(7)	0.2200(1)	0.0182(5)
Pattern Type	0.0929(9)	0.0044(9)	0.0034(10)	0.0045(10)	0.200(7)	0.44(9)

Rank Aggregation Techniques

For ensembles of numerous feature ranking algorithms, a variety of combinations or rank aggregation techniques have been used to provide aggregated feature ranking lists. A well-known issue called rank aggregation occurs when rival "rank orderings" for the same group of candidates work together to produce a "better" ordering [12, 21, 25]. According to Lin et.al. (2018) [22], rank aggregation is a fundamental technique with numerous applications. As explained in Section 4.1, various methods of feature selection provide distinct ranks. In this section, four rank-

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aggregating strategies for generating a single rank are examined.

Rank Aggregation

This section describes Algorithm 2 as well as the calculation of the approach established by for rank aggregation [4].

Algorithm 2:

m*n dataset with m instances and n features fj, where

j=1,2,3,...,n

Initialize aggregate rank list "E = φ"

Assume that "F1, F2,….., and Fk" are

aggregating Feature selection algorithms

For each "Fi, i=1,2,…k"

Calculate the rank score of each feature and construct the ranked lists "R_i",

i = 1, 2,……, k

Sort each Ri in descending order of rank scores Assign a sequence number "m=1,2,…. , n"; to all features in each "Ri" starting from the top

ENDFOR

For each feature fj, j = 1, 2, , n

For each sorted ranked list Ri, i = 1, 2, , k

For sequence no. m = 1, 2,….,n;

Rankorder = n – m +1

Aggregate rank score

Ej =("$rankscoreji*rankorderji$") ki

E = E U Ej END FOR

END FOR

END FOR

Using aggregate rank scores, sort the ranked list E in decreasing order. E is an ordered ensemble rank list including the features and their respective ensemble rank scores. Table 3 (CS, IG, and MI), Table 4 (GR and SU), Table 5 (relief), and Table 6 (rank score) display the computation of the supplied dataset for the individual feature selection methods (aggregated ranks).

Table 3. Rank order and Rank score of Chi-Square (CS), Information Gain (IG) & Mutual Information (MI)

S. No.	Features	Chi-Square (CS) (F1)	Rank List (R1) (CS)	Rank Order (n-m+1)	Rank Score Individual	Information Gain (IG) (F2)	Rank List (R2) (IG)	Rank Order (n-m+1)	Rank Score Individual	Mutual Information (MI) (F6)	Rank List (R6) (MI)	Rank Order (n-m+1)	Rank Score Individual
1	Season	0.228	1	12	12	0.025	1	12	12	0.228	1	12	12
2	Style	0.219	2	11	22	0.024	2	11	22	0.219	2	11	22
3	Neck Line	0.213	3	10	30	0.023	3	10	30	0.213	3	10	30
4	Price	0.199	4	9	36	0.02	4	9	36	0.199	4	9	36
5	Decoration	0.189	5	8	40	0.018	5	8	40	0.189	5	8	40
6	Sleeve Length	0.158	6	7	42	0.012	6	7	42	0.158	6	7	42
7	Fabric Type	0.140	7	6	42	0.009	7	6	42	0.140	7	6	42
8	Material	0.117	8	5	40	0.006	8	5	40	0.117	8	5	40
9	Pattern Type	0.092	9	4	36	0.004	9	4	36	0.092	9	4	36
10	Waise line	0.075	10	3	30	0.002	10	3	30	0.075	10	3	30
11	Size	0.065	11	2	22	0.002	11	2	22	0.065	11	2	22
12	Rating	0	12	1	12	0	12	1	12	0	12	1	12

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Table 4. Rank order and Rank Score of Gain Ratio (GR) & Symmetrical Uncertainty (SU)

	Gain Ratio(GR)					**Symmetrical Uncertainty (SU)**				
S. No	Features	Gain Ratio (GR) (F3)	Rank List (R3) (GR)	Rank Order (n-m+1)	Rank Score Individual	Features	Symmetrical Uncertainty (SU) (F4)	Rank List (R4) (Symmetrical Uncertainty)	Rank Order (n-m+1)	Rank Score Individual
1	Season	0.0192	1	12	12	Season	0.0255	1	12	12
2	Neck Line	0.0187	2	11	22	Neck Line	0.0243	2	11	22
3	Price	0.0174	3	10	30	Price	0.0218	3	10	30
4	Style	0.0147	4	9	36	Style	0.0209	4	9	36
5	Fabric Type	0.0103	5	8	40	Decoration	0.0139	5	8	40
6	Sleeve Length	0.0094	6	7	42	Sleeve Length	0.0126	6	7	42
7	Decoration	0.0094	7	6	42	Fabric Type	0.012	7	6	42
8	Waise line	0.0047	8	5	40	Material	0.0061	8	5	40
9	Material	0.0043	9	4	36	Pattern Type	0.0045	9	4	36
10	Pattern Type	0.0034	10	3	30	Waise line	0.0044	10	3	30
11	Size	0.0015	11	2	22	Size	0.0021	11	2	22
12	Rating	0	12	1	12	Rating	0	12	1	12

Table 5. Rank order and Rank Score of Relief

S.No	Features	Relief (F5)	Rank List (R5) (Relief)	Rank Order (n-m+1)	Rank Score Individual
1	Decoration	0.22	1	12	12
2	Waiseline	0.12	2	11	22
3	Rating	0.1175	3	10	30
4	Neck Line	0.1	4	9	36
5	Size	0.06	5	8	40
6	Fabric Type	0.04	6	7	42
7	Pattern Type	0.02	7	6	42
8	Sleeve Length	-0.02	8	5	40
9	Material	-0.06	9	4	36
10	Price	-0.06	10	3	30
11	Style	-0.08	11	2	22
12	Season	-0.12	12	1	12

Table 6. Aggregated rank order

Features	**Aggregated Rank Order**	**Rank**
Sleeve Length	42+42+42+42+42+40=250	1
Fabric Type	42+42+42+42+42+40=250	2
Material	40+40+40+36+40+36=232	3
Pattern.Type	36+36+36+30+36+42=216	4
Decoration	40+40+40+42+40+12=214	5
Price	36+36+36+30+30+30=198	6
Waiseline	30+30+30+40+30+22=182	7
Neck Line	30+30+30+22+22+36=170	8
Style	22+22+22+36+36+22=160	9
Size	22+22+22+22+22+40=150	10
Rating	12+12+12+12+12+30=90	11
Season	12+12+12+12+12+12=72	12

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3s
DOI: https://doi.org/10.17762/ijritcc.v11i3s.6160
***Article Received**: 08 December 2022 **Revised**: 14 January 2023 **Accepted**: 20 January 2023*

Borda Count

A position-based ensemble scoring method called the BC incorporates feature rating findings from multiple FS techniques. It has been looked into in relation to the rank fusion issue [23]. The BC is a component's average rank in the "input rankings"[24,26].

Borda(i)=∑∏j (f_i), where j=1 to n (9)

Simply, "j(f_i)" is the rank of feature "f_i" in ranking "j".

scorefinal= ∑scorepos(i,j), where i=1 to ….(10)

where "n" denotes the number of FS methods and "pos(i,j)" represents the "j^{th}" rank of thefeature in the "i^{th} FS" approach.

Algorithm 3:

"m*n" is a dataset with "m" instances and "n" features "fj", where j=1,2,3…,n

Suppose that F1, F2, , and Fk are the "feature selection"methods used for the ensemble for each "fi", i= 1, 2 , k

The BC of the component is its mean position in the input rankings:

"Borda(I)"=" j"=1to n , ∑$\prod_j$ (f_i),

where "∏j (f_i)" is the rank of feature "f_i" in the ranking "$\prod_j$".

Return Borda(i)

The BC method is depicted in diagram form in Figure 1

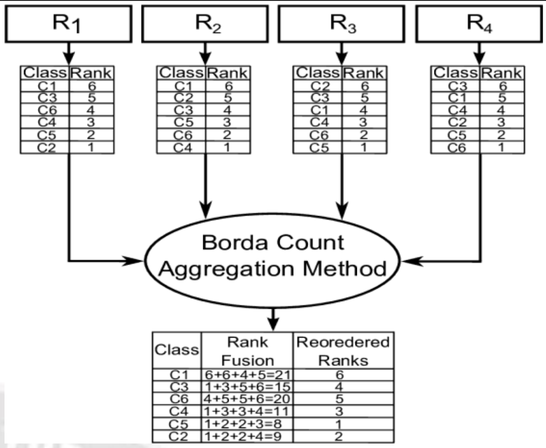

Figure 1. A Borda Count rank aggregation example [27]

The top-k searches on large multidimensional datasets are expensive to evaluate, and the BC cannot handle multi-valued objects with inconsistent cardinality [27]. To employ the BC approach, it is first necessary to compute the multiple feature rankings that are produced from separate feature selection procedures. That is the objective of Table 2. Table 7 presents the ranks calculated using the BC technique.

Table 7: Borda Count Results

Features	Borda Count	Ranks Calculated
Style	25	3
Price	28	5
Rating	63	12
Size	60	11
Season	17	2
NeckLine	17	1
SleeveLength	38	6
Waiseline	50	9
Material	50	8
FabricType	39	7
Decoration	28	4
Pattern.Type	53	10

Score and rank combination

This method combines the findings of numerous scoring techniques. By employing a variety of normalized score functions resulting from various feature selection methods and methodologies to assign a score to a feature in the FS, we create the rank combination [28]. The normalized value for each attribute Nj is,

Algorithm 4:

Dataset "m*n" holding "m" instances and "n" features "fj", where j=1,2,3…,n

Suppose that F1, F2, , and Fk are the features selection techniques used for the ensemble

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***Article Received**: 08 December 2022 **Revised**: 14 January 2023 **Accepted**: 20 January 2023*

For each f_i, i= 1, 2, , k
Ranks of features 1,2,..n on the attribute importance value
j=1,2….n
$N_j=f_j/\max(f_j)$,

where "fj" is the attribute importance value for the feature selection methodology, and "max(fj)" is the highest value that can be determined using that method.

Combination rank (C) $=\sum N_j$,

where j=1 to n

The rank scores and normalized values of the CS, IG, GR, symmetrical uncertainty, relief, and MI approaches are displayed in Table 8. The findings of the Score as well as rank combination approach are displayed in Table 9.

Table 8: Rank score, normalized values, and the following statistics are also included: Chi-Square, Information Gain, Gain Ratio, Symmetrical Uncertainty, Relief, & Mutual Information.

Features	Chi-Squae(CS) (F1)	Normalized Value (F1)	Information Gain (IG)(F2)	Normalized Value (F2)	Gain Ratio (GR) (F3)	Normalized Value (F3)	Symmetrical Uncertainty (F4) (SU)	Normalize Value (F4)	Relief (F5)	Normalized Value (F5)	Mutual Information (MI) (F6)	Normalized Value (F6)
Style	0.219	0.961	0.024	0.945	0.014	0.765	0.020	0.819	-0.080	0.765	0.024	0.945
Price	0.199	0.876	0.020	0.772	0.017	0.906	0.021	0.854	-0.060	0.906	0.020	0.772
Rating	0.000	0	0.000	0	0.000	0	0.000	0	0.117	0	0.000	0
Size	0.065	0.286	0.002	0.081	0.001	0.078	0.002	0.082	0.060	0.078	0.002	0.081
Season	0.228	1	0.025	1	0.019	1	0.025	1	-0.120	1	0.025	1
Neck Line	0.213	0.936	0.023	0.911	0.018	0.973	0.024	0.952	0.100	0.973	0.023	0.911
Sleeve Length	0.158	0.693	0.012	0.494	0.009	0.489	0.012	0.494	-0.020	0.489	0.012	0.494
Waise line	0.075	0.330	0.002	0.108	0.004	0.244	0.004	0.172	0.120	0.244	0.002	0.108
Material	0.117	0.514	0.006	0.266	0.004	0.223	0.006	0.239	-0.060	0.223	0.006	0.266
Fabric Type	0.140	0.616	0.009	0.378	0.010	0.536	0.012	0.470	0.040	0.536	0.009	0.378
Decor ation	0.189	0.830	0.018	0.702	0.009	0.489	0.013	0.545	0.220	0.489	0.013	0.545
Pattern. Type	0.092	0.407	0.004	0.169	0.003	0.177	0.004	0.176	0.092	0.407	0.004	0.169

Table 9: Rank and score combination results

Features	Score Combination	Ranks on basis of Score Combination(C)
Neck Line	5.1406	1
Price	3.9091	5
Rating	0.5340	12
Fabric Type	2.5622	7
Season	4.4545	2
Decoration	4.2707	3
Sleeve Length	2.5750	6
Size	0.8822	11
Waise line	1.5097	8
Material	1.2381	9
Style	4.0753	4
Pattern Type	1.1916	10

Unified Feature Score (UFS)

The best parameters are chosen using this procedure. A self-contained feature ranking system called the UFS tries to standardize different feature selection criteria. It uses a naturalistic approach to ensemble learning and incorporates the outcomes of different feature ranking algorithms to produce a final ranked list [29]. The scaled value results for the six feature selection techniques are presented in Table

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3s
DOI: https://doi.org/10.17762/ijritcc.v11i3s.6160
***Article Received**: 08 December 2022 **Revised**: 14 January 2023 **Accepted**: 20 January 2023*

10, whereas the UFS rank results are displayed in Table 11. The goal of the UFS strategy is to:

- Minimize the possibility of picking a useless feature.
- Create more consistent subsets of features.
- Develop the categorization accuracy.

Algorithm 5:
For each feature selection technique used, determine the feature selection gain rank (FSGR) that is

$FSGR_i$= (value-min/max-min).
Subsequently, calculate the combined ranks (CR):
CR= ∑ "$FSGR_i$", where "i=1" to "k"
FW= CR/TR,
Where "TR=∑CR", "FW" is Feature Weight
FS=CR/k , where "FS" is Feature Score and "k" is the no of techniques used
"FP= FW*FS", where "FP" is Feature Priority
The position is determined by the feature's priority.

Table 10. Scale values of Chi-Square (CS), Mutual information (MI), Information Gain (IG), Gain Ratio (GR), Symmetrical Uncertainty (SU), & Relief

Features	Chi-Squared (CS)	Scale Rank (CSSR)	Information Gain (IG)	Scale Rank (IGSR)	Gain Ratio (GR)	Scale Rank (GRSR)	Symmetrical Uncertainty (SU)	Scale Rank (SUSR)	Relief (R)	Scale Rank (RSR)	Mutual Information (MI)	Scale Rank (MISR)
Style	0.219	0.961	0.024	0.945	0.01	0.765	0.0209	0.8196	-0080	-0.363	0.024	0.945
Price	0.199	0.876	0.020	0.772	0.01	0.906	0.0218	0.8549	-0.060	-0.272	0.020	0.772
Rating	0.000	0	0.000	0	0.00	0	0.0000	0	0.117	0.534	0.000	0
Size	0.065	0.286	0.002	0.081	0.001	0.078	0.0021	0.0823	0.060	0.272	0.002	0.081
Season	0.228	1	0.025	1	0.019	1	0.0255	1	-0.120	-0.545	0.025	1
NeckLine	0.213	0.936	0.023	0.911	0.018	0.973	0.0243	0.9529	0.100	0.454	0.023	0.911
Sleeve Length	0.158	0.693	0.012	0.494	0.009	0.489	0.0126	0.4941	-0.020	-0.090	0.012	0.494
Waiseline	0.075	0.330	0.002	0.108	0.004	0.244	0.0044	0.1725	0.120	0.545	0.002	0.108
Material	0.117	0.514	0.006	0.266	0.004	0.223	0.0061	0.2392	-0.060	-0.272	0.006	0.266
Fabric Type	0.140	0.616	0.009	0.378	0.010	0.536	0.0120	0.4705	0.040	0.181	0.009	0.378
Decoration	0.189	0.830	0.018	0.702	0.009	0.489	0.0139	0.5450	0.220	1	0.018	0.702
Pattern Type	0.092	0.407	0.004	0.169	0.003	0.177	0.0045	0.1764	0.020	0.090	0.004	0.169

Table 11. Rank unified feature scoring results

Features	Combined Ranks (CR=CSSR+IGSR+GRSR+SUSR+RSR+MISR)	Feature Weights (FW) (FW=CR/TR)	Feature Score (FS) (FS=CR/6)	Feature Priorities (FP)	Rank
Style	4.075	0.126	0.021	0.002	4
Price	3.909	0.120	0.020	0.002	5
Rating	0.534	0.016	0.002	4.544E-0	12
Size	0.882	0.027	0.004	0.0001	11
Season	4.454	0.137	0.022	0.003	2
Neck Line	5.140	0.158	0.026	0.004	1
Sleeve Length	2.575	0.079	0.013	0.001	6
WaiseLine	1.509	0.046	0.007	0.0003	8
Material	1.238	0.038	0.006	0.0002	9
Fabric Type	2.562	0.079	0.013	0.001	7
Decoration	4.270	0.132	0.022	0.0029	3
Pattern Type	1.191	0.036	0.006	0.0002	10

Where,
CSSR= "Chi-Squared Scale Rank", IGSR= "Information Gain Scale Rank", GRSR= "Gain Ration Scale Rank", SUSR= "Symmetrical Uncertainty Scale Rank", RSR= "Relief Scale Rank", MISR= "Mutual Information Scale Rank"

Ensembling of combined rankings

As evidenced by the results presented in Section 4.2, distinct rank aggregating methods produce distinct feature ranks. That is, even aggregating ranks do not ensure unique feature ranks. Two options are recommended for obtaining a unique rank, as described in the following section.

Ensemble majority vote is used to rank different features selection methods

This section covers the diversity outputs of the feature rankings based on the outcomes of the six various feature selection approaches as illustrated in Table 12.

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 3s
DOI: https://doi.org/10.17762/ijritcc.v11i3s.6160
***Article Received**: 08 December 2022 **Revised**: 14 January 2023 **Accepted**: 20 January 2023*

Utilization of ensemble majority voting on ranks generated via four rank aggregation techniques

This section discusses the distinctive results of the feature rankings depending on the outcomes of the six different feature selection approaches shown in Table 13 in this paragraph.

More details on the Spearman correlations among individual feature selection techniques as well as rank aggregate feature selection processes are provided in Tables 14 and 15.

Table 12. Final rank of features by ensembling (majority role) ranks of individual feature selection techniques

Features	Chi-Square (CS)	Information Gain (IG)	Gain Ratio (GR)	Symmetrical Uncertainty (SU)	Relief	Mutual Information (MI)	MajorityVoting(%)	FinalRank
Fabric Type	7	7	5	7	6	7	66%	7
Price	4	4	3	3	10	4	50%	4
Waise line	10	10	8	10	2	10	66%	10
Size	11	11	11	11	5	11	83%	11
Season	1	1	1	1	12	1	83%	1
Neck Line	3	3	2	2	4	3	50%	3
Style	2	2	4	4	11	2	50%	2
Sleeve Length	6	6	6	6	8	6	83%	6
Material	8	8	9	8	9	8	66%	8
Rating	12	12	12	12	3	12	83%	12
Decoration	5	5	7	5	1	5	66%	5
Pattern Type	9	9	10	9	7	9	66%	9

Table 13. Final rank of features based on ranks of four aggregation technique using majority voting ensemble technique

Features	**Rank in Rank Aggregation**	**Rank in Borda Count(BC) Method**	**Rank in Score Combination**	**Rank in UFS**	**Major Voting**	**Final Rank**
Style	9	3	4	4	50%	4
Price	6	5	5	5	75%	5
Rating	11	12	12	12	75%	12
Size	10	11	11	11	75%	11
Season	12	2	2	2	75%	2
Neck Line	8	1	1	1	75%	1
Sleeve Length	1	6	6	6	75%	6
Waise line	7	9	8	8	50%	8
Material	3	8	9	9	50%	9
Fabric Type	2	7	7	7	75%	7
Decoration	5	4	3	3	50%	3
Patter Type	4	10	10	10	75%	10

Table 14. Spearman positions of different feature selection methods correlation

Techniques	**Chi-Square (CS)**	**Information Gain(IG)**	**GainRatio(GR)**	**Symmetrical Uncertainty (SU)**	**Relief**	**Mutual Information (MI)**
Chi-Square	1	1	0.930	0.979	-0.559	1
Information Gain	1	1	0.930	0.979	-0.559	1
Gain Ratio	0.930	0.930	1	1	-0.489	0.930
Symmetrical Uncertainty	0.979	0.979	1	1	-0.503	0.979
Relief	**-0.559**	**-0.559**	**-0.489**	**-0.503**	**1**	**-0.559**
Mutual Information	1	1	0.930	0.979	-0.559	1

Table 15. Spearman correlation between the rankings of rank aggregation feature selection approach

Techniques	Rank Aggregation method	Borda Count Method	Score Combination method	UFS method
Rank Aggregation method	1	-0.062	-0.062	-0.062
Borda Count Method	-0.062	1	0.986	0.986
Score Combination method	-0.062	0.986	1	1
UFS method	-0.062	0.986	1	1

V. CONCLUSION AND FUTURE SCOPE

The research concludes that the six feature selection approaches identified the value of the 12 features with a mix of similarities and differences. These similarities and differences were determined using the Spearman rank correlation values derived for each of the six feature selection procedures listed in Table 14. The strategy that differed the least from the other feature selection strategies was found to be relief. The ranks based on four rank aggregation methods were also investigated for similarities and dissimilarities. It can be seen from the Spearman Rank Correlation coefficients presented in Table 15 that the rank aggregation and BC methods yielded the most diverse results.

The results of the majority voting are more closely linked to the IG, CS, and GR, as shown in Table 12. Similarly, these results in the case of rank aggregation demonstrate that it is most closely related to the score combination and UFS as exhibited in Table 13.

It can be concluded that the ranks calculated with individual feature section techniques alone should not be considered for feature selection. To produce realistic ranks and importance's, three-step processes (individual method-based rank, aggregation method-based rank, and ranks using any ensemble method) should be applied for reducing the number of features. The results of the three-step process for the feature section produced better results for the same data and on other data sets [30, 31]. In the end, it is suggested that a three-step process may be used to reduce the variability in the ranks of the features to be included in the machine learning classification models.

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