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ЕЖЕМЕСЯЧНЫЙ НАУЧНЫЙ ЖУРНАЛ

Медицинские новости Грузии

საქართველოს სამედიცინო სიახლენი

GEORGIAN MEDICAL NEWS

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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.

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ARTIFICIAL INTELLIGENCE IN CLINICAL DIAGNOSTICS FOR EARLY DETECTION OF CHRONIC DISEASES: A SYSTEMATIC REVIEW

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Abstract.

Introduction: Early detection of chronic diseases is critical for reducing morbidity and alleviating the overall healthcare burden. Artificial intelligence (AI) has emerged as a promising tool for enhancing diagnostic accuracy, risk prediction, and clinical decision support. This review synthesizes recent evidence on AI-driven diagnostic systems across diverse chronic diseases.

Methods: A systematic review was conducted following the PRISMA guidelines. Peer-reviewed English-language studies published between January 2020 and November 2025 were retrieved from PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Embase.

Results: Thirty-two studies from 13 countries were included, with most originating from China, India, and Saudi Arabia. The studies examined metabolic/cardiometabolic conditions (20 studies), musculoskeletal disorders (3), pulmonary diseases (3), cancer/hematological conditions (3), neurodegenerative diseases (1), and ophthalmologic/dental conditions (2). Hybrid AI models were the most commonly used overall (56%), especially in metabolic diseases, followed by machine learning (25%) and deep learning (19%). Validation approaches included k-fold cross-validation, 80/20 train-test splits, electronic health record (EHR)-based validation, and external validation. Across subgroups, predictive performance was high, with AUC ranging from 0.7467 to 1.0, accuracy from 77.08% to 99.97%, sensitivity from 77% to 100%, and specificity from 59.2% to 100%.

Discussion: AI models, particularly hybrid approaches, demonstrate potential for early detection of chronic diseases by integrating laboratory, clinical, and imaging-based multimodal data. However, heterogeneity in datasets, retrospective study designs, limited external validation, and inconsistent reporting constrain generalizability. These findings highlight the need for prospective multicenter trials, standardized datasets, and improved methodological transparency to support clinical implementation.

Key words. Machine learning, deep learning, Artificial intelligence, chronic diseases, early detection, diagnostic accuracy.

Introduction.

It is crucial to identify and manage long-term conditions in the field of global health. The burden of noncommunicable diseases such as diabetes, heart disease, chronic respiratory disease, and some cancers, continue to put major pressure on the world's health care systems due to the high levels of morbidity and mortality associated with these conditions [1,2]. Increased disease progression resulting in more advanced disease presentation, missed treatment opportunities, and associated higher costs are caused by referrals' accessibility issues and delays in diagnosis [3,4]. The use of advanced digital technologies like Artificial Intelligence (AI) may facilitate rapid, remote, and flexible access to diagnostic screening for early disease detection [5,6]. Machine Learning (ML), one of the most significant branches of AI, helps improve the diagnosis, treatment, and prognosis of precision medicine by assimilating clinical data from specific subpopulations [7].

Different methods include traditional machine learning (ML) methods, as well as modern deep learning (DL) frameworks combined with large language models (LLMs) for use in clinical applications [8,9]. Within healthcare, large language models are applied to analyze clinical documentation, medical imaging, wearable sensor data, and electronic health records. AI has the potential to detect patterns that the human eye is unable to see, which could lead to identifying diseases at an earlier stage and at a lower cost. This is not only more efficient, but also more effective [10,11]. Recent studies show that prediction of disease progression, treatment optimization, and mortality reduction, ML and DL algorithms across various fields such as radiology, pathology, cardiology, oncology, and infectious diseases have very high diagnostic accuracy. For early detection and personalized diagnosis, advanced models involve transfer learning and optimized CNNs, especially EfficientNet-B2 and VER-Net, which have performed exceptionally [12,13].

Although there have been several advancements, there remain inconsistencies, difficulties, and due to data heterogeneity, a lack of consistent backward validation and limited prospective assessment, generalization across clinical contexts is challenging. These gaps between available knowledge, AI model performance, and diagnostic accuracy introduce complications in synthesizing evidence and limit confidence in applying these systems across diverse populations. Remaining challenges include the ethics and operations of data confidentiality and algorithmic bias, along with clinical adaptation and transparency [14,15]. Thus, systematic assessments using

proven methodological approaches are crucial for obtaining a readiness for clinical implementation, as well as for directing future research.

AI's potential and challenges for early detection can be illustrated best by dermatology. Image-based AI systems trained on dermoscopic and clinical photos perform well for skin lesion classification, and recent studies can differentiate scalp psoriasis from seborrheic dermatitis with accuracy comparable to a dermatologist [16,17]. The integration of smartphone-connected dermatoscopes and point-of-care imaging, coupled with deep learning, has the potential to enhance early triage in primary care and telehealth contexts. However, there is a need for meticulous evaluation of the datasets across various types of dermatoscopic images and skin types [18]. LLMs give real-time decision support and triage by fusing various free-text clinical notes. While these analysis methods are quite promising, robust domain-specific validation can be very helpful for other issues like model hallucinations, oversimplification, and safety concerns [19]. The integration of multimodal AI techniques shows the ability of these technologies to work together. However, in order to integrate these technologies to the clinic safely, validation and responsible deployment of these approaches is needed

Aim.

To systematically review and summarize the use of AI approaches, including ML, DL, and hybrid models, for early detection of diverse chronic diseases in clinical diagnostics.

Research Question.

What is the current evidence (2020-2025) on the diagnostic accuracy, predictive performance, and clinical applicability of AI methods for early detection of diverse chronic diseases across metabolic/cardiometabolic, musculoskeletal, pulmonary, cancer/hematological, neurodegenerative, and ophthalmologic/dental subgroups?

PICO framework.

Figure 1 presents the PICO framework, which systematically structures this study by defining the population as individuals with, or at risk of, diverse chronic diseases; the intervention as AI-based diagnostic approaches, including ML, DL, and hybrid models; no comparator, as this review focuses exclusively on AI performance; and the outcomes as early disease detection, diagnostic accuracy, predictive capability, and clinical readiness for clinical deployment.

Methodology.

Study design: A systematic review was conducted on studies published from 2020 to 2025.

Eligibility criteria: Studies published between 2020 and 2025 in English and reporting clinical or validation data on AI-based diagnostic models were considered eligible. Preprints, non-peer-reviewed articles, and studies lacking clear methodology or clinical diagnostic data were excluded.

Information sources: A systematic search was performed across multiple electronic databases, including PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Embase. Reference lists of included studies were also screened to identify additional relevant articles. Grey literature, organizational websites, and trial registers were not consulted. All searches were last conducted on 29 November 2025.

Search strategy: A comprehensive search strategy was conducted in PubMed/MEDLINE, Scopus, Web of Science, IEEE Xplore, and Embase using Boolean operators and keywords, including ("Artificial Intelligence" OR AI OR "Machine Learning" OR "Deep Learning" OR "Neural Networks" OR "Natural Language Processing") AND ("Clinical Diagnostics" OR Diagnosis OR "Clinical Decision Support Systems") AND ("Early Detection" OR "Early Diagnosis" OR "Predictive Analytics" OR "Risk Prediction") AND ("Chronic Diseases" OR "Chronic Disease"). Only peer-reviewed English-language studies reporting clinical or validation data between 2020 and 2025 were included.

Selection process: Study selection followed a structured, bias-minimizing procedure. Duplicates were removed using Microsoft Excel. Two reviewers independently screened titles and abstracts against inclusion/exclusion criteria. Disagreements were resolved through discussion, with a third reviewer consulted when necessary. Full-text articles were then independently assessed by the same reviewers.

Inter-rater agreement showed high consistency with Cohen's Kappa: $\kappa = 0.82$ for title/abstract screening and $\kappa = 0.87$ for

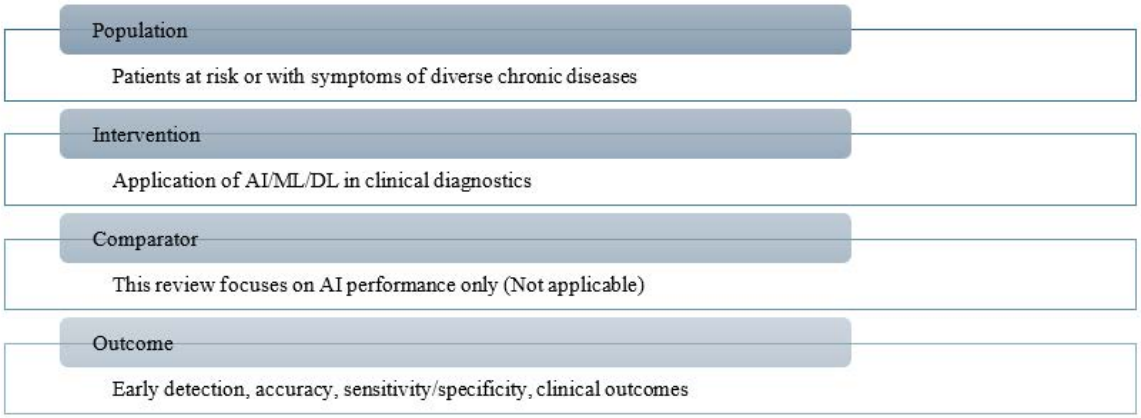

Figure 1. *PICO framework.*

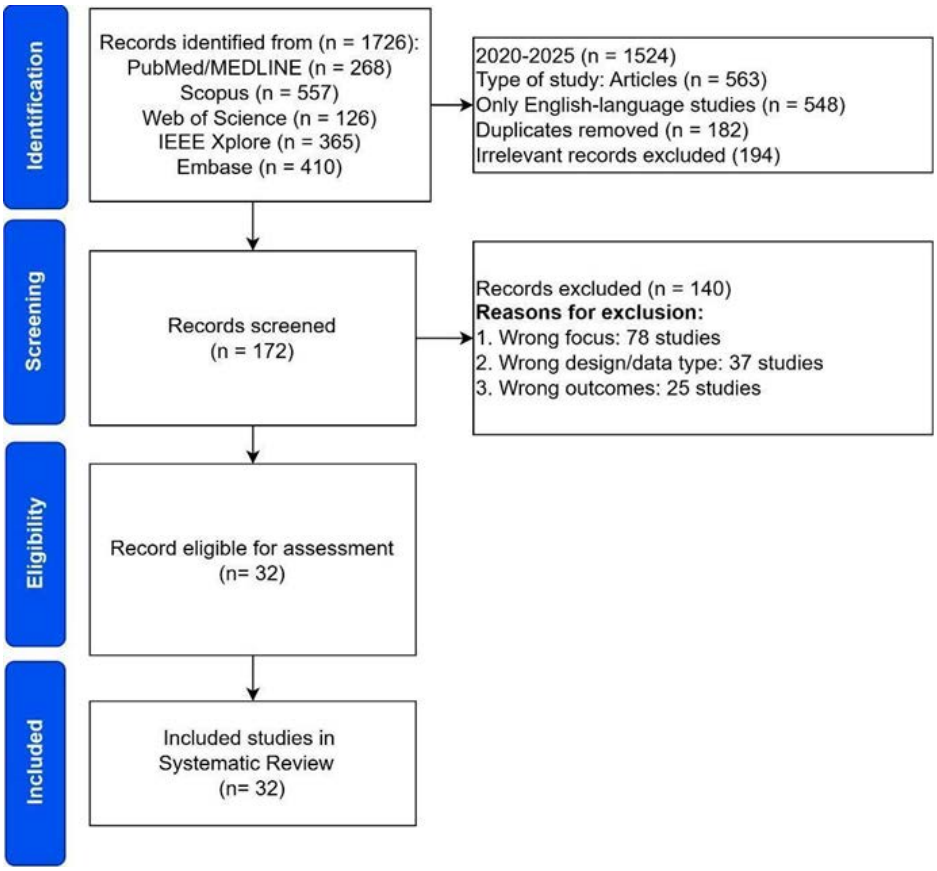

Figure 2. *PRISMA flow diagram.*

full text review. Just 6% of the decisions were referred to the third reviewer. No automation was used in any of the screening stages. Finally, 32 full text studies [20–51] were added as illustrated in Figure 2.

Data extraction: A standardized Excel spreadsheet was utilized and the following fields were recorded: author(s), year, country, chronic condition studied, type of AI used (ML, DL, hybrid), sample size, study design, type of validation, AI model, performance metrics (AUC, accuracy, sensitivity, specificity, precision, F1-score), predictive capability, and clinical readiness.

To confirm the consistency, clarity, and completeness of the extraction form, it was pilot-tested on five randomly selected studies. Authors were emailed when key model metrics or details about the validation were unaccounted for. When authors were unresponsive, absence of data was noted. For studies with multiple models or outcomes, all pertinent outcomes were retrieved.

Quality assessment: Table 1 summarizes the QUADAS-2 assessment. Most studies showed low risk of bias across patient selection, index test, reference standard, and flow & timing, except for a few instances of moderate or high risk [25,31,42]. Most studies employed suitable methodology, although some shortcomings presented possible bias that could compromise the accuracy of the studies.

Table 2 presents PROBAST assessment of prediction model studies. Most models had low risk of bias in participants, predictors, outcomes, and analysis domains. Some studies had high or unclear risk, particularly in predictors [22,35], analysis [30,44], and participants [29,47]. These findings indicate that while included models are generally of good quality, methodological limitations in certain studies could affect the depth and scope of their conclusions.

Results.

A comprehensive literature search revealed 1,726 publications from various databases, which include: 268 from PubMed/ MEDLINE, 557 from Scopus, 126 from Web of Science, 365 from IEEE Xplore, and 410 from Embase. 1,524 publications were released within the 2020-2025 timeframe illustrating an increasing interest in the AI-based diagnostic models. Following the removal of duplicates 182 publications, 366 publications were left for preliminary screening. During the title and abstract review 194 studies were excluded and 172 records remained. Of the 172 records, 140 were excluded for inappropriate focus 78, study design or data type 37, and outcome measures 25, which left 32 full-text articles for inclusion, as shown in Figure 2. Analysis of these studies revealed several notable patterns. Most studies were published in 2024-2025, indicating a recent increase in volume of published research. DL techniques were more often used than traditional ML methods, especially in diagnostic applications employing images. While other diagnostic areas were underserved, chronic disease, especially dermatological and heart diseases, were most often studied. Study sizes differed greatly, with larger studies usually describing better performance metrics. This suggests a possible connection between study size and the reported accuracy of

Table 1. *Quality Assessment of Included Diagnostic Accuracy Studies Using QUADAS-2.*

Author & Year	Risk of Bias				Applicability Concerns		
	Patient Selection	Index Test	Reference Standard	Flow & Timing	Patient Selection	Index Test	Reference Standard
Chen et al. 2025 [20]	Low	Low	Low	Low	Low	Unclear	Low
Ali 2025 [25]	Low	Low	Low	High	Low	Low	Low
Javed et al. 2025 [26]	Low	Unclear	Low	Low	Low	Low	Low
Rimaru et al. 2024 [31]	Low	Low	Low	Low	Low	Low	High
Lan et al. 2024 [32]	Low	Low	Low	Unclear	Low	Low	Low
Raje et al. 2024 [33]	Low	Low	Low	Low	Low	Low	Low
Chen et al. 2024 [37]	Unclear	Low	Low	Low	Low	Low	Low
Khalid et al. 2023[40]	Low	Low	Low	Low	Low	Unclear	Low
Uppamma et al. 2023 [41]	Low	Low	Low	Low	Low	Low	Low
Alsubai 2023 [42]	High	Unclear	Low	Low	Low	Low	Low
Aurangzeb et al. 2023 [43]	Low	Low	Low	Low	Low	Low	Unclear
Mondal et al. 2021[50]	Low	Low	High	Low	Low	Low	Low
Chen et al. 2020 [51]	Low	Low	Low	Low	Low	Low	Low

Table 2. *Quality Assessment of Prediction Model Studies Using PROBAST.*

Author & Year	Participants	Predictors	Outcomes	Analysis	Overall
Nie et al. 2025 [21]	Low	Low	Low	Low	Low
Alomari 2025 [22]	Unclear	High	Low	Low	Low
Xhaferra et al. 2025 [23]	Low	Low	Low	Low	Low
Sinha et al. 2025 [24]	Low	Low	Low	Unclear	Low
Li et al. 2024 [27]	Low	Low	Low	Low	Low
Nagle et al. 2024 [28]	Low	Low	Low	Low	Low
Oladimeji et al. 2024 [29]	High	Low	Low	Low	Low
ALGHAMDI et al. 2024 [30]	Low	Low	Low	High	Low
Al-Shanableh et al. 2024 [34]	Low	Low	Low	Low	Low
Vaiyapuri et al. 2024 [35]	Low	Unclear	Low	Unclear	Low
Sheta et al. 2024 [36]	Low	Low	Low	Low	Low
Abnoosian et al. 2023 [38]	Low	Low	Unclear	Low	Low
Nilashi et al. 2023 [39]	High	Low	Low	Low	Low
Onur Sevli 2023 [44]	Low	Unclear	Low	High	Low
Islam et al. 2023 [45]	Low	Low	Low	Low	Low
Ikechukwu et al. 2022 [46]	Low	Low	Low	Low	Low
Miriyala et al. 2022 [47]	High	Low	Low	Low	Low
Elseddawy et al. 2022 [48]	Low	Low	Low	Low	Low
Yang et al. 2021 [49]	Low	Unclear	Low	Low	Low

the diagnosis. Furthermore, prospective studies more often included external validation, while retrospective studies more frequently used internal validation. This shows a positive difference in methodological robustness. The emerging trends make it easier to understand the rapidly changing role of AI in clinical diagnostics, and help to make sense of the varied model performance analyses in the studies reviewed.

Table 3 presents the characteristics of the included studies. A total of 32 studies published between 2020 and 2025 were analyzed. These studies originated from China, USA, India, Saudi Arabia, Egypt, Pakistan, Nigeria, UK, Jordan, Turkey, Iraq, Malaysia, and Bangladesh. The studies addressed a wide range of chronic diseases, including all forms of diabetes (T1 and T2), heart disease, chronic kidney disease, lung cancer, osteoarthritis, chronic obstructive pulmonary disease (COPD), cardiovascular diseases, Alzheimer's disease, diabetic retinopathy, glaucoma, leukemia, pulmonary emphysema, and tooth caries. Although all included conditions are classified as chronic diseases, they represent diverse clinical domains and diagnostic approaches, including laboratory-based, clinical, and imaging-based assessments. Sample sizes varied considerably, ranging from 19 to 1,500,000 participants.

Diabetes and related metabolic and cardiometabolic disorders were the most mentioned in the included studies (20). A few other categories of diseases were noted: musculoskeletal and joint diseases (3), pulmonary diseases (3), cancer/hematological diseases (3), neurodegenerative diseases (1), ophthalmologic and dental diseases (2).

The reported AI techniques were classified as ML, DL, and hybrid models. The ML strategies utilized were RF, SVM, DT, KNN, LR, Naïve Bayes, XGBoost, ANN, GB, and AdaBoost. DL methods included CNNs, Fully Connected Neural Networks, ResNet, U-Net, Autoencoders, GANs, and ColonSegNet. Hybrid models integrate various AI techniques, including neural architectures, genetic algorithms, and ensemble techniques. Validation strategies included k-fold cross-validation, 3-fold,

Table 3. *Characteristics of included studies.*

Subgroup	Author & Year	Country	Chronic Disease	AI Technique	Sample Size	Study Design	Validation Type
Metabolic Diseases	Nie et al. 2025 [21]	USA	Diabetes	Deep Learning (FCNN)	9329	Retrospective	External validation
	Xhaferra et al. 2025 [23]	North Macedonia	Diabetes	ML (DT, LR, RF, SVM)	4600	Retrospective	3-fold CV
	Li et al. 2024 [27]	China	Diabetes	Hybrid (GA-XGBoost)	438693	Retrospective	5-fold CV
	Alomari 2025 [22]	USA	Heart Disease, Diabetes	Hybrid (GPT-4o, GPT-4o-mini)	3065	Retrospective	Cross-validation
	Nagle et al. 2024 [28]	India	Diabetes, Cardiac Arrest	Hybrid (M-GWO, Stacking)	997	Retrospective	Cross-validation
	Oladimeji et al. 2024 [29]	Nigeria	Diabetes	ML (KNN, J48, Naïve Bayes, RF)	520	Retrospective	10-fold CV
	ALGHAMDI et al. 2024 [30]	Saudi Arabia	Heart Failure, CVD	Hybrid (SVM, kNN, LR, RF, ANN, XGBoost)	299	Retrospective	Cross-validation
	Rimaru et al. 2024 [31]	UK	Diabetic Retinopathy	Deep Learning (CNN)	3662	Retrospective	K-fold CV
	Al-Shanableh et al. 2024 [34]	Jordan	Diabetes Mellitus (T1 & T2)	Hybrid (Ensemble)	500000	Retrospective	10-fold CV
	Vaiyapuri et al. 2024 [35]	Saudi Arabia	Diabetes	Hybrid (ABiGRU, POA)	768	Retrospective	Cross-validation
	Sheta et al. 2024 [36]	USA	Diabetes Mellitus (T1 & T2)	ML (RF, KNN, DT, SVM, GB, ANN)	768	Retrospective	Cross-validatio
	Abnoosian et al. 2023 [38]	Iraq	Diabetes	Hybrid (Ensemble)	1000	Retrospective	K-fold CV
	Nilashi et al. 2023 [39]	Malaysia	Diabetes Mellitus (T2)	Hybrid (DBN, SVD, SOM)	768	Retrospective	5-fold CV
	Uppamma et al. 2023 [41]	India	Diabetic Retinopathy	Hybrid (SqueezeNet, AVO)	516	Retrospective	EHR management
	Onur Sevli 2023 [44]	Turkey	Diabetes Mellitus (T2)	ML (SVM, LR, KNN, RF, AdaBoost)	768	Retrospective	5-fold CV
	Miriyala et al. 2022 [47]	India	Diabetes Mellitus (T2)	ML (Naïve Bayes, KNN, RF, LR, DT, XGBoost)	768	Retrospective	5-fold CV
	Elseddawy et al. 2022 [48]	Egypt	Diabetes Mellitus (T2)	ML (ANN, SVM, RF, DT)	768	Retrospective	10-fold CV
	Yang et al. 2021 [49]	China	CKD, Hypertension, Diabetes	ML (XGBoost, LR, DT, SVM, RF)	42256	Retrospective	10-fold CV
	Chen et al. 2020 [51]	China	Chronic Kidney Disease	Hybrid (AHDCNN, CNN)	100	Retrospective	Cross-validation
	Islam et al. 2023 [45]	Bangladesh	Chronic Kidney Disease	ML (XGBoost, RF, KNN, DT)	400	Retrospective	10-fold CV
Musculoskeletal / Joint Diseases	Ali 2025 [25]	Egypt	Osteoarthritis (OA)	Deep Learning (CNN)	8260	Retrospective	Cross-validation
	Chen et al. 2024 [37]	Canada	Osteoarthritis	Deep Learning (CNN, RF, XGBoost)	782	Retrospective	Cross-validation
	Khalid et al. 2023 [40]	Saudi Arabia	Knee Osteoarthritis	Hybrid (CNN, FFNN, PCA)	11436	Retrospective	Cross-validatio
Pulmonary Diseases	Sinha et al. 2025 [24]	India	COPD	ML (RF, MLP, LR, XGBoost)	7199	Retrospective	K-fold CV
	Raje et al. 2024 [33]	India	COPD	Hybrid (CNN, Autoencoders, GANs)	5863	Retrospective	10-fold CV
	Mondal et al. 2021 [50]	India	COPD	Hybrid (FRCNN, ALTP, RDA)	19	Retrospective	Cross-validation
Cancer / Hematological Diseases	Chen et al. 2025 [20]	China	Lung Cancer	Hybrid (DQN, RF, XGBoost, SVM, DNN)	1.5M	Retrospective	10-fold CV
	Lan et al. 2024 [32]	China	Lung Cancer	ML (RF, SVM, DT)	276	Retrospective	80/20 split
	Ikechukwu et al. 2022 [46]	India	Leukemia (ALL)	Deep Learning (CNN, ResNet-50, VGG-19, i-Net)	3202	Retrospective	Cross-validation
Neurodegenerative Diseases	Javed et al. 2025 [26]	Pakistan	Alzheimer's Disease	Deep Learning (ResNet-101, U-Net)	6,400	Retrospective	80/20 split
Ophthalmic / Dental	Alsubai 2023 [42]	Saudi Arabia	Tooth Caries	Hybrid (Ensemble, XGBoost, RF, Extra Trees, PCA, Chi-Square)	10375	Retrospective	5-fold CV
	Aurangzeb et al. 2023 [43]	Saudi Arabia	Glaucoma, DR	Hybrid (Deep Learning, ColonSegNet)	189	Retrospective	Cross-validation

Table 4. *Diagnostic performance of AI models for early detection of chronic diseases.*

Subgroup	Author & Year	AI Model	Metrics	Predictive Capability	Clinical Readiness Level
Metabolic Diseases	Nie et al. 2025 [21]	FCNN	AUC: 0.9399 (Training), 0.9601 (Testing), Accuracy: 93.21%	Predicts diabetes risk	Web-based tool for self-assessment
	Xhaferra et al. 2025 [23]	Decision Tree, LR, RF, SVM	Accuracy: 99.97% (IoT), 59.2% (Lab Data)	Real-time diabetes prediction	IoT systems for clinical adoption
	Li et al. 2024 [27]	GA-XGBoost (Stacking Ensemble)	AUC: 98.9%, Accuracy: 94.86%, F1-Score: 95.82%	Diabetes risk prediction	High, clinical decision support
	Alomari 2025 [22]	GPT-4o, GPT-4o-mini	Accuracy: 77.08% (PIDD), 85.52% (Heart Disease)	Predicts chronic diseases	Clinical decision support ready
	Nagle et al. 2024 [28]	M-GWO, Stacking (SVM, RF, DT, MLP, KNN)	Accuracy: 99%, F1-Score: 99.16%, Sensitivity: 99%	Silent heart attack prediction	High, real-time health data prediction
	Oladimeji et al. 2024 [29]	RF, Naïve Bayes, KNN, J48	Accuracy: 98.3%, Sensitivity: 99%, Specificity: 98%	Diabetes prediction	High, early detection in remote areas
	ALGHAMDI et al. 2024 [30]	AutoML (XGBoost, RF, SVM, kNN, LR, ANN)	Accuracy: 88%, XGBoost: 82.22%	Heart failure risk prediction	High, clinical heart failure detection
	Rimaru et al. 2024 [31]	CNN, MobileNetV3	Accuracy: 96.72%, Sensitivity: 97%, Specificity: 96%	Diabetic retinopathy classification	High, mobile app for DR detection
	Al-Shanableh et al. 2024 [34]	Stacking Ensemble	Accuracy: 99.94%, Sensitivity: 99.88%, Specificity: 99.88%	Diabetes presence and complications prediction	High, integration into healthcare systems
	Vaiyapuri et al. 2024 [35]	ABiGRU (Bidirectional GRU)	Accuracy: 97.14%, Precision: 97.27%, Recall: 96.41%	Diabetes prediction	High, IoT real-time monitoring
	Sheta et al. 2024 [36]	RF, SVM, KNN, DT, GB, ANN	Accuracy: 94.5% (RF), F1-Score: 0.79	Diabetes presence and stages prediction	High, healthcare systems deployment
	Abnoosian et al. 2023 [38]	k-NN, SVM, DT, RF, AdaBoost, Naive Bayes	Accuracy: 98.87%, AUC: 1.0	Diabetes, prediabetes prediction	High, clinical use for early intervention
	Nilashi et al. 2023 [39]	DBN, SOM, SVD	Accuracy: 98.32%, Sensitivity: 97.91%, Specificity: 98.05%	Diabetes classification	High, potential in diagnostic tools
	Uppamma et al. 2023 [41]	SqueezeNet + AVO	Accuracy: 94.2%, Sensitivity: 94.8%, Specificity: 93.4%	Diabetic retinopathy prediction	High, clinical use with secure EHR management
	Onur Sevli 2023 [44]	RF (IHT under-sampling), GB, AdaBoost	Accuracy: 96.29%, F1-Score: 96.22%, AUC: 96.29%	Diabetes risk prediction	High, healthcare systems for early detection
	Miriyala et al. 2022 [47]	XGBoost, RF, DT, KNN, LR, Naïve Bayes	Accuracy: 88.2%, AUC: 0.95	Diabetes mellitus prediction	High, clinical decision support
	Elseddawy et al. 2022 [48]	ANN, SVM, RF, DT	Accuracy: 92.2%, Sensitivity: 84.5%, AUC: 0.89	Diabetes onset prediction	High, clinical systems for management
	Yang et al. 2021 [49]	XGBoost, LR, DT, SVM, RF	AUC: 0.9139, Accuracy: 86.43%, F1-score: 0.7467	Renal failure risk prediction	High, clinical decision support
	Chen et al. 2020 [51]	AHDCNN, CNN	Accuracy: 97.14%, Sensitivity: 77%, Specificity: 93%	CKD progression prediction	High, IoMT-based kidney disease prediction
	Islam et al. 2023 [45]	XGBoost, RF, KNN, DT	Accuracy: 98.33%, F1-score: 98%, AUC: 0.99	CKD detection	High, clinical prediction of CKD

Musculoskeletal / Joint Diseases	Ali 2025 [25]	VGG16 (CNN)	Accuracy: 97.9%, Sensitivity: 100%, Specificity: 100%	Osteoarthritis prediction	High, clinical use in severity classification
	Chen et al. 2024 [37]	DL (Sequential & non-sequential NN), RF, XGBoost, SVM	Accuracy: 97%, Sensitivity: 85%, AUC: 0.92–0.94	Early arthritis prediction	High, screening tool for diagnostics
	Khalid et al. 2023 [40]	VGG-19 CNN, ResNet-101 CNN, FFNN	AUC: 99.25%, Accuracy: 99.1%, Sensitivity: 98.81%	Knee osteoarthritis severity prediction	High, clinical detection and staging
Pulmonary Diseases	Sinha et al. 2025 [24]	RF, MLP, LR, XGBoost	Accuracy: 94.5%, AUC: 0.98, Sensitivity: 89%, Specificity: 93%	Medication adherence prediction	High, deployable in clinical settings
	Raje et al. 2024 [33]	CNN, Autoencoders, GANs, XGBoost	Accuracy: 97%, Sensitivity: 96%, Precision: 97%	COPD early detection	High, deployment in clinical settings
	Mondal et al. 2021 [50]	FRCNN, ALTP	Accuracy: 98.12%, Sensitivity: 95.83%, F1-Score: 97.24%	Pulmonary emphysema diagnosis	High, clinical imaging application
Cancer / Hematological Diseases	Chen et al. 2025 [20]	DQN, RF, XGBoost, SVM, DNN	AUC: 0.937–0.953, Precision: >0.87, Recall: >0.86, F1: >0.87	Predicts lung cancer risk	Experimental, high external validation
	Lan et al. 2024 [32]	RF, SVM, DT	AUC: 0.9917 (SVM), Accuracy: 92.85%	Lung cancer prediction	High, clinical use in screening
	Ikechukwu et al. 2022 [46]	CNN, ResNet-50, VGG-19, i-Net	Accuracy: 99.18%, Sensitivity: 99.30%, F1-Score: 99.19%	Leukemia classification	High, clinical support for leukemia diagnosis
Neurodegenerative Diseases	Javed et al. 2025 [26]	ResNet-101 (Transfer Learning)	Accuracy: 96.06%, Sensitivity: 98.46%, Specificity: 99.67%	Alzheimer's disease stage prediction	High, IoMT-based systems
Ophthalmic / Dental	Alsubai 2023 [42]	Voting Classifier (XGBoost + RF + Extra Trees)	Accuracy: 97.36%, F1-Score: 96.65%	Tooth caries detection	High, clinical application for prevention
	Aurangzeb et al. 2023 [43]	ColonSegNet	Accuracy: 97.72%, Sensitivity: 98.2%, AUC: 0.979	Glaucoma, diabetic retinopathy detection	High, retinal imaging for eye diseases

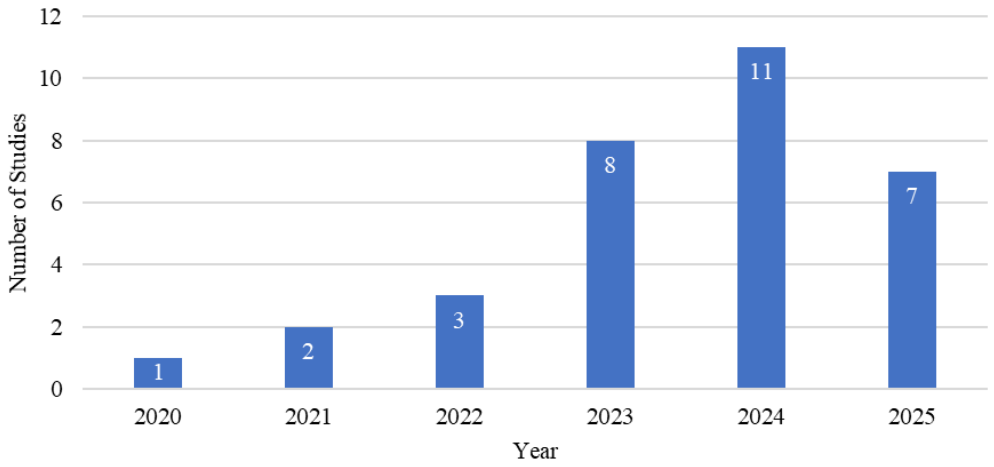

Figure 3. *Distribution of included studies by year of publication.*

5-fold, and 10-fold CV, 80/20 train-test splits, external validation, and EHR-based validation.

Table 4 illustrates how the AI models' diagnostic performance, demonstrated high accuracy and predictive capability across a variety of chronic diseases. In the field of chronic metabolic diseases, AI models such as FCNN, Random Forest, XGBoost, CNN, and the ensemble approaches attained an accuracy of 77.08% to 99.97%, and AUC scored as high as 1.0. Sensitivity and specificity for predicting diabetes, heart disease, chronic kidney disease, and diabetic retinopathy were nearly always high, frequently exceeding 95% in multiple studies. In the same vein, musculoskeletal disease models such as VGG16, VGG19, and ResNet-101, reported an accuracy ranging from 97% to 99.1% and, for the most part, reported sensitivity and specificity above 98%, mostly concerning the detection of osteoarthritis and early arthritis. AI models for pulmonary diseases, including Random Forest, CNN, and Autoencoders, have obtained AUC values up to 0.98 and predicted the early stages of COPD and pulmonary emphysema in addition to medication adherence with accuracies ranging from 94.5% to 98.12%.

For cancer and hematological diseases, models including CNN, ResNet-50, VGG-19, DQN, and Random Forest reported accuracy between 92.85% and 99.18%, with AUC values as high as 0.9917, applied to lung cancer and leukemia prediction. In neurodegenerative disease detection, ResNet-101 achieved 96.06% accuracy, with sensitivity and specificity above 98% for Alzheimer's disease stage prediction. Ophthalmic and dental disease models, such as ColonSegNet and voting classifiers combining XGBoost, Random Forest, and Extra Trees, achieved accuracy between 97.36% and 97.72%, with sensitivity above 96% and AUC up to 0.979 for tooth caries, glaucoma, and diabetic retinopathy detection. Across all subgroups, the AI models were reported to be ready for clinical deployment, web-based or mobile applications, and real-time monitoring systems.

The included studies' distribution by publication year is shown in Figure 3. One study was published in 2020, followed by two in 2021, three in 2022, eight in 2023, eleven in 2024, and seven in 2025.

Figure 4 presents the distribution of included studies by geographical region. India contributed the highest number of studies (7), followed by China (5) and Saudi Arabia (5). The USA contributed 3 studies, Egypt 2 studies, and Pakistan, Nigeria, North Macedonia, UK, Jordan, Canada, Iraq, Malaysia, Turkey, and Bangladesh each contributed 1 study.

Figure 5 presents the distribution of AI model types applied across different chronic disease subgroups. In metabolic diseases, a total of 18 studies were reported, including 10 hybrid models, 4 ML models, and 2 DL models. Pulmonary diseases included 6 studies, with 3 hybrid, 2 ML, and 1 DL model. 3 studies represented musculoskeletal and joint diseases, 2 of which were hybrid and 1 was a DL model. Cancer and hematological diseases involved 3, of which 2 were hybrid and 1 was an ML model. Ophthalmic and dental diseases had 3, evenly distributed with 1 hybrid, 1 ML, and 1 DL model. Neurodegenerative diseases included 1 study, which utilized a DL model.

Discussion.

This systematic review considered the use, predictive power, and clinical applicability of AI to detect a broad spectrum of chronic illnesses from 2020 to 2025. The review focused on AI-based systems for the diagnosis and management of metabolic and cardiometabolic diseases, chronic kidney disease, lung cancer, musculoskeletal conditions like osteoarthritis, pulmonary diseases such as COPD and emphysema, cancers including leukemia, neurodegenerative diseases like Alzheimer's, and ophthalmologic/dental conditions such as diabetic retinopathy, glaucoma, and tooth caries. A total of 32 studies from 13 countries used retrospective designs, incorporated ML, DL, or AI hybrid models, and validation approaches such as k-fold, 80/20 split, and external validation.

The results showed that many AI models achieved success in diagnosing these diverse chronic illnesses and reported high

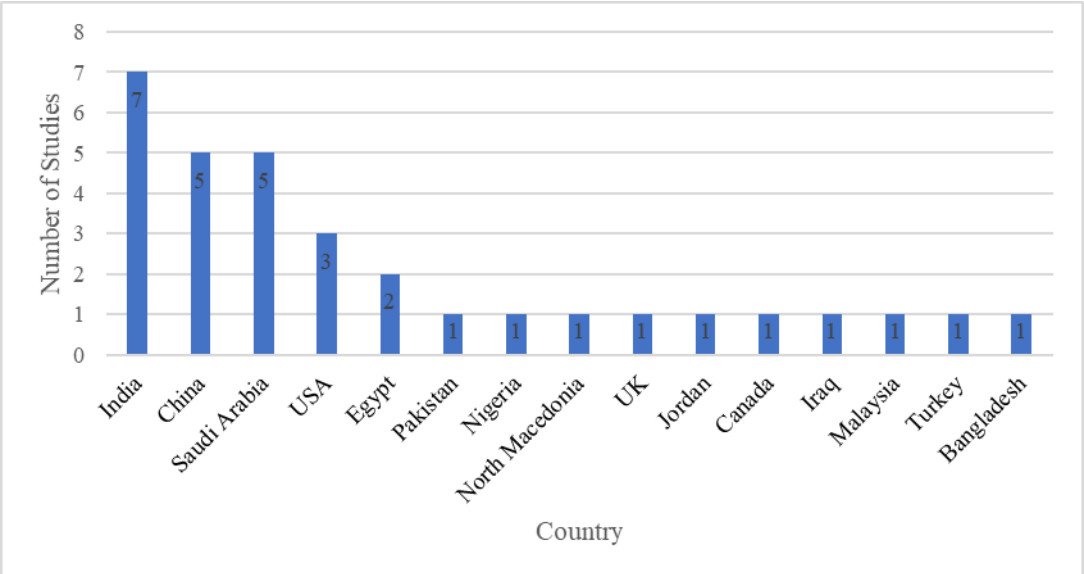

Figure 4. *Distribution of included studies by geographical region.*

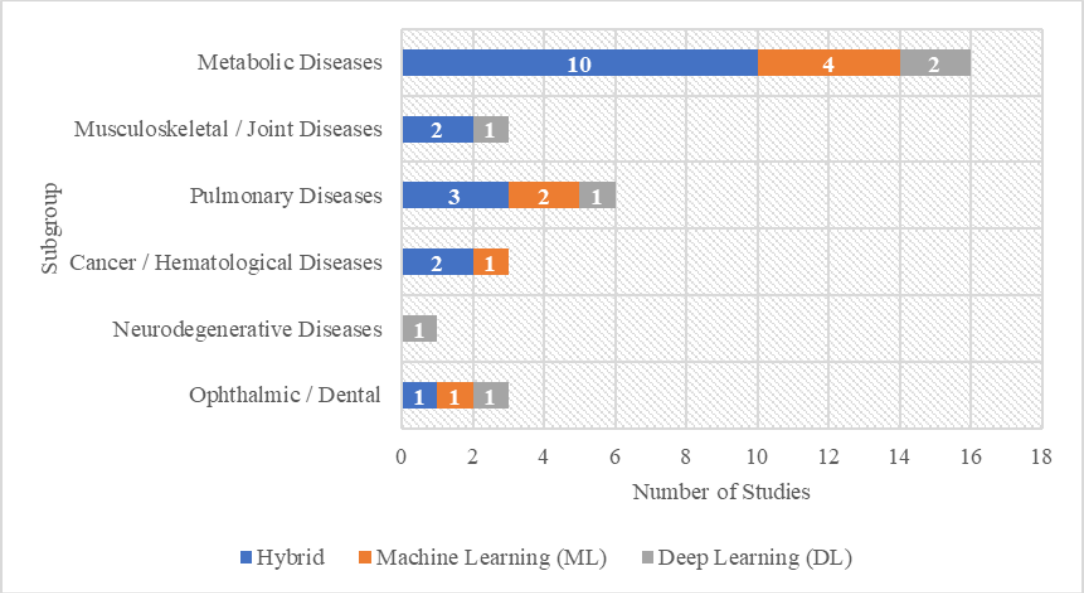

Figure 5. *Distribution of included studies by AI methods type.*

values for accuracy, sensitivity, specificity, and AUC. Across disease subgroups, machine learning models showed AUC values ranging from 0.7467 to 1.0, with reported accuracy from 77.08% to 99.97%, sensitivity 77%-100%, and specificity 59.2%-100%. For instance, in metabolic diseases, models like FCNN, Random Forest, XGBoost, CNN, and ensembles reached these peaks; musculoskeletal models hit 97%-99.1% accuracy with >98% sensitivity/specificity for osteoarthritis; pulmonary models achieved 94.5%-98.12% accuracy for COPD/emphysema; cancer models reported 92.85%-99.18% accuracy for lung cancer/leukemia; neurodegenerative detection with ResNet-101 gave 96.06% accuracy for Alzheimer's staging; and ophthalmic/dental models reached 97.36%-97.72% accuracy for caries/glaucoma/diabetic retinopathy. Overall, these AI models also managed in real-time settings to identify high-risk, chronic, or advanced-stage cases and classify them by stage. A number of the findings demonstrated the increased but considered underutilized capability in chronic disease prediction [52-54]. In contrast with previous reviews which concentrated solely on diabetes and cardiovascular diseases, this review examined the comparative performance of AI across a much larger, diverse, and heterogeneous set of chronic diseases and clinical domains.

The trends in publishing increased over time. This demonstrates how AI-focused healthcare research has rapidly developed, in particular after the COVID-19 pandemic which sped up the digitalization and adoption of AI of diagnostic and treatment systems [55-57]. The leading research output came from developed countries and, in parallel, emerging economies also showed significant contributions, in line with recent studies on the AI adoption from lower and middle-income countries [58]. China, India, and Saudi Arabia had the highest number of publications, and that of Saudi Arabia is connected to its Vision 2030 and AI national initiatives [59,60].

Hybrid models dominated across chronic disease subgroups, particularly in metabolic diseases where they were most prevalent. Balanced distributions emerged in other instances as well, with hybrids (56%) consistently dominating alongside ML (25%) and DL (19%) approaches. This trend emphasizes hybrid models' unprecedented adaptability and computational efficacy across a wide range of clinical applications for the prediction and management of chronic diseases [61-63]. For instance, a combination of NN, NF, SVM, and XGBoost classifiers achieved a remarkable 99.94% accuracy rate in predicting the incidence of diabetes and cardiovascular disease [64,65]. The same results were evident in advanced challenges, such as predicting the progression of Hepatitis C using an ensemble methods approach [66]. However, studies reporting very high-performance metrics were primarily based on retrospective designs with internal validation, which may limit generalizability.

Interpretable machine learning techniques are often used because they are a good fit for the type of structured data found in medicine. In terms of imaging-based diagnosis for Alzheimer's, diabetic retinopathy, lung cancer, etc. DL models performed well. This was in line with previous literature that established CNNs as the gold standard for medical imaging [67-69]. Hybrid strategies, such as the GA-XGBoost and CNN AutoEncoder architecture, demonstrate considerable potential for Multifactorial Prediction. Although AI models achieved strong performance on small or homogeneous datasets, particularly when enhanced by transfer learning or ensemble strategies, near-perfect results derived from limited internal validation should be interpreted conservatively. Small sample sizes, repeated cross-validation on the same datasets, and insufficient separation between training and evaluation data may artificially boost reported performance [70].

Numerous frameworks showcased their clinical readiness for deployment in mobile and web-based screening, clinical-decision support, and IoT/IoMT systems focusing on diabetes, chronic kidney disease, osteoarthritis, COPD, and related conditions [71-74]. However, most models remain in preclinical or experimental stages and require broader validation, particularly multicenter and large-scale trials.

Variation has been noted in various studies. For instance, one model predicted diabetes with an accuracy of just 59.2%,

which is very low when compared to other studies which reported accuracies over 95% across subgroups. Data quality, the types of variables included, and the characteristics of the study population are the main sources of differentiability and highlight the need for standardized data and protocols. Near-perfect performance reported in some models should therefore be interpreted cautiously, particularly when derived from small or homogeneous datasets. Meta-analyses generally report strong predictive abilities of ML models in chronic disease, however, they also note significant variability and poor quality of the included studies [75-78]. In medical imaging, particularly in the area of diabetic retinopathy and related fields, the pooled sensitivity and specificity values are considerable. However, the experts cite lack of external validation, inconsistent pre-processing steps, and non-representative data as key drivers of variability [79,80]. Similar to other research using limited datasets, research employing vague outcome definitions document internal metrics that are likely to be overly positive. When the PRISMA-DTA guidelines describe the scattering of metrics that for the most part perform well internally, they describe the phenomenon most accurately, internally sourced metrics seem to be accurate [81,82]. AI has great potential for the early detection of chronic diseases, but for claims of diagnostic performance to be accurate, they need to be substantiated by rigorous external validation and solid methodological defense. Future studies need to focus more on independent validation cohorts, standardized data flows, and clear data reporting to translate the metrics they present into safe and effective clinical practice.

Limitations.

The review is not without limitations. Most importantly, the review is limited to publications in the English language from 2020 to 2025, which potentially overlooks pertinent literature in other languages. Despite having carried out a comprehensive search across various databases, the review is limited in scope as it did not include grey literature, trial registries, and organizational websites. As this is a systematic review, no meta-analysis, forest plots, or sensitivity analyses were conducted. The findings mainly represent a qualitative evidence synthesis, and no quantitative synthesis was possible due to the diverse set of AI models and chronic disease subgroups, differing diagnostic methods, and varying outcomes.

Key Insights.

This review integrates evidence regarding the potential of AI to facilitate the early detection and prediction of various subgroups of chronic illnesses, including metabolic/cardiometabolic, musculoskeletal, pulmonary, cancer/hematological, neurodegenerative, and ophthalmologic/dental conditions. It emphasizes the diagnostic precision, predictive performance, and clinical applicability of ML, DL, and hybrid AI models, coupled with the latest trends of integrating multimodal AI methods for the management of chronic diseases and preventive healthcare.

Practical Implications.

AI could improve clinical workflows by streamlining early diagnosis, risk assessment, disease categorization, and tailored treatment strategies. The integration of hybrid AI models has the potential to alleviate clinician burdens, facilitate telemedicine, and enhance access to healthcare in low-resource settings. When combined with intelligent sensors, electronic health records, and real-time health monitoring, hybrid AI models enable continuous tracking and the rapid identification of chronic diseases.

Future Research Directions.

Future studies should emphasize the need to enhance AI models' explainability, interpretability, transparency, and fairness across diverse populations with chronic diseases. The findings need to be validated in prospective multicenter clinical trials and in real-world studies using standardized data sets. The ethical and effective integration of AI into healthcare requires input from clinicians, AI developers, data scientists, and policymakers, along with the establishment of frameworks concerning bias, data privacy, and equitable access.

Conclusion.

This systematic review successfully accomplished its goal in evaluating the extent, diagnostic precision, and clinical applicability of the AI in the early detection of various chronic diseases including metabolic, pulmonary, musculoskeletal, cancer/hematological, neurodegenerative, and ophthalmologic/dental diseases.

AI, especially hybrid models, showed the best predictive performance in the greatest number of chronic diseases, such as diabetes, heart disease, chronic kidney disease, lung cancer, Alzheimer's disease, COPD, osteoarthritis, leukemia, glaucoma, diabetic retinopathy, pulmonary emphysema, and tooth caries. DL models have performed well with imaging-based diagnosis, while interpretable ML performed robustly with the structured clinical data. Hybrid models utilizing ensemble techniques, genetic algorithms, and neural architectures consistently yielded better results than pure ML or DL approaches. AI technologies applied to risk assessment, disease staging, clinical monitoring, mobile apps, IoT/IoMT devices, decision support, EHR integration, and real-time analytics improve early detection, reduce clinician workload, support customized and adaptive treatment strategies, increase accessibility to healthcare, and enable support for precision medicine.

Nevertheless, the majority of the studies focused on retrospective data, which has little or no external validation, thus constraining applicability to the real world. The lack of uniformity in terms of conditions, methodologies, populations, and outcomes, combined with inconsistent quality and reporting of the data, resulted in an impediment to direct comparisons. The legal, ethical, and financial aspects remain insufficiently examined.

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Data availability statement.

The publicly available scientific sources provided all of the data used in this systematic review. The article and its supplemental materials provide comprehensive documentation of the selection procedure, inclusion and exclusion criteria, and the complete list of examined research. The writers may offer more information or explanations upon reasonable request.

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