GEORGIAN MEDICAL NEWS

ISSN 1512-0112

NO 12 (357) Декабрь 2024

ТБИЛИСИ - NEW YORK

ЕЖЕМЕСЯЧНЫЙ НАУЧНЫЙ ЖУРНАЛ

Медицинские новости Грузии

საქართველოს სამედიცინო სიახლენი

GEORGIAN MEDICAL NEWS

Monthly Georgia-US joint scientific journal published both in electronic and paper formats of the Agency of Medical Information of the Georgian Association of Business Press. Published since 1994. Distributed in NIS, EU and USA.

GMN: Georgian Medical News is peer-reviewed, published monthly journal committed to promoting the science and art of medicine and the betterment of public health, published by the GMN Editorial Board since 1994. GMN carries original scientific articles on medicine, biology and pharmacy, which are of experimental, theoretical and practical character; publishes original research, reviews, commentaries, editorials, essays, medical news, and correspondence in English and Russian.
GMN is indexed in MEDLINE, SCOPUS, PubMed and VINITI Russian Academy of Sciences. The full text content is available through EBSCO databases.

GMN: Медицинские новости Грузии - ежемесячный рецензируемый научный журнал, издаётся Редакционной коллегией с 1994 года на русском и английском языках в целях поддержки медицинской науки и улучшения здравоохранения. В журнале публикуются оригинальные научные статьи в области медицины, биологии и фармации, статьи обзорного характера, научные сообщения, новости медицины и здравоохранения. Журнал индексируется в MEDLINE, отражён в базе данных SCOPUS, PubMed и ВИНИТИ РАН. Полнотекстовые статьи журнала доступны через БД EBSCO.

GMN: Georgian Medical News – საქართველოს სამედიცინო სიახლენი – არის ყოველთვიური სამეცნიერო სამედიცინო რეცენზირებადი ჟურნალი, გამოიცემა 1994 წლიდან, წარმოადგენს სარედაქციო კოლეგიისა და აშშ-ის მეცნიერების, განათლების, ინდუსტრიის, ხელოვნებისა და ბუნებისმეტყველების საერთაშორისო აკადემიის ერთობლივ გამოცემას. GMN-ში რუსულ და ინგლისურ ენებზე ქვეყნდება ექსპერიმენტული, თეორიული და პრაქტიკული ხასიათის ორიგინალური სამეცნიერო სტატიები მედიცინის, ბიოლოგიისა და ფარმაციის სფეროში, მიმოხილვითი ხასიათის სტატიები.
ჟურნალი ინდექსირებულია MEDLINE-ის საერთაშორისო სისტემაში, ასახულია SCOPUS-ის, PubMed-ის და ВИНИТИ РАН-ის მონაცემთა ბაზებში. სტატიების სრული ტექსტი ხელმისაწვდომია EBSCO-ს მონაცემთა ბაზებიდან.

WEBSITE

www.geomednews.com

К СВЕДЕНИЮ АВТОРОВ!

При направлении статьи в редакцию необходимо соблюдать следующие правила:

1. Статья должна быть представлена в двух экземплярах, на русском или английском языках, напечатанная через **полтора интервала на одной стороне стандартного листа с шириной левого поля в три сантиметра**. Используемый компьютерный шрифт для текста на русском и английском языках - **Times New Roman** (**Кириллица**), для текста на грузинском языке следует использовать **AcadNusx.** Размер шрифта - **12**. К рукописи, напечатанной на компьютере, должен быть приложен CD со статьей.

2. Размер статьи должен быть не менее десяти и не более двадцати страниц машинописи, включая указатель литературы и резюме на английском, русском и грузинском языках.

3. В статье должны быть освещены актуальность данного материала, методы и результаты исследования и их обсуждение.

При представлении в печать научных экспериментальных работ авторы должны указывать вид и количество экспериментальных животных, применявшиеся методы обезболивания и усыпления (в ходе острых опытов).

4. К статье должны быть приложены краткое (на полстраницы) резюме на английском, русском и грузинском языках (включающее следующие разделы: цель исследования, материал и методы, результаты и заключение) и список ключевых слов (key words).

5. Таблицы необходимо представлять в печатной форме. Фотокопии не принимаются. **Все цифровые, итоговые и процентные данные в таблицах должны соответствовать таковым в тексте статьи**. Таблицы и графики должны быть озаглавлены.

6. Фотографии должны быть контрастными, фотокопии с рентгенограмм - в позитивном изображении. Рисунки, чертежи и диаграммы следует озаглавить, пронумеровать и вставить в соответствующее место текста **в tiff формате**.

В подписях к микрофотографиям следует указывать степень увеличения через окуляр или объектив и метод окраски или импрегнации срезов.

7. Фамилии отечественных авторов приводятся в оригинальной транскрипции.

8. При оформлении и направлении статей в журнал МНГ просим авторов соблюдать правила, изложенные в «Единых требованиях к рукописям, представляемым в биомедицинские журналы», принятых Международным комитетом редакторов медицинских журналов - http://www.spinesurgery.ru/files/publish.pdf и http://www.nlm.nih.gov/bsd/uniform_requirements.html
В конце каждой оригинальной статьи приводится библиографический список. В список литературы включаются все материалы, на которые имеются ссылки в тексте. Список составляется в алфавитном порядке и нумеруется. Литературный источник приводится на языке оригинала. В списке литературы сначала приводятся работы, написанные знаками грузинского алфавита, затем кириллицей и латиницей. Ссылки на цитируемые работы в тексте статьи даются в квадратных скобках в виде номера, соответствующего номеру данной работы в списке литературы. Большинство цитированных источников должны быть за последние 5-7 лет.

9. Для получения права на публикацию статья должна иметь от руководителя работы или учреждения визу и сопроводительное отношение, написанные или напечатанные на бланке и заверенные подписью и печатью.

10. В конце статьи должны быть подписи всех авторов, полностью приведены их фамилии, имена и отчества, указаны служебный и домашний номера телефонов и адреса или иные координаты. Количество авторов (соавторов) не должно превышать пяти человек.

11. Редакция оставляет за собой право сокращать и исправлять статьи. Корректура авторам не высылается, вся работа и сверка проводится по авторскому оригиналу.

12. Недопустимо направление в редакцию работ, представленных к печати в иных издательствах или опубликованных в других изданиях.

При нарушении указанных правил статьи не рассматриваются.

REQUIREMENTS

Please note, materials submitted to the Editorial Office Staff are supposed to meet the following requirements:

1. Articles must be provided with a double copy, in English or Russian languages and typed or compu-ter-printed on a single side of standard typing paper, with the left margin of **3** centimeters width, and **1.5** spacing between the lines, typeface - **Times New Roman** (**Cyrillic**), print size - **12** (referring to Georgian and Russian materials). With computer-printed texts please enclose a CD carrying the same file titled with Latin symbols.

2. Size of the article, including index and resume in English, Russian and Georgian languages must be at least 10 pages and not exceed the limit of 20 pages of typed or computer-printed text.

3. Submitted material must include a coverage of a topical subject, research methods, results, and review.

Authors of the scientific-research works must indicate the number of experimental biological species drawn in, list the employed methods of anesthetization and soporific means used during acute tests.

4. Articles must have a short (half page) abstract in English, Russian and Georgian (including the following sections: aim of study, material and methods, results and conclusions) and a list of key words.

5. Tables must be presented in an original typed or computer-printed form, instead of a photocopied version. **Numbers, totals, percentile data on the tables must coincide with those in the texts of the articles.** Tables and graphs must be headed.

6. Photographs are required to be contrasted and must be submitted with doubles. Please number each photograph with a pencil on its back, indicate author's name, title of the article (short version), and mark out its top and bottom parts. Drawings must be accurate, drafts and diagrams drawn in Indian ink (or black ink). Photocopies of the X-ray photographs must be presented in a positive image in **tiff format**.

Accurately numbered subtitles for each illustration must be listed on a separate sheet of paper. In the subtitles for the microphotographs please indicate the ocular and objective lens magnification power, method of coloring or impregnation of the microscopic sections (preparations).

7. Please indicate last names, first and middle initials of the native authors, present names and initials of the foreign authors in the transcription of the original language, enclose in parenthesis corresponding number under which the author is listed in the reference materials.

8. Please follow guidance offered to authors by The International Committee of Medical Journal Editors guidance in its Uniform Requirements for Manuscripts Submitted to Biomedical Journals publication available online at: http://www.nlm.nih.gov/bsd/uniform_requirements.html
http://www.icmje.org/urm_full.pdf
In GMN style for each work cited in the text, a bibliographic reference is given, and this is located at the end of the article under the title "References". All references cited in the text must be listed. The list of references should be arranged alphabetically and then numbered. References are numbered in the text [numbers in square brackets] and in the reference list and numbers are repeated throughout the text as needed. The bibliographic description is given in the language of publication (citations in Georgian script are followed by Cyrillic and Latin).

9. To obtain the rights of publication articles must be accompanied by a visa from the project instructor or the establishment, where the work has been performed, and a reference letter, both written or typed on a special signed form, certified by a stamp or a seal.

10. Articles must be signed by all of the authors at the end, and they must be provided with a list of full names, office and home phone numbers and addresses or other non-office locations where the authors could be reached. The number of the authors (co-authors) must not exceed the limit of 5 people.

11. Editorial Staff reserves the rights to cut down in size and correct the articles. Proof-sheets are not sent out to the authors. The entire editorial and collation work is performed according to the author's original text.

12. Sending in the works that have already been assigned to the press by other Editorial Staffs or have been printed by other publishers is not permissible.

Articles that Fail to Meet the Aforementioned Requirements are not Assigned to be Reviewed.

ავტორთა საყურადღებოდ!

რედაქციაში სტატიის წარმოდგენისას საჭიროა დავიცვათ შემდეგი წესები:

1. სტატია უნდა წარმოადგინოთ 2 ცალად, რუსულ ან ინგლისურ ენებზე,დაბეჭდილი სტანდარტული ფურცლის 1 გვერდზე, 3 სმ სიგანის მარცხენა ველისა და სტრიქონებს შორის 1,5 ინტერვალის დაცვით. გამოყენებული კომპიუტერული შრიფტი რუსულ და ინგლისურენოვან ტექსტებში - **Times New Roman** (**Кириллица**), ხოლო ქართულენოვან ტექსტში საჭიროა გამოვიყენოთ **AcadNusx.** შრიფტის ზომა – 12. სტატიას თან უნდა ახლდეს CD სტატიით.

2. სტატიის მოცულობა არ უნდა შეადგენდეს 10 გვერდზე ნაკლებს და 20 გვერდზე მეტს ლიტერატურის სიის და რეზიუმეების (ინგლისურ,რუსულ და ქართულ ენებზე) ჩათვლით.

3. სტატიაში საჭიროა გაშუქდეს: საკითხის აქტუალობა; კვლევის მიზანი; საკვლევი მასალა და გამოყენებული მეთოდები; მიღებული შედეგები და მათი განსჯა. ექსპერიმენტული ხასიათის სტატიების წარმოდგენისას ავტორებმა უნდა მიუთითონ საექსპერიმენტო ცხოველების სახეობა და რაოდენობა; გაუტკივარებისა და დაძინების მეთოდები (მწვავე ცდების პირობებში).

4. სტატიას თან უნდა ახლდეს რეზიუმე ინგლისურ, რუსულ და ქართულ ენებზე არანაკლებ ნახევარი გვერდის მოცულობისა (სათაურის, ავტორების, დაწესებულების მითითებით და უნდა შეიცავდეს შემდეგ განყოფილებებს: მიზანი, მასალა და მეთოდები, შედეგები და დასკვნები; ტექსტუალური ნაწილი არ უნდა იყოს 15 სტრიქონზე ნაკლები) და საკვანძო სიტყვების ჩამონათვალი (key words).

5. ცხრილები საჭიროა წარმოადგინოთ ნაბეჭდი სახით. ყველა ციფრული, შემაჯამებელი და პროცენტული მონაცემები უნდა შეესაბამებოდეს ტექსტში მოყვანილს.

6. ფოტოსურათები უნდა იყოს კონტრასტული; სურათები, ნახაზები, დიაგრამები - დასათაურებული, დანომრილი და სათანადო ადგილას ჩასმული. რენტგენოგრამების ფოტოასლები წარმოადგინეთ პოზიტიური გამოსახულებით **tiff** ფორმატში. მიკროფოტოსურათების წარწერებში საჭიროა მიუთითოთ ოკულარის ან ობიექტივის საშუალებით გადიდების ხარისხი, ანათალების შეღებვის ან იმპრეგნაციის მეთოდი და აღნიშნოთ სურათის ზედა და ქვედა ნაწილები.

7. სამამულო ავტორების გვარები სტატიაში აღინიშნება ინიციალების თანდართვით, უცხოურისა – უცხოური ტრანსკრიპციით.

8. სტატიას თან უნდა ახლდეს ავტორის მიერ გამოყენებული სამამულო და უცხოური შრომების ბიბლიოგრაფიული სია (ბოლო 5-8 წლის სიღრმით). ანბანური წყობით წარმოდგენილ ბიბლიოგრაფიულ სიაში მიუთითეთ ჯერ სამამულო, შემდეგ უცხოელი ავტორები (გვარი, ინიციალები, სტატიის სათაური, ჟურნალის დასახელება, გამოცემის ადგილი, წელი, ჟურნალის №, პირველი და ბოლო გვერდები). მონოგრაფიის შემთხვევაში მიუთითეთ გამოცემის წელი, ადგილი და გვერდების საერთო რაოდენობა. ტექსტში კვადრატულ ფჩხილებში უნდა მიუთითოთ ავტორის შესაბამისი N ლიტერატურის სიის მიხედვით. მიზანშეწონილია, რომ ციტირებული წყაროების უმეტესი ნაწილი იყოს 5-6 წლის სიღრმის.

9. სტატიას თან უნდა ახლდეს: ა) დაწესებულების ან სამეცნიერო ხელმძღვანელის წარდგინება, დამოწმებული ხელმოწერითა და ბეჭდით; ბ) დარგის სპეციალისტის დამოწმებული რეცენზია, რომელშიც მითითებული იქნება საკითხის აქტუალობა, მასალის საკმაობა, მეთოდის სანდოობა, შედეგების სამეცნიერო-პრაქტიკული მნიშვნელობა.

10. სტატიის ბოლოს საჭიროა ყველა ავტორის ხელმოწერა, რომელთა რაოდენობა არ უნდა აღემატებოდეს 5-ს.

11. რედაქცია იტოვებს უფლებას შეასწოროს სტატია. ტექსტზე მუშაობა და შეჯერება ხდება საავტორო ორიგინალის მიხედვით.

12. დაუშვებელია რედაქციაში ისეთი სტატიის წარდგენა, რომელიც დასაბეჭდად წარდგენილი იყო სხვა რედაქციაში ან გამოქვეყნებული იყო სხვა გამოცემებში.

აღნიშნული წესების დარღვევის შემთხვევაში სტატიები არ განიხილება.

Содержание:

ANALYSIS OF CHALLENGES AND POSSIBILITIES OF USING ARTIFICIAL INTELLIGENCE IN MEDICAL DIAGNOSTICS

Tetiana Fartushok[1]*, Dmytro Bishchak[2], Iryna Bronova[3], Olena Barabanchyk[4], Yuriy Prudnikov[5].

[1]*PhD in Medicine, Associate Professor, Department of Obstetrics & Gynecology, Medical Faculty, Danylo Halytsky Lviv National Medical University, Lviv, Ukraine.*

[2]*PhD student, Assistant, Department of Software Engineering, Ternopil Ivan Puluj National Technical University, Ternopil, Ukraine.*

[3]*PhD in Medicine, Associate Professor, Department for Dermatovenerology and Surgical Dermatology, Educational and Research Institute for Postgraduate Education, Kharkiv National Medical University, Kharkiv, Ukraine.*

[4]*MD, PhD in Medicine, Associate Professor, Department of Internal Medicine, Educational and Scientific Centre "Institute of Biology and Medicine," Taras Shevchenko National University of Kyiv, Kyiv, Ukraine.*

[5]*MD, PhD in Medicine, MEcon, MPA, Professor, Scientific Department, Institute of Medical Sciences, WSB University, Dabrowa Gornicza, Poland.*

Abstract.

Background: This study aims to analyze the geographical distribution of different AI types and applications, document implementation challenges, and assess outcomes of interest as well as potential opportunities for increasing healthcare efficiency.

Methodology: A systematic review analyzed 24 studies (2019-2024) from IEEE Xplore, PubMed, and Google Scholar using MeSH keywords, following specific inclusion and exclusion criteria.

Results: Results show that AI was applied to almost all spheres of life, with multi-modal AI, deep learning and machine learning models having promising applications in precision medicine, early diagnostics and integration of work processes. Common challenges included data shortages, bias in the algorithm, ethics and regulation, which indicated the need for appropriate guidelines and cross-disciplinary partnerships. Trends, however, included multi-modal data integration, increased automation and international convergence of standards. AI's benefits, advanced diagnostic accuracy, greater clinical predictability, and clinical processing efficiency are evidence of its ability to change the face of healthcare while removing significant barriers to its broader use.

Conclusion: AI can improve diagnostic processes in medicine by increasing their accuracy, improving their speed, and further adapting them to individual patients.

Key words. Automated diagnostics, clinical solutions, data processing, machine learning, personalized medicine.

Introduction.

Artificial Intelligence (AI) in recent years has become an important technological tool in a wide range of sectors, with healthcare ranked among the most promising application areas [1]. In particular, the use of AI in disease diagnosis has attracted significant interest over the past few years as it promises to change significantly how diseases are diagnosed, tracked and treated [2]. These days, AI systems can now use complex algorithms, machine learning, and neural networks to study large volumes of medical data, look for trends, and draw conclusions that ordinary methods of diagnosis could once only dream of [3]. The agreement between technology and medicine as they are viewed in the modern world is bound to change the future of healthcare, bringing more effectiveness, less time-consuming processes, and higher levels of diagnosis availability. AI in healthcare today spans diverse applications, aiding in disease diagnosis, patient outcome prediction, and personalized treatment planning in clinical settings [4].

Hybrid artificial intelligence systems demonstrate high potential for analyzing abnormal movement patterns (e.g., those associated with Parkinson's disease), utilizing neural networks to enhance diagnostic accuracy. By integrating multiple data sources (e.g., EEG signals and spiral drawings from graphics tablets) and improving interpretability, these systems effectively address critical barriers to patient-centered care [5]. Furthermore, it has been established that mathematical modelling and system identification techniques help address the challenges accompanying AI's application in medical diagnosis and the vast data set through efficient computational methods [6]. Additionally, forensic examinations solve unofficial infringements in the medical profession, including protecting human rights. These approaches emphasize the necessity of systematic methods and the legal environment in attaining desired standards in accuracy, precision, and ethics in medical diagnosis [7].

The use of AI in medical diagnostics can be accounted for its ability to analyze a large volume of data with speed and accuracy. Although conventional diagnostic practices are efficient, they are mostly dependent on the healthcare providers' skills and have a greater susceptibility to errors, biases, and diverse interpretations [8,9]. On the other hand, AI applications can examine medical scans, EHRs, and DNA information through molecular medicine at such a rate that enables them to detect illnesses when treatment is most likely to succeed. For instance, AI image processing tools have proven more reliable in radiology, pathology and oncology, where image recognition algorithms can identify several abnormalities, including tumours or fractured parts, with equal or even greater accuracy than human professionals [10,11]. AI in dermatology has advanced substantially in the sphere of skin cancer diagnosis, especially melanoma, in recent years. AI systems are now capable of being trained on images, including mole and skin lesion photographs and spotting signs of early melanoma. Such AI systems have demonstrated their ability to recognize malignant lesions with the same accuracy as competent dermatologists, which is an effective tool for treatment during the initial phases. Moreover, AI systems have displayed potential in distinguishing various forms of skin cancer which would help with better management of the disease [12,13].

Optimization algorithms have also contributed to enhancing how diabetic and skin diseases are handled. The ability of AI to analyze extensive databases permits the recognition of a number of skin conditions, such as eczema, psoriasis and acne, with the use of imaging and symptoms reported by patients. In this regard, AI systems can facilitate a timelier diagnosis of these skin conditions, thereby minimizing complications and enhancing treatment results. The application of AI technology in dermatology is expected to change the methods of diagnosis and treatment for these widespread diseases, increasing access to health services for patients in rural and urban areas [14].

The integration of genomic, imaging, and clinical data through robust multimodal deep learning models is extremely beneficial for precision oncology for melanoma, and it is expected that dermatology will be the most personalized any time soon. With the combination of a patient’s genetic makeup, imaging studies, and a detailed medical history, more precise treatment plans are feasible. To illustrate, AI systems provide predictions of the metastatic likelihood towards melanoma, and this helps clinicians customize the therapy to consider the provided tumour. This practice indicates a better approach to therapy, which is less aggressive during management and enhances the survival of melanoma patients [15,16].

AI also allows for the tailoring of treatment to each patient by interpreting the patient’s data to evaluate the treatment that would be the most beneficial and likely. Machine learning models can determine the existence of reliable biomarkers associated with risk or responses to treatment, which will lead to focused efforts toward the individual’s right to health [17,18]. AI can eliminate inequalities in health care provision, especially in less developed countries, by performing diagnostic procedures and providing telemedicine services [19]. Such a feature could level the medical care provision disparities in certain deprived parts of the world.

Regardless of its promising capabilities, the application of AI in medical diagnostics has some problems. One major problem is the quality and representativeness of the data used to train the AI models. Medical data are often fragmented, held in separate systems, and hidden under confidentiality protection, making aggregate databases challenging to obtain. Furthermore, there is bias in the training data. In that case, it may mean that AI models do not perform well across different populations of patients and, hence, may contribute to health inequities [20].

Another challenge is the opacity and interpretability of many AI models, including deep learning models [21]. Although they are widely successful in terms of performance, the excessive “black box” labeling makes it impossible for clinicians to gain insight into the decision-making processes. This interpretability crisis erodes confidence in AI systems, and many health care practitioners and patients are wary of suggestions that are not self-evident or rationalizing [22].

On the other hand, among the barriers, ethical and regulatory issues remain the most relevant barriers to AI technology implementation within the healthcare sector. AI is an innovative tool for medical professionals since its deployment is always bound by strict rules and frameworks to protect patients [23]. Concerns regarding data confidentiality, informed consent, and any resulting malpractice will need to be addressed to ensure that AI is utilized fairly. Another difficult but not impossible question is who is responsible when an AI-generated diagnosis results in an adverse effect [24,25]. Addressing these challenges requires cooperation from many actors, such as technology developers, healthcare providers, policymakers, and patients. The involvement of multiple disciplines is important to ensure not only that the AI systems are developed in the right way but also that they meet the expectations of the healthcare industry [26]. If AI systems are constructed with the input of practising clinicians, then these systems will be more readily applied clinically. Likewise, helping patients appreciate AI's benefits and the risks accompanying it might contribute to building trust in this technology [27]. Collaboration is also essential in formulating uniform guidelines for sharing and integrating data [28]. Efforts that enhance the compatibility of electronic health records systems and make it possible to share statistically anonymized medical information can effectively address data challenges while protecting patients' identities [29]. Moreover, international collaboration is crucial because AI systems that have access to worldwide data are more likely to work well in multiple populations and healthcare environments [30].

AI is likely to become a powerful tool in developing personalized medicine, combining genomic, proteomic, and metabolomic approaches to decipher the complex pathogenesis of diseases and devise tailored strategies. Drug development, especially targeting novel therapeutic areas such as rare genetic and some chronic diseases, is already facilitated through AI-enabled platforms for rapid drug discovery [31].

The use of AI is projected to optimize the efficiency of the healthcare system by taking over repetitive tasks like assessing patients and making diagnostic reports, among others. AI performance betterment improves not only the total output of healthcare but also the satisfaction of the patients since clinicians are now able to focus on complex cases and face patients more. Furthermore, the application of AI alongside technological advancements, such as robotics and augmented reality, might enable an effective diagnostic and treatment technique [32,33].

Developing AI is one thing, but the challenge is always taming it, scaling its opportunities while mitigating risks. In AI design, the bulk of crucial components such as being inclusive and accountable, such that the AI would up enhancing the whole of humanity. Also, education and training of people working in the healthcare sector needs to be adapted because they ought to be AI literate, so that they will understand and use the generated AI insights appropriately [34].

Policymakers have a significant task in facilitating an ecosystem in which Artificial Intelligence in medical diagnostics can flourish. This also includes developing policies that promote creativity without compromising the welfare of patients and putting resources in place that ensure that there is fairness in how the AI tools are utilized. Campaigns directed at the public can assist in substituting the mystique surrounding AI, encourage trust in its uses, and allow patients to be well-informed consumers of the healthcare services they seek [35,36]. The artificial intelligence revolution in medical services is an advancement that can change the manner in which healthcare is delivered and the results achieved. The issues of data quality, interpretability, regulation, and ethics are undoubtedly important, but they can be overcome [37].

This study aims to identify and analyze the geographical distribution and study designs of research on artificial intelligence (AI) applications in medical diagnostics. It seeks to categorize and evaluate the various types of AI and their specific applications across different medical fields while exploring and documenting the common challenges associated with AI implementation. Additionally, the study assesses the key outcomes and possibilities of AI in enhancing medical diagnostics.

Methodology.

Study Design:

A systematic review followed PRISMA guidelines to analyze AI in medical diagnostics. It focused on study characteristics, challenges, benefits, and outcomes through thematic synthesis for structured and reliable insights.

Search Strategy:

The systematic review adhered to the PRISMA framework, detailing the study selection process through a flow diagram, as shown in Figure 1. Overall, three databases yielded 18922 records, more specifically: IEEE Xplore 207, PubMed 615, and Google Scholar 18100. The keywords and Boolean operators ("Artificial Intelligence" OR "Machine Learning") AND ("Medical Diagnostics" OR "Precision Medicine") AND ("Challenges" OR "Possibilities") were selected through an iterative process. This process involved multiple rounds of expert consultation with specialists in artificial intelligence and medical diagnostics, ensuring that the search terms comprehensively covered relevant concepts, terminologies, and emerging areas in the field. Synonyms and related terms were systematically evaluated to maximize retrieval efficiency while minimizing irrelevant results. Google Scholar was included to broaden the scope of the review and capture a wide array of potentially relevant publications, particularly those not indexed in traditional databases such as conference proceedings and preprints. Although Google Scholar includes grey literature, rigorous filtering was applied to exclude non-peer-reviewed sources, aligning its use with PRISMA guidelines. This approach ensured a comprehensive yet curated dataset.

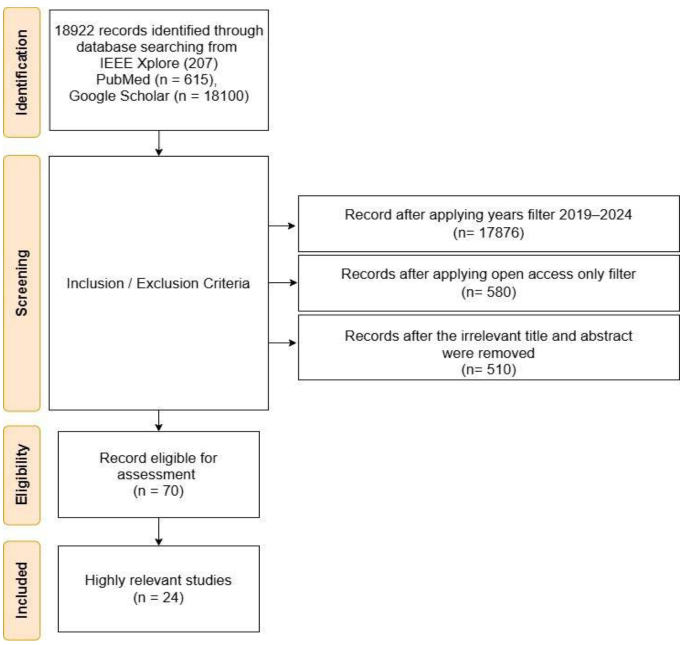

Figure 1. *PRIMSA Flow Diagram.*

After implementing a filter based on the year of the publication (2019-2024), the number of records decreased to 17876. Open access papers were then selected for further refinement, resulting in 580 records. Relevant publications were only included after reviewing the titles and the abstracts, a stage that excluded 510 records. After comprehensive eligibility checks, 70 records were selected for full-text review. Finally, a total of 24 [38-61] documents meeting the inclusion criteria of this systematic literature review were identified. Such an approach enabled the preparation of a coherent and comprehensive dataset for further analysis.

Inclusion and Exclusion Criteria:

The inclusion and exclusion criteria were formulated to enhance the quality and relevance of the studies included in the systematic review. Studies that dealt with artificial intelligence or machine learning were selected for medical diagnosis or medicine. Relevance criteria, such as "not sufficiently relevant," were clearly defined as studies that did not explicitly focus on AI's application in medical diagnostics, including those addressing unrelated topics or broader themes without a diagnostic emphasis. Lack of methodology was identified by the absence of critical details, such as study design, data collection methods, or analysis procedures, which are essential for assessing the reliability and validity of findings. Peer-reviewed journals and international conference proceedings were verified using indexing databases such as PubMed and IEEE Xplore. Such target intervention studies were published between 2019 and 2024 in peer-reviewed journals or international conference proceedings and written in English. Only articles with public access to the text were included.

The exclusion criteria comprised studies that did not pertain to medical diagnostics, any form of grey literature, editorials, or reviews devoid of original data. Also excluded were works written in foreign languages and those studies that were not sufficiently relevant or did not have a methodology. Such methodology permitted a filtering mechanism of studies considered extremely relevant to the study's problem.

Data Extraction:

The data extraction process was carried out in a consistent and structured manner through the use of a template. Such an approach aided in the comprehensiveness of all studies included in this review. Extracted variables included country, study design, AI type, medical field, challenges identified, primary benefits identified, possibilities identified, outcomes, key findings and implications. To ensure the accuracy of extracted variables, particularly qualitative data, two independent reviewers cross-checked each entry against the original study documents. Discrepancies between the reviewers were discussed and resolved through consensus meetings, ensuring the reliability of the data. Inter-rater reliability was calculated using Cohen's kappa to quantify agreement levels, with a threshold of ≥ 0.8 considered acceptable for consistency. This information included important information such as what AI model was used and what it was utilized for. It was possible to collect some of the main impediments, including data availability, ethics, the possibility of generalization, and legal constraints, while also including the major advantages and possibilities that AI has the potential to bring about, such as precision medicine, automation, and international cooperation. This systematic process furthered understanding of the patterns, gaps and trends of AI in medical diagnostics, which constituted the sound basis for thematic synthesis and further analysis.

Quality Assessment:

Table 1 provides a general overview of the quality appraisal of the included studies according to the study design, presenting the studies in consideration, the assessment tools used, quality scores, and quality levels. Multiple tools were used to ensure appropriate assessment across study designs: the CASP checklist for SLRs and NLRs, the Newcastle-Ottawa Scale (NOS) for observational studies, and the Cochrane Risk of Bias tool (RoB 2) for experimental studies. These tools were chosen for their established reliability and their ability to assess specific design-related criteria, such as methodological rigour, relevance, and bias. Scores were standardized to a 10-point scale for comparability. For instance, scores from the NOS (originally on a 9-point scale) were proportionally adjusted to fit the standardized scale. This approach ensured that studies of varying designs could be evaluated on a consistent quality benchmark. Studies scoring below 7 were excluded to maintain high quality. Systematic reviews scored between 8 and 10, indicating high to very high quality. Observational studies scored between 6 and 8, classified as moderate to high quality. One qualitative study scored 8, reflecting high quality. An experimental study scored 9, indicating very good quality. The scoring ranges were crucial in determining the inclusion or exclusion of studies, ensuring that only robust, reliable, and relevant research contributed to the systematic review. This structured appraisal strengthened the reliability and relevance of the dataset.

Data Synthesis:

Thematic synthesis categorized data into "applications," "challenges," and "opportunities." Applications included cancer diagnosis, tuberculosis detection, and multimodal integration in radiology and genomics [38-48,49-52]. Deep learning excelled in oncology and tuberculosis, while machine learning and explainable AI-enhanced interpretability in diagnostics [41,43,44,46,53-56,57-59,60]. Challenges encompassed data limitations, ethical concerns, computational complexity, integration barriers, and resource inequalities [38,43,44,46,47,50 ,52,54,60,61]. Opportunities highlighted multimodal integration for personalized treatments, early detection, automation, and regulatory advances [40-42,47,49,51,55-60]. AI reduced diagnostic errors, improved clinical workflows, and enabled tailored treatments in neurology and oncology [45,51,52,54,57]. Global collaboration, telemedicine integration, and innovation further underscored AI's transformative role [41,55,56,59,61]. These insights emphasized AI's ability to enhance precision diagnostics and patient care while addressing critical barriers to effective implementation.

Results.

The systematic literature review on the challenges and possibilities of using artificial intelligence in medical diagnostics analyzed 24 studies from diverse geographical and methodological contexts. Contributions came from leading AI research nations like the USA [47,55] and China [42,46,48,49,51,52,54], as well as European countries including Switzerland [50], Germany [60], Ireland [57], Italy [40], and Serbia [61]. Asian nations also played a significant role, with studies from South Korea [59], India [44,45], the UAE [38], and Ukraine [58]. Globally focused research [41] and contributions from Australia [39,43], Bulgaria [53] and Kuwait [56] further enhanced the analysis. Predominantly, SLRs synthesized existing knowledge to address both challenges, such as ethical concerns, data integration issues, and algorithmic inequity, and opportunities, including improved diagnostics, predictive modelling, and personalized treatment. Observational, experimental, and narrative studies enriched the findings, emphasizing AI's transformative potential while acknowledging barriers to its effective implementation.

The systematic review focused on the aforementioned artificial intelligence (AI) techniques developed in various fields of medicine, as shown in Table 3. For instance, stroke, orthopaedic and cancer conditions were diagnosed more accurately with the use of imaging, clinical, and genomic data by means of multimodal AI techniques [38,48,54,57,61]. Deep learning

Table 1. *Quality Assessment.*

Study Design	Studies	Tool	Quality Score	Quality Level
Systematic Literature Review (SLR)	Shurrab et al. 2024 [38], Tran et al. 2021 [39], Rompianesi et al. 2022 [40], Ahn et al. 2023 [41], Shao et al. 2023 [42], Rauschert et al. 2020 [43], Talyshinskii et al. 2024 [44], Kalani et al. 2024 [45], Huang et al. 2024 [46], Tian et al. 2023 [47]	*CASP	8-10/10	High to Very High
Narrative Literature Review (NLR)	Su et al. 2024 [48], Chen et al. 2021 [49], Patcas et al. 2022 [50] Liang et al. 2022 [51], Ma et al. 2024 [52], Uchikov et al. 2024 [53], Wang et al. 2023 [54], Chen 2024 [55], Abdallah et al. 2023 [56]	*CASP	7-8/10	Moderate to High
Observational	Muhammad et al. 2024 [57], Sheliemina 2024 [58], Al-Antari 2023 [59]	**NOS	6-8/9	Moderate to High
Qualitative	Pumplun et al. 2021 [60]	*CASP	8/10	High
Experimental	Tair et al. 2022 [61]	***RoB 2	9/10	High

***CASP:** *Critical Appraisal Skills Programme (CASP) Checklist, ** NOS: Newcastle-Ottawa Scale (NOS), *** RoB 2: Cochrane Risk of Bias (RoB 2)*

Table 2. *Studies on Challenges and Possibilities of AI in Medical Diagnostics.*

Author's / Year	Country	Study Design	Database
Sheliemina 2024 [58]	Ukraine	Observational	Google
Tian et al. 2023, [47] Chen et al. 2024 [55]	USA	SLR, NLR	Google
Shurrab et al. 2024 [38]	UAE	SLR	IEEE
Patcas et al. 2022 [50]	Switzerland	NLR	PubMed
Al-Antari et al. 2023 [59]	South Korea	Observational	Google
Tair et al. 2022 [61]	Serbia	Experimental	Google
Rompianesi et al. 2022 [40]	Italy	SLR	PubMed
Muhammad et al. 2024 [57]	Ireland	Observational	IEEE
Talyshinskii et al. 2024, [44] Kalani et al. 2024 [45]	India	SLR	PubMed
Pumplun et al. 2021 [60]	Germany	Qualitative	Google
Ahn et al. 2023 [41]	Global Perspective	SLR	PubMed
Shao et al. 2023 [42], Huang et al. 2024 [46], Su et al. 2024 [48], Chen et al. 2021 [49], Liang et al. 2022 [51], Ma et al. 2024 [52], Wang et al. 2023 [54]	China	NLR, SLR	IEEE, PubMed
Uchikov et al. 2024 [53]	Bulgaria	NLR	PubMed
Tran et al. 2021, [39] Rauschert et al. 2020 [43]	Australia	SLR	PubMed
Abdallah et al. 2023 [56]	Kuwait	NLR	Google

Table 3. *AI Types and Their Applications in Medical Fields.*

AI Type Group	Medical Field Group	Studies
Multimodal AI and Advanced Hybrid Models	Stroke, Orthopedics, Genitourinary cancers, Gastrointestinal cancer, Multimodal diagnostics	[38,48,54,57,61]
Deep Learning and Neural Networks	Oncology (various types), Facial diagnostics, Pulmonary tuberculosis, Bladder cancer	[39,40,42,47,49–52]
Machine Learning (ML) and Explainable AI (XAI)	Breast cancer, Epigenetics, Prostate cancer, Hepatocellular carcinoma, Rare Genetic Disorders	[41,43,44,46,56,57,59,60]
AI in Radiomics and Imaging	Oncology, Breast cancer, Pulmonary tuberculosis, Hepatocellular carcinoma, Imaging	[40,41,46,51,55]
General and Quantum AI	Diagnostic medicine, General diagnostics, Personalized medicine	[58–60]
Optimization Algorithms and AI	Breast Cancer, Diabetes, Erythemato-Squamous Disease Diagnostics	[61]

Table 4. *Common Challenges in the Application of Artificial Intelligence in Medical Diagnostics.*

Challenge Group	Common Challenges	Studies
Data Limitations and Standardization	Limited diversity, labeled datasets, standardization issues, imbalanced data, data quality, missing data, and high dimensionality (curse of dimensionality).	[38,43,44,46,48,52,54,60,61]
Generalizability and Validation	Generalizability issues, reliance on single-institution datasets, limited external validation, and challenges in low-resource settings.	[40,41,45,47,49,51,56]
Ethical, Legal, and Privacy Concerns	Ethical concerns, patient consent, data privacy, security, bias in algorithms, liability, and transparency.	[47,50,52,55,56,58–60]
Computational and Model Interpretability	High computational demands, lack of transparency (black-box models), limited interpretability, and the need for confidence measures in predictions.	[39,41,43,46,47,50,56–58]
Regulatory, Integration, and Workflow Issues	Regulatory needs, clinical integration challenges, and difficulty adapting AI into existing healthcare workflows.	[40,41,45,46,51,52,55,58,59]
Bias and Representation Issues	Bias in training data, inadequate representation of rare scenarios, imbalance in datasets, and lack of fairness.	[41,43,52–54,56,59]
Technological and Implementation Challenges	Need for multimodal integration, feature selection, hyperparameter optimization, and addressing complexity in multidimensional datasets.	[40,42,47,48,53,58,61]
Cost and Resource Constraints	High cost of implementation, lack of resources in low-income settings, and unequal access to AI technologies.	[40,51,56,58]

and neural networks dominated oncology, facial diagnostics, and tuberculosis detection, leveraging large datasets to identify complex patterns [39,40,42,47,49-52]. Machine learning and explainable AI were applied to breast cancer, epigenetics, and rare genetic disorders, offering interpretability in diagnostic recommendations [41,43,44,46,56,57,59,60]. Radiomics and imaging AI focused on oncology and imaging diagnostics, aiding early disease detection [40,41,46,51,55]. General AI and quantum computing addressed diagnostic and personalized medicine, demonstrating scalability [58-60]. Optimization algorithms improved efficiency in managing diabetes and skin diseases [61]. These findings underscore AI's adaptability and transformative potential in enhancing precision diagnostics, addressing diverse medical challenges, and improving clinical outcomes.

Table 4 identifies key challenges in applying AI to medical diagnostics, categorized into eight groups. Data limitations include issues with diversity, quality, imbalanced datasets, and dimensionality [38,43,44,46,48,52,54,60,61]. Generalizability remains problematic due to reliance on single-institution datasets and limited external validation [40,41,45,47,49,51,56]. Ethical concerns such as data privacy, security, algorithmic bias, and lack of transparency are prevalent [47,50,52,55,56,58-60]. Computational demands and the lack of interpretability in black-box models add to the complexity [39,41,43,46,47,50,56-58]. Integration challenges, regulatory barriers, and adapting workflows further hinder adoption [40,41,45,46,51,52,55,58,59]. Bias in training data and inadequate representation of rare scenarios exacerbate fairness issues [41,43,52-54,56,59]. Technological challenges like multimodal integration and hyperparameter optimization persist [40,42,47,48,53,58,61] alongside high costs and unequal resource access in low-income settings [40,51,56,58]. These challenges highlight the need for strategic solutions to enhance the effective integration of AI in healthcare.

Table 5 highlights the significant possibilities of artificial intelligence (AI) in medical diagnostics, categorized into nine groups. Multimodal integration and personalization are advancing through robust multimodal deep learning models, integrating genomic, imaging, and clinical data for personalized treatments and precision oncology [38-40,42,43,46,49]. Improved interpretability and transparency, achieved through explainable AI and tools like heatmaps, enhance clinician trust and model usability [47,48,50,54,57]. AI in precision and personalized medicine enables tailored treatments, efficacy assessments, and predictive treatment responses using genomic and clinical data [40-42,47,49,52]. AI also expands to new medical fields, such as neurology and oncology, aiding in predictive tasks like metastasis, disease progression, and recurrence [45,51,52,54,57].

Clinical workflow integration reduces physician workload, improves diagnostic decision-making, and fosters AI-professional collaboration [41,44,50,55,60]. AI's role in diagnostics and early detection includes improving diagnostic accuracy, disease marker identification, and non-invasive methods for early disease detection [40,43,46,51,58]. Automation and decision support use AI to automate tasks like segmentation and stratification, streamlining clinical processes [44,47,50,53,60]. Ethical, equity and regulatory advancements address regulatory needs, promote equity, explore ethical concerns, and establish frameworks for AI acceptance in healthcare [47,55,56,59,60]. Finally, collaboration and global

Table 5. *Potential Opportunities and Advancements of AI in Medical Diagnostics.*

Possibility Group	Common Possibilities	Studies
Multimodal Integration and Personalization	Development of robust multimodal deep learning models, integration of genomic, imaging, and clinical data for personalized treatment, multi-omic data for precision oncology.	[38–40,42,43,46,49]
Improved Interpretability and Transparency	Enhancing model transparency and interpretability (e.g., through explainable AI, heatmaps), improving clinician trust, and integrating better interpretability tools.	[47,48,50,54,57]
AI in Precision and Personalized Medicine	Use of AI in precision medicine, tailored treatments, personalized treatment efficacy assessments, integrating genomic and clinical data, predicting treatment responses.	[40–42,47,49,52]
Expansion to New Medical Fields and Diseases	Application of AI to new fields (neurology, oncology, respiratory diseases), predictive tasks like metastasis, recurrence, disease progression, and personalized treatment plans.	[45,51,52,54,57]
Clinical Workflow Integration	AI integration into clinical workflows, improving diagnostic and treatment decision-making, reducing physician workload, and enhancing collaboration between AI and healthcare professionals.	[41,44,50,55,60]
AI in Diagnostics and Early Detection	AI’s role in improving diagnostic accuracy, early disease detection, identifying disease markers, and advancing non-invasive diagnostic methods (e.g., genetic mutation prediction).	[40,43,46,51,58]
AI for Automation and Decision Support	Use of AI for automating tasks (e.g., segmentation, stratification), decision support, and streamlining clinical decision-making processes.	[44,47,50,53,60]
Ethics, Equity, and Regulatory Advancements	Addressing regulatory needs, promoting equity in healthcare, exploring ethical concerns, and establishing frameworks for AI integration in healthcare delivery and physician-patient acceptance.	[47,55,56,59,60]
Collaboration and Global Expansion	Enhancing global collaboration in AI research, standardization of AI tools, expanding AI into different datasets and cloud computing, integrating AI with telemedicine, and exploring new AI paradigms.	[41,55,56,59,61]

Table 6. Key Outcomes of AI Implementation in Medical Diagnostics.

Outcome Group	Key Outcomes	Studies
Accuracy and Performance Improvement	AI-based models demonstrate superior diagnostic accuracy in various tasks (e.g., cancer diagnosis, tumor detection, disease prediction), outperforming traditional methods and human experts.	[38,40–42,48,49,51,54]
AI in Diagnostic Automation	AI models automate diagnostic processes (e.g., prostate segmentation, lung cancer detection), improving efficiency and reducing physician workload.	[44,45,51–53]
Predictive Power and Personalized Treatment	AI models predict patient outcomes (e.g., survival, recurrence) and treatment responses, leading to more personalized treatment strategies and improved patient management.	[40,42,46,49,52]
Clinical Decision Support and Workload Reduction	AI aids in clinical decision-making, reducing diagnostic errors, speeding up interpretation, and easing clinician workloads, particularly in imaging and pathology.	[41,47,50,52,53]
Multi-modal Data Integration	Integration of various data types (e.g., imaging, genomics, epigenetics) significantly enhances diagnostic accuracy and disease classification, especially in complex conditions like cancer and TB.	[39,43,44,54,57]
AI in Early Detection and Risk Prediction	AI's role in early disease detection (e.g., aggressive cancers, lung diseases) is emphasized, allowing for earlier intervention and improved prognosis.	[41,42,47,53]
AI in Rare Diseases and Genetic Disorders	AI has transformative potential in diagnosing rare genetic disorders, improving precision medicine and streamlining clinic processes for better outcomes in specialized conditions.	[56,59,60]
Regulatory and Ethical Challenges	AI's integration requires careful consideration of regulatory frameworks, ethical issues, and data privacy, with the need for proper management to ensure safe and effective use in clinical practice.	[50,58,59]
Clinical Efficiency and Operational Impact	AI revolutionizes clinical practices by improving operational efficiency, streamlining workflows, and enhancing diagnostic processes in healthcare settings.	[55,60,61]

expansion foster global AI research, standardization of tools, integration with telemedicine, and exploration of innovative AI paradigms [41,55,56,59,61]. These possibilities emphasize AI's transformative potential in advancing medical diagnostics and healthcare delivery.

Table 6 highlights the key outcomes of artificial intelligence (AI) implementation in medical diagnostics, showcasing its transformative potential across various domains. AI-based models have demonstrated superior diagnostic accuracy in cancer diagnosis, tumour detection, and disease prediction, often outperforming traditional methods and human experts [38,40-42,48,49,51,54]. AI also automates diagnostic processes like prostate segmentation and lung cancer detection, significantly improving efficiency and reducing physician workload [44,45,51-53]. In predictive power and personalized treatment, AI enables tailored strategies by predicting patient outcomes, including survival and recurrence, thereby enhancing patient management [40,42,46,49,52]. AI aids clinical decision-making by reducing diagnostic errors, speeding up interpretations, and easing clinician workloads, especially in imaging and pathology [41,47,50,52,53]. Integrating multi-modal data, such as imaging, genomics, and epigenetics, improves diagnostic accuracy and disease classification in complex conditions like cancer and tuberculosis [39,43,44,54,57]. AI has also been instrumental in early detection and risk prediction for aggressive cancers and lung diseases, enabling earlier interventions and better prognoses [41,42,47,53]. In rare diseases and genetic disorders, AI streamlines precision medicine and enhances outcomes [56,59,60]. However, regulatory and ethical challenges, including data privacy concerns, emphasize the need for robust frameworks for safe integration into clinical practices [50,58,59]. Moreover, AI revolutionizes clinical workflows by improving operational efficiency and streamlining healthcare processes [55,60,61]. These outcomes underscore AI's ability to significantly redefine medical diagnostics and improve patient care.

Discussion.

The Current SLR provides a comprehensive overview of the 24 included studies, highlighting their global distribution, diverse study designs, and database utilization. The United States and China led in AI research, with notable contributions from Europe and Asia. Systematic and narrative literature reviews dominated the methodologies, supported by observational and experimental studies. The reliance on databases like Google, PubMed, and IEEE underscores the interdisciplinary nature of AI in medical diagnostics. Unlike previous research that broadly examines AI techniques, this review uniquely categorizes AI applications across medical specialities, such as oncology and neurology, while specifically highlighting the transformative potential of multimodal AI, deep learning, and explainable AI. Similarly, other literature shows that t reviews range from analyzing 180 to over 10,000 machine learning algorithms across different studies. For instance, one review examined 220 SLRs covering 10,462 machine-learning algorithms [62].

The Current SLR categorizes AI applications across medical fields, emphasizing the transformative potential of multimodal AI, deep learning, and machine learning models. Applications include cancer detection, genomic data integration, and imaging diagnostics. Explainable AI models addressed interpretability issues, while general AI and optimization algorithms demonstrated versatility. The findings highlight AI's adaptability in enhancing precision diagnostics and its scalability for broader healthcare applications, including rare diseases and general diagnostics. This review offers new insights by emphasizing explainable AI's role in addressing interpretability issues and showcasing AI's scalability for broader healthcare applications, such as rare diseases and general diagnostics. Similarly, other literature shows that common AI types include machine learning techniques such as neural networks, support vector machines (SVM), and random forests. These are frequently employed for tasks like disease prediction and diagnosis. The primary medical fields addressed include oncology and neurology, with significant applications also noted in cardiology and other specialities and highlight that oncology and neurology are particularly prevalent due to their impact on patient outcomes [63].

Furthermore, SLRs identify several challenges associated with the implementation of AI in medical diagnostics. Many studies lack robust validation processes, with only 53% reporting internal validation and less than 1% reporting external validation. This review highlights that key performance metrics, such as precision (missing in 44% of studies), sensitivity (72%), and specificity (75%), are often omitted, potentially due to inconsistent reporting standards and limitations in available data. Conversely, the potential benefits of AI in diagnostics include improved accuracy, efficiency in medical processes, and enhanced patient care through timely interventions [64]. Additionally, a study analyzed machine learning algorithms, primarily focusing on clinical prediction and disease prognosis in areas like oncology and neurology and found that AI and ML have demonstrated greater accuracy in predicting cancer than clinicians [65]. Furthermore, most studies employ various AI methodologies, including machine learning and deep learning, emphasising neural networks, support vector machines, and decision trees. Data sources for these studies often include medical imaging datasets and electronic health records, which are critical for training AI models [66].

The current systematic literature review (SLR) identifies significant challenges to implementing artificial intelligence (AI) in healthcare, including data limitations, generalizability issues, ethical concerns, and high computational demands. The lack of precision, sensitivity, and specificity metrics in many studies undermines the reliability and applicability of their results, creating barriers to adoption in clinical practice. Further impediments include disparities in the availability of resources, making incorporation of AI models into clinical practice more difficult due to the imposition of more regulatory hurdles and financial issues. Promoting healthy practices will promote strong frameworks, harmonization, and cooperation between all stakeholders involved to warrant disadvantaged inclusion and participation in healthcare systems that adopt AI elements. However, across many AI healthcare studies, this area has been reported to suffer from poor quality, which is the most pressing problem of interest. Methodological weaknesses, such as inadequate validation procedures and potential biases in data samples, were evident in several studies, limiting the robustness of their findings. For example, A survey examines AI bias, its sources, societal impacts, and mitigation strategies, emphasizing generative AI's unique challenges, ethical considerations, and interdisciplinary approaches for developing fair and unbiased AI systems [67]. Internal validation is 53%, and external 1% of the studies are reporting the usage of AI irrespective of inaccuracy, which is also key in AI implementation and adoption [68].

This does raise the question of the applicability and reliability of AI across countries. In addition, other concerns include insufficient characterization of the datasets that are used to create the models and any biases that arise when there is a large amount of missing data [69,70]. The practicality of incorporating AI in the scope of healthcare comes with hurdles, such as integration with functionality [71]. Also, patients' confidentiality and data protection ethics continue to be a concern [72]. Though neural networks are widely applied, they are not equally effective for all diseases and types of data [73]. Also, the absence of established norms for AI appraisal makes its appraisals even more complex [74]. These limitations collectively reduce the generalizability of the findings, emphasizing the need for larger, diverse datasets and improved validation methods to enhance trust in AI applications.

The current systematic literature review (SLR) reviews the role of AI in medical diagnostics with respect to advances in AI, such as multimodal integration, precision medicine, and early disease detection. Importantly, AI integrated into advanced diagnostics takes care of workflow automation, expansion to new medical specialities, and diagnostics itself. Based on more transparent medical models, enhanced trust among clinicians, and interdependence, AI applications are going to improve diagnosis and patient care processes completely. AI algorithms are very accurate in handling complex medical datasets, thereby minimizing the chances of human error. For example, AI decisively beats operators in the detection of breast cancer among mammograms and assists in other domains such as rapid burning and wound treatment assessment [75].

AI accelerates diagnosis after examining vast volumes of data - critical in a life-threatening situation [76]. There are advantages of AI tools for the doctor; these include inroads into previously rare diseases and merging strategies with EHR for timely decision-making [77]. Through tailored AI-powered medicine, drugs best suited for the individual patient based on their medical history are selected to achieve optimal intervention effects [78,79]. Not only that, AI can also fill in the gaps in remote requirements monitoring and future outpatient attendance needs in low-resource regions [80]. Nonetheless, there are still concerns. The challenges include costs, training and embedding with the existing systems and processes [81]. Ethical challenges regarding patient data confidentiality, absence of regulations and dependence on precise input data are also barriers [82,83]. So, overcoming these restrictions is essential for deploying the appropriate use of AI technology, which enhances patients' and clients' well-being and optimizes how healthcare services are delivered.

The current systematic literature review indicates the radical changes AI brings to health care, including improvement in accuracy, the extent of automation and predictive power. AI supports healthcare practitioners who integrate multi-modal data and face operational bottlenecks, especially in oncology, imaging and rare diseases. Furthermore, the capability of AI systems to identify patients with high-risk conditions at an early stage increases the chances of a better prognosis. At the same time, the need for multiple checks thereby makes automation significantly reduce the burden of work on physicians. Medical images, such as those associated with breast cancer, are analyzed with AI algorithms trained to identify delicate patterns with greater accuracy than radiology experts [84]. Machine learning approaches can model the course of the disease and the expected patient outcome, which helps the clinician identify potential complications and weigh the anticipated benefits during the treatment [85].

Diagnosis by automated systems provides for speed, while other innovations, like AID-SLR, allow for streamlining the work while achieving an accuracy rate of 98.04% for relevant studies, thus speeding up the research and decision-making [86]. According to AI, recommendations are based on evidence, which means that the clinician's cognitive effort is made easier, and confidence is boosted [87]. AI creates more time for healthcare providers by taking over the mundane tasks, and the focus shifts toward more complex cases and patients, resulting in higher job satisfaction [88]. On the other hand, there are some factors that impede AI usage, which include privacy concerns, cost of integration, fear of new technology and lack of skills training [89,90]. Tackling these challenges through systematic policies and education is crucial to ensure that AI can reach its full potential in improving diagnostic and patient management issues.

Limitations.

Several limitations of the present study should be noted. The focus of the author is on the literature written in English and published between 2019 and 2024, which may have excluded relevant publications in other languages and those published before the year 2019. Also, resources such as PubMed, IEEE Xplore and Google Scholar were required, and this may have resulted in the omission of some research that was absent from the databases. However, the limited range of peer-reviewed works provided some benefit in the quality of the review by limiting the scope, but it may also have meant that some recent or relevant works were not incorporated into the review. Furthermore, the construction was built mostly on the studies that were included, and though there were many of good quality, some studies were seen to be below standards in quality of reporting. Last but not least, the review raises general issues of trends and issues on the use of AI. However, the reader is not made clear on the role of various AI tools and what particular AI examples bring to the industry. It would be ideal if these gaps were tackled in subsequent studies as such would give a clearer perspective of the discipline.

Conclusion.

This systematic review assembles 24 high-quality studies to provide detailed information on the barriers, prospects, and results offered by the use of artificial intelligence in medical diagnostics. Besides providing a broad overview that depicts the interdisciplinary and cross-political boundaries of AI research and deployment, substantial adjustments still need ample attention.

The studies show that AI for medical diagnostics has gained global attention with notable contributions from the US, China, Germany and India. The wide variety of study designs and approaches employed, including systematic reviews, observational studies and experimental designs, explains the cross-disciplinary nature of the field. AI models have been applied across oncology precision medicine and diagnostics for rare diseases. These AI models include but are not limited to machine learning, deep learning, multimodal AI, and explainable AI. Deep learning is notable for tasks involving large data sets, while multimodal AI increases the accuracy of diagnosis using genomic, imaging and clinical. Explainable AI makes the decisions that AI has made understandable and trusted.

AI possesses immense possibilities in precision medicine, early detection, and workflow. Overall, it increases accuracy in diagnosis while alleviating the workload for the clinician, contributing to more personalised medical treatment. Some opportunities include using multimodal data, expanding into less-tapped areas, and telemedicine. For AI to be extensively applied across the world, especially in low-resource countries, there is a need for stronger global partnerships as well as standardization to mitigate arising inequalities in medical care.

Suggestions for Future Research.

Nonetheless, some issues remain, such as gaps in evidence and ethical and regulatory issues. These difficulties are further compounded by high implementation costs and limited resources, especially in poorer settings. Overcoming these barriers requires an operational framework through which fair, portable, and accountable AI-based solutions may be constructed. In the final analysis, it can be stated with firmness that AI indeed requires a fundamental shift in approaches, particularly with reference to medical diagnostics. If the existing problems are solved and the development is responsible, it will be allowed and contribute to our healthcare systems being more efficient and more universal worldwide.

There is an evident gap in the evidence on AI efficacy in medical diagnosis, which future studies should consider carrying out multicentre studies. Issues of ethics, such as bias in algorithms and patient confidentiality, also need to be considered more deeply. Creating affordable and easily usable AI models that have been adapted for low-resourced areas is key to helping level the global health imbalance. There is also a need to devise strong mechanisms through which AI can be used in practice with an emphasis on usability, interoperability and other end-user needs. Research into new domains that have so far been neglected, such as mental health and paediatrics, would ease the impact of the AI revolution. Collaborative initiatives should focus on various outreach activities and benchmarks in relation to the use of AI and integrate guidance on the regulation of AI to build trust and scale AI in a cost-effective manner.

REFERENCES

1. Secinaro S, Calandra D, Secinaro A, et al. The role of artificial intelligence in healthcare: a structured literature review. BMC Med Inform Decis Mak. 2021;21:1-23.

2. Panayides AS, Amini A, Filipovic ND, et al. AI in Medical Imaging Informatics: Current Challenges and Future Directions. IEEE J Biomed Health Inform. 2020;24:1837-57.

3. Qayyum MU, Sherani AMK, Khan M, et al. Revolutionizing Healthcare: The Transformative Impact of Artificial Intelligence in Medicine. BIN: Bulletin Of Informatics. 2023;1:71-83.
4. DuBois KN. DEEP MEDICINE: How Artificial Intelligence Can Make Healthcare Human Again. Perspectives on Science and Christian Faith. 2019;71:199.
5. Mudryk I, Petryk M. Hybrid artificial intelligence systems for complex neural network analysis of abnormal neurological movements with multiple cognitive signal nodes. Proceedings of the 2020 IEEE 3rd International Conference on Data Stream Mining and Processing, DSMP 2020. 2020:108-11.
6. Mykhaylo P, Tomasz G, Oleksander K. Methods mathematical modeling and identification of complex processes and systems on the basis of high-performance calculations. ELARTU. 2021:195.
7. Shevchuk O, Matyukhina N, Davydenko S, et al. Forensic examination in cases on the protection of human rights in the sphere of healthcare in Ukraine: legal issues. Juridical Tribune-Review of Comparative and International Law. 2022;12:552-65.
8. Dlamini Z, Skepu A, Kim N, et al. AI and precision oncology in clinical cancer genomics: From prevention to targeted cancer therapies-an outcomes based patient care. Inform Med Unlocked. 2022;31.
9. Shevchuk OM, Milash VV, Goncharenko GA, et al. Conflicts of interest in the healthcare sector: legal aspects. Wiadomosci Lek. 2023;76:2283-7.
10. Bi WL, Hosny A, Schabath MB, et al. Artificial intelligence in cancer imaging: Clinical challenges and applications. Ca. 2019;69:127.
11. Tsekhmister YV, Stepanenko VI, Konovalova T, et al. Analysis of Physicochemical Natures of Modern Artifacts in MRI. International Journal of Online and Biomedical Engineering (IJOE). 2022;18:89-100.
12. Melarkode N, Srinivasan K, Qaisar SM, et al. AI-Powered Diagnosis of Skin Cancer: A Contemporary Review, Open Challenges and Future Research Directions. Cancers (Basel). 2023;15:1183.
13. Patel RH, Foltz EA, Witkowski A, et al. Analysis of Artificial Intelligence-Based Approaches Applied to Non-Invasive Imaging for Early Detection of Melanoma: A Systematic Review. Cancers (Basel). 2023;15:4694.
14. De A, Sarda A, Gupta S, et al. Use of Artificial Intelligence in Dermatology. Indian J Dermatol. 2020;65:352.
15. Bhinder B, Gilvary C, Madhukar NS, et al. Artificial Intelligence in Cancer Research and Precision Medicine. Cancer Discov. 2021;11:900.
16. Dougherty SC, Flowers WL, Gaughan EM. Precision Oncology in Melanoma: Changing Practices. Journal of Nuclear Medicine. 2024;65:1838.
17. Hakami MA. Harnessing machine learning potential for personalised drug design and overcoming drug resistance. J Drug Target. 2024;32:918-930.
18. Shevchuk O, Matyukhina N, Babaieva O, et al. The human right to security in the implementation of the concept of the" right to health protection". Juridical Tribune Journal. 2021;11:535-548.
19. Nwankwo EI, Emeihe EV, Ajegbile MD, et al. Integrating Telemedicine and AI to Improve Healthcare Access in Rural Settings. International Journal of Life Science Research Archive. 2024;7:059-77.
20. Gangwal A, Ansari A, Ahmad I, et al. Current strategies to address data scarcity in artificial intelligence-based drug discovery: A comprehensive review. Comput Biol Med. 2024;179:108734.
21. Shevchuk O, Bululukov O, Lysodyed O, et al. Human right to virtual reality in the healthcare: legal issues and enforcement problems. Juridical Tribune. 2021;11.
22. Shevchuk O, Zui V, Maryniv I, et al. Human right to internet access in healthcare in the "Right to health Concept": legal issues. European Journal of Sustainable Development. 2021;10:286.
23. Beltempo L, Zerrer J, Härting RC, et al. Barriers of Artificial Intelligence in the Health Sector. Intelligent Systems Reference Library. 2023;229:251-273.
24. Magrabi F, Ammenwerth E, McNair JB, et al. Artificial Intelligence in Clinical Decision Support: Challenges for Evaluating AI and Practical Implications. Yearb Med Inform. 2019;28:128-134.
25. Mennella C, Maniscalco U, De Pietro G, et al. Ethical and regulatory challenges of AI technologies in healthcare: A narrative review. Heliyon. 2024;10:e26297.
26. Berikkhanova K, Taigulov E, Bokebaev Z, et al. Drug-loaded erythrocytes: Modern approaches for advanced drug delivery for clinical use. Heliyon. 2024;10:e23451.
27. Lin TH, Chung HY, Jian MJ, et al. An Advanced Machine Learning Model for a Web-Based Artificial Intelligence–Based Clinical Decision Support System Application: Model Development and Validation Study. J Med Internet Res. 2024;26:e56022.
28. Aldoseri A, Al-Khalifa KN, Hamouda AM. Re-Thinking Data Strategy and Integration for Artificial Intelligence: Concepts, Opportunities, and Challenges. Applied Sciences. 2023;13:7082.
29. Dove ES, Phillips M. Privacy Law, Data Sharing Policies, and Medical Data: A Comparative Perspective. Medical Data Privacy Handbook. 2015:639-78.
30. Juhn Y, Liu H. Artificial intelligence approaches using natural language processing to advance EHR-based clinical research. Journal of Allergy and Clinical Immunology. 2020;145:463-9.
31. Md Tajul Islam, Abdullah Al Hossain Newaz, Rakesh Paul, et al. AI-Driven Drug Repurposing: Uncovering Hidden Potentials of Established Medications for Rare Disease Treatment. Library Progress International. 2024;44:21949-65.
32. Rajpurkar P, Chen E, Banerjee O, et al. AI in health and medicine. Nat Med. 2022;28:31-38.
33. Maleki Varnosfaderani S, Forouzanfar M. The Role of AI in Hospitals and Clinics: Transforming Healthcare in the 21st Century. Bioengineering. 2024;11:337.
34. Singhal A, Neveditsin N, Tanveer H, et al. Toward Fairness, Accountability, Transparency, and Ethics in AI for Social Media and Health Care: Scoping Review. JMIR Med Inform. 2024;12:E50048.

35. Davenport T, Kalakota R. The potential for artificial intelligence in healthcare. Future Healthc J. 2019;6:94-98.
36. Olawade DB, David-Olawade AC, Wada OZ, et al. Artificial intelligence in healthcare delivery: Prospects and pitfalls. Journal of Medicine, Surgery, and Public Health. 2024;3:100108.
37. Bashkirova L, Kit I, Havryshchuk Y, et al. Comprehensive Review of Artificial Intelligence in Medical Diagnostics and Treatment: Challenges and Opportunities. Futurity Medicine. 2024;3.
38. Shurrab S, Guerra-Manzanares A, Magid A, et al. Multimodal Machine Learning for Stroke Prognosis and Diagnosis: A Systematic Review. IEEE J Biomed Health Inform. 2024.
39. Tran KA, Kondrashova O, Bradley A, et al. Deep learning in cancer diagnosis, prognosis and treatment selection. Genome Medicine. 2021;13:1-17.
40. Rompianesi G, Pegoraro F, Ivan Troisi R, et al. Artificial intelligence in the diagnosis and management of colorectal cancer liver metastases. World J Gastroenterol. 2022;28:108.
41. Ahn JS, Shin S, Yang SA, et al. Artificial Intelligence in Breast Cancer Diagnosis and Personalized Medicine. J Breast Cancer. 2023;26:405.
42. Shao J, Feng J, Li J, et al. Novel tools for early diagnosis and precision treatment based on artificial intelligence. Chinese Medical Journal Pulmonary and Critical Care Medicine. 2023;1:148.
43. Rauschert S, Raubenheimer K, Melton PE, et al. Machine learning and clinical epigenetics: a review of challenges for diagnosis and classification. Clin Epigenetics. 2020;12:51.
44. Talyshinskii A, Hameed BMZ, Ravinder PP, et al. Catalyzing Precision Medicine: Artificial Intelligence Advancements in Prostate Cancer Diagnosis and Management. Cancers (Basel). 2024;16:1809.
45. Kalani M, Anjankar A. Revolutionizing Neurology: The Role of Artificial Intelligence in Advancing Diagnosis and Treatment. Cureus. 2024;16:e61706.
46. Huang Y, Qian H. Advancing Hepatocellular Carcinoma Management Through Peritumoral Radiomics: Enhancing Diagnosis, Treatment, and Prognosis. J Hepatocell Carcinoma. 2024;11:2159.
47. Tian M, Shen Z, Wu X, et al. The Application of Artificial Intelligence in Medical Diagnostics: A New Frontier. Academic Journal of Science and Technology. 2023;8:57-61.
48. Su Z, Zhou Y, Zhou J, et al. BoneCLIP-XGBoost: A Multimodal Approach for Bone Fracture Diagnosis. IEEE Access 2024.
49. Chen ZH, Lin L, Wu CF, et al. Artificial intelligence for assisting cancer diagnosis and treatment in the era of precision medicine. Cancer Commun. 2021;41:1100.
50. Patcas R, Bornstein MM, Schätzle MA, et al. Artificial intelligence in medico-dental diagnostics of the face: a narrative review of opportunities and challenges. Clin Oral Investig. 2022;26:6871.
51. Liang S, Ma J, Wang G, et al. The Application of Artificial Intelligence in the Diagnosis and Drug Resistance Prediction of Pulmonary Tuberculosis. Front Med (Lausanne). 2022;9:935080.
52. Ma X, Zhang Q, He L, et al. Artificial intelligence application in the diagnosis and treatment of bladder cancer: advance, challenges, and opportunities. Front Oncol. 2024;14:1487676.
53. Uchikov P, Khalid U, Vankov N, et al. The Role of Artificial Intelligence in the Diagnosis and Treatment of Ulcerative Colitis. Diagnostics. 2024;14:1004.
54. Wang S, Wang S, Wang Z. A survey on multi-omics-based cancer diagnosis using machine learning with the potential application in gastrointestinal cancer. Front Med (Lausanne). 2023;9:1109365.
55. Chen X. AI in Healthcare: Revolutionizing Diagnosis and Treatment through Machine Learning. MZ Journal of Artificial Intelligence. 2024;1.
56. Abdallah S, Sharifa M, Almadhoun MKI, et al. The Impact of Artificial Intelligence on Optimizing Diagnosis and Treatment Plans for Rare Genetic Disorders. Cureus. 2023;15:e46860.
57. Muhammad D, Ahmed I, Ahmad MO, et al. Randomized Explainable Machine Learning Models for Efficient Medical Diagnosis. IEEE J Biomed Health Inform. 2024.
58. Sheliemina N. The Use of Artificial Intelligence in Medical Diagnostics: Opportunities, Prospects and Risks. Health Economics and Management Review. 2024;5:104-124.
59. Al-Antari MA. Artificial Intelligence for Medical Diagnostics—Existing and Future AI Technology! Diagnostics. 2023;13:688.
60. Pumplun L, Fecho M, Wahl N, et al. Adoption of machine learning systems for medical diagnostics in clinics: Qualitative interview study. J Med Internet Res. 2021;23:e29301.
61. Tair M, Bacanin N, Zivkovic M, et al. A Chaotic Oppositional Whale Optimisation Algorithm with Firefly Search for Medical Diagnostics. Computers, Materials & Continua. 2022;72:959-982.
62. Kolasa K, Admassu B, Hołownia-Voloskova M, et al. Systematic reviews of machine learning in healthcare: a literature review. Expert Rev Pharmacoecon Outcomes Res. 2024;24:63-115.
63. Soori M, Arezoo B, Dastres R. Artificial intelligence, machine learning and deep learning in advanced robotics, a review. Cognitive Robotics. 2023;3:54-70.
64. Kumar Y, Koul A, Singla R, et al. Artificial intelligence in disease diagnosis: a systematic literature review, synthesizing framework and future research agenda. J Ambient Intell Humaniz Comput. 2023;14:8459-86.
65. Zhang B, Shi H, Wang H. Machine Learning and AI in Cancer Prognosis, Prediction, and Treatment Selection: A Critical Approach. J Multidiscip Healthc. 2023;16:1779.
66. Sarker IH. Deep Learning: A Comprehensive Overview on Techniques, Taxonomy, Applications and Research Directions. SN Comput Sci. 2021;2:1-20.
67. Tavares S, Ferrara E. Fairness and Bias in Artificial Intelligence: A Brief Survey of Sources, Impacts, and Mitigation Strategies. Sci. 2024;6:3.
68. Youssef A, Pencina M, Thakur A, et al. External validation of AI models in health should be replaced with recurring local validation. Nat Med. 2023;29:2686-7.
69. Norori N, Hu Q, Aellen FM, et al. Addressing bias in big data and AI for health care: A call for open science. Patterns. 2021;2:100347.

70. Alwateer M, Atlam E-S, El-Raouf MMA, et al. Missing Data Imputation: A Comprehensive Review. Journal of Computer and Communications. 2024;12:53-75.
71. Bhagat S V, Kanyal D. Navigating the Future: The Transformative Impact of Artificial Intelligence on Hospital Management- A Comprehensive Review. Cureus. 2024;16:e54518.
72. Farhud DD, Zokaei S. Ethical Issues of Artificial Intelligence in Medicine and Healthcare. Iran J Public Health. 2021;50:i.
73. Sarker IH. Machine Learning: Algorithms, Real-World Applications and Research Directions. SN Comput Sci. 2021;2:1-21.
74. Alowais SA, Alghamdi SS, Alsuhebany N, et al. Revolutionizing healthcare: the role of artificial intelligence in clinical practice. BMC Medical Education. 2023;23:1-15.
75. Artificial Intelligence in Medical Diagnosis: Medical Diagnostics and AI n.d.2024. https://www.spectral-ai.com/blog/artificial-intelligence-in-medical-diagnosis-how-medical-diagnostics-are-improving-through-ai/
76. Kulkarni PA, Singh H. Artificial Intelligence in Clinical Diagnosis: Opportunities, Challenges, and Hype. JAMA. 2023;330:317-8.
77. Khalifa M, Albadawy M, Iqbal U. Advancing clinical decision support: The role of artificial intelligence across six domains. Computer Methods and Programs in Biomedicine Update. 2024;5:100142.
78. Schork NJ. Artificial Intelligence and Personalized Medicine. Cancer Treat Res. 2019;178:265.
79. Jake-Schoffman DE, Pires IM, Chandra Banik P, et al. Artificial Intelligence Solutions to Increase Medication Adherence in Patients With Non-communicable Diseases. Front Digit Health. 2021;3:669869.
80. Jiang L, Wu Z, Xu X, et al. Opportunities and challenges of artificial intelligence in the medical field: current application, emerging problems, and problem-solving strategies. Journal of International Medical Research. 2021;49.
81. Petersson L, Larsson I, Nygren JM, et al. Challenges to implementing artificial intelligence in healthcare: a qualitative interview study with healthcare leaders in Sweden. BMC Health Serv Res. 2022;22:1-16.
82. Mondal H, Mondal S. Ethical and social issues related to AI in healthcare. Methods in Microbiology. 2024;55:247-281.
83. Lysaght T, Lim HY, Xafis V, et al. AI-Assisted Decision-making in Healthcare: The Application of an Ethics Framework for Big Data in Health and Research. Asian Bioeth Rev. 2019;11:299-314.
84. da Silva HEC, Santos GNM, Leite AF, et al. The use of artificial intelligence tools in cancer detection compared to the traditional diagnostic imaging methods: An overview of the systematic reviews. PLoS One. 2023;18:e0292063.
85. Ahsan MM, Luna SA, Siddique Z. Machine-Learning-Based Disease Diagnosis: A Comprehensive Review. Healthcare. 2022;10:541.
86. Lee K, Datta S, Paek H, et al. AID-SLR: A Generative Artificial Intelligence-Driven Automated System for Systematic Literature Review. MedRxiv. 2024:2024.07.03.24309897.
87. Devi KJ, Alghamdi W, Divya N, et al. Artificial Intelligence in Healthcare: Diagnosis, Treatment, and Prediction. E3S Web of Conferences. 2023;399.
88. Yelne S, Chaudhary M, Dod K, et al. Harnessing the Power of AI: A Comprehensive Review of Its Impact and Challenges in Nursing Science and Healthcare. Cureus. 2023;15:e49252.
89. Imtiaz S, Jillani SAQ. The impact of artificial intelligence on medical diagnostics: A letter to the editor. J Pak Med Assoc. 2024;74:1035-6.
90. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. Nature Medicine. 2019;25:44-56.