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Surplus value quantification of overdue medical devices based on Kohonen network algorithm

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With the continuous updating and progress of medical equipment, the overdue medical device has problems such as management difficulties, resource waste, and potential security risks. Therefore, this paper used the Kohonen network algorithm to quantitatively evaluate and analyze the surplus value of overdue medical devices. In this paper, the Kohonen network algorithm was used to build a quantitative model of the surplus value of the overdue medical device, and the self-organization characteristics and data-driven learning ability of the Kohonen network were used to predict the surplus value of the equipment more accurately. Support vector machine was used to quantitatively evaluate and predict the surplus value of overdue medical devices, and further optimize the model performance, to provide more accurate and reliable decision support for medical equipment management. The Kohonen network algorithm used in this paper evaluated the correlation between the service life and maintenance cost of eight types of overdue medical devices and quantitatively predicted the surplus value of overdue medical devices with the random forest algorithm. According to the comparison of prediction bias, the maximum deviation between the expected surplus value and the actual surplus value is only 1, and the deviation value by the random forest algorithm is as low as 6, the Kohonen network algorithm in this paper has better prediction performance than the random forest algorithm. In the experiment of comparative analysis and verification by introducing the decision tree algorithm, the average error rate of the Kohonen network algorithm in this paper was only 20.57%, which was far lower than 46.34% of the random forest algorithm and 65.31% of decision tree algorithm. The Kohonen network algorithm used in this paper can effectively quantitatively evaluate and predict the surplus value of overdue medical devices, thus improving the efficiency of medical equipment management, reducing costs, and ensuring patient safety.

Keywords Overdue Medical device, Surplus value, Kohonen Network Algorithm, Quantitative Assessment, Unsupervised learning

With the continuous progress of medical equipment technology, medical institutions are actively updating and purchasing new equipment, resulting in a large number of overdue medical devices. These outdated devices not only occupy valuable space and increase the burden of management tasks but also fail to meet the evolving needs of medical institutions. However, because they still retain certain practical value in terms of technology and functionality, they cannot be directly scrapped, leading to potential waste. Therefore, it is of great significance for the asset management and decision-making of medical institutions to reasonably evaluate the surplus value of overdue service equipment[1]. As highlighted by Yan et al., effective analysis of the utilization efficiency of large-scale medical equipment plays a crucial role in planning, managing, and making informed decisions about the replacement of medical devices[2]. Traditional evaluation methods are often limited by subjective factors and incomplete data, making it difficult to accurately reflect the actual value of the equipment. To address this issue, this article proposed a quantitative method based on the Kohonen network algorithm.

Evaluation of the residual value of the equipment. Liu Q proposed a model for evaluating expired medical devices based on lifecycle cost theory[3]. Aghasizadeha Z explored preventive measures to reduce maintenance costs through research on dynamic system simulation models[4]. Santana J proposed a quantitative analysis framework based on risk assessment, considering factors such as equipment technical performance, maintenance costs, and environmental risks to evaluate the residual value of expired equipment[5]. NAR NH developed a questionnaire that includes KPIs (Key Performance Indicators) related to project structure to quantitatively evaluate the residual value of expired medical devices[6].

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Miri Lavassani K used various network centrality and clustering algorithms to measure each enterprise's influence within the entire supply chain structure. Additionally, a scenario was run to simulate the elimination of Chinese enterprises from the global supply chain, and all centrality measures were recalculated. Regression analysis was used to assess the impact of supply chain network centrality on the performance of supply chains with and without Chinese enterprises[7].Khider MO and other scholars have begun to explore and apply the Kohonen network algorithm, developing a model for evaluating the residual value of equipment. This model can accurately predict the residual value of expired medical devices, aiding healthcare institutions in more effectively managing equipment maintenance and replacement[8]. Jain A built an equipment residual value evaluation model based on the Kohonen network, integrating historical usage data, maintenance records, and technical indicators to accurately estimate the equipment's residual value[9].

This paper presents a quantitative method based on Kohonen network algorithm to evaluate the residual value of expired medical devices. Different from traditional supervised learning, this method can make use of the self-organizing characteristics and data-driven learning ability of Kohonen network in unsupervised learning to find the similarity and clustering among devices, and more accurately predict the residual value of devices based on multiple indicators, thus providing medical institutions with more scientific decision support[10]. With this approach, medical organizations can improve the efficiency of equipment management and reduce operating costs, thereby improving the quality of service. This quantitative method based on Kohonen network algorithm has high accuracy and reliability, which is of great significance to the operation management of medical institutions[11].

Quantification of surplus value of overdue medical device

Data preprocessing

In recent years, with the continuous development of medical technology, medical equipment has played an increasingly important role in clinical practice. Intravenous infusion machines, electrocardiographs, ventilators, centrifuges, physiotherapists, hemodialysis machines, magnetic resonance scanners, and surgical instruments are eight common types of equipment. The use of these devices not only improves medical effectiveness but also provides doctors with more accurate diagnostic results, thereby improving the quality of life of patients and prolonging their lives[12,13].

To further understand the development of overdue medical devices, it is crucial to construct corresponding datasets. The dataset collected in this article contains information on the technical parameters, usage instructions, and operating procedures of different devices, providing strong support for researchers and defibrillators. By analyzing this data, it is possible to better understand the performance characteristics of different devices, optimize the way they are used, and even explore new medical applications. Common medical devices are shown in Fig. 1.

An examination of the medical device dataset in Fig. 1 determined if there were any missing values, outliers, or incorrect values. If present, there is an option to delete these data or to fill or correct them using an appropriate method. First, a batch of data related to equipment that reached the end of their service life in 2020 was selected and quantified for subsequent normalization operations. The service life of the equipment was directly quantified; the maintenance records were weighted and scored according to the number of maintenance times and the replacement of important components; the frequency of equipment use was scored by the average daily usage time; the equipment use environment was scored by its humidity (0 points for a dry environment and 1 point for a humid environment); and the functional status of the equipment was scored by assessing whether the equipment had faults and whether it needed to be upgraded. After these processes, data of different dimensions

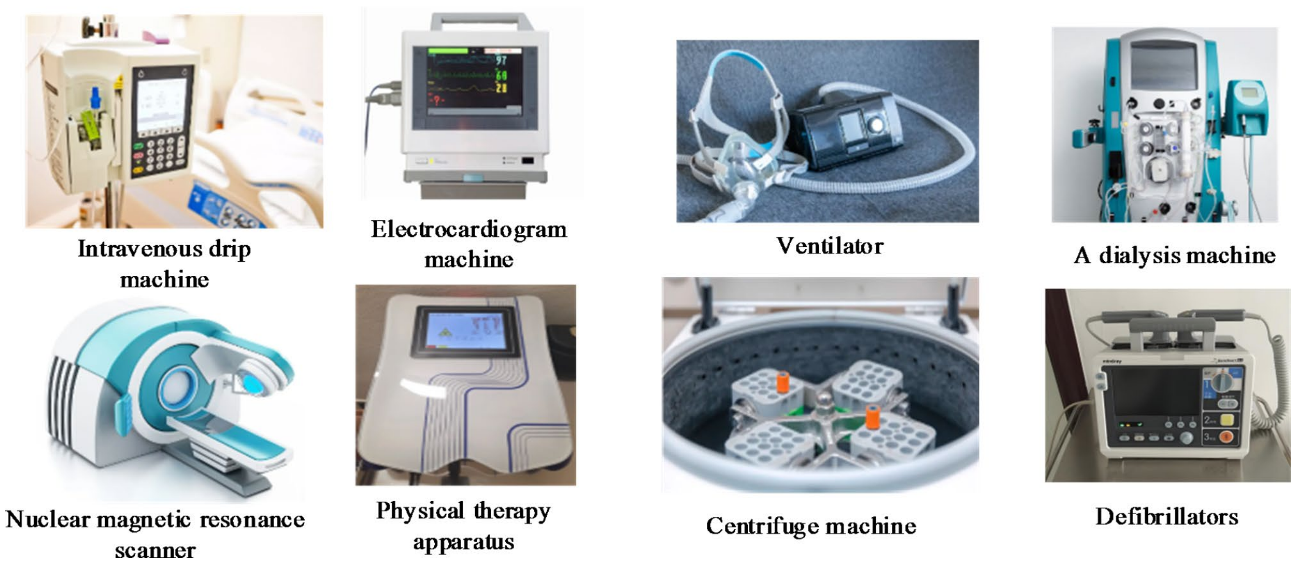

Fig. 1. Common medical equipment.

were normalized and converted to values of the same range. This paper adopts a standardized method to convert the data into a distribution with a mean of 0 and a variance of 1. Table 1 shows some of the data sets after data preprocessing.

Pre-processing of data from out-of-service medical devices is to improve the quality and accuracy of the data for subsequent analysis and modeling[14].

Kohonen network model construction

In the field of overdue medical device management, it is crucial to discover the relationship between the characteristics of equipment and surplus value in advance. However, traditional supervised learning methods rely on labeled data, and in practical applications, it is difficult to obtain a large number of accurate equipment surplus value data. To solve this problem, the unsupervised learning method has become an attractive choice. Among them, the Kohonen network model, as a classic self-organizing map algorithm, can build a cluster structure according to the characteristics of equipment and consider the difference in surplus value[15]. This paper aimed to explore the construction of an overdue medical device model based on the Kohonen network algorithm. Through unsupervised learning, the similarity and cluster between equipment can be found, to provide decision support for equipment management and maintenance. Next, this article will demonstrate the construction of the Kohonen network to demonstrate its potential and advantages in the field of overdue medical devices. The block diagram of the Kohonen network model is shown in Fig. 2.

The construction process of the Kohonen network model is as follows:

The first is the input data vector, represented as p, $p = (p_1, p_2, \cdots, p_n)$; n represents the dimension of input data. The next is to import the weight vector, denoted by e, and $e = (e_1, e_2, \cdots, e_m)$, which represents the weight between the neuron node and the input data vector.

A two-dimensional grid structure is used to represent the topological relationships of neuron nodes, with each neuron node having a position coordinate. The position of neuron nodes in a two-dimensional grid can be represented by (i, j). The specific Formula of neuron responsivity is:

$$W(j) = \sum_{k=1}^{n} (p_k - e_k(j))^2 \tag{1}$$

For input sample p_n, the Euclidean distance formula to each neuron in the network is calculated as:

$$\mathrm{dist}(p_n, e_m) = \|p_n - e_m\| \tag{2}$$

The neuron x that minimizes $\mathrm{dist}(p_n, e_m)$ is found, which is called the winning neuron. The weights of the winning neurons and their neighboring neurons would be adjusted to better match the input samples. For the winning neuron x and its neighboring neuron k, the formula for updating weights is:

$$\Delta e_x = \eta(t) * h(i, x) * (p_n - e_x) \tag{3}$$

$$\Delta e_k = \eta(t) * h(i, k) * (p_n - e_m) \tag{4}$$

Among them, Δe_x is the weight update amount of the winning neuron x. Δe_k is the weight update amount of the neighboring neuron k. η(t) is a function of Learning rate, which controls the speed of weight update, and it gradually decreases with time t. $h(i, x)$ is a neighborhood function, which measures the distance between the i-th input sample and the winning neuron x, usually measured by the Gaussian function or matrix topological neighborhood function.

In the medical industry, long-term use of medical equipment may result in extended service, meaning that the equipment has reached the recommended service life but is still in use. This may increase the risk of equipment failure, thereby affecting the treatment effectiveness and safety of patients[16,17]. Overdue medical devices may have issues with technical aging and performance degradation. As the equipment usage time increases, the risk of wear, aging, and damage to equipment components increases, which may lead to a decrease in the reliability and accuracy of the equipment[18]. This may lead to equipment malfunctions, incorrect diagnostic results, and inaccurate treatment processes, thereby affecting the treatment effectiveness and safety of patients. Secondly,

Equipment	Electrocardiogram machine	Nuclear magnetic resonance scanner	Ventilator
Years of service/ Score	8 years/0.27	10 years/1.07	4 years/-1.34
Maintenance record/ Score	Three repairs were made, one of which was to replace the power panel/-0.27	Five repairs were performed, one of which was to replace the Magnetic Resonance Imaging probe/1.34	Two repairs were performed, one of which was to replace the pressure sensor/-1.07
Frequency of device use/ Score	It was used for an average of 3 h per day/-1.16	It was used for an average of 6 h per day/-0.12	It was used for an average of 10 h per day/1.28
Equipment use environment/ Score	It is used in the cardiology department of the hospital, where the environment is relatively dry/-1.41	It is used in the radiology department of the hospital, where the environment is relatively humid/0.71	It is used in the intensive care unit of a hospital in a relatively humid environment/0.71
Equipment functional status/ Score	Some function buttons fail, requiring manual operation/1.72	Image processing software needs to be upgraded to improve image quality and resolution/4.75	Oxygen concentration sensors need to be calibrated regularly to ensure accurate oxygen supply/1.72

Table 1. Partial dataset of medical devices after pretreatment.

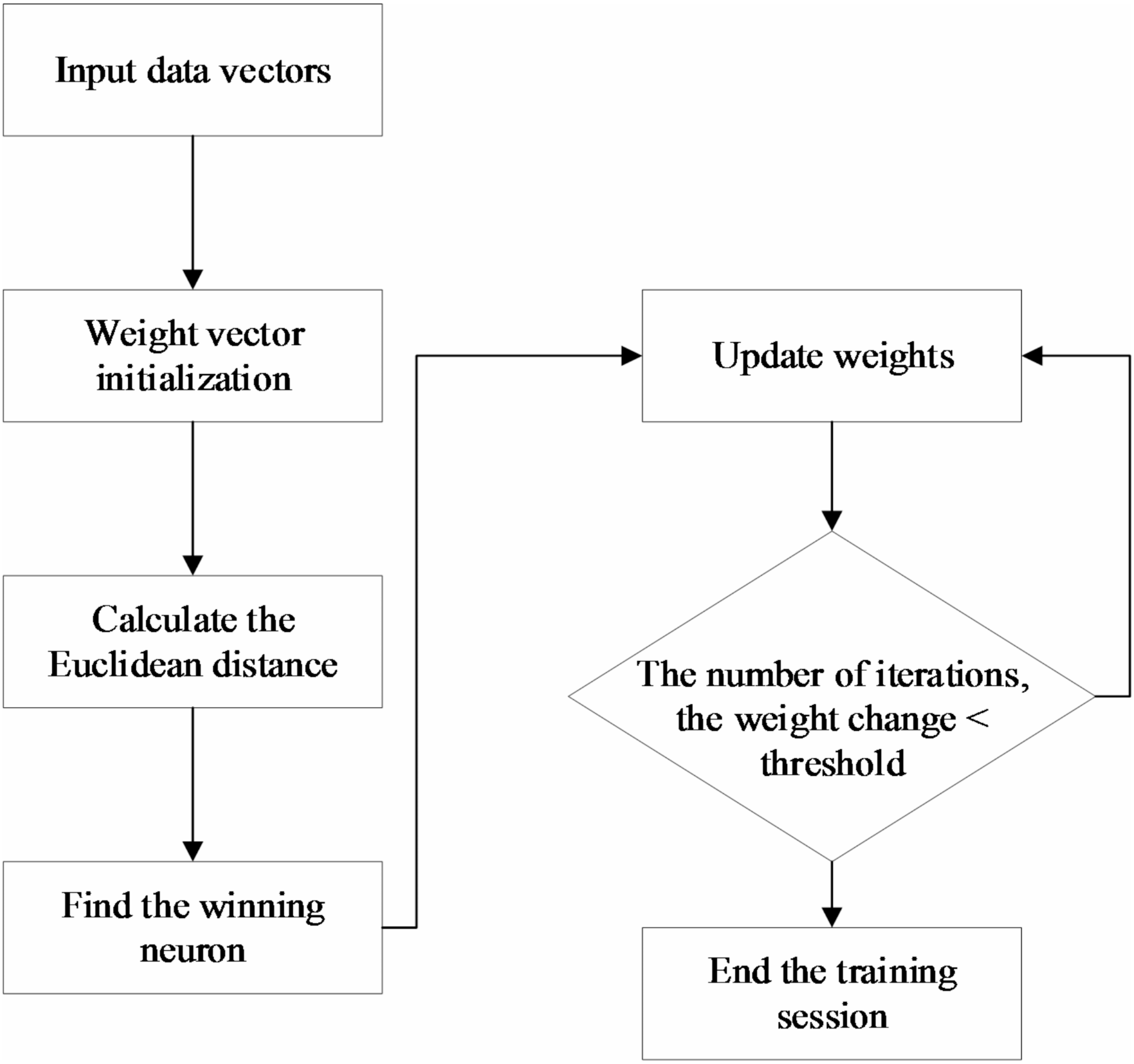

Fig. 2. Block diagram of the construction of the Kohonen network model.

equipment that has exceeded its service period may not receive timely manufacturer support and maintenance services. Medical equipment manufacturers usually provide maintenance and technical support for new equipment, but for overdue devices, they may lack corresponding support and maintenance services. This may lead to extended equipment maintenance cycles, increased maintenance costs, and difficulty in obtaining the latest technological upgrades and updates. This article constructed a Kohonen network model based on the above steps and converted it into a visual page. Figure 3 is a visual schematic diagram of the structure of the overdue medical device model constructed in this article.

Evaluation and prediction of surplus value

In the management of medical equipment, it is very important to accurately evaluate and predict the surplus value of overdue medical devices. Surplus value assessment can help medical institutions reasonably arrange equipment maintenance and update plans to maximize equipment life and optimize resource utilization. At the same time, accurate prediction of surplus value can help institutions make wise decisions on how to deal with overdue equipment, whether to repair or scrap it, and when to replace it[19,20]. However, due to the complexity of equipment use environment and maintenance, it is not easy to accurately assess and predict surplus value. Therefore, it is very important to adopt advanced data analysis and machine learning technology. This paper selected the support vector machine method to quantitatively evaluate and predict the surplus value of overdue medical devices. By comparing the results of different parameter configurations, the model performance is further optimized to provide more accurate and reliable decision support for medical equipment management.

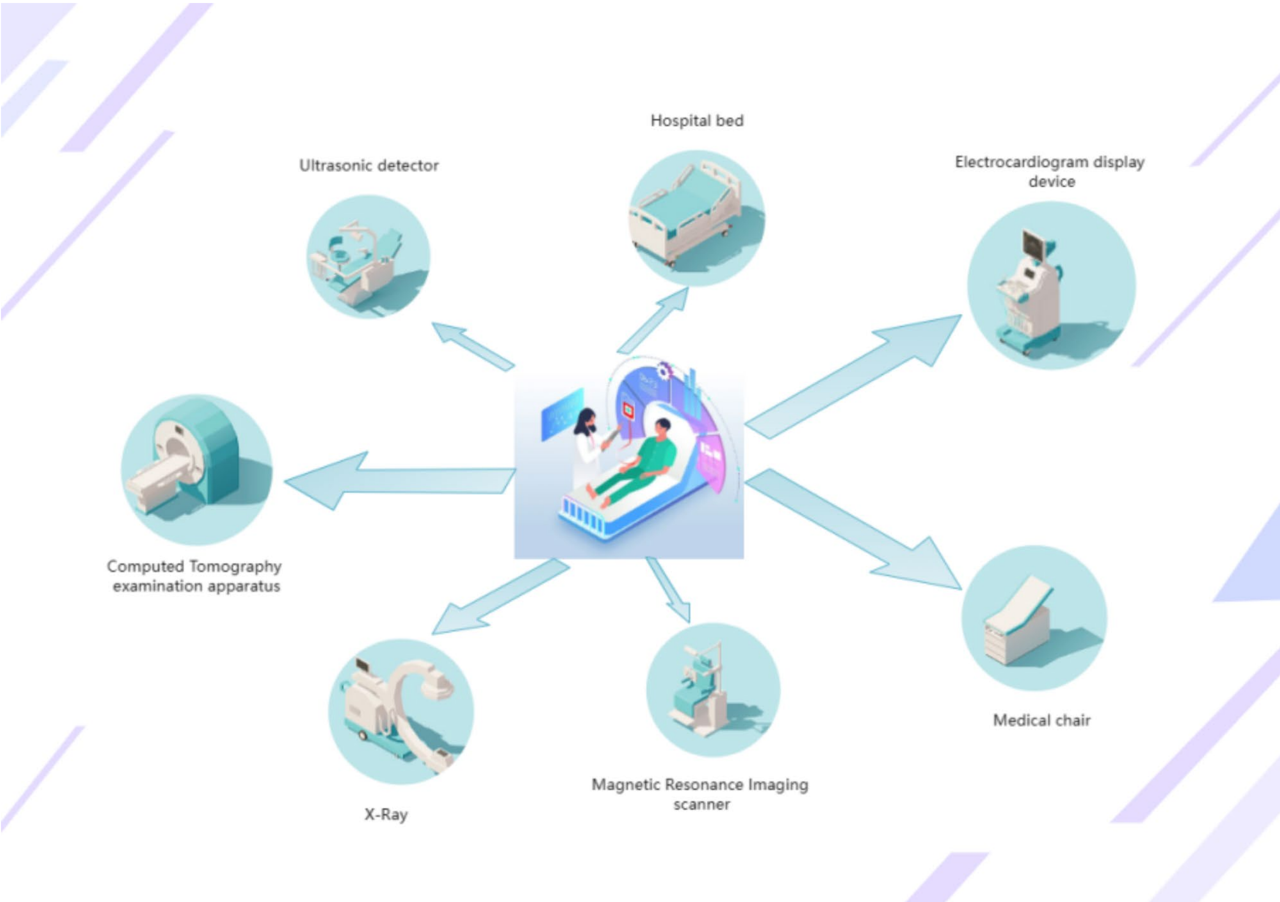

Fig. 3. Schematic diagram of visualization of the model structure of overdue medical device.

Equipment number	Original value (ten thousand yuan)	Surplus value (Ten thousand yuan)
001	20	2
002	32	3
003	45	3
004	18	2
005	67	5

Table 2. Surplus value assessment of overdue medical device.

With the increasing speed of updating and upgrading medical equipment, the number of overdue medical devices is constantly increasing, which has triggered the importance of managing and utilizing these equipment. Although these devices have exceeded their designed lifespan, they still have certain practical value[21]. Therefore, to better manage and use these equipment, it is particularly critical to evaluate their surplus value. By evaluating the surplus value of overdue medical devices, equipment management can be optimized and resource utilization efficiency can be improved, which can contribute to environmental protection. This evaluation has important guiding value and practical significance for medical institutions and decision-makers. The surplus value assessment of overdue medical devices is shown in Table 2.

According to the data in Table 2, the surplus value of this overdue medical device is generally low, which is significantly lower than the original value, indicating that they have exceeded their normal service life and may no longer be able to provide high-quality medical services. Therefore, for these devices, it may be necessary to consider updating or replacing them to provide better medical equipment and services.

With the continuous progress of technology and the upgrading of medical equipment, medical institutions are facing an important problem: how to reasonably manage and utilize overdue medical devices? Equipment that has exceeded its service period may not only have malfunctions and safety hazards but may also affect the efficiency and quality of medical services. To help institutions better manage this equipment, the surplus value prediction table of overdue medical devices came into being. In this paper, a specific prediction table of the residual value of overdue medical devices is given based on the opinions of experts after testing the device, as shown in Table 3. This table can help organizations evaluate the surplus value of equipment and provide a decision-making basis.

To ensure the reliability of the data, a panel of 5 experts with an average of 10 years of experience in medical equipment evaluation was consulted. Their collective expertise has been instrumental in developing the prediction model and ensuring that the table accurately reflects the typical decline in the value of overdue medical devices.

It can be seen from Table 3 that with the increase in the service life of the equipment, its surplus value was gradually declining. Over time, the rate of decline in the value of equipment gradually accelerated. In the first year, the surplus value of most equipment dropped by more than 50%; in the second year, the surplus value dropped more, and some equipment even only left about 20% of the original value; in the third year, most of the equipment had almost no remaining value and could be considered scrap. Therefore, it is very important to update overdue medical devices promptly to safeguard the quality and safety of medical treatment.

According to the surplus value forecast, it can help to formulate the equipment obsolescence plan. When the surplus value of equipment is lower than the predetermined threshold or cannot meet medical needs, equipment replacement or renewal can be considered to ensure the normal operation of medical facilities and improve service quality.

Quantitative effect assessment of surplus value of overdue medical device

Assessment of overdue medical device

During the use of medical equipment, the issue of overdue service has always been a concern. Devices that exceed their service life may experience performance degradation, increased failure rates, and safety risks, which can have adverse effects on medical services. To better manage overdue equipment, it is necessary to understand the relationship between its service life and maintenance costs. This article examines 8 common medical devices (devices A-H) and draws a relationship diagram between their service life and maintenance costs to help medical institutions make reasonable decisions.

Analyzing the relationship between service life and maintenance costs can help medical institutions develop scientific and reasonable equipment management strategies. This would help improve the efficiency and quality of medical services, and ensure the safety and health of patients. The relationship between the service life and maintenance cost of these devices is shown in Fig. 4.

In Fig. 4, the horizontal axis indicates that the equipment has lost more than half of its surplus value to its service life, and the vertical axis indicates the maintenance cost of this medical equipment, in 10,000 yuan. By collecting and analyzing a large amount of data, the maintenance cost of each type of equipment under different service lives can be obtained. By observing Fig. 4, it can be observed that the maintenance cost of the equipment gradually increased with the increase of service life. This meant that as the usage time of the equipment was prolonged, the cost of maintenance would gradually increase. However, as the service life of the equipment increases, it may experience more malfunctions and problems, requiring more frequent maintenance and repairs. overdue service device is usually no longer considered critical equipment, and companies may reduce their maintenance investment, thereby reducing maintenance costs. This is an important reference factor for medical institutions because they need to weigh the surplus value of equipment and maintenance costs to decide whether to update or repair the equipment.

With the prolonged use of medical equipment, its performance often gradually deteriorates, which may lead to a decrease in the quality of medical services and an increase in safety risks. To better evaluate the performance degradation of overdue medical devices, this article also designed a comparative evaluation table, which can assist medical institutions in conducting regular evaluations of overdue devices, to promptly identify and address performance degradation issues, and ensure the quality and safety of medical services. This table selected some of the above equipment for evaluation and comparison, as shown in Table 4.

According to Table 4, the performance degradation comparison and evaluation table of overdue medical devices can be analyzed as follows:

① The extended service life of device A was 10 years, and the initial investment was 100,000 yuan. The average annual performance degradation rate was 5%, and the final performance was 50%. This means that the performance of device A decreases by 5% annually, and after 10 years, its performance will drop to half of its original performance. Due to the high-performance degradation rate, the performance degradation rate of device A is relatively fast.

Equipment number	Original value (ten thousand yuan)	Surplus value after 1 year (ten thousand yuan)	Surplus value after 2 years (ten thousand yuan)	Surplus value after 3 years (ten thousand yuan)
001	20	6	4	2
002	35	10	6	3
003	40	15	8	4
004	55	15	10	8
005	60	20	13	5

Table 3. Forecast of surplus value of overdue medical device.

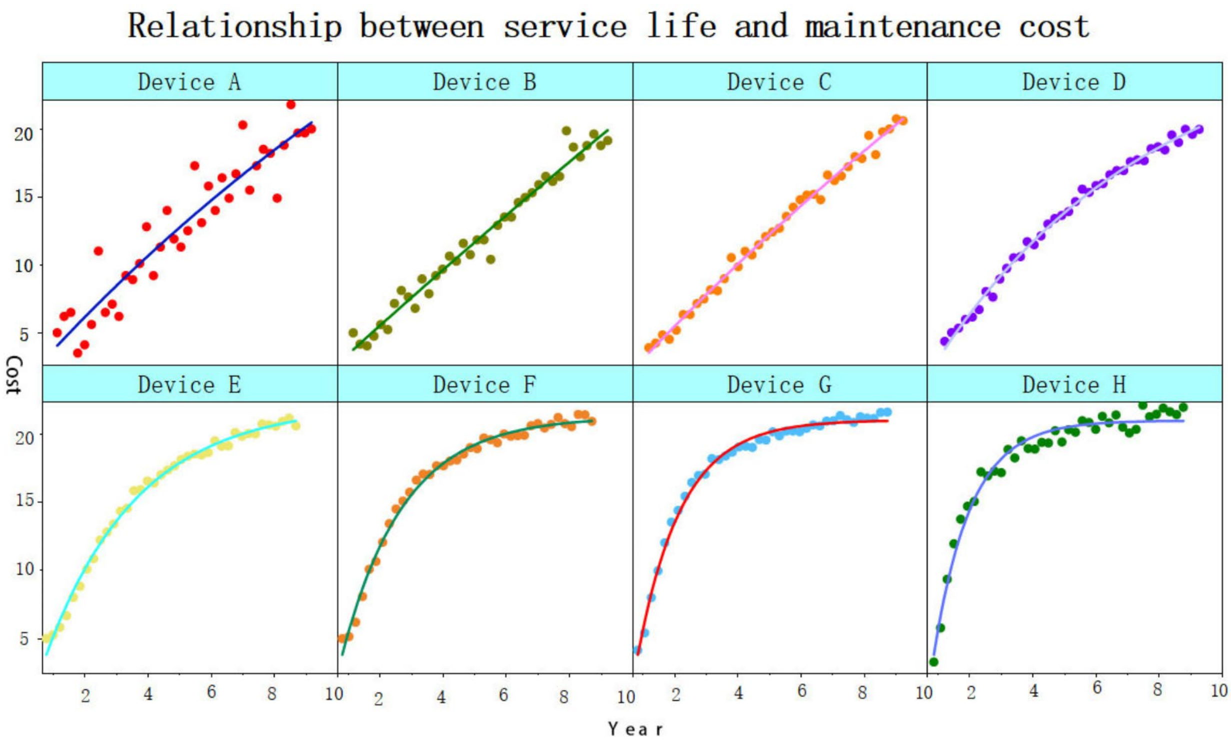

Fig. 4. Correlation between service life and maintenance costs.

Argument	Device A	Device B	Device C
Extended service life	10 years	12 years	15 years
Initial investment	100,000	120,000	150,000
Average annual performance degradation	5%	4.5%	3.2%
Final performance	50%	46%	52%

Table 4. Comparative evaluation of the degradation of medical device performance.

② Equipment B has been extended for 12 years, with an initial investment of 120,000 yuan and an average annual performance degradation rate of 4.5%. After 12 years, the performance dropped to 46%. Compared to device A, device B has a slower performance decline.

③ Equipment C has an extended service life of 15 years, with an initial investment of 150,000 yuan. The average annual performance degradation rate is 3.2%, and the final performance is 52%. Device C had the slowest degradation rate and the lowest annual performance degradation rate. After 15 years, the performance of device C degraded to approximately 52% of its original performance.

Overall, device A had the fastest performance degradation rate, followed by device B, and device C had the slowest degradation rate. During the extended service period, the degradation of equipment performance would affect the quality and effectiveness of medical services provided. Therefore, it is necessary to weigh factors such as the remaining service life of the equipment, initial investment, and degradation rate to evaluate whether and when to replace this overdue medical device, to ensure the provision of high-quality medical services.

Comparison of predicted and actual surplus value

To better evaluate the actual surplus value of overdue medical devices, this paper used two different algorithms to predict and draw a comparison chart. Method 1 used the random forest algorithm[22], while method 2 used the Kohonen network algorithm proposed in this paper.

In this comparison chart, the horizontal axis represents the service life of the equipment, and the vertical axis represents the actual surplus value of the equipment. By collecting and analyzing a large amount of data, the actual surplus value of each kind of equipment in different service life can be obtained. Next, the random forest algorithm and Kohonen network algorithm were used to predict the actual surplus value of the equipment, and the prediction results were compared with the real value. The actual surplus value comparison chart includes the prediction results of the random forest algorithm and Kohonen network algorithm, as shown in Fig. 4.

According to Fig. 5, by comparing the deviation between the predicted results of the two methods and the actual value, for method 1, the predicted deviation of surplus value (predicted value actual value) of each year

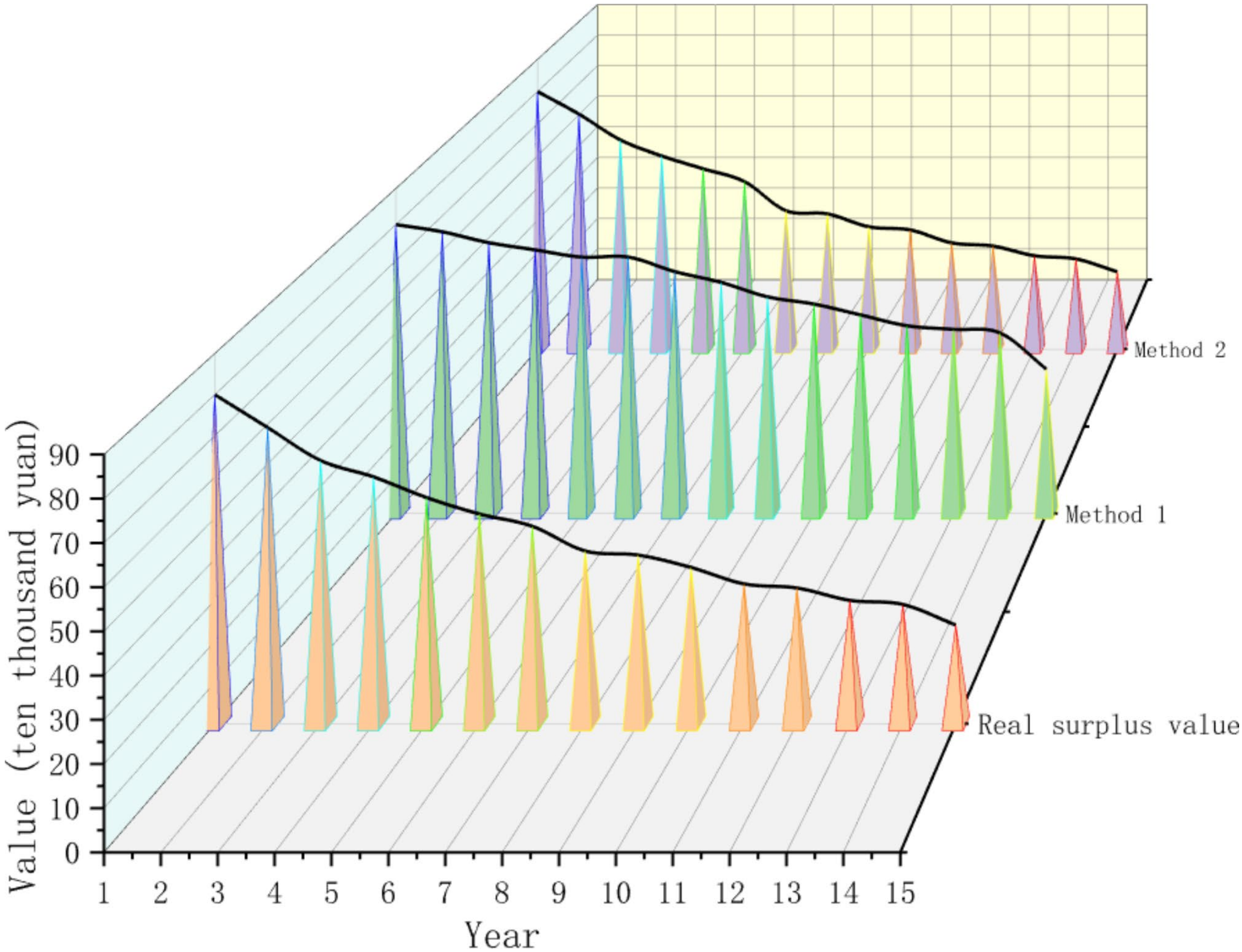

Fig. 5. Comparison of predicted and actual surplus value.

can be calculated: 0, 6, 11, 13, 16, 20,…, 21, 16. For method 2, the forecast deviation of surplus value (forecast value actual value) of each year can also be calculated: 0, 1, 1, 0, 1, 1…, 1, 0. By using the confusion matrix to compare the predicted results of the model with the real results, The prediction deviation of method 2 (Kohonen network algorithm) was mostly smaller than that of method 1 (random forest algorithm). This indicated that method 2 was closer to the actual value and had higher prediction accuracy compared to method 1.

In summary, Method 2 (Kohonen network algorithm) has better predictive performance than Method 1 (random forest algorithm) and can more accurately predict the residual value of medical equipment. The actual residual value comparison chart helps medical institutions more accurately evaluate the value of equipment in extended services, thereby deciding whether to update or repair equipment, improve the efficiency and quality of medical services, and ensure patient safety and health.

Quantitative impact assessment is a crucial part of a project or research process, through which the actual effectiveness and results of the project or research can be objectively measured. Quantitative evaluation provides data support to help understand the success level of a project and guide future decision-making and practical improvement. The quantitative effect evaluation form is an effective tool for displaying evaluation results and analysis, presenting data in the form of a table, and quantifying the evaluation results through various indicators and indicators, providing objective references and comparative benchmarks. By analyzing the quantitative impact assessment form, we can gain a deeper understanding of the actual impact and benefits of the project or research, providing strong support for further improvement and decision-making. This article has conducted corresponding quantitative effect evaluations on several types of devices, as shown in Table 5.

According to the analysis of relevant data in Table 5, the percentage of quantitative effect evaluation can be obtained by calculating the ratio of surplus value to the original value of each equipment. Different types of devices have different degrees of value loss, which may be due to differences in the speed of technological updates and changes in market value after use.

In summary, through this quantitative effect evaluation form, a preliminary understanding of the degree of equipment value loss can be obtained. This information may be helpful for decision-makers when evaluating the economic benefits of equipment and reinvestment plans.

Equipment number	Device type	Time of use	Original value (ten thousand yuan)	Surplus value (ten thousand yuan)	Quantitative effectiveness evaluation
001	X-ray machine	8 years	50	8	16%
002	Computed Tomography scanner	13years	100	18	18%
003	Ultrasonic equipment	6 years	30	4	13.3%
004	Magnetic Resonance Imaging scanner	10 years	150	25	16.7%
005	electrocardiograph	4 years	20	3	15%

Table 5. Quantitative effect evaluation of a sample of investigated medical devices.

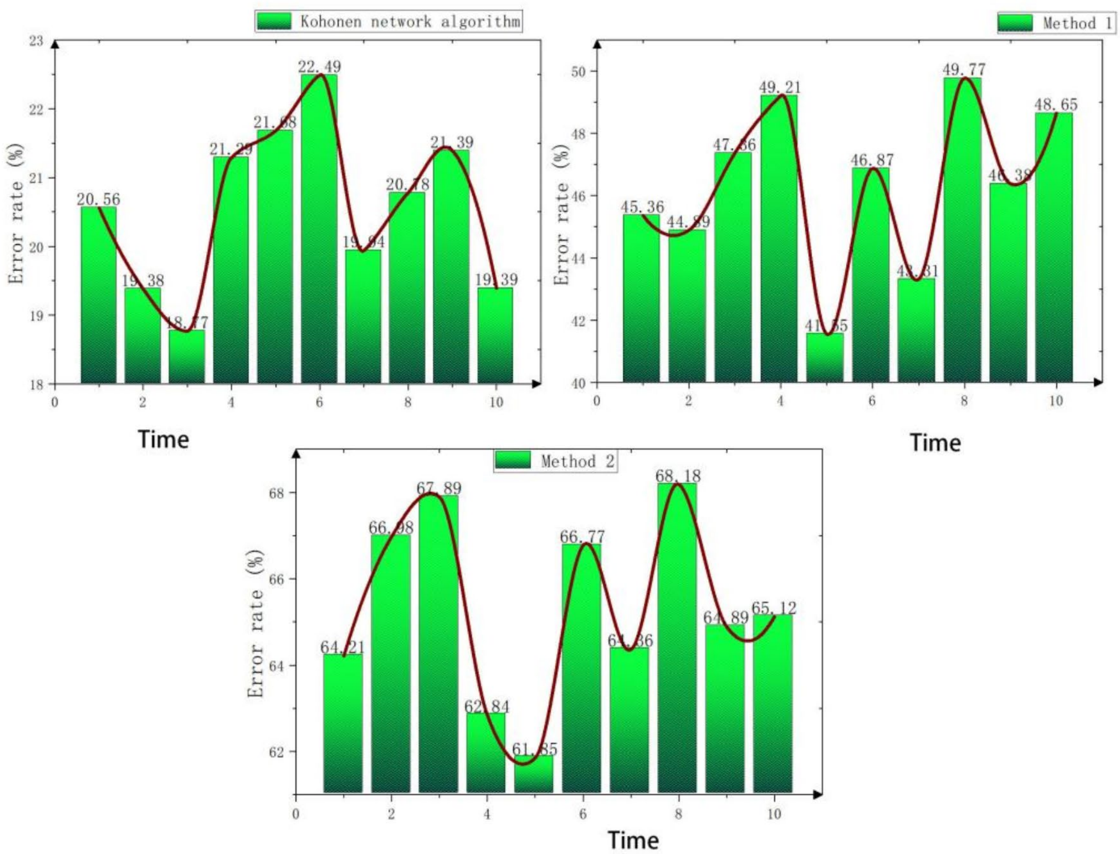

Fig. 6. Error comparison analysis.

Error distribution

In recent years, with the continuous progress of medical technology, the speed of updating and upgrading medical equipment has also become faster and faster. However, how to accurately evaluate the surplus value of medical equipment has become an important issue after its extended service. To address this issue, researchers have proposed various algorithms and methods. In previous studies, the random forest algorithm (method 1) and the decision tree algorithm[23] (method 3) were widely used to evaluate the quantitative effect of the surplus value of overdue medical devices. However, to further improve the accuracy of the evaluation, this paper introduced the Kohonen network algorithm and compared it with the random forest algorithm and the decision tree algorithm.

An empirical study was conducted to compare the effectiveness of the three algorithms. This paper compared the prediction results of the three algorithms and plotted a comparative error distribution analysis, as shown in Fig. 5.

The results of the three algorithms in terms of performing 10 error comparisons can be seen in Fig. 6. The error rate of the Kohonen network algorithm in this article fluctuated between 18.77% and 22.49%, with an average error rate of only 20.57%. The random forest algorithm fluctuated between 41.55% and 49.77%, with an average error rate of 46.34%. The decision tree algorithm oscillated between 61.85% and 68.18%, with an average error rate of 65.31%. The Kohonen network algorithm in this article showed good predictive ability in these 10 error comparisons, and its overall error value was relatively low. The error values of method 1 and method 3 were relatively high. The prediction ability of the Kohonen network algorithm was superior to the other two methods, with lower error values.

To sum up, by introducing the Kohonen network algorithm for comparative analysis, it was found that the Kohonen network algorithm in this paper has better performance in the quantitative effect evaluation of the surplus value of overdue medical devices. It has the advantages of high prediction accuracy and low error rate in the determination of the residual value of expired medical devices, so the Kohonen network algorithm is selected in the determination of the residual value of expired medical devices. This research result has important guiding significance for decision-makers when evaluating the economic benefits and return on investment of equipment.

Conclusion

With the continuous updating and progress of medical equipment, the number of overdue medical devices is gradually increasing in medical institutions. For these overdue service equipment, a reasonable assessment of their surplus value is of great significance for the asset management and decision-making of medical institutions. Based on the Kohonen network algorithm, this research proposed a data-driven method to quantitatively evaluate the surplus value of overdue medical devices. By collecting the relevant attributes and historical maintenance records of the equipment, the Kohonen network was used for unsupervised learning and cluster analysis of the equipment. According to the cluster and other attribute information of the equipment, the surplus value evaluation model was established. The experimental results showed that the method can accurately classify the overdue medical device, and effectively predict and quantify its surplus value. This has important guiding value for medical institutions in equipment maintenance and replacement decision-making.

Data availability

The datasets used and/or analyzed during the current study available from the corresponding author on reasonable request.

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References

1. Salim, S. & Hajar Decision-making Framework for Medical Equipment Maintenance and replacement in private hospitals. *Int. J. Sustainable Constr. Eng. Technol.* **14** (3), 320–338 (2023).
2. Huifang, Y. et al. Application of large medical equipment uses benefit analysis in medical equipment management[J]. *China Med. Equip.* **36** (01), 143–146 (2021).
3. Liu, Q., Zhang, X. & Zhang, E. Research on the application of PDCA cycle combined with intensive maintenance Quality Management Mode in Hospital Medical equipment maintenance management. *Acad. J. Sci. Technol.* **2** (2), 31–34 (2022).
4. Aghasizadeha, Z. Improving the allocation of resources to different strategies of Medical Equipment Maintenance and repair with System Dynamics Approach Case study: Razavi Hospital of Mashhad. *Practice.* **1** (3), 92–108 (2022).
5. Santana, J. & Waheed, S. Analysis of medical device reports involving ventilator-related incidents in a clinical setting: insights and lessons learned. *J. Clin. Eng.* **47** (2), 107–115 (2022).
6. Normalinda, N. A. R. N. H. & Yazid, Y. Determination of service key performance indicators for emergency departments of teaching hospitals in Malaysia: a fuzzy Delphi method. *Med. J. Malay.* **76** (6), 792–798 (2021).
7. Miri Lavassani, K., Iyengar, R. & Movahedi, B. Multi-tier analysis of the medical equipment supply chain network: empirical analysis and simulation of a major rupture. *Benchmarking: Int. J.* **30** (2), 333–360 (2023).
8. Khider, M. O. & Hamza, A. O. Medical equipment maintenance management system: design and implementation. *J. Clin. Eng.* **48** (3), 107–117 (2023).
9. Jain, A. & Rayal, S. Managing medical equipment capacity with early spread of infection in a region. *Prod. Oper. Manage.* **32** (5), 1415–1432 (2023).
10. Begum, M., Das, B. C. & Hossain, M. Z. An improved Kohonen self-organizing map clustering algorithm for high-dimensional data sets. *Indonesian J. Electr. Eng. Comput. Sci.* **24** (1), 600–610 (2021).
11. Simanjuntak, B. E., Situmorang, M. & Humaidi, S. Indentification of Beef in Beef and Chicken experiments using conducting polymer Sensor Series and Kohonen Algorithm Method. *Int. J. Res. Vocat. Stud. (IJRVOCAS).* **2** (4), 48–55 (2023).
12. Wang, T. Identifying major impact factors affecting the continuance intention of Health: a systematic review and multi-subgroup meta-analysis. *Npj Digit. Med. 2022 Sep.* **15**, 5(1):145. https://doi.org/10.1038/s41746-022-00692-9
13. Mkalaf, K. A., Al-Hadeethi, R. H. & Gibson, P. Application of overall equipment effectiveness for optimizing ventilator reliability in Intensive Care Units and Emergency Departments. *J. Techniques.* **5** (2), 187–196 (2023).
14. Hayhurst, C. Powering down retirement strategies for medical equipment. *Biomedical Instrum. Technol.* **53** (1), 12–23 (2019).
15. Chen, B., Kuang, L. & He, W. Cheerleading athlete's action safety in sports competition based on Kohonen neural network. *Neural Comput. Appl.* **35** (6), 4369–4382 (2023).
16. Qodirov, F. & Muhitdinov, X. Features that increase efficiency in the provision of medical services and factors affecting them. *Ta'lim va. Rivojlanish Tahlili Onlayn Ilmiy Jurnali.* **2** (7), 192–199 (2022).
17. Ginting, C. N. & Ginting, R. Analysis of Medical Health Equipment Treatment at Royal Prima Medan General Hospital. *Int. J. Health Pharm. (IJHP).* **2** (3), 606–611 (2022).
18. Sukma, D. I., Prabowo, H. A. & Setiawan, I. Implementation of total productive maintenance to improve overall equipment effectiveness of linear accelerator synergy platform cancer therapy. *Int. J. Eng.* **35** (7), 1246–1256 (2022).
19. Srinivasa, K. G., Sowmya, B. J., Shikhar, A., Utkarsha, R. & Singh, A. Data Analytics Assisted Internet of Things Towards Building Intelligent Healthcare Monitoring Systems: Iot for Healthcare, *J. Organizational End. User Comput.*, **30**(4): 83–103. (2018).
20. Shah, J., Essar, M. Y. & Qaderi, S. Respiratory health and critical care concerns in Afghanistan. *Lancet Respiratory Med.* **10** (3), 229–231 (2022).
21. Koenig, K. L., Bey, C. K., Marty, A. M. & Monkeypox : a primer and identify-isolate-inform (3I) tool for emergency medical services professionals. Prehospital and Disaster Medicine, 2022, **37**(5): 687–692. (2022).
22. Hamar, Á. et al. Mohammed Daryan; Váradi Alex; Herczeg Róbert; Balázsfalvi Norbert; Fülesdi Béla,. COVID-19 mortality prediction in Hungarian ICU settings implementing random forest algorithm [J]. Scientific Reports, **14** (1): 11941–11941. (2024).

23. Majid, R., Ali, E. & Homayun, M. Evaluation of predicted fault tolerance based on C5.0 decision tree algorithm in irrigation system of paddy fields[J]. *Int. J. Intell. Comput. Cybernetics*. **17** (2), 253–305 (2024).

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Declarations

Competing interests
The authors declare no competing interests.

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