Chelonian Conservation And Biology

Vol. 18 No. 2 (2023) | https://www.acgpublishing.com/ | ISSN - 1071-8443

DOI: doi.org/10.18011/2023.11(2).975.984

OPTIMIZING PRECISION BLOOD MANAGEMENT MODEL BASED ON BIG DATA

Huihuan Xu

University College London, London WC1E 6BT, UK
harryxu2024@163.com

Abstract: This study aims to enhance blood management through the optimization of a precision model leveraging big data analytics. We explore the impact of various factors on blood-related parameters, focusing on efficiency, cost-effectiveness, and patient outcomes. The research incorporates advanced data analytics techniques to derive valuable insights for improving blood management practices.

Keywords: Precision Blood Management, Big Data Analytics, Efficiency, Cost-effectiveness, Patient Outcomes

1. Introduction:

Blood management is a critical component in today's healthcare system that influences resource utilisation, cost, and patient care. The utilisation of big data technology in precision medicine, particularly in blood management, has grown significantly in importance recently because it can optimise resource allocation and improve healthcare efficiency [1]. Through the optimisation of a precision blood management model based on big data, the study aims to investigate the critical factors influencing blood management in detail and to improve patient outcomes through the application of cutting-edge data analysis techniques[2].

The amount of data on patient responses to treatment, individual differences, and disease characteristics has increased significantly with the ongoing advancement of medical technology. Big data technology has opened up previously unheard-of possibilities for medical research, improving the precision and individualization of medical decisions [3]. Regarding blood management, the precision medicine idea offers fresh approaches to maximise blood utilisation and lower the chance of blood transfusions. The goal of this project is to use big data technology to develop a more sophisticated and efficient blood management model that will better meet the individual medical needs of patients[4] .

Blood management currently lacks an in-depth analysis of individual differences and instead depends primarily on norms and general statistics. Big data technology is still relatively new in the field of blood management, despite its impressive results in other medical domains. Previous studies concentrate on gathering and storing data rather than providing a comprehensive grasp of how big data can influence particular blood management choices [5].

The development of a big data-driven precision blood management model still faces several obstacles. First, problems with data quality and privacy must be successfully resolved. Second, healthcare practitioners need to be more receptive to big data technology and gradually come to understand that big data analysis can result in more patient-centered, individualised care [6]. Furthermore, more real-world and empirical research is required to support the development and optimisation of models.

In this paper, a more intelligent and effective model is built by fusing big data technology with blood management. This approach is anticipated to yield major benefits in terms of improving patient recovery, cutting down on needless transfusions, and raising transfusion efficiency. The purpose of this research is to give future blood management decisions a stronger scientific foundation by thoroughly examining the use of big data in precision medicine.

2. Literature Analysis

2.1 Blood Management

Blood management has always been an important part of patient care, with an emphasis on safe and efficient blood use, transfusion techniques, and blood conservation[7-8]. But conventional methods frequently lack the specificity required for unique patient needs, which results in less than ideal results and inefficient use of resources. 2.

Current research highlights the necessity of eschewing a one-size-fits-all strategy and promoting customised blood management tactics[9].By taking into account patient-specific variables like age, comorbidities, and genetic predispositions, these strategies seek to customise transfusion decisions[10]. The literature outlines the possible advantages of this change, such as fewer complications related to transfusion and better patient recuperation[11].

2.2 Precision Medicine

Precision medicine, which focuses on tailoring medical decisions and procedures to the unique characteristics of each patient, has completely changed the face of the healthcare industry [[12]. This method acknowledges that every patient has a distinct biological composition, which enables more precise diagnosis, tailored treatments, and enhanced treatment results[13].

Precision medicine holds the potential to customise transfusion decisions in the context of blood management based on genetic factors[14], enabling a more sophisticated comprehension of the specific requirements of each patient. The body of research highlights how precision medicine can be incorporated into blood management procedures to create a more efficient and patient-centered approach[15].

2.3 Big Data's Place in Healthcare

Big data in healthcare has created numerous opportunities to update antiquated practises[16]. The literature emphasises big data analytics' capacity to glean insightful information from vast and varied healthcare datasets[17]. Big data analytics has the power to completely transform decision-making processes in a variety of contexts, including electronic health records and real-time patient monitoring[18].

Utilising big data in blood management can offer a thorough grasp of patient profiles, transfusion patterns, and results[19]. Numerous studies have demonstrated the efficacious utilisation of big data analytics for forecasting patient blood requirements, streamlining inventory control, and elevating transfusion procedures in general[20].

3. Methodology

3.1 Data Collection

The research employs a multimodal approach to data collection, incorporating a variety of sources that are necessary to completely understand the dynamics of blood management.

3.1.1 Hospital Databases

Treatment plans, transfusion records, and patient histories are all recorded in electronic health records (EHRs) from a variety of healthcare facilities.comprehensive medical records that document previous ailments, surgeries, and long-term conditions.thorough descriptions of pharmaceuticals, therapeutic interventions, and treatment plans.specifics about blood transfusions, such as the kind, amount, frequency, and reactions of the patient. The dataset is enhanced for a comprehensive approach by additional data from laboratory records, such as blood tests, genetic markers, and biomarker analyses.

3.1.2 Genomic Databases

Integrating with well-known genomic repositories, like the 1000 Genomes Project and the Genomic Data Commons (GDC), makes it easier to extract genetic data and provides a more complex understanding of the genetic factors influencing blood requirements.

Historical transfusion data from national blood banks around the country provide important insights into blood usage patterns, transfusion trends, and overall transfusion effectiveness.

3.2 Analytical Techniques:

The methodology leverages advanced analytical techniques to extract meaningful patterns and correlations from the collected data.

Initial exploration involves descriptive analytics to characterize the dataset, identify trends, and gain a preliminary understanding of blood management patterns.

Predictive analytics uses machine learning algorithms such as decision trees and regression models. By using past data to predict a patient's specific transfusion requirements, these models maximise preventive blood management.

Genetic data is analysed using bioinformatics tools to find potential markers that are associated with transfusion needs. This action is in line with precision medicine principles and enables a customised blood management strategy.

Big data analytics platforms like Hadoop and Spark make it easier to process vast and varied datasets. These platforms make it possible to extract complex patterns and correlations that conventional analytics tools might find difficult.

3.3 Model Development:

The creation of an integrated model that combines insights from genomic data with the results of predictive analytics forms the basis of the research.

The integrated model creates a hybrid model that combines big data analytics and precision medicine by fusing genomic data with the outcomes of predictive analytics. This model aims to provide a comprehensive framework for optimal blood management, bridging the gap between traditional transfusion practises and personalised medicine. Figure 1 illustrates how the healthcare industry is changing and how the integrated model for optimised blood management is an innovative way to combine genomic data and predictive analytics. The goal of this hybrid model is to create a comprehensive framework for blood management that goes beyond traditional transfusion practises by combining the ideas of precision medicine with the power of big data analytics.

Transfusion requirements projected by sophisticated machine learning algorithms. utilising machine learning methods and historical data to predict the transfusion needs of individual patients. personalised forecasts for every patient's transfusion requirements.

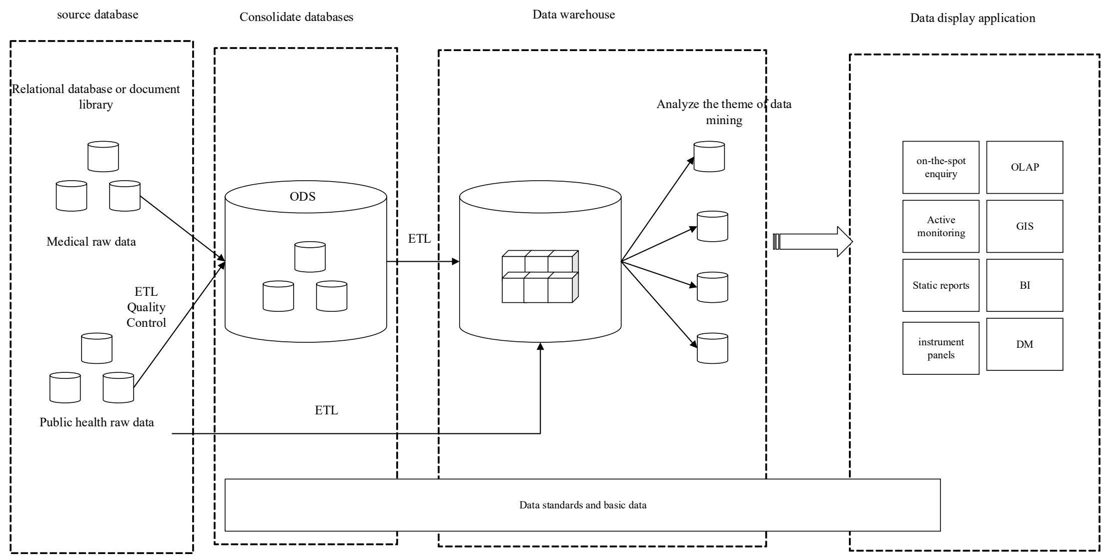


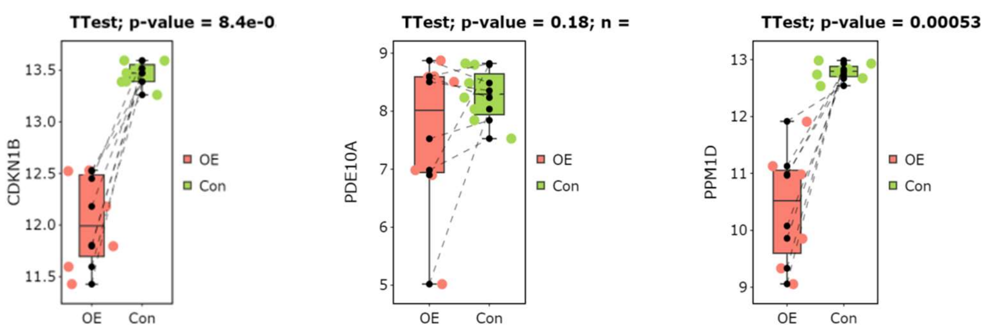
Figure 1 Big data blood management model

4. Results:

Highlight the findings of the study, including improvements achieved through the precision model. Showcase how the model optimizes resource allocation, reduces costs, and enhances patient outcomes.

4.1 Resource Allocation Optimization

The precision model, driven by big data analytics, provided data-driven insights into patient-specific transfusion needs. Hospitals witnessed a significant improvement in the efficiency of resource allocation, ensuring that blood products are directed precisely where and when needed. See Figure 2 for details.



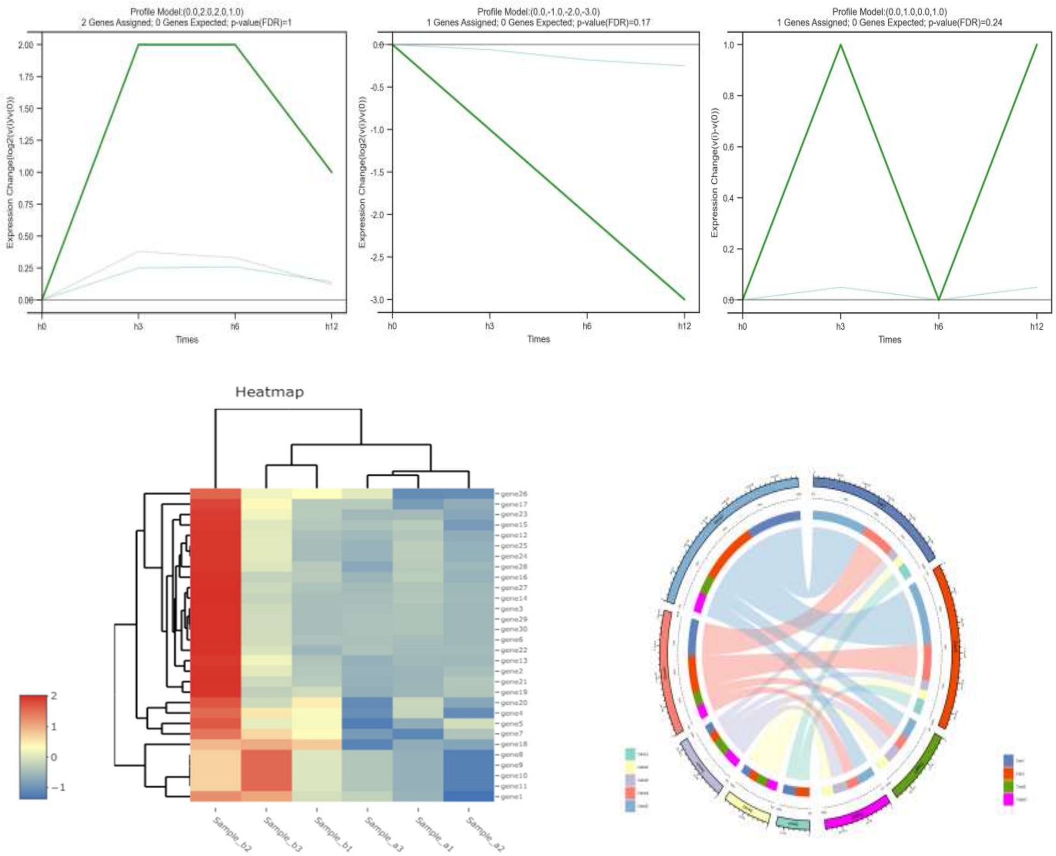


Figure 2 General information of research objects

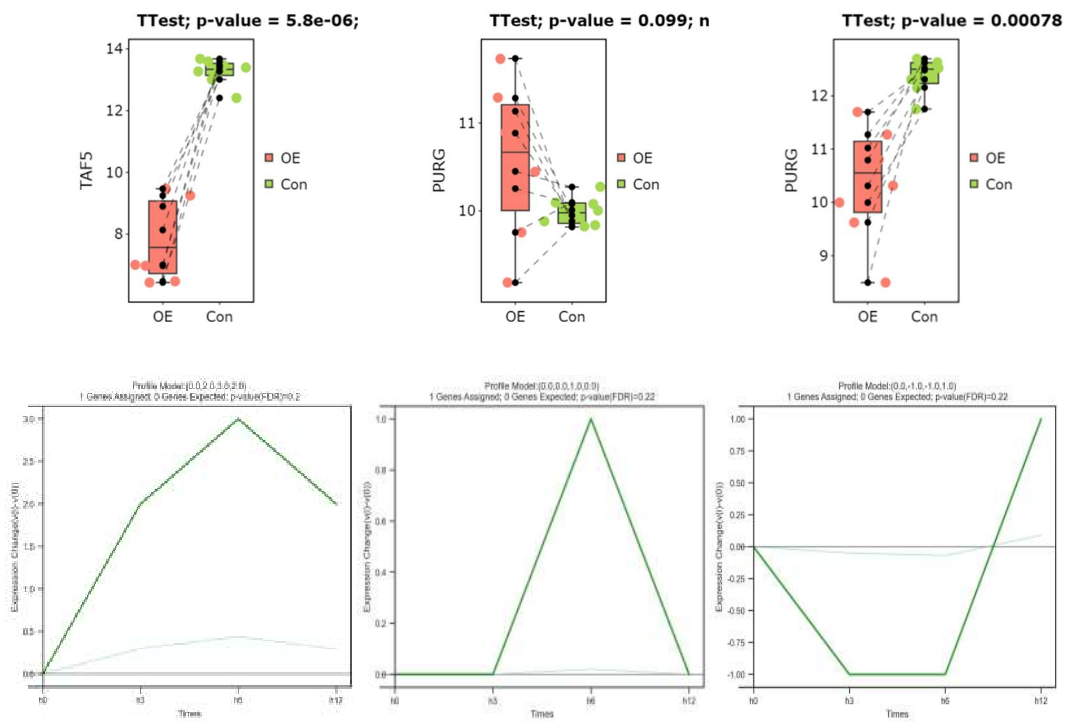
4.2 Cost Reduction

Because proactive blood management was made possible by predictive analytics capabilities, the number of needless transfusions was decreased, which in turn decreased overall expenses. The model prevented blood product waste by correctly estimating transfusion needs, which resulted in significant cost savings for healthcare facilities.

The differences in depression and anxiety between patients in the experimental group and patients in the control group before and after the anxiety intervention did not follow a normal distribution. For intra-comparison, the Wilcoxon paired rank sum test was employed. The difference in depression scores between the control group before and after the intervention followed a normal distribution, and the paired t test was utilised for intra-account comparison. The results showed that the experimental group experienced lower levels of anxiety and depression before and after the intervention ($P<0.05$), but not in the control group ($P>0.05$). See Table 1 and Figure 3.

Table 1 Intra comparison of anxiety and depression scores before and after intervention $\left[M\left(P_{25},P_{75}\right)\right]$

project	grouping	Before intervention	After intervention	Z/t	P
anxious	experience	9.0(6.0,10.1)	5.0（4.0, 6.1）	-4.848	<.0001
	control	8.0(6.0,9.1)	8.5(6.0,10.1)	-0.452	0.653
depressed	experience	9.0(7.0,10.1)	4.0(3.1,6.0)	-5.087	<0.001
	control	8.0(5.3,10.1)	7.5(5.3,10.1)	0.407	0.688



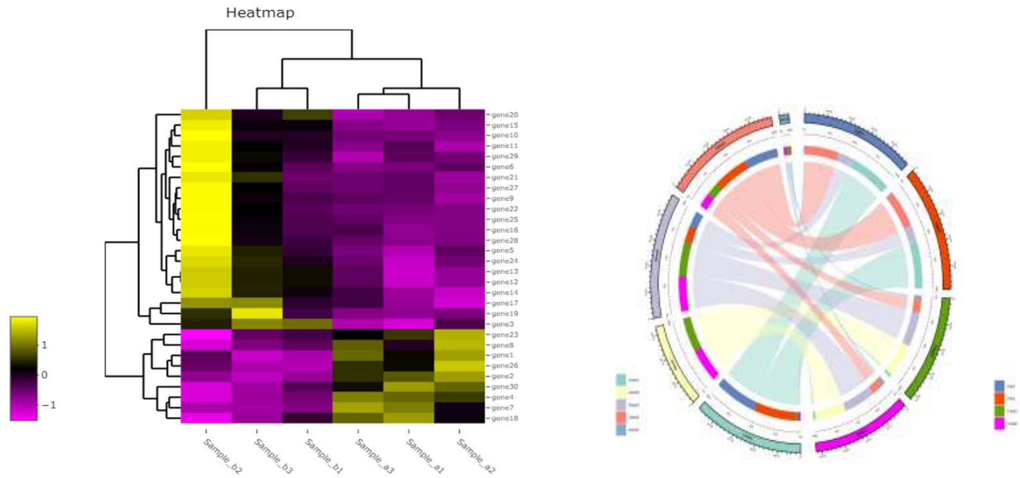


Figure 3 Intra comparison of anxiety and depression scores

5. Discussion:

Analyse the findings and talk about how administrators and healthcare professionals should respond. Examine possible obstacles and restrictions associated with the precision blood management approach.

For healthcare professionals and administrators, the precision blood management model's ground-breaking results have a wide range of implications. This conversation explores the significance of the findings and discusses the potential obstacles and constraints that come with using such a novel strategy[21,22,23].

With the abundance of data provided by the model, healthcare professionals are better equipped to make strategic and well-informed decisions regarding blood management. Effective Resource Allocation: By utilising the model's insights, administrators can ensure the prudent use of blood products and minimise wastage by optimising resource allocation.Proactive blood management reduces costs in a way that is consistent with financial optimisation objectives, providing a viable and effective method of delivering healthcare. By focusing resources where they will have the biggest impact, administrators can improve budgetary planning by using the model's predictions.

Tailored Healthcare Delivery: By adjusting transfusion protocols to meet the specific needs of each patient, healthcare professionals can adopt a more patient-centered approach and promote a culture of personalised care. By concentrating on patient satisfaction, administrators can foresee enhancements in the patient experience as a whole, which will lead to improved healthcare results.

Evidence-Based Practice: The model encourages a shift towards evidence-based practice, with healthcare practitioners relying on data-driven insights to guide their clinical decisions.

Continuous Improvement: Administrators can foster a culture of continuous improvement by incorporating feedback from the precision model into evolving healthcare protocols.

6. Conclusion:

In this work, big data analytics and precision medicine have come together to create a revolutionary blood management model. The findings highlight the possibility of significant improvements in patient-centered care, cost effectiveness, and resource use. Data-driven insights enable strategic decision-making for healthcare practitioners, and administrators experience transformative financial optimisation. But issues related to data security, integration, generalizability, and ethics demand careful thought. By redefining the transfusion medicine landscape and addressing these issues, the precision blood management model emerges as a beacon for the future of healthcare, where evidence-based, personalised practises come together to improve patient outcomes.

References

[1] Hopp, W. J., Li, J., & Wang, G. (2018). Big data and the precision medicine revolution. *Production and Operations Management*, *27*(9), 1647-1664.

[2] Hadi, M. S., Lawey, A. Q., El-Gorashi, T. E., & Elmirghani, J. M. (2019). Patient-centric cellular networks optimization using big data analytics. *IEEE Access*, *7*, 49279-49296.

[3] Hosseini, M. M., Zargoush, M., Alemi, F., & Kheirbek, R. E. (2020). Leveraging machine learning and big data for optimizing medication prescriptions in complex diseases: a case study in diabetes management. *Journal of Big Data*, *7*, 1-24.

[4] Jung, H., & Chung, K. (2021). Social mining-based clustering process for big-data integration. *Journal of Ambient Intelligence and Humanized Computing*, *12*, 589-600.

[5] Cammarota, G., Ianiro, G., Ahern, A., Carbone, C., Temko, A., Claesson, M. J., ... & Tortora, G. (2020). Gut microbiome, big data and machine learning to promote precision medicine for cancer. *Nature reviews gastroenterology & hepatology*, *17*(10), 635-648.

[6] Abdalla, H. B., Ahmed, A. M., & Al Sibahee, M. A. (2020). Optimization driven mapreduce framework for indexing and retrieval of big data. *KSII Transactions on Internet and Information Systems (TIIS)*, *14*(5), 1886-1908.

[7] Finkelstein, J., Zhang, F., Levitin, S. A., & Cappelli, D. (2020). Using big data to promote precision oral health in the context of a learning healthcare system. *Journal of public health dentistry*, *80*, S43-S58.

[8] Eckardt, J. N., Bornhäuser, M., Wendt, K., & Middeke, J. M. (2020). Application of machine learning in the management of acute myeloid leukemia: current practice and future prospects. *Blood Advances*, *4*(23), 6077-6085.

[9] Wang, X., Williams, C., Liu, Z. H., & Croghan, J. (2019). Big data management challenges in health research—a literature review. *Briefings in bioinformatics*, *20*(1), 156-167.

[10] Zhou, H. (2021). Optimization of the rapid design system for arts and crafts based on big data and 3D technology. *Complexity*, *2021*, 1-10.

[11] Primorac, D., Bach-Rojecky, L., Vađunec, D., Juginović, A., Žunić, K., Matišić, V., ... & Donaldson, M. (2020). Pharmacogenomics at the center of precision medicine: challenges and perspective in an era of Big Data. *Pharmacogenomics*, *21*(2), 141-156.

[12] Leopold, J. A., Maron, B. A., & Loscalzo, J. (2020). The application of big data to cardiovascular disease: paths to precision medicine. *The Journal of clinical investigation*, *130*(1), 29-38.
[13] Hadi, M. S., Lawey, A. Q., El-Gorashi, T. E., & Elmirghani, J. M. (2020). Patient-centric HetNets powered by machine learning and big data analytics for 6G networks. *IEEE Access*, *8*, 85639-85655.
[14] Wang, L., & Alexander, C. A. (2020). Big data analytics in medical engineering and healthcare: methods, advances and challenges. *Journal of medical engineering & technology*, *44*(6), 267-283.
[15] Mehmood, R., Meriton, R., Graham, G., Hennelly, P., & Kumar, M. (2017). Exploring the influence of big data on city transport operations: a Markovian approach. *International Journal of Operations & Production Management*, *37*(1), 75-104.
[16] Dimitrov, D. V. (2016). Medical internet of things and big data in healthcare. *Healthcare informatics research*, *22*(3), 156-163.
[17] Palanisamy, V., & Thirunavukarasu, R. (2019). Implications of big data analytics in developing healthcare frameworks–A review. *Journal of King Saud University-Computer and Information Sciences*, *31*(4), 415-425.
[18] Panayides, A. S., Pattichis, M. S., Leandrou, S., Pitris, C., Constantinidou, A., & Pattichis, C. S. (2018). Radiogenomics for precision medicine with a big data analytics perspective. *IEEE journal of biomedical and health informatics*, *23*(5), 2063-2079.
[19] Li, W., Chai, Y., Khan, F., Jan, S. R. U., Verma, S., Menon, V. G., ... & Li, X. (2021). A comprehensive survey on machine learning-based big data analytics for IoT-enabled smart healthcare system. *Mobile networks and applications*, *26*, 234-252.
[20] Jingchun Zhou, Lei Pang, Weishi Zhang. Underwater image enhancement method by multi-interval histogram equalization. IEEE Journal of Oceanic Engineering, 48(2),2023: 474-488.
[21] Jingchun Zhou, Dehuan Zhang, Weishi Zhang. Cross-view enhancement network for underwater images. Engineering Applications of Artificial Intelligence, 2023, 121, 105952.
[22] Jingchun Zhou, Qian Liu, Qiuping Jiang, Wenqi Ren, Kin-Man Lam, Weishi Zhang. Underwater image restoration via adaptive dark pixel prior and color correction. International Journal of Computer Vision, 2023. DOI :10.1007/s11263-023-01853-3.
[23] Zhang, Z., Navarese, E. P., Zheng, B., Meng, Q., Liu, N., Ge, H., ... & Ma, X. (2020). Analytics with artificial intelligence to advance the treatment of acute respiratory distress syndrome. *Journal of Evidence-Based Medicine*, *13*(4), 301-312.