

A Study of Arrhythmia Risk Level Discrimination Based on K-Means Algorithm and Analytic Hierarchy Method

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Abstract: Arrhythmia is one of the major causes of cardiac risk events, so the study and analysis of this cause can reduce the lethality of cardiac risk events. In this paper, based on the K-Means algorithm and hierarchical analysis method, a specific research and analysis of cardiac risk events is carried out. In this paper, the K-Means algorithm is used to establish the data classification model of abnormal heart beats, the Euclidean distance is chosen as the method of data similarity calculation, and the arrhythmia is classified through the analysis of the number of clusters, and through the deviation of the coordinates of the center point of the clusters, the corresponding objects are re-divided according to the minimum distance until the coordinates of the center point of the clusters are no longer shifted. The final field variability analysis was derived and solved for the frequency and percentage of classification for each category. Then, based on the comprehensive analysis of the classification results and the characteristics of each type of arrhythmia in sinus arrhythmia, five categories were derived: sinus arrhythmia, sinus bradycardia, sinus tachycardia, sinus conduction block, and sinus arrest. Further, this study used hierarchical analysis to establish an evaluation model to evaluate the risk level of each arrhythmia category, and the higher the score, the higher the risk level. A pairwise comparison matrix was constructed by comparing each category, and the weight vector and eigenvalues of each category were calculated, resulting in a ranking of the risk level of each arrhythmia category from highest to lowest: sinus arrest, sinus block, sinus tachycardia, sinus bradycardia, and sinus arrhythmia. This methodology enables healthcare organizations to more accurately assess arrhythmia categories and their corresponding risk levels, which provides an important reference for medical decision-making and contributes to more timely and effective interventions and treatments, thus improving patients' survival rates and quality of life.

Keywords: K-Means, AHP, Arrhythmia, Degree of danger

1. Introduction

In recent years, with the rapid development of cardiac electrophysiology research, cardiac dangerous events have received increasingly widespread attention. People have gained a deeper understanding of the electrophysiological phenomena of cardiac arrhythmias. Every heart beat is accompanied by complex electrophysiological phenomena. An in-depth study of the mechanisms of these electrophysiological phenomena, the characteristics of the electrocardiogram, and their clinical significance is essential for the accurate diagnosis and treatment of arrhythmias, especially in the diagnosis and treatment of complex arrhythmias. Ramanathan P, M J K, and Geoffrey L, in "Coherent mapping: a step toward physiological mapping of complex arrhythmias?"[1], explored the physiological mapping approach to understand the mechanisms of complex arrhythmias and assess the degree of risk, providing a new avenue for the field. Neira V, Santangeli P, Futyma P et al. in "Ablation strategies for intramural ventricular arrhythmias"[2] studied ablation strategies for ventricular arrhythmias in the inner wall of the heart, which provides ideas for the treatment of arrhythmias with high degree of risk. This has practical applications for guiding clinical practice and hazard level discrimination. Markman M T, Nazarian S in "Treatment of ventricular arrhythmias: What's New?"[3] summarized new developments in the treatment of ventricular

arrhythmias. Ventricular arrhythmias are a serious heart rhythm problem that can lead to sudden death. This study reviewed recent therapeutic strategies and techniques and provided useful information to improve the discrimination of risk level and treatment outcomes in patients with ventricular arrhythmias. J V B, Maksymilian P and Lucie C et al. in "Gene therapy for inherited arrhythmias"[4] examined gene therapy in inherited arrhythmias. The application of gene therapy in inherited arrhythmias provides new ideas for intervening in arrhythmias. This provides a new perspective for the discrimination of arrhythmia risk level and individualized intervention in high-risk groups, and helps to more accurately discriminate high-risk arrhythmias. In addition, K-means clustering method is widely used in large-scale data processing. Mi et al. proposed a large-scale K-means clustering method based on GPUs in "Large scale K-means clustering using GPUs"[5], which provides an efficient computational means for the analysis of arrhythmia data. And M. AI et al. in "K-means clustering algorithms: a comprehensive review, variants analysis, and advances in the era of big data"[6] provided a comprehensive evaluation and analysis of K-Means clustering algorithms that provides researchers with a more comprehensive selection of methods. Finally, Santa et al. in "Clinical-chatbot AHP evaluation based on "quality in use" of ISO/IEC 25010"[7] introduced a method for evaluating clinical chatbots based on hierarchical analysis. The method can be used to evaluate the quality of healthcare information systems. This method can be borrowed from the problem of arrhythmia risk level discrimination, where the weights of different discrimination indicators are evaluated and determined. Therefore, in this paper, the K-Means algorithm was used to determine the discriminatory criteria for each arrhythmia type, and the danger level of arrhythmia situations was graded by hierarchical analysis. This helps to discriminate the arrhythmia types earlier, so as to provide more timely first aid and improve the survival rate of patients. This is important for the resuscitation of different types of patients, especially in critical situations. To summarize, the research on the problem of discriminating the degree of danger of arrhythmia is attracting widespread attention. Through in-depth study of the electrophysiological phenomena of arrhythmia, exploration of new treatment pathways and introduction of advanced discrimination methods, it is expected that the degree of risk of arrhythmia can be more accurately assessed in clinical practice, and more effective rescue and management of patients can be provided.

2. Materials and Methods

2.1 Data acquisition and pre-processing

The data for this study were obtained from the 16th Mathematical China Mathematical Modeling Cyber Challenge (www.tzmcm.cn). The data were checked for missing values, outliers or erroneous data and processed accordingly. This includes filling in missing values, removing outliers, and correcting erroneous data to ensure the quality and accuracy of the data.

2.2 Methodology

2.2.1 K-Means Algorithm

The K-Means algorithm is a commonly used clustering algorithm, which was first proposed by computer scientist Stuart Lloyd in 1957, for dividing a set of data points into different clusters, such that data points within the same cluster have a higher degree of similarity and different clusters have a lower degree of similarity to each other. This algorithm is suitable for unsupervised learning, i.e., grouping data without pre-labeling. The main idea of the algorithm is to group the data points into K clusters by iterating, where K is the number of pre-specified clusters. Each cluster is represented by a center of mass which is the average of all the data points within the cluster. Its simple and easy to understand and is applicable to many clustering problems.

2.2.2 Analytic Hierarchy Process

Analytic Hierarchy Process (AHP) is a quantitative analysis method for multi-criteria decision-making problems that helps decision makers to make rational choices in complex decision-making situations. AHP was proposed by the American mathematician and operations researcher Thomas L. Saaty in the early 1970s. The main idea of AHP is to decompose a complex decision-making problem into multiple levels, each containing a series of specific criteria and choices. Each level contains a series of specific criteria and choices. By comparing and assigning weights to these criteria and choices, an optimal decision is finally reached.

3. Results

3.1 K-Means-based classification of arrhythmia classes

In this study, we find out the correlation between each data through the existing non-normal rhythm data, perform cluster analysis, derive the optimal number of clusters through the elbow rule, followed by aggregation of similar elements through K-Means algorithm to categorize arrhythmic conditions.

3.1.1 Confirm the number of clusters

The elbow rule is a common method used to help select the optimal number of clusters in cluster analysis. It helps find an optimal number of clusters based on the total variance corresponding to different cluster numbers. For different values of k (or number of clusters), the total internal variance w_k of their clustering results is computed, and the computed w_k for each cluster is summed up to obtain the total variance T . The change in the mean variance corresponding to each value of k is computed:

$$d_k = \frac{W_{k-1} - W_k}{W_1 + W_2 + \dots + W_n} \quad (1)$$

where k denotes the number of clusters in the current clustering, and W_{k-1} and W_k denote the total internal variance of $k-1$ and k clusters, respectively. n is the maximum number of clusters in the clustering, and $W_1 + W_2 + \dots + W_n$ is the total variance, T . Based on the elbow rule, the above graphs of the change in the mean variance with respect to k are derived as shown in Fig. 1 below.

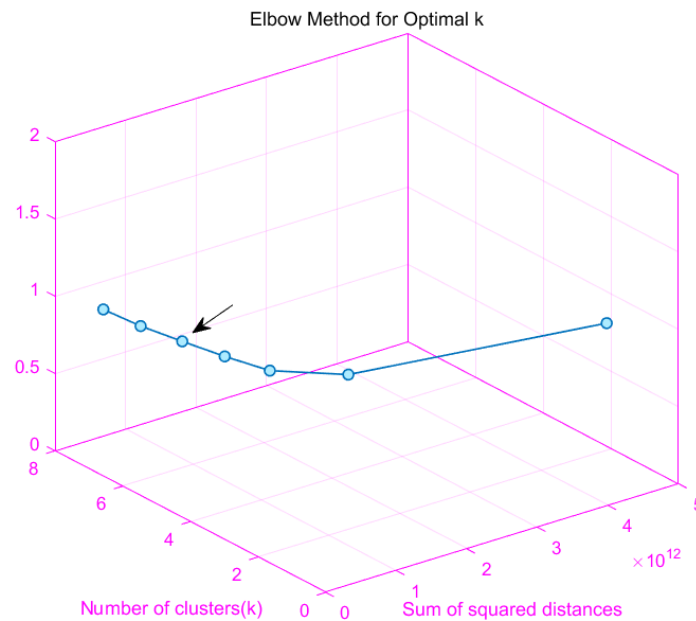


Figure 1: Comparison of the number of clusters

Figure 1 is used to select a better number of clusters, the horizontal coordinate is the number of clusters, and the vertical coordinate is the K-mean. The loss function for clustering is the sum of the squares of the distances of all the samples to the center of the category, also known as the sum of squares of the errors (the smaller the value, the better the clustering effect). After the number of clusters reaches 5, the rate of decline slows down, forming an "elbow-shaped" inflection point. This elbow point is the optimal number of clusters.

3.1.2 Compute the clustering center

In this study, K-means algorithm is used to classify n objects into 5 clusters by processing the non-normal data this paper with 5 as a parameter so that the objects within the clusters have a relatively high degree of similarity and a low degree of similarity between the clusters. The number of input clusters is K , and the database containing n data objects, the K-Means algorithm is used to derive the clusters of K that satisfy the criterion of minimum variance.

Firstly, 5 non-normal heartbeat objects are arbitrarily selected from n data objects as the initial clustering center, and the Euclidean distance is chosen as the method of data similarity calculation, which

is defined as:

$$d(x_p x_i) = \sqrt{\sum_{k=1}^p (x_{ik} - x_{jk})^2} \tag{2}$$

Through the Euclidean distance according to the mean value of all the objects in each clustered object to calculate the distance between each object and these center objects, and according to the minimum distance to re-divide the corresponding object, and from which a new clustering center is constantly derived, repeat the last two steps of the operation, so that each cluster no longer changes, that is, the final classification. The data were imported into the SPSS software, and the offset of the center coordinates of the clustering points was finally derived, as shown in Table 1 below.

Table 1: Cluster center point coordinate shifts

Type of clustering	Center value (5647.8)	Center value (16.035)	Center value (144.79)	Center value (75.07)	Center value (6.6121)	Center value (95.154)	Center value (2571.6)	Center value (1581.7)	Center value (22.264)
1	6840.111	19.739	145.520	217.822	255.792	245.461	517.654	565.786	489.417
2	748043.3	143.324	2420.623	5658.667	1267.190	909.190	2578.033	5054.193	96717.33
3	144158.7	784.657	1229.959	1031.486	986.141	2218.372	3424.758	31459.35	43387.84
4	577970.0	1164.113	18550.10	5844.400	2581.133	3130.767	9561.367	30085.67	184773.3
5	48770.77	107.848	1109.266	2028.737	1923.125	2187.635	2874.645	2896.970	3632.748

3.1.3 Arrhythmia clustering category classification

The data for each abnormal heartbeat was numbered from 1 and solved using SPSS software to produce an analysis of variance for each abnormal heartbeat data field, as shown in Table 2 below.

Table 2: Field Variability Analysis

	Clustering categories (mean ± standard deviation)					F	P
	Category 1 (n=738)	Category 2 (n=94)	Category 3 (n=30)	Category 4 (n=3)	Category 5 (n=3)		
1	6840.1±6866.3	48771±19399.5	144159±49351	748043±56016	577970.0±77841.7	4337.3	0.000***
2	19.7±47.2	107.8±180.7	784.7±908.5	143.3±237.6	1164.1±1447.9	136.6	0.000***
3	145.5±308.5	1109.3±1464.6	1230.0±1078.3	2420.6±2264.7	18550.1±10525.4	449.4	0.000***
4	217.8±555.0	2028.7±2455.8	1031.5±2422.3	5658.7±6237.5	5844.4±6690.5	86.7	0.000***
5	255.8±745.7	1923.1±2651.4	986.1±4609.1	1267.2±1044.9	2581.1±1084.5	32.7	0.000***
6	245.5±675.0	2187.6±3196.9	2218.4±9796.9	909.2±434.4	3130.8±1502.1	22.5	0.000***
7	517.7±989.0	2874.6±5071.6	3424.8±8874.8	2578.0±1657.9	9561.4±4451.4	35.6	0.000***
8	565.8±1140.8	2897.0±3066.8	31459±21352.8	5054.2±7693.2	30085.7±19034.5	407.4	0.000***
9	489.4±1191.8	3632.7±3638.0	43387.8±23959	96717±55808.6	184773.3±31092.7	1426.0	0.000***
10	608.1±1395.2	4777.5±7149.6	6203.6±9722.2	418353±39578	175866.7±46901.2	8020.3	0.000***

Due to the data is too large, the table only lists the data of the first 10 entries, through the field variability analysis can be derived from the data of each abnormal heart beat and the degree of match of each category, the data of each entry is classified, so as to make a certain degree of relevance. At the same time, the center of the clustering point will also change, at this time, then repeat the previous step of the operation, field variability analysis, and reclassify each data, and so on until the center of the clustering point does not change. Finally, the clustering scatterplot of the five categories is obtained, as shown in Figure 2 below.

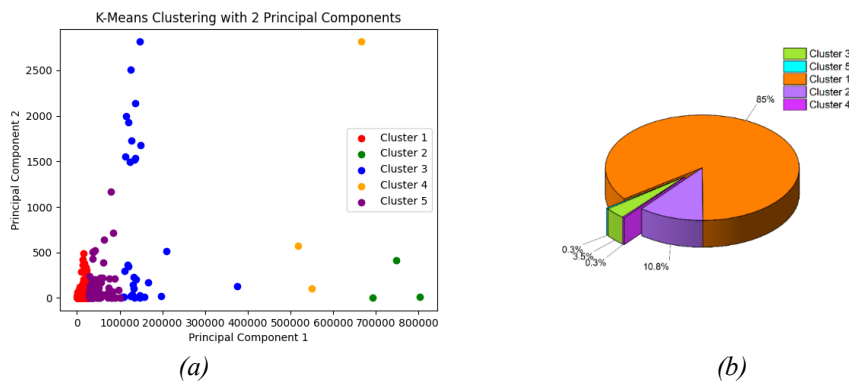


Figure 2: Clustered Scatter Plot(a)and Clustered Summary Plot(b)

The SPSS data statistics software resulted in the final clustered summary of non-normal heart beats, as shown in Table 3 below.

Table 3: Clustering Summary

Clustering category	Frequency	Percentage %
Clustering category 1	738	85.023
Clustering category 2	94	10.829
Clustering category 3	30	3.456
Clustering category 4	3	0.346
Clustering category 5	3	0.346
Add up the total	868	100.0

Table 3 demonstrates the results of the model clustering, including the number of frequencies, the percentage of the results of the clustering analysis shows that the clustering results are divided into five categories, the frequency of clustering category 1 is 738, and the percentage of the percentage of the clustering category 1 is 85.023%; clustering category 2 is 94, and the percentage of the percentage of the clustering category 2 is 10.829%; clustering category 3 is 30 and the percentage of the clustering category 3 is 3.456%; clustering category 4 is 3 and the percentage of the clustering category 5 is 0.346%. is 3 and the percentage is 0.346%; and the frequency of clustering category 5 is 3 and the percentage is 0.346%. As shown in Figure 3 above. The SPSS software allows the evaluation indicators to be derived as shown in Table 4 below.

Table 4: Evaluation Indicators

Contour Coefficient	DBI	CH
0.72	0.574	2846.088

The contour coefficient in Table 4 represents about a collection of samples, its contour coefficient is the average of all sample contour coefficients. The range of values of contour coefficient is [-1,1], the more similar the sample intervals are for category consistency, and the more distant the sample intervals are for category inconsistency, the higher the score, the better the clustering effect. Davies-Bouldin Index (DBI) metric is used to measure the ratio of intra-cluster interval to inter-cluster interval for any two clusters. The smaller the index, the better the clustering effect. Calinski-Harabasz Index (CH) measures the closeness of the class by calculating the sum of the squares of the distances between the center of the class and the points within the class (denominator), and the separateness of the data set by calculating the sum of the squares of the distances between the center of the data set and the center points between the classes (numerator). The CH index is obtained by the ratio of the closeness and the separateness, and the larger the CH is, the better the clustering effect is. The larger it is, the better the clustering effect is. Through Table 4, it can be concluded that the model clustering effect is better and the performance of the algorithm is higher.

With the above K-Means clustering results, the arrhythmias in this study were categorized into 5 categories as follows:

(1) Cluster Category I - Sinus Arrhythmia

The percentage of the first category is 85.023% and the frequency is 738, which is the largest, and its Hz corresponds to a relatively slow fluctuation of the data compared to the normal heart rhythm. Meanwhile, sinus arrhythmia is the most common type of arrhythmia among all the categories of arrhythmia, so the probability that the first category of arrhythmia is sinus arrhythmia. Sinus arrhythmia specifically refers to the onset of sinus rhythm is unchanged, but the rhythm is irregular, in the same lead on the P-P interval difference of > 0.12s called sinus arrhythmia (Figure 3 below), often with sinus bradycardia at the same time.



Figure 3: Sinus Arrhythmia

(2) Clustering Category II - Sinus Bradycardia

The percentage of the second category is 10.829%, and the frequency number is 94, and it can be seen from Fig. 2 that the scatter of cluster category 2 is repeated more than the scatter of cluster category 1, and represents the accompanying emergence, and the Hz corresponding to the data fluctuation is relatively slow compared to the normal rhythm, and the frequency interval after the wave peak is $>2.5\text{Hz}$, so this category is in line with the sinus bradycardia in the types of arrhythmia. This category is sinus bradycardia because it is often accompanied by sinus arrhythmia. Sinus bradycardia is specifically defined as a sinus rhythm of less than 60 beats per minute in adults. This is shown in Figure 4 below.



Figure 4: Sinus Bradycardia

(3) Cluster Category III - Sinus Tachycardia

The third category has a percentage of 3.456%, a frequency of 29, and relatively large fluctuations in Hz relative to the normal rhythm, and its frequency intervals after the peaks are $<1.5\text{ Hz}$ so this type of arrhythmia is sinus tachycardia. Sinus tachycardia is defined as a sinus rhythm of more than 100 beats/minute in adults. This is shown in Figure 5 below.

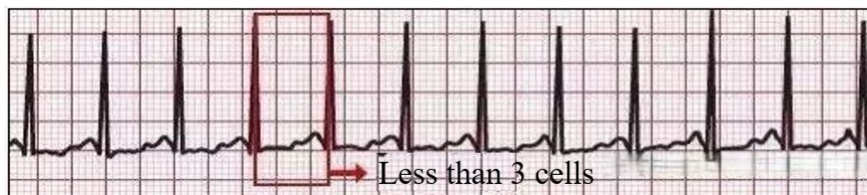


Figure 5: Sinus Tachycardia

(4) Clustering Category IV - Sinus Block

The percentage of the fourth category is 0.346% and the frequency number is 3. And as can be seen in Figure 2, the clustering category IV has fewer scatters and fewer frequencies, and there is one scatter far from the rest of the scatters in the scatter plot. At the same time, relative to the normal heart rhythm its Hz corresponding to the data have a long time in the same level, and its frequency interval after the trough in a long time without change, in this indicates that this type of arrhythmia belongs to sinus block. Sinus block is a delay or block in the conduction of impulses from the sinus node to the atria. This is shown in Figure 6 below.

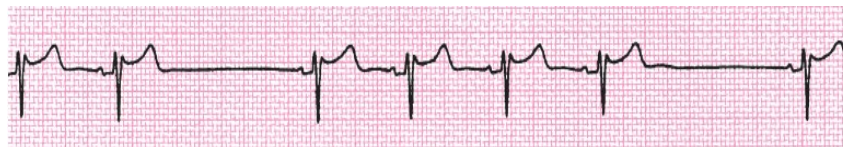


Figure 6: Sinus Block

(5) Clustering Category V - Sinus Arrest

The percentage of the fifth category is 0.346%, and the frequency number is 3. The percentage of this type is consistent with the category, indicating that the two have similar characteristics, and as can be seen from the clustering scatter plot Figure 2, the scatter distribution of the clustering category IV is more concentrated, indicating that the effects of this arrhythmia are basically the same, and at the same time, relative to the normal rhythm its Hz corresponds to data fluctuation is relatively slow and its in a certain break in time. The frequency interval is longer than the normal frequency interval. The qualifying condition is that the arrhythmia is a sinus arrest. Sinus arrest is the inability of the sinus node to generate impulses, indicated by the absence of normal P waves. This is shown in Figure 7 below.

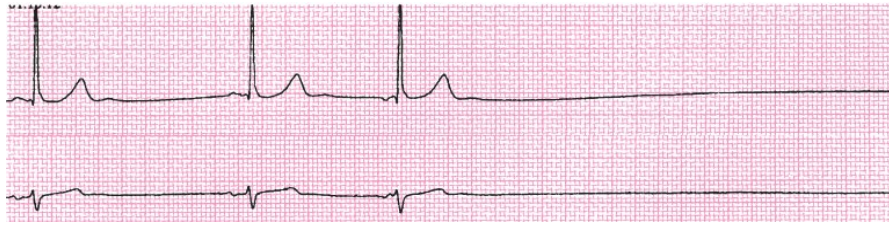


Figure 7: Sinus Arrest

3.2 Classification of arrhythmia risk level based on hierarchical analysis approach

3.2.1 Modeling hierarchical outcomes

In this study, by constructing a comprehensive evaluation system for the degree of danger of heart rate types, the relationship between indicators was determined by using a combination of systematic analysis, survey research, and expert discussion, and a two-tier architecture indicator system based on AHP was made, i.e., target tier and criterion tier, after considering the degree of urgency and danger between them.

In this study, we hope that by evaluating the degree of risk of each category of abnormal heart rate in two-by-two comparison, and combining the normal heart beat process with the evaluation and scoring of each arrhythmia category according to the degree of risk, so as to rank the degree of risk from the highest to the lowest, which will enable hospitals to better arrange for more time for their rescue treatment.

Arrange the levels in order of their positions according to the target layer and criterion layer and connect them according to their relationship. At the same time, in order to facilitate the quantitative analysis and representation later, *A* and *B* are used to represent the target layer and criterion layer respectively, and 1, 2, 3 and 4 are used to represent the different factors at the same level from left to right. The hierarchy thus constituted is shown in Figure 8.

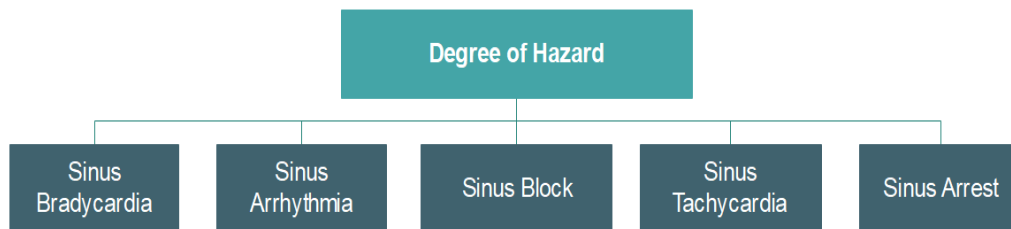


Figure 8: Hierarchical structure schematic

3.2.2 Construct the pairwise comparison matrix and assign values

The judgment matrix represents the comparison of the relative importance of all factors in this layer against a factor in the previous layer, and the elements of the judgment matrix, a_{ij} , are given on a scale of 1-9, as shown in Table 5 below.

Table 5: Scaling methods for determining the judgment matrix a_{ij}

Importance Scale	Meaning
1	Indicates that two elements have equal importance compared to each other
3	Indicates that the former is slightly more important than the latter when compared to two elements
5	Indicates that the former is significantly more important than the latter when compared to two elements
7	Indicates that the former is more important than the latter in comparison to two elements
9	Indicates that the former is more important than the latter in comparison to two elements
2,4,6,8	Represents the intermediate value of the above judgment
Count Backwards	If the importance ratio of element I to element j is a_{ij} , the importance ratio of element j to element I is $a_{ij} = 1/a_{ij}$

Let the criterion layers to be compared be $B_1, B_2, B_3 \dots B_n$, as shown in Fig. Apply the judgment matrix to the target to compare the indicators of the indicator layer two by two, resulting in the pairwise comparison matrix B of the criterion layer:

$$B = \begin{bmatrix} 1 & 1/8 & 1/7 & 1/8 & 1/5 \\ 8 & 1 & 4 & 1 & 5 \\ 7 & 1/4 & 1 & 1/4 & 4 \\ 8 & 1 & 4 & 1 & 5 \\ 5 & 1/5 & 1/4 & 1/5 & 1 \end{bmatrix} \quad (3)$$

3.2.3 Consistency Test

The eigenvectors, weight values, and maximum eigenroot and CI values of each item were calculated by Python, and the results are shown in Table 6 below:

Table 6: AHP hierarchical analysis results

Items	Eigenvector	Weighted value (%)	Maximum characteristic root	CI
Sinus Arrhythmia	0.214	2.889	5.395	0.099
Sinus Block	2.759	37.288		
Sinus Tachycardia	1.118	15.113		
Sinus Arrest	2.759	37.288		
Sinus Bradycardia	0.549	7.422		

The calculation of weights by hierarchical analysis method (square root method) showed that the weight of sinus arrhythmia was 2.889%, the weight of sinus block was 37.288%, the weight of sinus tachycardia was 15.113%, the weight of sinus arrest was 37.288%, and the weight of sinus bradycardia was 7.422%. Then the calculation results by hierarchical analysis method showed that the maximum characteristic root was 5.395, and the corresponding RI value was 1.11 according to the RI table, so $CR=CI/RI=0.089<0.1$, which passed the one-time test. When $C.R.<0.1$, it is considered that the consistency of the judgment matrix is feasible, and when $C.R.>0.1$, it is considered that the judgment matrix does not meet the consistency requirements and needs to be corrected. So it is concluded that the matrix passes the consistency test as shown in Table 7 below.

Table 7: Consistency test results

Maximum characteristic root	CI	RI	CR	Consistency test results
5.395	0.099	1.11	0.089	Pass

3.2.4 Draw the results

By calculating the weight value of each index this study evaluated and scored the degree of risk and finally arrived at a score of 0.373 for sinus arrest, 0.373 for sinus block, 0.151 for sinus tachycardia, 0.074 for sinus bradycardia, and 0.021 for sinus arrhythmia as shown in Figure 9.

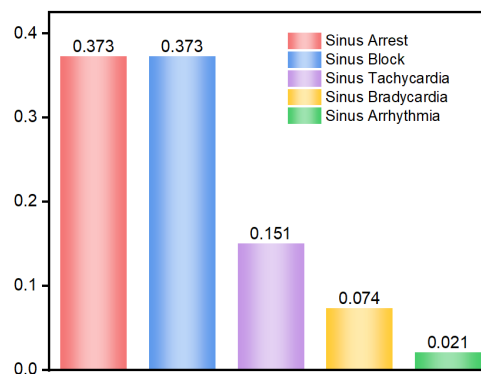


Figure 9: Final scores for each arrhythmia category

Ultimately, this paper concludes that the order of risk for each arrhythmia category, from highest to lowest, is sinus arrest, sinus block, sinus tachycardia, sinus bradycardia, and sinus arrhythmia.

4. Conclusions

In this study, arrhythmic cardiac risk events were studied in detail by using K-Means algorithm and

hierarchical analysis. Firstly, the data classification model for non-normal heart beats was constructed by using K-Means algorithm, and the different arrhythmia conditions were classified through cluster quantity analysis by adopting Euclidean distance as the similarity calculation method. By monitoring the offset of the cluster centroid coordinates, the minimum distance was taken to reclassify the corresponding objects until the cluster centroid coordinates were stable, and the field variability analysis was performed to derive the frequency and percentage of each category. Then, combining the characteristics of each type of arrhythmia, the clustering category 1 was determined as sinus arrhythmia, the clustering category 2 as sinus bradycardia, the clustering category 3 as sinus tachycardia, the clustering category 4 as sinus conduction block, and the clustering category 5 as sinus arrest. Then an evaluation model was developed using hierarchical analysis to score the degree of risk for different arrhythmia categories. Higher scores indicated a greater degree of risk. A pairwise comparison matrix was constructed by two-by-two comparison, and the weight vectors and eigenvalues of the categories were calculated, and the final ranking of the degree of risk of the different arrhythmia categories, from high to low, was determined as follows: sinus arrest, sinus block, sinus tachycardia, sinus bradycardia, and sinus arrhythmia. The K-MEANS algorithm model developed in this paper for the classification of cardiac dangerous events-arrhythmia types is more comprehensive and can be used to provide guidance and assistance for almost all theoretical studies on the classification of cardiac dangerous events, while the hierarchical analysis method can be used to provide guidance and assistance for the ranking of the degree of danger. Through this research methodology, hospitals will be able to more accurately assess different arrhythmia categories and their associated degree of risk, which will provide an important basis for medical decision-making and will help to intervene and treat patients more rapidly and effectively, thereby increasing the chances of survival and improving the quality of life.

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