technologies

Editorial

Perspectives, Challenges, and the Future of Biomedical Technology and Artificial Intelligence

Saul Tovar-Arriaga [1,†], Gerardo Israel Pérez-Soto [1,†], Karla Anhel Camarillo-Gómez [2,†], Marcos Aviles [1,*,†] and Juvenal Rodríguez-Reséndiz [1,*,†]

1 Facultad de Ingeniería, Universidad Autónoma de Querétaro, Querétaro 76010, Mexico; saul.tovar@uaq.mx (S.T.-A.); israel.perez@uaq.mx (G.I.P.-S.)
2 Departamento de Ingeniería Mecánica, Tecnológico Nacional de México en Celaya, Celaya 38010, Mexico; karla.camarillo@itcelaya.edu.mx
* Correspondence: marcosaviles@ieee.org (M.A.); juvenal@uaq.edu.mx (J.R.-R.)
† These authors contributed equally to this work.

1. Introduction

Biomedical technologies are the compound of engineering principles and technologies used to diagnose, treat, monitor, and prevent illness. Advances in science and engineering continuously improve them, and artificial intelligence (AI) is not getting behind. In the last few years, artificial intelligence has grown faster and has the potential to revolutionize the human experience [1]. With recent advances in generative models such as GPT-4 [2], advancements in biomedical technologies are expected to be realized at a faster pace [3]. In this manuscript, we aim to contribute to the growth of biomedical technologies boosted by AI.

2. The Challenges of Modern Healthcare

Each era in the history of medicine has had its own challenges. Modern medicine faces many challenges as well, such as economic constraints, a growing population, and increased life expectancy, to name just a few. Moreover, there is an alarming increase in cancer [4], cardiovascular [5], and neurodegenerative illnesses [6], many of which could be controlled if they are diagnosed on time. On the other hand, advancements in many areas of medicine have resulted in a high level of specialization [7]. Diagnosing rare illnesses requires years of study. Furthermore, some diseases have only recently been discovered, and it is documented that AI agents have diagnosed diseases that only a few specialists are able to find [8,9]. Although this advancement is generally positive, it conveys the need for costly equipment and the need to analyze complex data.

check for updates

Citation: Tovar-Arriaga, S.; Pérez-Soto, G.I.; Camarillo-Gómez, K.A.; Aviles, M.; Rodríguez-Reséndiz, J. Perspectives, Challenges, and the Future of Biomedical Technology and Artificial Intelligence. *Technologies* **2024**, *12*, 212. https://doi.org/10.3390/technologies12110212

Received: 12 October 2024
Accepted: 16 October 2024
Published: 24 October 2024

3. The Transition from Medicine 2.0 to Medicine 3.0

There is an increasing interest in going to the next medicine paradigm, known as Medicine 3.0 [10]. Medicine 1.0 refers to the medicine that our ancestors used, which in many cases worked, but they did not know how. In Medicine 2.0, the mechanics of the treatments are better understood, but it is more oriented to reactive care when the illness is already manifested. On the other hand, Medicine 3.0 is proactive, meaning it focuses more on prevention and quality of life. It considers the patient as unique, so the care should be done accordingly. We are transitioning from Medicine 2.0 to Medicine 3.0, but making this possible will require all the high-tech we have at our disposal.

4. The Uses of AI in Prevention and Treatment

Artificial Intelligence provides methods for analyzing large quantities of data in short periods of time. Since AI systems do not need to rest, they can support a large number of patients at any time. They can help orient patients in deciding how to get medical services or make clear the steps to take to get the prescribed drugs. Internists can also use the technologies to facilitate repetitive, time-consuming tasks such as requesting patient data or writing summaries of cases [3]. Some of the tasks that AI agents can do include classification, regression, prediction, counting, answers to prompts, generating images, sounds, etc. These capabilities can be used for many biomedical technologies, including medical imaging, diagnosis, administration of patient records, design of prosthetic, enhanced vaccine development, acceleration of drug discovery, and so on.

5. Diagnosis and Preventive Care

AI has been enhancing the area of medical imaging, which is crucial for diagnosis. The most well-known imaging techniques include magnetic resonance imaging, computed tomography (CT), and X-rays, but there are other techniques such as ultrasound, PET, and retinograph, to name a few. Different sources of data have also been explored, like signals obtained from biosensors such as BCIs (brain-computer interfaces), text (e.g., Twitter), voice, sounds of organs, wearable devices, etc.

6. Embedded Artificial Intelligence

Embedded artificial intelligence has emerged as a revolutionary innovation in healthcare and medicine, allowing the direct integration of AI algorithms into medical devices and monitoring systems [11]. This technology facilitates real-time data processing, which is crucial for applications requiring immediate responses, such as critical patient monitoring, early detection of abnormalities, and personalized treatment delivery [12].

Medical devices equipped with embedded artificial intelligence can analyze physiological data locally without transmitting information to remote servers, thereby reducing latency and improving system efficiency [13]. For example, wearable devices can monitor vital signs such as heart rate, blood pressure, and glucose levels, providing instant alerts to the patient and medical staff in case abnormal values are detected [14].

Furthermore, embedded AI in point-of-care diagnostic systems has improved diagnostic accuracy, especially in resource-limited settings [15]. These systems can assist healthcare professionals in interpreting medical images using deep learning algorithms trained to recognize patterns associated with various pathologies [16].

However, implementing embedded AI in medical devices presents significant challenges. Limitations in computational resources, such as processing and memory, require the design of efficient algorithms optimized for specific hardware [17]. Standardization and regulation are also critical aspects to consider. Medical devices with embedded AI must comply with strict regulations to ensure their efficacy and safety. Ethical frameworks that address issues related to automated decision-making and liability in the event of errors or malfunctions need to be developed [18].

7. AI in Prosthetic

Artificial intelligence has revolutionized the field of prostheses, significantly improving the functionality and control of artificial limbs [19]. Advanced machine learning algorithms allow modern prostheses to interpret biosignals and convert them into precise movements, providing users with a more natural experience [20]. For example, brain-machine interfaces allow prostheses to be controlled directly by EEG signals, increasing the efficiency and usability of these devices [21]. Furthermore, AI facilitates the continuous adaptation of the prosthesis to the user, learning and adjusting to individual movement patterns to improve performance over time [22]. However, despite these advances, sensory integration and haptic feedback challenges still need to be addressed to achieve a more intuitive interaction between the user and the prosthesis [23].

8. Automate Administrative

Artificial intelligence can transform administrative tasks in the medical field. Functions that could be automated include medical record management, appointment scheduling, billing, and patient tracking [3]. This automation will not only improve efficiency and reduce errors but also allow healthcare professionals to spend more time on direct patient care, thus optimizing the quality of medical care [24].

9. Accelerating Drug Discovery

There are a variety of difficulties throughout the entire drug discovery process: time, prior validation, and robust financial and scientific investment. As an alternative method in drug discovery and development, artificial intelligence allows more effective approaches, overcoming obstacles of traditional methods [25–27]. When artificial intelligence is applied correctly, there is a considerable advantage in laboratory methods, data generation, and computational algorithms, enabling optimal decision-making even when working with incomplete information [28,29]. However, there is significant concern regarding the ethical implications of applying artificial intelligence in pharmacological research, particularly in safeguarding data privacy and security, obtaining informed consent, and ensuring human oversight in decision-making processes, where some authors indicate robust frameworks and regulations are needed [27–31].

10. Surgical Robotics

AI-driven robotic surgery is reshaping the field of surgery by equipping surgeons with real-time advanced data such as force feedback and tactile information, enhancing the identification of surgical margins, and even automating certain parts of surgical procedures [32]. In recent years, one of the main problems is the assistance in real-time during surgery [33], as well as the importance of levels of autonomy and ethical and legal considerations related to advances in surgical robotics with AI [34–36]. This remains an open and constantly evolving topic.

11. Personalized Medicine

Also known as precision medicine, this approach to healthcare focuses on every patient's specific characteristics [37]. Not all people are the same; therefore, treatment should also be according to the individual's needs. To accomplish this, personalized medicine considers genetic data [38], medical records, environment, and lifestyle [39]. Advances in biomedical technology and AI will be crucial in making personalized medicine possible.

12. Editorial Remarks

This Editorial refers to the Special Issue "The Future of Healthcare: Biomedical Technology and Integrated Artificial Intelligence," which aims to showcase innovations using artificial intelligence as a main topic for solving problems in biomedical technology through developing technologies for health and quality of life. Twenty-eight manuscripts were submitted for consideration. All were rigorously peer-reviewed by specialists in their respective areas of expertise. Eleven papers were finally accepted for publication, eight of which are original articles and three are reviews. The list of the final published articles is presented next:

1. Alotaibi, R.; Abukhodair, F. Radiation dose tracking in computed tomography using data visualization. *Technologies* **2023**, *11*, 74.
2. Aviles, M.; Rodríguez-Reséndiz, J.; Ibrahimi, D. Optimizing EMG classification through metaheuristic algorithms. *Technologies* **2023**, *11*, 87.
3. Gonzalez-Moreno, M.; Monfort-Vinuesa, C.; Piñas-Mesa, A.; Rincon, E.Digital technologies to provide humanization in the education of the healthcare workforce: A systematic review. *Technologies* **2023**, *11*, 88.
4. Ortiz-Feregrino, R.; Tovar-Arriaga, S.; Pedraza-Ortega, J.C.; Rodríguez-Reséndiz, J. Segmentation of retinal blood vessels using focal attention convolution blocks in a UNET. *Technologies* **2023**, *11*, 97.
5. de Leon-Sanchez, E.R.P.; Mendiola-Santibáñez, J.D.; Dominguez-Ramirez, O.A.; Herrera-Navarro, A.M.; Vazquez-Cervantes, A.; Jimenez-Hernandez, H.; Senties-Madrid, H.

Fuzzy logic system for classifying multiple sclerosis patients as high, medium, or low responders to interferon-beta. *Technologies* **2023**, *11*, 109.
6. Cerón, A.V.; Domínguez, E.L.; Isidro, S.D.; Nieto, M.A.M.; De La Calleja, J.; Hernández, S.E.P. Level of technological maturity of telemonitoring systems focused on patients with chronic kidney disease undergoing peritoneal dialysis treatment: A systematic literature review. *Technologies* **2023**, *11*, 129.
7. Moltó-Balado, P.; Reverté-Villarroya, S.; Alonso-Barberán, V.; Monclús-Arasa, C.; Balado-Albiol, M.T.; Clua-Queralt, J.; Clua-Espuny, J.-L. Machine learning approaches to predict Major Adverse Cardiovascular Events in atrial fibrillation. *Technologies* **2024**, *12*, 13.
8. Chandel, T.; Miranda, V.; Lowe, A.; Lee, T.C. Blood pressure measurement device accuracy evaluation: Statistical considerations with an implementation in R. *Technologies* **2024**, *12*, 44.
9. Hasan, M.A.; Haque, F.; Sabuj, S.R.; Sarker, H.; Goni, M.O.F.; Rahman, F.; Rashid, M.M. An end-to-end lightweight multi-scale CNN for the classification of lung and colon cancer with XAI integration. *Technologies* **2024**, *12*, 56.
10. Avelar, M.C.; Almeida, P.; Faria, B.M.; Reis, L.P. Applications of brain wave classification for controlling an intelligent wheelchair. *Technologies* **2024**, *12*, 80.
11. Kim, M.; Hong, S. Integrating artificial intelligence to biomedical science: New applications for innovative stem cell research and drug development. *Technologies* **2024**, *12*, 95.

The contributions of the listed articles are summarized in the following lines:

- The study presented in [40] highlights the urgent need to improve radiation dose monitoring in patients undergoing CT scans due to the increase in their use and the risks of overexposure, such as the increased risk of developing cancer. The main challenge lies in the variability of factors influencing the dose received, such as patient characteristics, equipment, and procedure. Current solutions are static, and integration difficulties are present due to the heterogeneity of hospital information systems, limiting the accuracy of user queries. The study proposes a visual analysis approach using Tableau software. It allows automated data cleaning and organization in an interactive dashboard, with multiple simultaneous filters to facilitate its exploration and manipulation. The results, evaluated by experts, show a significant improvement in the radiation dose monitoring process, with a 100% success rate, increasing user satisfaction and providing a better understanding of the analysis. The tool enables individual and group monitoring of patients and procedures, supporting the justification and optimization of these procedures through accurate and easy-to-interpret data. The work contributes to a flexible, interactive, and effective solution for monitoring radiation doses in CT, benefiting health providers, regulators, researchers, and patients by facilitating decision-making, optimizing resources, and improving the quality of radiation-related data.
- On the other hand [41] proposes a metaheuristic-based approach for hyperparameter optimization in a multilayer perceptron (MLP) to improve electromyography signal (EMG) classification, focusing on optimizing the number of neurons, learning rate, epochs, and training batches using the Particle Swarm Optimization (PSO) and Gray Wolf Optimizer (GWO) algorithms. The results show that optimizing these hyperparameters significantly improves the performance of the MLP, achieving an accuracy of 93% in the validation phase. However, it is acknowledged that using a limited database might have affected the performance, so future research with more extensive databases and data augmentation techniques is suggested. The study highlights the effectiveness of the PSO and GWO algorithms in hyperparameter optimization, avoiding manual tuning and reducing model complexity. Although potential limitations, such as stagnation in local optima, are identified, the proposed approach is a promising strategy to improve EMG signal classification, with potential application in other signal processing problems.

- The article [42] analyses the lack of university educational programs combining humanization in healthcare with digital technologies for health sciences students. A systematic review of the literature identified six studies involving 295 students, mostly nursing students, over the last ten years. Only one of the studies integrated digital strategies to teach humanization skills, and another measured the level of humanization after training. The results highlight that, although humanization in care is recognized as essential, no standardized and empirically validated university curricula combine these skills with digital technology. The authors propose a training program based on the HUMAS model, focused on developing skills such as sociability, emotional understanding, and self-efficacy, using narrative methodologies, mindfulness, and digital health technologies such as virtual reality. The importance of designing programs that prepare future health professionals to incorporate humanistic skills in their clinical practice is emphasized, especially in an increasingly digitalized medical environment. Despite the potential benefits, the lack of studies with more diverse groups, including medical students, and the scarcity of digital humanization strategies stand out as critical limitations.
- The work [43] contributed to retinal vessel segmentation, which is essential in diagnosing several illnesses, such as hypertensive retinopathy, diabetic retinopathy, and macular edema. Although there are many methods for segmentation, the authors explore the use of visual transformers, which have been successful in other applications but have the disadvantage of large computational processing. To deal with this constraint, the authors adapted the attention module of visual transformers and integrated it into a convolutional neural network (CNN) based on UNET network, achieving superior performance compared to other models.
- In [44], the authors introduce a fuzzy logic-based system, supported by the knowledge of a neurology expert, to classify patients with relapsing-remitting multiple sclerosis into three categories: high, medium, and low response to interferon-beta treatment. The system showed 100% efficiency compared to a hierarchical clustering method, which only achieved 52%. In addition, a predictive model was developed using biomarkers associated with interferon-beta response to identify suitable candidates for treatment, reaching a test accuracy of 80%. The predictive model includes data normalization steps, principal component analysis compression, and an MLP learning algorithm, which optimizes patient classification and reduces processing time. The results suggest that this approach can help avoid ineffective therapies and improve patient selection for this treatment. Despite its promising results, the study points out limitations such as the small size of the test samples, which restricted cross-validation iterations. The authors highlight the importance of continuing research with other biomarkers and exploring more advanced predictive models, such as evolutionary or deep learning algorithms, to improve performance in predicting responses to treatment.
- The manuscript [45] analyzes fourteen works that propose telemonitoring systems focused on patients with chronic kidney disease (CKD) undergoing peritoneal dialysis (PD) to determine their Technology Readiness Level (TRL). From these works, eight were classified within TRL 9, two within TRL 7, three within TRL 6, and one within TRL 4. Also, the implementations of telemonitoring systems that reached the highest level of TRL correspond to studies developed with the use of proprietary devices and services of international companies specialized in telemedicine treatment of CKD with some limitations regarding their status as proprietary systems incompatible with other devices or systems. Their main limitation is that they are oriented only to treating patients in automated peritoneal dialysis, which limits the care of patients undergoing continuous ambulatory peritoneal dialysis. So, this paper contributes as a reference for researchers and technologists focused on developing telemonitoring systems for patients with CKD undergoing PD.

- In [46], researchers implemented five machine learning techniques to obtain predictors of major adverse cardiovascular events (MACE) in atrial fibrillation (AF) patients. They used two-thirds of the data for training, employing diverse approaches and optimizing to minimize prediction errors, while the remaining third was reserved for testing and validation. The features influencing predictions included the Charlson comorbidity index, diabetes mellitus, cancer, cognitive impairment, vascular disease, chronic obstructive pulmonary disease, the Wells scales, and CHA2DS2-VASc, with specific associations identified. The contribution of the manuscript is that the AdaBoost model was the most effective in predicting MACE in patients with newly diagnosed AF, with an accuracy of 99.99%, a recall of 100%, and an F1 score of 99.97%. Also, it contributes to the optimization of treatment decisions concerning the burden of AF according to the associated risks of thromboembolism and ischemic events.
- The article [47] proposes a methodology for evaluating the accuracy blood pressure (BP) measurement, which expands the method developed by the Committee of the US Association for the Advancement of Medical Instrumentation (AAMI) with the purpose of reducing the sample size stipulated in the International Standard ISO 81060-2. This methodology is based on statistical consideration with an implementation in R and can be used for the early evaluation of experimental devices, showing the potential effects of employing different sample sizes for validating a BP measurement device. Furthermore, it compares previous studies that investigated novel BP measurement methods with different sample sizes and assesses their adherence to the current standard.
- The manuscript [48] present a deep CNN model for detecting lung and colon cancer (LCC). The proposed model achieved an accuracy of 99.20% for the overall LCC class classification and is appropriate for real-time applications, such as mobile or Internet of Medical Things devices, because it has fewer computationally expensive parameters (1.1 million) than existing models. Integrating explainable artificial intelligence (XAI) algorithms, such as Grad-CAM and SHAP, enhances the model's interpretability by providing diverse and complementary insights into feature importance, enabling a more comprehensive understanding of the model's decision-making process.
- The work in [49] contributes to the development of a brain-computer interface (BCI) designed to control a smart wheelchair through motor imagery. Two data sets were used: the first from the IV BCI competition (A) and the second obtained in the laboratory with the Emotiv EPOC device (B). The results indicate that data set A, acquired under controlled conditions and with mobile electrodes, presented a better performance with an F1 score of 0.797 and a false positive rate of 0.150. On the other hand, data set B, obtained with Emotiv EPOC, showed a lower performance due to problems with the fixed placement of the electrodes and noise in the signal, although some subjects achieved good scores. Various feature extraction techniques were evaluated regarding the methodologies, highlighting the Filter Bank Common Spatial Pattern method, whose second version produced the best results. Although the current results are unsuitable for real-time applications, the study validates the concept and the developed architecture, proposing for future work the improvement in noise removal, the use of non-linear classifiers, and the expansion of the data set to increase the generalization of the model.
- Finally, ref. [50] highlight that cultivating and differentiating stem cells, as well as demonstrating their efficacy, is a time-intensive and complex process. Their review explores the applications and advancements of AI technology in drug development, regenerative medicine, and stem cell research. They specifically focus on CNN-based models from the literature, which are used to analyze stem cell images, predict cell types, and evaluate differentiation efficiency. This comprehensive review provides valuable insights into the current state of the field and underscores the growing role of AI in both present and future stem cell research.

13. Conclusions

In this editorial article, we present an overview of biomedical technology and integrated artificial intelligence. We state the importance of these multifaceted technologies and articulate some topics that could be addressed to advance the field. We describe published articles and summarize each contribution. As expected, we received articles from diverse research fields and nationalities. Since health concerns us all, advancing biomedical research and changing the paradigm from Medicine 2.0 to Medicine 3.0 will require the scientific community's work worldwide.

Author Contributions: Conceptualization, K.A.C.-G.; methodology, S.T.-A.; writing—original draft preparation, K.A.C.-G. and M.A; writing—review and editing, M.A., G.I.P.-S., K.A.C.-G. and J.R.-R.; supervision, J.R.-R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Kissinger, H.A.; Schmidt, E.; Huttenlocher, D. *The Age of AI: And Our Human Future*; Little, Brown and Company: Hachette, UK, 2021.
2. Achiam, J.; Adler, S.; Agarwal, S.; Ahmad, L.; Akkaya, I.; Aleman, F.L.; Almeida, D.; Altenschmidt, J.; Altman, S.; Anadkat, S.; et al. Gpt-4 technical report. *arXiv* **2023**, arXiv:2303.08774.
3. Lee, P.; Bubeck, S.; Petro, J. Benefits, limits, and risks of GPT-4 as an AI chatbot for medicine. *N. Engl. J. Med.* **2023**, *388*, 1233–1239. [CrossRef] [PubMed]
4. WHO. *Global Cancer Burden Growing, Amidst Mounting Need for Services*; Comunicado de Prensa; WHO: Geneva, Switzerland, 2024.
5. Mensah, G.A.; Fuster, V.; Murray, C.J.; Roth, G.A.; Global Burden of Cardiovascular Diseases and Risks Collaborators. Global burden of cardiovascular diseases and risks, 1990–2022. *J. Am. Coll. Cardiol.* **2023**, *82*, 2350–2473. [CrossRef] [PubMed]
6. Steinmetz, J.D.; Seeher, K.M.; Schiess, N.; Nichols, E.; Cao, B.; Servili, C.; Cavallera, V.; Cousin, E.; Hagins, H.; Moberg, M.E.; et al. Global, regional, and national burden of disorders affecting the nervous system, 1990–2021: A systematic analysis for the Global Burden of Disease Study 2021. *Lancet Neurol.* **2024**, *23*, 344–381. [CrossRef]
7. Marques, L.; Costa, B.; Pereira, M.; Silva, A.; Santos, J.; Saldanha, L.; Silva, I.; Magalhães, P.; Schmidt, S.; Vale, N. Advancing precision medicine: A review of innovative in silico approaches for drug development, clinical pharmacology and personalized healthcare. *Pharmaceutics* **2024**, *16*, 332. [CrossRef]
8. Gertz, R.J.; Dratsch, T.; Bunck, A.C.; Lennartz, S.; Iuga, A.I.; Hellmich, M.G.; Persigehl, T.; Pennig, L.; Gietzen, C.H.; Fervers, P.; et al. Potential of GPT-4 for detecting errors in radiology reports: Implications for reporting accuracy. *Radiology* **2024**, *311*, e232714. [CrossRef]
9. Ito, N.; Kadomatsu, S.; Fujisawa, M.; Fukaguchi, K.; Ishizawa, R.; Kanda, N.; Kasugai, D.; Nakajima, M.; Goto, T.; Tsugawa, Y. The accuracy and potential racial and ethnic biases of GPT-4 in the diagnosis and triage of health conditions: Evaluation study. *JMIR Med. Educ.* **2023**, *9*, e47532. [CrossRef]
10. Attia, P.; Gifford, B. *Outlive*; Harmony Books: New York, NY, USA, 2023.
11. Patel, S.; Park, H.; Bonato, P.; Chan, L.; Rodgers, M. A review of wearable sensors and systems with application in rehabilitation. *J. Neuroeng. Rehabil.* **2012**, *9*, 21. [CrossRef]
12. Chen, J.; Ran, X. Deep learning with edge computing: A review. *Proc. IEEE Inst. Electr. Electron. Eng.* **2019**, *107*, 1655–1674. [CrossRef]
13. Chen, M.; Hao, Y.; Hwang, K.; Wang, L.; Wang, L. Disease prediction by machine learning over big data from healthcare communities. *IEEE Access* **2017**, *5*, 8869–8879. [CrossRef]
14. Baig, M.M.; GholamHosseini, H.; Connolly, M.J. Mobile healthcare applications: System design review, critical issues and challenges. *Australas. Phys. Eng. Sci. Med.* **2015**, *38*, 23–38. [CrossRef] [PubMed]
15. Esteva, A.; Kuprel, B.; Novoa, R.A.; Ko, J.; Swetter, S.M.; Blau, H.M.; Thrun, S. Dermatologist-level classification of skin cancer with deep neural networks. *Nature* **2017**, *542*, 115–118. [CrossRef] [PubMed]
16. Litjens, G.; Kooi, T.; Bejnordi, B.E.; Setio, A.A.A.; Ciompi, F.; Ghafoorian, M.; van der Laak, J.A.W.M.; van Ginneken, B.; Sánchez, C.I. A survey on deep learning in medical image analysis. *Med. Image Anal.* **2017**, *42*, 60–88. [CrossRef] [PubMed]
17. Haris, J.; Gibson, P.; Cano, J.; Agostini, N.B.; Kaeli, D. SECDA: Efficient hardware/software co-design of FPGA-based DNN accelerators for edge inference. *arXiv* **2021**, arXiv:2110.00478.

18. Vayena, E.; Blasimme, A.; Cohen, I.G. Machine learning in medicine: Addressing ethical challenges. *PLoS Med.* **2018**, *15*, e1002689. [CrossRef]
19. Farina, D.; Aszmann, O. Bionic limbs: Clinical reality and academic promises. *Sci. Transl. Med.* **2014**, *6*, 257ps12. [CrossRef]
20. Micera, S.; Carpaneto, J.; Raspopovic, S. Control of hand prostheses using peripheral information. *IEEE Rev. Biomed. Eng.* **2010**, *3*, 48–68. [CrossRef]
21. Collinger, J.L.; Wodlinger, B.; Downey, J.E.; Wang, W.; Tyler-Kabara, E.C.; Weber, D.J.; McMorland, A.J.C.; Velliste, M.; Boninger, M.L.; Schwartz, A.B. High-performance neuroprosthetic control by an individual with tetraplegia. *Lancet* **2013**, *381*, 557–564. [CrossRef]
22. Kuiken, T.A.; Li, G.; Lock, B.A.; Lipschutz, R.D.; Miller, L.A.; Stubblefield, K.A.; Englehart, K.B. Targeted muscle reinnervation for real-time myoelectric control of multifunction artificial arms. *JAMA* **2009**, *301*, 619–628. [CrossRef]
23. Clemente, F.; Valle, G.; Controzzi, M.; Strauss, I.; Iberite, F.; Stieglitz, T.; Granata, G.; Rossini, P.M.; Petrini, F.; Micera, S.; et al. Intraneural sensory feedback restores grip force control and motor coordination while using a prosthetic hand. *J. Neural Eng.* **2019**, *16*, 026034. [CrossRef]
24. Lee, P.; Goldberg, C.; Kohane, I. *The AI Revolution in Medicine: GPT-4 and Beyond*; Pearson: Upper Saddle River, NJ, USA, 2023.
25. Vijayan, R.S.K.; Kihlberg, J.; Cross, J.B.; Poongavanam, V. Enhancing preclinical drug discovery with artificial intelligence. *Drug Discov. Today* **2022**, *27*, 967–984. [CrossRef] [PubMed]
26. Tripathi, A.; Misra, K.; Dhanuka, R.; Singh, J.P. Artificial intelligence in accelerating drug discovery and development. *Recent Pat. Biotechnol.* **2023**, *17*, 9–23. [CrossRef] [PubMed]
27. Tiwari, P.C.; Pal, R.; Chaudhary, M.J.; Nath, R. Artificial intelligence revolutionizing drug development: Exploring opportunities and challenges. *Drug Dev. Res.* **2023**, *84*, 1652–1663. [CrossRef] [PubMed]
28. Santa Maria, J.P., Jr.; Wang, Y.; Camargo, L.M. Perspective on the challenges and opportunities of accelerating drug discovery with artificial intelligence. *Front. Bioinform.* **2023**, *3*, 1121591. [CrossRef]
29. Mak, K.K.; Wong, Y.H.; Pichika, M.R. Artificial intelligence in drug discovery and development. In *Drug Discovery and Evaluation: Safety and Pharmacokinetic Assays*; Springer International Publishing: Cham, Switzerland, 2023; pp. 1–38.
30. Singh, S.; Kumar, R.; Payra, S.; Singh, S.K. Artificial intelligence and machine learning in pharmacological research: Bridging the gap between data and drug discovery. *Cureus* **2023**, *15*, e44359. [CrossRef]
31. Visan, A.I.; Negut, I. Integrating artificial intelligence for drug discovery in the context of revolutionizing drug delivery. *Life* **2024**, *14*, 233. [CrossRef]
32. Knudsen, J.E.; Ghaffar, U.; Ma, R.; Hung, A.J. Clinical applications of artificial intelligence in robotic surgery. *J. Robot. Surg.* **2024**, *18*, 102. [CrossRef]
33. Panesar, S.; Cagle, Y.; Chander, D.; Morey, J.; Fernandez-Miranda, J.; Kliot, M. Artificial intelligence and the future of surgical robotics. *Ann. Surg.* **2019**, *270*, 223–226. [CrossRef]
34. Yang, G.Z.; Cambias, J.; Cleary, K.; Daimler, E.; Drake, J.; Dupont, P.E.; Hata, N.; Kazanzides, P.; Martel, S.; Patel, R.V.; et al. Medical robotics-Regulatory, ethical, and legal considerations for increasing levels of autonomy. *Sci. Robot.* **2017**, *2*, eaam8638. [CrossRef]
35. Laterza, V.; Marchegiani, F.; Aisoni, F.; Ammendola, M.; Schena, C.A.; Lavazza, L.; Ravaioli, C.; Carra, M.C.; Costa, V.; De Franceschi, A.; et al. Smart operating room in digestive surgery: A narrative review. *Healthcare* **2024**, *12*, 1530. [CrossRef]
36. Finocchiaro, M.; Banfi, T.; Donaire, S.; Arezzo, A.; Guarner-Argente, C.; Menciassi, A.; Casals, A.; Ciuti, G.; Hernansanz, A. A framework for the evaluation of human machine interfaces of robot-assisted colonoscopy. *IEEE Trans. Biomed. Eng.* **2024**, *71*, 410–422. [CrossRef] [PubMed]
37. Suwinski, P.; Ong, C.; Ling, M.H.; Poh, Y.M.; Khan, A.M.; Ong, H.S. Advancing personalized medicine through the application of whole exome sequencing and big data analytics. *Front. Genet.* **2019**, *10*, 49. [CrossRef] [PubMed]
38. Filipp, F.V. Opportunities for artificial intelligence in advancing precision medicine. *Curr. Genet. Med. Rep.* **2019**, *7*, 208–213. [CrossRef] [PubMed]
39. Johnson, K.B.; Wei, W.Q.; Weeraratne, D.; Frisse, M.E.; Misulis, K.; Rhee, K.; Zhao, J.; Snowdon, J.L. Precision medicine, AI, and the future of personalized health care. *Clin. Transl. Sci.* **2021**, *14*, 86–93. [CrossRef] [PubMed]
40. Alotaibi, R.; Abukhodair, F. Radiation dose tracking in computed tomography using data visualization. *Technologies* **2023**, *11*, 74. [CrossRef]
41. Aviles, M.; Rodríguez-Reséndiz, J.; Ibrahimi, D. Optimizing EMG classification through metaheuristic algorithms. *Technologies* **2023**, *11*, 87. [CrossRef]
42. Gonzalez-Moreno, M.; Monfort-Vinuesa, C.; Piñas-Mesa, A.; Rincon, E. Digital technologies to provide humanization in the education of the healthcare workforce: A systematic review. *Technologies* **2023**, *11*, 88. [CrossRef]
43. Ortiz-Feregrino, R.; Tovar-Arriaga, S.; Pedraza-Ortega, J.C.; Rodriguez-Resendiz, J. Segmentation of retinal blood vessels using focal attention convolution blocks in a UNET. *Technologies* **2023**, *11*, 97. [CrossRef]
44. Ponce de Leon-Sanchez, E.R.; Mendiola-Santibañez, J.D.; Dominguez-Ramirez, O.A.; Herrera-Navarro, A.M.; Vazquez-Cervantes, A.; Jimenez-Hernandez, H.; Senties-Madrid, H. Fuzzy logic system for classifying multiple sclerosis patients as high, medium, or low responders to interferon-beta. *Technologies* **2023**, *11*, 109. [CrossRef]

45. Villanueva Cerón, A.; López Domínguez, E.; Domínguez Isidro, S.; Medina Nieto, M.A.; De La Calleja, J.; Pomares Hernández, S.E. Level of technological maturity of telemonitoring systems focused on patients with chronic kidney disease undergoing peritoneal dialysis treatment: A systematic literature review. *Technologies* **2023**, *11*, 129. [CrossRef]
46. Moltó-Balado, P.; Reverté-Villarroya, S.; Alonso-Barberán, V.; Monclús-Arasa, C.; Balado-Albiol, M.T.; Clua-Queralt, J.; Clua-Espuny, J.L. Machine learning approaches to predict Major Adverse Cardiovascular Events in atrial fibrillation. *Technologies* **2024**, *12*, 13. [CrossRef]
47. Chandel, T.; Miranda, V.; Lowe, A.; Lee, T.C. Blood pressure measurement device accuracy evaluation: Statistical considerations with an implementation in R. *Technologies* **2024**, *12*, 44. [CrossRef]
48. Hasan, M.A.; Haque, F.; Sabuj, S.R.; Sarker, H.; Goni, M.O.F.; Rahman, F.; Rashid, M.M. An end-to-end lightweight multi-scale CNN for the classification of lung and colon cancer with XAI integration. *Technologies* **2024**, *12*, 56. [CrossRef]
49. Avelar, M.C.; Almeida, P.; Faria, B.M.; Reis, L.P. Applications of brain wave classification for controlling an intelligent wheelchair. *Technologies* **2024**, *12*, 80. [CrossRef]
50. Kim, M.; Hong, S. Integrating artificial intelligence to biomedical science: New applications for innovative stem cell research and drug development. *Technologies* **2024**, *12*, 95. [CrossRef]