Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org
 Volume 26, Issues 2, pp. 880–887, DOI 10.12694/scpe.v26i2.4053

THE MEDICAL TESTING EQUIPMENT MANAGEMENT SYSTEM BASED ON ARTIFICIAL INTELLIGENCE

HONGLI PEI,* LEI SUN,† AND WENTAO GUO‡

Abstract. This study focuses on developing a medical testing equipment management system based on artificial intelligence. The system integrates advanced sensor technology to monitor patient's physiological characteristics data in real-time, such as heart rate, blood pressure, body temperature, etc. and processes the data through a differential entropy analysis algorithm to extract key health indicators. Then, this study constructed a deep learning neural network model to predict the changing trend of patient health status and optimized the configuration and use of medical detection equipment accordingly. This paper proposes a feature extraction method based on neural network model, which can effectively identify abnormal patterns in physiological signals and provide high-quality input data for subsequent prediction models. Simulation results show that the proposed neural network model has high accuracy and practicability in predicting patients' health status. The model can assist healthcare workers in identifying potential health risks in time to improve treatment results and patients' quality of life.

Key words: Artificial intelligence; Medical testing equipment management; Sensor; Physiological characteristics data; Differential entropy; Neural network model; Algorithm design; Model simulation.

1. Introduction. In today's rapidly developing medical science and technology field, the application of artificial intelligence (AI) is gradually changing the traditional medical service model. In particular, as an essential part of medical services, the medical testing equipment management system's intelligent upgrade is significant for improving medical efficiency, reducing costs, and enhancing patient experience. Researching medical testing equipment management systems has always been a hot spot in medical engineering. In the research field of medical testing equipment management systems, literature [1] proposed a real-time monitoring system based on the Internet of Things (IoT), which realized remote monitoring and status assessment of medical equipment by integrating a variety of sensors, effectively improving the efficiency and response speed of equipment management. However, the data processing capabilities of the system still need to be strengthened, especially for real-time analysis and decision support in the face of large-scale data flows. Literature [2] focuses on analyzing physiological feature data and proposes a feature extraction method based on differential entropy, which can extract essential information reflecting heart health status from electrocardiogram (ECG) signals. Studies have shown that the differential entropy algorithm has high sensitivity and specificity in identifying early signs of heart disease. However, the scalability of this method in processing multi-channel or multi-type physiological signals has not been fully verified. The application of neural network models in medical data analysis is also increasing. A convolutional neural network (CNN) model was constructed in reference [3] to identify and classify diseased areas in medical images automatically. The model performs well on multiple public datasets, but the size and diversity of the datasets limit its generalization ability. Literature [4] proposes a system combining sensor technology and recurrent neural networks (RNN) to monitor patients' daily activities and physiological states with chronic diseases. The system can analyze patients' movement patterns and vital signs in real time, which provides a basis for formulating personalized treatment plans. However, the long-term stability of the system and its adaptability to different patient populations still require further study. Literature [5] discusses the application of differential entropy in electroencephalogram (EEG) signal analysis and proposes a new feature extraction process that can effectively distinguish between normal and abnormal brain wave patterns. The results show that the differential entropy algorithm has potential application value in

*Department of Equipment Management and Maintenance, Liaocheng People's Hospital, Liaocheng, 252000, China
†Department of Equipment Management and Maintenance, Liaocheng People's Hospital, Liaocheng, 252000, China
‡Department of Equipment Management and Maintenance, Liaocheng People's Hospital, Liaocheng, 252000, China (Corresponding author, guown2024@163.com)

EEG signal processing, but its computational complexity and real-time processing ability are urgent problems to be solved. Literature [6] proposes a fault prediction model for medical testing equipment based on deep learning, which predicts potential failure modes by analyzing the historical operation data of the equipment. The experimental results show that the model is efficacious in improving the initiative of equipment maintenance and reducing unplanned downtime. However, the model's interpretability and universality to different medical device types still need improvement.

Current research has made positive progress in managing medical detection equipment, physiological characteristics data analysis, and the application of neural network models, but it still faces challenges in data processing speed, model generalization ability, and system stability. Future research should focus on developing more efficient and intelligent algorithms to meet the demand for precision and personalized services in the medical field. Firstly, this paper designs a comprehensive medical testing equipment management system that can collect and analyze the physiological characteristics data from various medical testing equipment in real-time [7]. Secondly, the differential entropy algorithm is introduced, which can extract the key health indicators from the complex physiological signals. Finally, this paper constructs a prediction model based on a neural network, which can predict the change in patients' health status according to the extracted feature data and provide decision support for the configuration and use of medical detection equipment [8]. The results show that the proposed AI-based medical testing equipment management system can significantly improve the quality and efficiency of medical services and provide patients with more personalized and accurate medical services.

2. Design of testing equipment management system.

2.1. System Structure Design. The system consists of four modules: the medical equipment in use status management module, the daily maintenance management module, the medical equipment annual inspection information management module and the query and data processing module [9]. Among them, query and data processing are standard components that realize information query, report printing and output. This paper presents a hospital testing equipment management system based on SSH2+ MVC. The specific system structure is shown in Figure 2.1 (the picture is quoted in the Journal of Healthcare Engineering, 2021, 2021(1): 6685456.).

The system realizes the interaction of each function module through the DAO interface and database. The primary data table consists of the permission data table, equipment basic information table, equipment annual inspection data table, routine maintenance test data table, and failed equipment information table [10]. These data tables are associated with specified values. Authorization data forms are used to set user rights. The primary instrument data form records the basic instrument data during the inspection. The annual inspection data of instruments is the statistical analysis of the annual inspection of hospital instruments. The routine maintenance check data table results from a routine maintenance check on the device. The Retired Equipment Information form is used to record the retired equipment information.

2.2. System module design. The whole system has the characteristic of modularity. This paper gives a detailed analysis of each functional module (Figure 2.2).

2.2.1. Medical equipment in use management module. The status quo and fundamental data of hospital equipment were analyzed and divided into four parts: new, deactivated, scrapped, and transferred [11]. This component data is stored in the primary data table of the device. There are hospital numbers, equipment names, use departments, situations, annual inspection cycles, test units, etc. The system automatically generates new equipment with a unique number to ensure its unified management. Remove the obsolete equipment data from the equipment basic data form and enter it into the equipment information form to ensure it does not have relevant data during routine maintenance and annual inspections. So as not to cause administrative confusion [12]. The transfer of equipment can be achieved by changing the department of use in the primary data table to the department currently used. The basic information of the equipment can be displayed in the report by inputting the hospital code of the hospital equipment. You can also perform fuzzy queries by device name and department. The basic information about the equipment will be presented in the report.

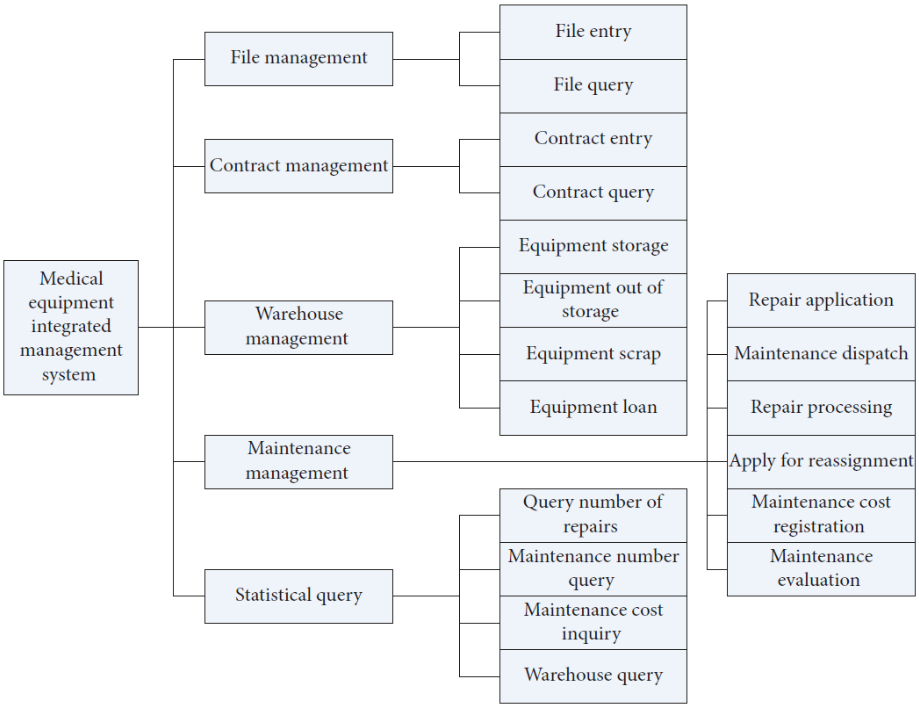

Fig. 2.1: *Overall architecture of hospital testing equipment management system.*

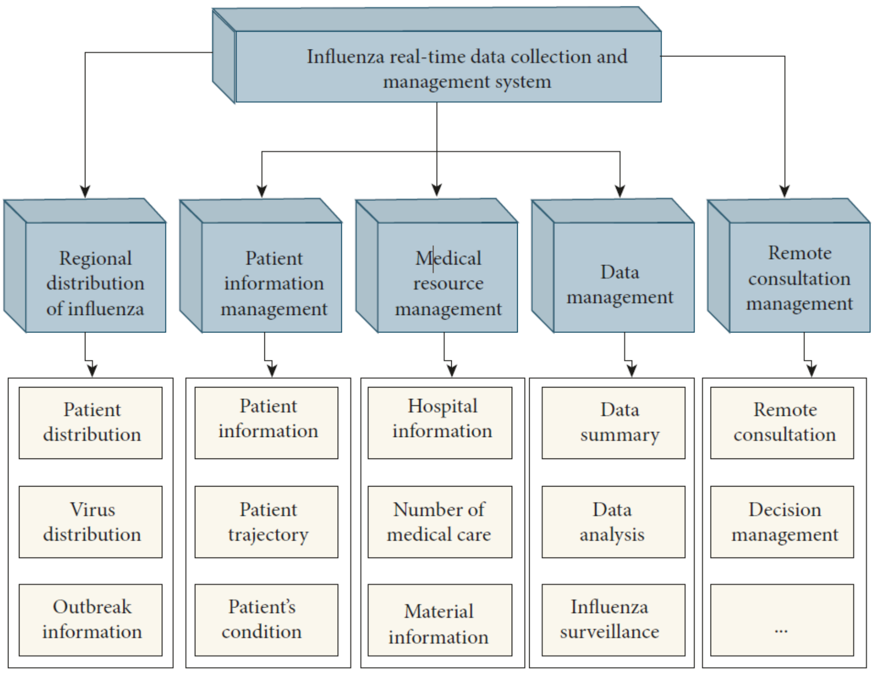

Fig. 2.2: *Functional module architecture of medical testing equipment system.*

2.2.2. Routine repair and maintenance module of health equipment. This module's data is mainly based on daily maintenance test data, including hospital number, maintenance status, post-maintenance inspection, daily inspection, inspection time, inspection personnel, maintenance methods, etc. The data table is linked to the data in the device basic data table by particular keywords, namely the hospital number. When equipment needs maintenance, a distribution work order is generated [13]—to record maintenance and inspection status after maintenance. When the inspection time approaches, the system will pop up an "inspection prompt," prompting maintenance personnel to inspect the relevant facilities regularly.

2.2.3. Annual inspection information module of hospital inspection instruments. The data of this system is based on the annual inspection data of the hospital, which includes the number of the hospital, the annual inspection time, the certificate number, the validity period and so on. This module can complete the retrieval of annual inspection records and original inspection certificates.

2.2.4. Information retrieval and information processing module. This module is a public module that realizes data query, report printing and output. By using departments, equipment names and annual inspection time, the equipment's basic information, annual inspection information and maintenance information can be retrieved and output in the form of reports [14]. In this system, the instruments that must be checked can be checked. The staff can print and output the report of the instrument.

3. Medical detection equipment system based on artificial intelligence algorithm. In the Internet of Things hardware network composed of multiple sensors, how to accurately and effectively identify the required information from the massive data is crucial to the operation of the medical inspection system. This paper presents a data mining method based on a neural network. Data exploration is a processing method to extract hidden information from extensive data [15]. It requires not only a specific data structure but also according to a specific calculation method to construct the processing process. This paper uses the artificial neural network method to construct the mining process. Firstly, feature extraction is carried out on the hardware of the sensor system [16]. Finally, the training samples are imported into the artificial neural network to achieve accurate medical information identification.

3.1. Feature Extraction. Medical information usually has the characteristics of differential entropy, rational asymmetry, energy spectrum, difference asymmetry, etc. Differential entropy is used to describe the random uncertainty of each band quantitatively. That is, the logarithm of the energy spectrum of a particular band is the difference entropy. ES is the average value of signals in 5 frequency bands, so this paper defines differential entropy as the characteristics of 5 frequency bands [17]. Asymmetric structures include rational asymmetry and differential asymmetry. DASM is defined as:

$$DASM = DE\left(B_{\text{left}}\right) - DE\left(B_{\text{right}}\right) \tag{3.1}$$

RASM is defined as:

$$RASM = DE\left(B_{\text{left}}\right) / DE\left(B_{\text{right}}\right) \tag{3.2}$$

DASM is used to represent the entropy difference of 28 groups of data. RASM represents the scaling property. These characteristics are treated with gradient dimension reduction [18]. The model is calculated according to the following formula:

$$f\left(a_n / a_{n-1}\right) = G\left(a_n \mid W a_{n-1}, \Delta\right) \tag{3.3}$$

$$f\left(c_n / a_n\right) = G\left(c_n \mid \Lambda a_n, \Theta\right) \tag{3.4}$$

where c_n represents the observed variable of the initial characteristics of the computer. a_n stands for implicit variable. W stands for implicit variable transformation matrix. Where Δ, Θ is the parameter of the neural network. Λ is the transmission matrix of the neural network.

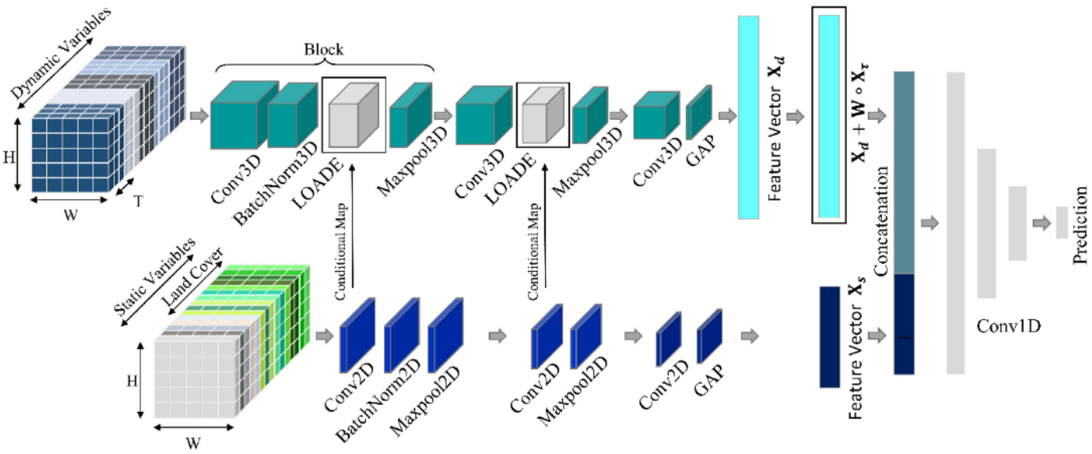

Fig. 3.1: *Structure diagram of adaptive neural network.*

3.2. Neural network model. The neural network structure designed in this paper is shown in Figure 3.1.

It can be seen from Figure 3.1 that the weight sum of the ANN network on excitation output at k_n is:

$$F_{j,t}\left(k_n\right)=\sum_{i\in G_{k-1}}\sum_{k=1}^{K_{jit,-1}}\chi_{jik,t-1}a_{i,t-1}\left(k_n-\gamma_{jik,t-1}\right) \tag{3.5}$$

In layer j Part l, the output of the excitation is:

$$a_{j,t}\left(k_n\right)=h\left[F_{j,t}\left(k_n\right)\right] \tag{3.6}$$

$h(a)$ is an excitation function, which is widely used in neural networks [19]. All Mses of the neural network at time k_n are:

$$S\left(k_n\right)=\frac{1}{2}\sum_{j\in G_2}\left[s_j\left(k_n\right)-a_{j,2}\left(k_n\right)\right]^2 \tag{3.7}$$

$s_j\left(k_n\right)$ is the expected output of the i neuronal network at time k_n. In most cases, the gradient descent algorithm is used to reduce error $O\left(k_n\right)$:

$$\Delta\chi_{jk,t-1}=-\gamma_1\frac{\partial S\left(k_n\right)}{\partial\chi_{jkt,-1}},t=1,2 \tag{3.8}$$

$$\Delta\gamma_{jk,t-1}=-\gamma_2\frac{\partial S\left(k_n\right)}{\partial\gamma_{jkt,t-1}},t=1,2 \tag{3.9}$$

The chain method is used to adjust the weight of the neural network:

$$\frac{\partial S\left(k_n\right)}{\partial\chi_{jk,t-1}}=\frac{\partial S\left(k_n\right)}{\partial F_{j,t}}*\frac{\partial F_{jL}\left(k_n\right)}{\partial\chi_{jk,t-1}} \tag{3.10}$$

and because:

$$\frac{\partial F_{j,t}\left(k_n\right)}{\partial\chi_{jik,t-1}}=a_{il-1}\left(k_n-\gamma_{jk,t,-1}\right) \tag{3.11}$$

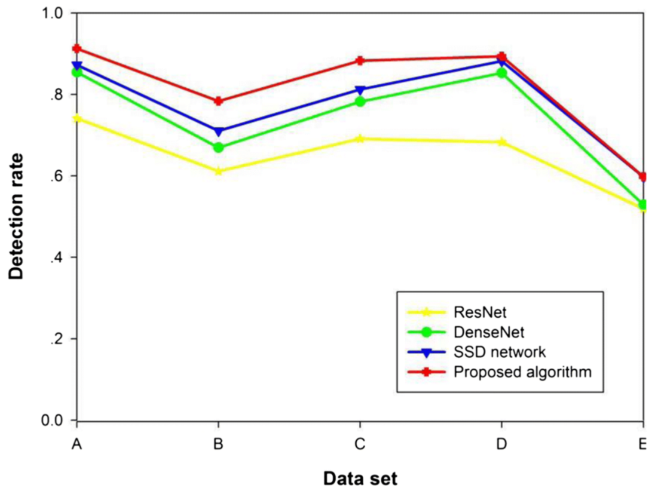

Fig. 4.1: *Efficiency diagram of the data processing algorithm.*

Table 4.1: *Success rate of system experiment.*

Number of experiments	Success rate (%)
100	98.96
200	96.88
300	95.83
400	93.75
500	92.71

There is:

$$\Delta\chi_{jkk,t-1} = \gamma_1 \xi_{j/t}\left(k_n\right) a_{L,t-1}\left(k_n - \gamma_{jk,t-1}\right), t = 1, 2 \tag{3.12}$$

The correction of the delay parameters is done in the same way:

$$\Delta\gamma_{j\pi t,-1} = \gamma_2 \xi_{j,t}\left(k_n\right) \chi_{jd,t-1} a_{i,t-1} \cdot \left(k_n - \gamma_{jk,t-1}\right), t = 1, 2 \tag{3.13}$$

To reduce the error in the artificial neural network identification process, the parameters obtained are more accurate by adjusting the weight and the lag time [20].

4. Simulation experiment. Finally, the management system of the medical testing instrument is tested and verified. Firstly, the data processing time consumption of the designed artificial intelligence algorithm and the literature method are compared. The experimental results show that the method has good performance [21]. As shown in Figure 4.1, when the amount of data required is small, the neural network algorithm designed takes the same time as other algorithms. However, with the increase in data size, the calculation time of these methods will change significantly, and the calculation time of the method proposed by Resnet will increase the most [22]. The results show that the proposed AI algorithm has more obvious advantages and can meet real-time processing needs. Finally, the comprehensive performance of the method is tested. The results are shown in Table 4.1.

As shown in Table 4.1, with a small number of tests, the method's success rate reached 98.96%. When the number of tests increases, the accuracy of the test will decrease, but the overall performance can meet the accuracy requirements. From the point of view of real-time and accuracy, the medical testing instrument management system with artificial intelligence technology proposed in this paper has a better working effect. It can be well adapted to the needs of the medical industry.

5. Conclusion. This study realized real-time monitoring and acquisition of patients' physiological characteristics data by integrating advanced sensor technology. The differential entropy algorithm is used to analyze the data deeply, and the critical information reflecting the health status of patients is extracted. The neural network model is constructed. This model can predict the health trends of patients based on historical data and provide decision support for the scheduling and optimization of medical detection equipment. The results show that the proposed system improves the management efficiency of medical testing equipment and significantly enhances the accuracy and foresight of medical services. Through the application of differential entropy algorithm, the system can effectively identify abnormal patterns in physiological signals, which provides the possibility for early diagnosis of diseases. The predictive function of the neural network model provides valuable early warning information for the medical staff and helps to adjust the treatment plan in time.

REFERENCES

[1] KHodadadi, V., Bakrani, A., & Vafaie, M. H. (2021). Factors affecting medical equipment management in the COVID-19 pandemic crisis: A mixed qualitative and quantitative study. Hospital Practices and Research, 6(1), 23-28.
[2] Hanifah, N. A., Kairudin, W. N. H. W., Mohd, E., & Ismail, M. N. (2021). Medical Equipment Maintenance Management System with Fingerprint Authentication. Evolution in Electrical and Electronic Engineering, 2(1), 236-245.
[3] Belhouideg, S. (2020). Impact of 3D printed medical equipment on the management of the Covid19 pandemic. The International journal of health planning and management, 35(5), 1014-1022.
[4] Kudratillaev, M., & Yakhshiboyev, R. E. (2023). The Role of Indigenous Medical Devices and Equipment Development in Medicine. Economics and Innovative Technologies, 11(5), 327-341.
[5] Chaminda, J. L. P., Dharmagunawardene, D., Rohde, A., Kularatna, S., & Hinchcliff, R. (2023). Implementation of a Multicomponent Program to Improve Effective Use and Maintenance of Medical Equipment in Sri Lankan Hospitals. WHO South-East Asia Journal of Public Health, 12(2), 85-92.
[6] Liu, Q., Zhang, Q., Guo, W., & Wang, T. (2022). Application Effect Analysis of RCA on Improving the Management of Medical Equipment-Related Near-Miss Events in ICU of Hospital. MEDS Clinical Medicine, 3(4), 115-120.
[7] Jain, A., & Rayal, S. (2023). Managing medical equipment capacity with early spread of infection in a region. Production and operations management, 32(5), 1415-1432.
[8] Aunión-Villa, J., Gómez-Chaparro, M., & García Sanz-Calcedo, J. (2020). Assessment of the maintenance costs of electromedical equipment in Spanish hospitals. Expert Review of Medical Devices, 17(8), 855-865.
[9] Khinvasara, T., Ness, S., & Tzenios, N. (2023). Risk Management in Medical Device Industry. J. Eng. Res. Rep, 25(8), 130-140.
[10] Daki, A. M., Mugop, N. S., Berinyuy, F. C., & Mbinkong, S. R. (2020). An assessment of measures medical imaging personnel use to avoid the breakdown of diagnostic radiologic equipment in some health facilities in Northwest and Southwest regions of Cameroon. Int J Innov Sci Res Technol, 5(8), 36-42.
[11] Suarez, O. M. D., Mármol, A. L., & Camperos, J. A. G. (2023). RCM-PMBOK hybrid methodology for managing the maintenance of critical biomedical equipment in IPS of medium complexity. Journal of Applied Engineering Science, 21(3), 795-809.
[12] Salami, S. R., Bamdadsoofi, J., Khatami Firouz Abadi, S. M. A., & Shafiee, M. (2021). Formation and Development of Technological Innovation Capability in New Technology Base Firms in the Medical Equipment Sector of Fars Province. Journal of Improvement Management, 15(1), 69-94.
[13] Ma, C., & Wen, L. (2020). Discussion on standardization management mode of medical equipment based on whole process quality control. Zhongguo yi liao qi xie za zhi= Chinese journal of medical instrumentation, 44(3), 270-275.
[14] Ali, H. (2024). Utilizing Predictive Analytics for Lifecycle Management and Maintenance of Medical Equipment: Utilizes machine learning algorithms to predict maintenance needs for medical equipment, reducing downtime and improving operational efficiency in healthcare facilities. Journal of AI in Healthcare and Medicine, 4(1), 57-70.
[15] Rahoma, M., Hwisa, S. A., Jira, M. A., Faraj, M. M., Ramih, E. A., Almesawey, S. A., & Godid, F. A. S. (2023). Evaluation of medical equipment of the infertility treatment centers in North western of Libya. Libyan Journal of Medical Research, 17(2), 154-167.
[16] Sarfraz, M., & Pamucar, D. (2024). A parametric similarity measure for spherical fuzzy sets and its applications in medical equipment selection. J. Eng. Manag. Syst. Eng, 3(1), 38-52.
[17] Li, K., Zhao, Y., Yang, Y., & Qian, Y. (2023). Introduction to Quality control guidelines for cleaning and sterilizing equipment. Sterile Supply, 1(3), 81-85.
[18] Singh, N., Tang, Y., & Ogunseitan, O. A. (2020). Environmentally sustainable management of used personal protective equipment. Environmental science & technology, 54(14), 8500-8502.
[19] Sutejo, J., Setiawan, S., & Syam, B. (2022). The experience of nurse managers implementing a nursing management system in COVID-19 wards: A descriptive phenomenology study. Jurnal Keperawatan Padjadjaran, 10(1), 73-82.
[20] Wang, X., Zhang, X., & He, J. (2020). Challenges to the system of reserve medical supplies for public health emergencies: reflections on the outbreak of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) epidemic in China. Bioscience trends, 14(1), 3-8.
[21] Singh, N., Ogunseitan, O. A., & Tang, Y. (2022). Medical waste: Current challenges and future opportunities for sustainable

management. Critical Reviews in Environmental Science and Technology, 52(11), 2000-2022.
[22] Kumar, M., Fatma, A., & Bharti, N. (2022). Access to Medicines and Medical Equipment during COVID-19: Searching Compatibility between the WTO and the WHO. India Quarterly, 78(1), 68-87.

Edited by: Hailong Li
Special issue on: Deep Learning in Healthcare
Received: JMay 28, 2024
Accepted: Aug 3, 2024