ORIGINAL ARTICLE

Development of a Cost Model for Telemedicine Based on Medical Image Processing

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ABSTRACT

Telemedicine has become an essential platform for delivering remote clinical services, particularly in specialties that are dependent on medical imaging. While AI-driven image-processing technologies can enhance diagnostic accuracy and improve workflow efficiency, most current telemedicine evaluations overlook their economic implications. This paper seeks to fill this gap by developing a dedicated economic framework for the costs and benefits of medical image processing. A three-phase approach was adopted. In the first place, a structured

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search across the major academic databases evaluated whether already published economic models included image-processing costs. Then, technical and financial parameters were integrated into a quantitative break-even model. Finally, experts in telemedicine, medical imaging, and health technology assessment reviewed the model, and its components were evaluated using Content Validity Index scores. The literature review revealed no previous models focused on image-processing costs, whereas expert assessment confirmed strong clarity and relevance in all components of this model. This validated framework provides a comprehensive basis for detailed estimates of implementation expenses, quantified potential savings, and the required patient volume to achieve financial sustainability. Further research should apply and test this model within a variety of clinical contexts.

Keywords: Telemedicine, Medical Image Processing, Artificial Intelligence, Cost-Benefit Analysis

INTRODUCTION

Telemedicine has emerged as a significant innovation in modern healthcare, addressing the shortage of medical specialists and reducing disparities in access to clinical services, particularly in rural and underserved regions. By leveraging information and communication technologies, telehealth enables remote clinical evaluation and expert consultation without the need for in-person visits. Telehealth broadly refers to the delivery of healthcare services through information and communication technology (ICT) (1), with one of its primary objectives being the provision of timely and accurate diagnoses regardless of patient location (2).

The rapid expansion of digital technologies has positioned artificial intelligence (AI) as a transformative element in telemedicine. Advanced machine learning and deep learning methods support automated, precise analysis of clinical data, improving diagnostic reliability, reducing human error, and enhancing operational efficiency across telemedicine workflows (3-5). Among AI applications, medical image processing is particularly critical due to its central role in remote diagnostics. With the increasing volume and complexity of imaging data, AI-driven image analysis enables the extraction of clinically relevant features and improves diagnostic confidence, while advancements in digital infrastructure have facilitated the transmission of large medical image files essential to telesurgery and teleconsultation (4, 6). Despite these advancements, the economic implications of incorporating computationally intensive image-processing technologies into telemedicine systems remain insufficiently addressed in the existing literature (7).

Medical image processing requires substantial computational resources due to the size and complexity of imaging data and the need for high diagnostic precision (8). Furthermore, because medical images contain highly sensitive patient information, ethical and regulatory requirements often prohibit processing on public cloud servers, as external data transfers increase the risk of privacy breaches (9). Consequently, healthcare institutions must deploy secure, high-performance, on-premises infrastructure to support image-processing tasks, thereby significantly increasing the initial implementation cost of telemedicine systems that rely on medical imaging.

One of the fundamental challenges in implementing telemedicine systems is achieving economic efficiency and reducing operational costs. However, in the context of artificial intelligence, particularly medical image processing, the need for high-performance computational infrastructure, dedicated servers, and advanced hardware substantially increases initial and ongoing costs. Therefore, evaluating the break-even point between the costs and the benefits of integrating image processing technologies into telemedicine becomes essential for determining their economic feasibility and long-term sustainability.

Objectives

This study first investigated whether an established economic framework or cost model for such telemedicine systems has been previously proposed in the literature. Subsequently, based on the characteristics of image-processing algorithms, user demand, hardware requirements, and available economic parameters, a quantitative break-even analysis model was developed to provide a clear and evidence-based foundation for assessing the financial justification of deploying image-processing-enabled telemedicine platforms.

METHODS

This study employed a design-science and applied economic-modeling approach to develop and validate a cost model for telemedicine systems incorporating medical image processing. This study was conducted in three methodological phases. In the first phase, a structured search was conducted across major academic databases to determine whether previous studies have considered the costs of medical image processing in the economic evaluations of telemedicine systems. In the second phase, the technical and operational parameters influencing image-processing costs were identified and defined, and, based on these parameters, a break-even equation was formulated to assess the financial feasibility of implementing image-processing–enabled telemedicine systems. In the third phase, the proposed model and its break-even equation were evaluated and validated by experts in telemedicine, medical imaging, and health technology assessment to ensure technical accuracy, clinical relevance, and economic validity.

Phase 1: Systematic Literature Review

To determine whether previous studies have considered the costs associated with image processing in the economic evaluation of telemedicine systems, a structured search was conducted across PubMed, Scopus, and Web of Science using a comprehensive set of keywords related to artificial intelligence, telemedicine, and medical image processing. The search was performed in January 2025, with no restrictions on publication year, and was limited to English-language peer-reviewed articles. The complete search strategy and database queries are provided in Appendix 1.

Studies were included if they: (1) reported an economic evaluation, cost analysis, cost model, or financial assessment related to telemedicine; (2) involved telehealth or telemedicine systems that utilized medical imaging or image-processing workflows; (3) provided information on technical, computational, or infrastructure-related costs; (4) incorporated artificial intelligence, machine learning, or image-analysis techniques within telemedicine contexts; (5) were published as full-text peer-reviewed research articles; and (6) were written in English.

Studies were excluded if they: (1) reported only clinical diagnostic outcomes without any economic or cost-related analysis; (2) described telemedicine systems without the involvement of medical image processing; (3) were non-research publications such as commentaries, editorials, letters, or conference abstracts; (4) lacked accessible full text; (5) focused solely on the development of technical algorithms without discussing economic implications; or (6) were published in languages other than English.

The initial database search yielded 742 records. After removal of 312 duplicates, 430 unique studies remained for title and abstract screening. At this stage, 374 studies were excluded for failing to meet the predefined criteria. Full-text assessment was performed for 56 articles, of which 18 were excluded due to insufficient cost information, lack of relevance to image-processing workflows, or incomplete data availability. Ultimately, 38 studies met all inclusion criteria and were incorporated into the final evidence synthesis (7, 10-46). Notably, none of these studies addressed the computational costs of medical image processing or incorporated these costs into telemedicine economic evaluations, underscoring a substantial gap in the literature and the need for the cost model developed in this study.

Phase 2: Cost Model Development and Mathematical Derivation

The cost calculation model incorporates the primary technical and operational factors involved in developing and deploying a medical image-processing system. These factors include the total duration required for software development, the number of programmers participating in the project, the average compensation paid to each developer, the cost of acquiring or renting the necessary server infrastructure, and the expenses associated with maintaining and supporting the server environment. Together, these components determine the initial investment required to implement the system, which underlies the subsequent economic evaluation.

In the second step of the model, the diagnostic performance of the AI-based image-processing algorithm is compared with the guideline-based standard approach to determine the extent to which the algorithm reduces diagnostic errors or delays. The economic consequence of an incorrect or delayed diagnosis is then estimated as the additional treatment cost per affected patient, and an average incremental cost is used to account for variability across individuals. To quantify the financial impact of improved diagnostic accuracy, the AI algorithm's reduction in diagnostic errors is calculated for a cohort of 100 patients. The avoided diagnostic errors are multiplied by the average cost per error to obtain the total economic benefit generated by using the AI-based software. The variables and formulas used to compute the economic costs and benefits of deploying the software for 100 telemedicine visits are presented below.

In the final step of the economic model, the total implementation cost of the software is compared with the financial benefit generated per 100 telemedicine visits. To determine the number of patient visits required to reach the break-even point, the total system cost is divided by the economic benefit per block of 100 visits. The resulting value indicates how many sets of 100 patients are needed for the system to financially recover its initial investment. This value is then multiplied by 100 to identify the total number of patients required to reach the break-even point. To estimate the time needed for cost recovery, the average daily number of telemedicine visits is calculated, and the total required number of patients is divided by the average daily visit volume. This yields the number of days necessary for the system to achieve financial break-even. All symbols, definitions, units, and sources used in the economic model are summarized in Table 1 to enhance clarity and ensure reproducibility of the derivation process.

TABLE I. NOMENCLATURE OF VARIABLES USED IN THE ECONOMIC COST MODEL

Symbol	***Definition***	***Unit***	***Source***
T_d	Duration of software development	Months	Engineering estimation based on project timeline
N_p	Number of programmers involved	Count	Project team structure
S_p	Average salary or hourly rate per programmer	Local currency	Market compensation rates
C_s	Cost of acquiring or renting server hardware	Local currency	Hardware vendor pricing
C_m	Server maintenance and operational support cost	Local currency	Vendor or IT department estimate
Total Cost	Total system development and infrastructure cost	Local currency	Computed from the model
r_{guide}	Diagnostic error rate under guideline-based care	Percentage	Literature-based estimate
r_{AI}	Diagnostic error rate using the AI algorithm	Percentage	Algorithm validation results
Δr	Improvement in diagnostic performance (error reduction)	Percentage	$r_{\text{guide}} - r_{\text{AI}}$
C_{err}	Average cost of an incorrect or delayed diagnosis	Local currency	Healthcare economic studies
B	Number of 100-visit blocks required to reach break-even	Count	Computed from the model
$N_{\text{breakeven}}$	Total number of patient visits required for break-even	Visits	100×B
V_{day}	Average number of telemedicine visits per day	Visits/day	Operational clinic data
$T_{\text{breakeven}}$	Time required to reach break-even	Days	Nbreakeven / Vday

The economic model sequentially computes the total system cost, the diagnostic error-reduction benefit, and the required number of patient visits and days to achieve financial break-even. The pseudo-code for this computational process is presented in Figure 1.

INPUT:

T_d , N_p , S_p , C_s , C_m , r_{guide} , r_{AI} , C_{err} , V_{day}

STEP 1: Compute total system implementation cost

$$\text{Total Cost} = (T_d \times N_p \times S_p) + C_s + C_m$$

STEP 2: Compute diagnostic error reduction

$$\Delta r = r_{\text{guide}} - r_{\text{AI}}$$

$$\text{Avoided Errors}_{100} = 100 \cdot \Delta r$$

$$S_{100} = 100 \cdot \Delta r \cdot C_{\text{err}}$$

$$B = \frac{\text{Total Cost}}{S_{100}}$$

STEP 3: Compute break-even patient volume

$$N_{\text{breakeven}} = 100 \times B$$

STEP 4: Compute time required to reach break-even

$$T_{\text{breakeven}} = \frac{N_{\text{breakeven}}}{V_{\text{day}}}$$

OUTPUT:

TotalCost

$N_{breakeven}$

$T_{breakeven}$

FIGURE I. PSEUDO-CODE REPRESENTATION OF THE ECONOMIC BREAK-EVEN CALCULATION MODEL

Phase 3: Expert Validation Using Content Validity Index (CVI)

In the third phase of the study, the proposed economic model was evaluated by nine experts with professional experience in medical image processing and telemedicine applications. These experts assessed the relevance, clarity, and adequacy of each component of the model using a Content Validity Index (CVI)(47). A four-point Likert scale was employed, in which 1 = not relevant, 2 = somewhat relevant, 3 = quite relevant, and 4 = highly relevant. For each item, the CVI was calculated as the proportion of experts who assigned a rating of 3 or 4. According to established CVI guidelines, a minimum CVI value of 0.78 was considered acceptable for validation when the number of experts ranged from 6 to 10. Items scoring below this threshold were revised or refined based on expert feedback to ensure the accuracy and appropriateness of the final model.

Ethical Statement

This study did not involve human participants or identifiable data and, therefore, did not require ethical approval.

RESULTS

All components related to the model's structural and computational integrity achieved strong expert agreement and exceeded the required CVI threshold. The cost calculation framework, including the identification and integration of technical and operational parameters, received unanimous approval (CVI = 1.00), indicating that experts found the approach comprehensive and methodologically sound. Likewise, the model's applicability to telemedicine environments and the overall usefulness of the framework in supporting economic decision-making were fully endorsed by all reviewers. The detailed CVI scores for all evaluated components of the model are presented in Table 2.

TABLE III. CONTENT VALIDITY INDEX (CVI) SCORES FOR THE PROPOSED ECONOMIC MODEL COMPONENTS

No.	*Model Component Evaluated*	*Rating 3 or 4*	*CVI Value*	*Acceptable (≥ 0.78)*
1	Definition of cost parameters	8 / 9	0.89	Accepted
2	Structure of the cost calculation model	9 / 9	1.00	Accepted
3	Accuracy of economic benefit estimation	8 / 9	88.89	Accepted
4	Clarity of the break-even formula	9 / 9	0.89	Accepted
5	Logical consistency of variable definitions	7 / 9	0.78	Accepted
6	Applicability of the model in telemedicine	9 / 9	1.00	Accepted
7	Clinical relevance of error-reduction metrics	8 / 9	88.89	Accepted
8	Suitability of computational workflow	8 / 9	88.89	Accepted
9	Overall usefulness of the model	9 / 9	1.00	Accepted

All items supporting the model's structural and computational validity achieved high expert consensus and exceeded the minimum threshold for CVI. The cost calculation framework, including the identification and integration of technical and operational parameters, received unanimous approval, with a CVI of 1.00 for comprehensiveness and methodological soundness. Similarly, the model's applicability in telemedicine environments and the overall usefulness of the framework for economic decision-making were fully supported by all reviewers.

Items related to the clarity of the break-even formula, the clinical relevance of error-reduction metrics, and the suitability of the computational workflow demonstrated similarly strong validation scores, with CVI values ranging from 0.89 to 0.89. These high ratings denote expert consensus that the model effectively captures the essential financial mechanisms required for evaluating AI-based image-processing systems in telemedicine. The accuracy of the economic benefit estimation also received a high CVI score of 0.89, reinforcing confidence in the model's analytical foundations.

DISCUSSION

In this study, a comprehensive and innovative model was developed for the economic evaluation of telemedicine systems based on medical image processing. For the first time, the model integrates technical variables, including software development duration, number of programmers, server costs, and AI-based diagnostic error reduction, with economic indicators. The model not only calculates the total implementation cost but also estimates the break-even point and the number of consultations required to achieve a return on investment. Expert assessments demonstrated that all components of the model are acceptable in terms of variable accuracy, computational structure, and usability in clinical settings, and in many cases, they were rated as excellent. Therefore, it can serve as a reliable decision-making tool in the digital health domain.

The findings indicate that implementing telemedicine systems based on medical image processing requires highly powerful computational and storage infrastructures, which significantly increase both the initial and maintenance costs of the system. This result aligns with the study by Scholl et al. (2011), who emphasized that medical image processing demands expensive servers and computing equipment due to high data volumes and algorithmic complexity. (48) Furthermore, evidence from studies in the field of tele-ultrasonography shows that the use of deep learning models requires high-performance GPUs and substantial bandwidth, imposing considerable financial burdens (49). However, our findings are not fully consistent with the perspective of Luo et al. (2023), who suggest that employing edge–cloud architectures can relatively reduce costs (50). Even with edge processing, the need for central servers for final processing and data integration persists, and the possibility of significantly eliminating or reducing centralized infrastructure remains limited.

Within the framework of the economic model developed in this study, it was found that the majority of the initial investment is allocated to the development of specialized software and the provision of computational infrastructure. This finding is consistent with the results of Deserno et al. (2013), who demonstrated that the increasing volume of medical imaging data necessitates highly powerful servers and computing environments, advanced software tools, and high-performance storage infrastructure (51). Studies by Campbell et al. (2019) and Garbey et al. (2024) also indicate that designing image analysis software for telemedicine requires relatively substantial computational resources and development infrastructure. Therefore, the cost share of software and computational capacity represents a significant portion of the initial investment

There are other important costs, such as bandwidth and data transmission costs, data costs, recruitment and retention costs, equipment depreciation and upgrades, regulatory compliance, and user training, and these secondary yet significant costs affect all telemedicine projects economically. These findings corroborate those presented by Rosaline and Paulraj (2025), who also highlighted the need for expensive, high-capacity network infrastructure to transmit large volumes of imaging data, although some of these costs may be mitigated by smart compression. Moreover, expenses related to compliance with regulations such as HIPAA and GDPR, as well as the need for personnel training, play a crucial role in determining the initial break-even point of such systems (52, 53).

This study demonstrates that the economic evaluation of medical image-based telemedicine systems should extend beyond initial costs to include technical, infrastructural, and operational factors such as software development, computational infrastructure, maintenance, data security, regulatory compliance, and user training. The proposed model integrates these variables into a quantitative framework, enabling precise estimation of the break-even point, return on investment, and financial reliability. Findings also highlight that even with distributed and edge computing technologies, reliance on central infrastructure and high-performance resources remains significant, and relative savings cannot replace essential hardware and software investments. Overall, the study emphasizes the need for tailored economic models that comprehensively capture all components of telemedicine systems and serve as practical, reliable tools for strategic decision-making.

Limitations

This study had several limitations. The proposed cost model is based on theoretical parameters rather than real implementation data, which may limit its applicability in different telemedicine settings. Moreover, healthcare costs, reimbursement structures, and clinical guidelines vary widely across regions and institutions, making it impossible to achieve precise, fully generalizable cost estimates. The economic and technical variables used—such as server cost, programmer workload, and diagnostic error reduction—are averaged estimates and may differ in real-world scenarios. The literature search was also limited to major English-language databases, potentially missing studies from other sources. Additionally, expert validation was conducted with a relatively small group of specialists, which may not reflect broader professional perspectives.

CONCLUSION

The economic evaluation of remote medical image-based telemedicine systems involves more than just the initial costing of the software and the development of computing architecture. There are ongoing costs. There are ongoing costs for maintaining and updating the software and architecture, as well as regulatory oversight. Even with edge and distributed computing, there must still be a central computing resource. The model suggested offers a good balance and converges toward the practical, allowing a robust assessment of multiple, interrelated economic targets such as ROI, break-even, and financial viability and reliability.

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Declaration of the Use of Artificial Intelligence Tools

The authors used artificial intelligence tools (ChatGPT from OpenAI) solely to improve the clarity, grammar, and structure of the manuscript. All scientific content, study design, model development, data interpretation, and conclusions were created solely by the authors. The authors reviewed and approved all AI-assisted edits.

Contributorship Statement

Author 1: Literature review, data interpretation, methodological refinement, manuscript revision.

Author 2: Conceptualization, study design, model development, data analysis, drafting of the manuscript.

All authors read and approved the final version of the manuscript, as well as taking responsibility for its content.

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Declaration Of Conflicting Interests

The authors declare that they have no conflicts of interest related to this work.

Data Availability Statements

No datasets were generated or analyzed in the current study. All materials used in the development and validation of the model are included within the manuscript.

REFERENCES

1. Wade VA, Karnon J, Elshaug AG, Hiller JE. A systematic review of economic analyses of telehealth services using real time video communication. BMC health services research. 2010;10(1):233. https://doi.org/10.1186/1472-6963-10-233
2. Desta GT, Gebre DW, Haileyesus MM. The Role of Telemedicine in Improving Patient Outcomes: A Comprehensive Review. International Journal of Medical Information and Knowledge Insights. 2025;1(1):20-7. https://doi.org/10.62951/ijmiki.v1i1.3
3. Gupta R, Gamad R, Bansod PJCE. Telemedicine: A brief analysis. 2014;1(1):966459
4. Magdy M, Hosny KM, Ghali NI, Ghoniemy S. Security of medical images for telemedicine: a systematic review. Multimedia Tools and Applications. 2022;81(18):25101-45. https://doi.org/10.1007/s11042-022-11956-7
5. Castellano NN, Gazquez JA, Salvador RMG, Gracia-Escudero A, Fernandez-Ros M, Manzano-Agugliaro F. Design of a real-time emergency telemedicine system for remote medical diagnosis. Biosystems engineering. 2015;138:23-32. https://doi.org/10.1016/j.biosystemseng.2015.03.017
6. Gupta R, Gamad R, Bansod P. Telemedicine: A brief analysis. Cogent Engineering. 2014;1(1):966459. https://doi.org/10.1080/23311916.2014.966459
7. Saini DJB, Choubey S, Choubey A, Kidwai M, Mehrotra M, Kolekar S, et al. Early detection of glaucoma integrated with deep learning models over medical devices. Biosystems. 2024;238. https://doi.org/10.1016/j.biosystems.2024.105156
8. Scholl I, Aach T, Deserno TM, Kuhlen T. Challenges of medical image processing. Computer science-Research and development. 2011;26(1):5-13. https://doi.org/10.1007/s00450-010-0146-9
9. Zhu Y, Yin X, Wee-Chung Liew A, Tian H, editors. Privacy-Preserving in Medical Image Analysis: A Review of Methods and Applications. Parallel and Distributed Computing, Applications and Technologies; 2025 2025//; Singapore: Springer Nature Singapore;
10. Abdalla PA, Mahmood BS, Hama NR. MyKidney: A Web-based AI tool for automated kidney stone detection from CT imaging. 2025;5. https://doi.org/10.1016/j.inv.2025.100046
11. Ara T, Mishra VP, Bali M, Yenkikar A. Hybrid quantum-classical deep learning framework for balanced multiclass diabetic retinopathy classification. MethodsX. 2025;15. https://doi.org/10.1016/j.mex.2025.103605
12. Boyle L, Moosmann J, Baumann N, Heo S, Magno M. DSORT-MCU: Detecting Small Objects in Real Time on Microcontroller Units. IEEE Sensors J. 2024;24(24):40231-9. https://doi.org/10.1109/JSEN.2024.3425904
13. Cai FFZ, Jiang CQ, Cheung RCC, Lam AHF. An AIoT LoRaWAN Control System With Compression and Image Recovery Algorithm (CIRA) for Extreme Weather. IEEE Internet Things J. 2024;11(20):32701-13. https://doi.org/10.1109/jiot.2024.3450590
14. Chyad HS, Mustafa RA, Haleot RA. An effective protocol and algorithmic approach for disaster management using wireless sensor networks. J Adv Res Dyn Control Syst. 2018;10(13 Special Issue):2405-10
15. Coyner AS, Swan R, Campbell JP, Ostmo S, Brown JM, Kalpathy-Cramer J, et al. Automated Fundus Image Quality Assessment in Retinopathy of Prematurity Using Deep Convolutional Neural Networks. Ophthalmol Retin. 2019;3(5):444-50. https://doi.org/10.1016/j.oret.2019.01.015
16. Gani VKU, Shanmugasundaram N. Cheetah optimized CNN: A bio-inspired neural network for automated diabetic retinopathy detection. AIP Adv. 2025;15(5). https://doi.org/10.1063/5.0264083
17. Garbey M, Lesport Q, Girma H, Öztosun G, Abu-Rub M, Guidon AC, et al. Application of digital tools and artificial intelligence in the Myasthenia Gravis Core Examination. Frontiers in Neurology. 2024;15. https://doi.org/10.3389/fneur.2024.1474884
18. Katada Y, Ozawa N, Masayoshi K, Ofuji Y, Tsubota K, Kurihara T. Automatic screening for diabetic retinopathy in interracial fundus images using artificial intelligence. Intell Based Med. 2020;3-4. https://doi.org/10.1016/j.ibmed.2020.100024
19. Kim J, Kim M, Youn H, Lee S, Kwon S, Park KH. Method for Enhancing AI Accuracy in Pressure Injury Detection Using Real and Synthetic Datasets. Appl Sci. 2024;14(20). https://doi.org/10.3390/app14209396

20. Lesport Q, Joerger G, Kaminski HJ, Girma H, McNett S, Abu-Rub M, et al. Eye Segmentation Method for Telehealth: Application to the Myasthenia Gravis Physical Examination. Sensors. 2023;23(18). https://doi.org/10.3390/s23187744
21. Li FF, Li GX, Yu XX, Zhang ZH, Fu YN, Wu SQ, et al. Integrating prior knowledge with deep learning for optimized quality control in corneal images: A multicenter study. Comput Methods Programs Biomed. 2025;267. https://doi.org/10.1016/j.cmpb.2025.108814
22. Li R, St George RJ, Wang X, Lawler K, Hill E, Garg S, et al. Moving towards intelligent telemedicine: Computer vision measurement of human movement. Comput Biol Med. 2022;147. https://doi.org/10.1016/j.compbiomed.2022.105776
23. Liu Y, Chen J, Hu C, Ma Y, Ge D, Miao S, et al. Vision-Based Method for Automatic Quantification of Parkinsonian Bradykinesia. IEEE Trans Neural Syst Rehabil Eng. 2019;27(10):1952-61. https://doi.org/10.1109/TNSRE.2019.2939596
24. Liu Y, Yan B, Zhang R, Liu K, Jeon G, Yang X. Multi-Scale Mixed Attention Network for CT and MRI Image Fusion. Entropy. 2022;24(6). https://doi.org/10.3390/e24060843
25. Loganathan L, Kaliyaperumal K. A bi-directional associative memory based multiple image watermarking on cover video. Multimedia Tools and Applications. 2016;75(12):7211-56. https://doi.org/10.1007/s11042-015-2642-1
26. Luo Z, Ding X, Hou N, Wan J. A Deep-Learning-Based Collaborative Edge–Cloud Telemedicine System for Retinopathy of Prematurity. Sensors. 2023;23(1). https://doi.org/10.3390/s23010276
27. Maqsood S, Damasevicius R. Multiclass skin lesion localization and classification using deep learning based features fusion and selection framework for smart healthcare. Neural Networks. 2023;160:238-58. https://doi.org/10.1016/j.neunet.2023.01.022
28. Merle DA, Heidinger A, Horwath-Winter J, List W, Bauer H, Weissensteiner M, et al. Automated Measurement and Three-Dimensional Fitting of Corneal Ulcerations and Erosions via AI-Based Image Analysis. Curr Eye Res. 2024;49(8):835-42. https://doi.org/10.1080/02713683.2024.2344197
29. Nahen K, Benyamini G, Loewenstein A. Evaluation of a Self-Imaging SD-OCT System for Remote Monitoring of Patients with Neovascular Age Related Macular Degeneration. Klinische Monatsblatter Fur Augenheilkunde. 2020;237(12):1410-8. https://doi.org/10.1055/a-1271-6834
30. Ozbilgin F, Kurnaz Ç, Aydın E. Prediction of Coronary Artery Disease Using Machine Learning Techniques with Iris Analysis. Diagn. 2023;13(6). https://doi.org/10.3390/diagnostics13061081
31. Park SM, Kwon S, Ji Y, Sakthivel H, Leem JW, Kwak Y, et al. Machine reading and recovery of colors for hemoglobin-related bioassays and bioimaging. Sci Adv. 2025;11(23). https://doi.org/10.1126/sciadv.adt4831
32. Prasanth P, Sundarrajan M, Choudhry MD, Akshya A. Enhancing security of medical images using code-based intermittent encryption and convolutional neural network. Comput J. 2025;68(5):539-51. https://doi.org/10.1093/comjnl/bxae130
33. Raizman R, Ramírez García Luna JL, Newaz T, Wang SC, Berry GK, Kong LY, et al. Empowering Patients and Caregivers to Use Artificial Intelligence and Computer Vision for Wound Monitoring: Nonrandomized, Single-Arm Feasibility Study. J Particip Med. 2025;17. https://doi.org/10.2196/69470
34. Rosaline S, Paulraj D. Deep learning-based compression and encryption of CT images for secure telemedicine applications. Evolving Systems. 2025;16(1). https://doi.org/10.1007/s12530-024-09652-y
35. Selcuk Nogay HS, Noğay NH, Adeli H. Detection of hyperglycemia and hypoglycemia using deep learning from facial images obtained with an AI image generator. Biomed Signal Process Control. 2026;111. https://doi.org/10.1016/j.bspc.2025.108351
36. Shen Y, Zhang H, Fan Y, Lee AP, Xu L. Smart Health of Ultrasound Telemedicine Based on Deeply Represented Semantic Segmentation. IEEE Internet Things J. 2021;8(23):16770-8. https://doi.org/10.1109/JIOT.2020.3029957
37. Simmatis L, Barnett-Tapia C, Marzouqah R, Taati B, Boulos M, Yunusova Y. Reliability of Automatic Computer Vision-Based Assessment of Orofacial Kinematics for Telehealth Applications. Digit Biomarkers. 2022;6(2):71-82. https://doi.org/10.1159/000525698
38. Sirwal SA, Ahmad B, Koul M. Vision-assisted vibrotactile haptic feedback for guidance in teleoperation. Ind Robot. 2025. https://doi.org/10.1108/IR-03-2025-0101
39. Sitnova AV, Valitov ER, Svetozarskiy SN. Application of Deep Learning Algorithms Based on the Multilayer YOLOv8 Neural Network to Identify Fungal Keratitis. Sovremennye Tehnologii V Medicine. 2024;16(4):5-13. https://doi.org/10.17691/stm2024.16.4.01

40. Varshitha DN, Gowrishankar BS, Mulakaluri S, Chaitra NJ, Choudhary S, Varshiya TV, et al. Automated Detection of Polycystic Ovary Syndrome Using Convolutional Neural Networks on Ultrasound Images. Salud Cienc Tecnol. 2025;5. https://doi.org/10.56294/saludcyt20252272.
41. Vieira-Marques P, Almeida R, Teixeira JF, Valente J, Jácome C, Cachim A, et al. InspirerMundi-Remote Monitoring of Inhaled Medication Adherence through Objective Verification Based on Combined Image Processing Techniques. Methods of Information in Medicine. 2021;60:E9-E19. https://doi.org/10.1055/s-0041-1726277
42. Vodrahalli K, Ko J, Chiou AS, Novoa R, Abid A, Phung M, et al. Development and Clinical Evaluation of an Artificial Intelligence Support Tool for Improving Telemedicine Photo Quality. JAMA Dermatol. 2023;159(5). https://doi.org/10.1001/jamadermatol.2023.0091
43. Wang J, Shan C, Liu Z, Zhou S, Shu M. Physiological Information Preserving Video Compression for rPPG. IEEE J Biomedical Health Informat. 2025;29(5):3563-75. https://doi.org/10.1109/JBHI.2025.3526837
44. Wang Z, Yin S, Wang Y, Yin W, Xiang X, Yi Y, et al. Shape-Prior Enhanced Myocardium Segmentation for Cardiac CT Analysis Driven by the Internet of Medical Things. IEEE Internet Things J. 2025;12(16):33945-57. https://doi.org/10.1109/JIOT.2025.3578242
45. Xiong J, Ou W, Liu Z, Gou J, Xiao W, Liu H. GraphPhys: Facial video-based physiological measurement with graph neural network. Comput Electr Eng. 2024;113. https://doi.org/10.1016/j.compeleceng.2023.109022
46. Yousofvand L, Dowlatshahi MB, Beiranvand MP. Pneumonia detection in chest X-ray images using Convolutional Neural Network and fuzzy VIKOR. Iranian Journal of Fuzzy Systems. 2025;22(5):159-79. https://doi.org/10.22111/ijfs.2025.51603.9119
47. Polit DF, Beck CT. The content validity index: are you sure you know what's being reported? Critique and recommendations. Research in nursing & health. 2006;29(5):489-97
48. Scholl I, Aach T, Deserno TM, Kuhlen TJCs-R, development. Challenges of medical image processing. 2011;26(1):5-13
49. Shen Y, Zhang H, Fan Y, Lee AP, Xu L. Smart health of ultrasound telemedicine based on deeply represented semantic segmentation. IEEE Internet Things J. 2020;8(23):16770-8. https://doi.org/10.1109/JIOT.2020.3029957
50. Luo Z, Ding X, Hou N, Wan J. A deep-learning-based collaborative edge–cloud telemedicine system for retinopathy of prematurity. Sensors. 2022;23(1):276. https://doi.org/10.3390/s23010276
51. Deserno TM, Handels H, Maier-Hein KH, Mersmann S, Palm C, Tolxdorff T, et al. Viewpoints on medical image processing: from science to application. Current medical imaging reviews. 2013;9(2):79-88
52. Magdy M, Hosny KM, Ghali NI, Ghoniemy SJMT, Applications. Security of medical images for telemedicine: a systematic review. 2022;81(18):25101-45
53. Ansarian M, Baharlouei Z. Applications and Challenges of Telemedicine: Privacy-Preservation as a Case Study. 2023;26(11):654-61. https://doi.org/10.34172/aim.2023.96