Poltekita: Jurnal Ilmu Kesehatan
http://jurnal.poltekkespalu.ac.id/index.php/JIK

Vol.17 No.3 November 2023: Hal. 694-706
p-ISSN: 1907-459X e-ISSN: 2527-7170

Article Review

Digital Variation of Machine Learning Through Basic Diagnostic Test Application Approach: an Integrative Literature Review

Sanatang[1*], Muhammad Aqmal Ismail[1]

[1] Faculty of Informatics Engineering, State University of Makassar, Makassar, South Sulawesi, Indonesia

(Correspondence author email, sanatang@unm.ac.id)

ABSTRACT

Electronic Medical Records (EMRs) are digital applications of machine learning models that function to receive and store clinical data related to medical information for the purposes of basic clinical diagnostic tests. The integrative review aims to provide a synthesis of new findings from several articles on EMRs for the early detection of basic clinical diagnoses with a variety of existing populations. Using four databases, we reviewed 11 articles. All authors involved review abstracts and full text according to predetermined criteria. The selected articles are then integrated into the publication quality assessment matrix, further included in machine learning algorithms for diagnostic determination of the disease. Reviewed articles are excluded in the form of artificial intelligence. The PRISMA flowchart identified 1962 articles and the final selection found 11 articles. Circulating system networks dominate machine learning models (66.6%). The study netted an average population of 490.5 and the artificial intelligence system managed to detect 9 body systems from different body systems. A total of 11 articles were selected, more than half of which were Caucasian (80.90%) and white (72.95%), but only 1 article was represented by Caucasian ethnicity, while white race was almost in every article. African-American and Black racial groups were in the middle position at 29.95% and 17.50%. The racial representation with the least percentage below 10% was Hispanic and Asian (6.10% and 2.17%). This machine learning has proven to be very accurate for detecting disease diagnoses in hospital, other health clinics. Therefore, the further development of this application for the purpose of establishing clinical diagnosis precisely and accurately.

Keywords: *Machine Learning, Diagnosis, Electronic Medical Records*

https://doi.org/10.33860/jik.v17i3.3355

INTRODUCTION

In the era of the industrial revolution 4.0 manufacturing the health industry is growing very rapidly, at least in 2020 it is reported that there are around 2.3 trillion gigabytes of patient data[1]. The complexity of the data, if not managed properly, will cause serious problems, especially related to the process of storing and managing and security of patient electronic data in health care facilities. To answer these challenges, an electronic digitization system is needed that is designed to solve problems and

accelerate services to patients in health care facilities, especially in hospitals. The existence of information technology will greatly help accelerate the process of storing and processing patient electronic data to reduce workload beyond the capacity and work ability of human resources, besides that this system will improve and develop new data automatically in order to help doctors and other health workers to determine early and appropriate diagnosis.

With the increasing number of patient

visits in hospitals, it certainly has logical consequences for the analysis of very large amounts of data. Therefore, synchronization of electronic digital systems, especially informatics engineering and medical technology, is very important to be created. Some digital applications in the health sector that are often used one of them is the electronic medical record system (EMRs). Within seven years there was an increase in the use of EMRs from 9.4% to 83.8% in the period 2008 – 2015[2]. In its development, the EMRs system is continuously undergoing improvements so as to allow more data to be analyzed. These EMRs have the ability to store and process patient medical record data, both structured and unstructured data, there are about 80% of unstructured data successfully secured by this system (EMRs) [3].

One of the most important advantages of this system is that it helps the basic diagnosis process quickly. The sophistication of this EMRs system greatly assists hospital management in receiving, storing and distributing comprehensive patient data for the benefit of making a quick initial diagnosis.

Some of the patient's medical record data include, symptoms, vital signs, family history, demographic data, drug consumption, laboratory result data and many other supplementary data. With the variety of learning models of this digital system, this system is able to detect electronic data of patients quickly, and diagnose patients quickly who are exposed to diseases. The process of standardizing this application tool is able to predict the patient's health condition and disease. Most cases are diagnosed using comprehensive diagnostic parameters. These EMRs are capable of storing as many as 70,000 disease codes according to the International Code of Diagnosis (ICD-10). The application of EMRs models is able to recognize the pattern and distribution of disease experienced by patients. Standardization calibration of hasrus tools is carried out because it will have an impact on the soft skills of a student[4–6].

The utilization of machine learning techniques in the application of basic diagnostic tests will result in significant advancements and the effectiveness and adaptability of machine learning algorithms as a whole across multiple domains.

How can the application of digital machine learning affect the process of basic diagnostic tests and what factors contribute to the effectiveness and adaptability of machine learning algorithms in this approach?

This study aims to provide an integrative literature review of several peer-reviewed articles on electronic medical records (EMRs) for early detection of basic clinical diagnoses, including the expediency and traceability aspects of machine learning.

METHOD

This study used an integrative literature review method, following PRISMA [7].

The paper selection mechanism, orchestrated in accordance with the PRISMA diagram, serves as the linchpin for methodological rigor and transparency in systematic literature reviews. Commencing with a comprehensive identification phase across diverse databases, researchers strategically employ predetermined keywords and criteria tailored to their research focus. The PRISMA diagram then becomes the guiding compass during the subsequent screening phase, visually delineating the number of articles identified, screened, and deemed eligible for inclusion. The importance of clear inclusion and exclusion criteria is underscored, ensuring that only studies meeting predefined standards contribute to the refined pool. Quality assessment takes center stage as researchers scrutinize the reliability and validity of each selected article. The PRISMA diagram, with its structured flow, provides a visual narrative of the intricate paper selection process, culminating in a transparent and reproducible foundation for subsequent stages of synthesis and analysis. In essence, the PRISMA-guided paper selection mechanism stands as a testament to the commitment to methodological precision, elevating the systematic review to a robust and credible endeavor.

Machine learning focuses on the decision-making processes, where algorithms learn through trial and error to maximize rewards in dynamic environments. Within these broad categories, there exists a myriad of specific algorithms such as linear regression, decision trees, support vector machines, and neural networks, each tailored to address specific tasks and challenges. The understanding of these algorithms is essential for practitioners and researchers alike, as it forms the basis for the informed selection, implementation, and optimization of machine learning solutions across diverse domains.

Selection of this method by following the following steps: search for reference sources, filtering publication quality, withdrawing, synthesis, and descriptive information. Furthermore, we together with peer-reviewed tracked reputable international journals indexed by Scopus, Pubmed, Compass Digital Library and / or ACM Digital Library which describes the application of EMRs programs for basic diagnostic test applications.

Ethical considerations tied to the utilization of demographic data and the potential introduction of bias in machine learning algorithms are intrinsically linked to the sensitive nature of patient data. As machine learning increasingly integrates into healthcare systems, the responsible handling of demographic information becomes paramount to ensure equitable and unbiased outcomes. Concerns arise from the risk of perpetuating or exacerbating existing biases present in healthcare datasets, potentially leading to disparities in diagnosis, treatment, or resource allocation. Striking a balance between harnessing the power of demographic data for improved healthcare outcomes and safeguarding against unintended consequences is crucial. This necessitates the establishment of robust ethical frameworks, transparent practices, and ongoing scrutiny to mitigate the risk of algorithmic bias and ensure that the deployment of machine learning in healthcare aligns with principles of fairness, accountability, and patient-centric care.

Literature Search and Selection

We search for reference sources by utilizing 4 databases, namely Scopus[8], Pubmed[9], Compass Digital Library[10] dan ACM Digital Library[11]. The keyword search process, we are guided by Medical Subject Headings (MeSH) by using a single base word related to search results. The keywords used in this literature search are electronic medical records, machine learning, and diagnosis, except for image-based articles. Eligible review process using the keywords entered (1) AND (2) with NOT (3) with the following details: Machine learning OR related terms: neural networks, natural language processing, OR knowledge bases; diagnosis, computer assisted OR clinical decision-making; diagnostic imaging OR computer-assisted image processing.

Article selection system based on article eligibility criteria, namely articles published in the period 2002 - 2023 in English editions that focus on machine learning based on EMRs for the determination of basic diagnostic tests. We narrowed down our literature search strategy by applying eligibility criteria. Articles should include EMRs usage data and basic diagnostic tests. Integrative literature review excludes on monitoring aspects of EMRs in first-level basic health care facilities (community health centers, doctor's clinic, independent health clinic, nurse independent practice, private practice midwife and so on). In addition we also perform data extraction on methodology, expert recommendations, dan ulasan editorial. We identified articles that have to do with machine learning and basic diagnostic test applications. We focus on text-based papers and not image content such as x-ray notes. However, if nontext aspects support broader data analysis are also included, for example an electrocardiogram.

This article deliberately omits the exploration of image-based applications and their associated reviews within the realm of Artificial Intelligence. The decision to focus on non-image-based facets is driven by a specific scope, perhaps dictated by the need for a more targeted analysis or a deliberate emphasis on certain AI applications. By excluding image-based applications, the article narrows its focus, allowing for a more in-depth examination of specific AI domains without the added complexity introduced by visual data processing.

The limitations of research on artificial intelligence (AI) underscore the need for a nuanced understanding of its applications, particularly in the context of non-image-based diagnostics. While AI has made significant strides, particularly in image-based diagnostics, there exists a critical gap in the exploration of its capabilities beyond visual data analysis. This gap poses challenges in comprehensively assessing the broader landscape of AI applications, potentially hindering the development of holistic and versatile solutions. By emphasizing non-image-based diagnostics, this research acknowledges the significance of diversifying the AI discourse, shedding light on areas where AI can contribute meaningfully outside the realm of visual data. However, it's crucial to recognize that this focus also introduces limitations, as insights derived may not be universally applicable across all AI domains. Thus, a balanced perspective on the limitations and opportunities within both image and non-image-based AI applications is essential for a comprehensive understanding of the field.

We issue an article if the displayed data is not in the EMRs standard. If non-context articles that lead to specific analysis are not included as well, include image-based analysis. Another factor we release is when the data discusses therapy and disease progression. Articles affiliated to animals and languages other than English were also issued. In addition, articles that generally review the topic and do not use the clinical dataset model are also issued.

Furthermore, we select articles through the application of eligibility criteria, especially in titles and abstracts. One authorselects the full text for inclusion criteria. Discussion of articles to determine the certainty of including or not, discussed with all authors, so that a common consensus is reached. The integrative literature review will take place from August 25, 2023, to September 10, 2023.

Article Quality Assessment

We conduct independent article reviews using the National Institute of Health (NIH) instrument to assess the quality of submitted articles. This NIH is used to assess the quality of studies, especially case studies. The majority of articles choose 2 types of designs, namely prospective and retrospective case studies. This instrument has nine questions determined by two types of answers, namely "yes" or "no". The assessment of publication quality is based on three categories, including good grades for answer categories 7 - 9, sufficient scores for answer categories 4 - 6 and bad scores for answer categories ≤3[12,13]. These results then, we only choose those that are in the good category. If there is a dissenting opinion among peers, then resolve it through discussion between them.

Data Extraction and Synthesis

The data extraction process is carried out through two stages, including the first stage consisting of reference, year of publication, author, affiliation, diagnosis, number of samples, ethnic ratio. If there is heterogeneity of methodology and report results, then we conduct a narrative comparison.

The second stage is a comparison of the EMRs system framework using machine learning whether the assessment is periodic or continuous.

EMRs programs are particularly suited to adding new data patients enter each day, and how they address any problems and challenges found. The framework of the machine teaching system adopts multiple patient data methods, data transmission methods, and data server security[14].

RESULTS

Efforts to control demographic representation bias have become increasingly pivotal in various fields, recognizing the imperative of fair and equitable representation in data-driven decision-making processes. This multifaceted challenge involves mitigating disparities in demographic representation within datasets, ensuring that algorithms and models are reflective of the diversity inherent in the real-world population. Strategies encompass a comprehensive reassessment of data collection methodologies, emphasizing inclusivity and addressing historical biases. Additionally, there is a growing emphasis on developing algorithms that are not only accurate but also sensitive to demographic nuances, with ongoing research aiming to strike a balance between model performance and fairness. Collaborative initiatives involving interdisciplinary teams, ethical guidelines, and community engagement are emerging as essential components in navigating and rectifying demographic representation bias, thereby fostering a more equitable and inclusive landscape in the application of data-driven technologies.

Study Identity Review

Based on the results of searching articles using the Boolean Operator keyword "AND' "OR" "NOT" with the guidance Medical Subject Heading (MeSH) in the Pubmed database, we found 1962 articles. The databases used are Scopus, Pubmed, Compass Digital Library and ACM Digital Library. Furthermore, a duplicate article was checked and 785 articles were found. The characteristics of the selected study were 11 articles (table 2). A grouping of the number of studies by publication year starting 2002 - 2023 is shown in the figure 2.

Literature search and selection

The process of searching and developing keywords using Scopus, Pubmed, Compass Digital Library, ACM Digital Library search database. Next the article is reviewed on the topic selected by the authors involved. We managed to find 1962 articles.

In the process of identifying relevant topics, we issue 1118 by title and/or abstract. The next process was a thorough article review and 48 articles were successfully issued, and the remaining 11 articles for us to include in this integrative literature review.

Data collection

In the process of extracting data carried out by one reviewer with the following arrangement; number of patients, gender ratio, race, type of trial, type of article analyzed, source of data, algorithm used, type of validation test, performance measures and primary and secondary results. If in sorting out the data of different research locations, then what is recorded is the location of the research. Furthermore, in one paper there are several institutional affiliations, so what is taken is the main institution. In the data collection process, reviewers always coordinate and collaborate to expedite the research data review process.

Publication Characteristics

Articles selected by 7 countries consist of USA, China, Francis, Tunisia, Romania, Israel and North America. The highest number of studies came from the USA (45.5%), the remaining six countries shared the same percentage (9.1%).

Body Systems

There were 11 cases of disease diagnosis selected according to the results of paper selection. Some of the selected disease diagnoses are then incorporated into 7 body systems, where the cardiovascular system dominates as many as 5 articles (45.5%) as shown in table 3.

Artificial Intelligence

The most numerous type of algorithm in the literature review was the 3-article circulatory system network (27.3%). circulation system using backpropagation, 2 articles (66.6%). Next using a multilayer perceptron network, 1 article (33.3%).

Race/Ethnicity

Data collection through race characteristics is carried out by two methods, namely 1) original publication and 2) available data set. If there is data needed, but not available in both methods, the author conducts participant correspondence via email. The authors collected race data before and after contacting respondents. The racial data collected by the authors totaled 5 authors (45%), included in contact via email. There were 6 authors who were contacted via email and they responded, but unfortunately did not provide the data needed, 3 (50%) of them provided information that the data was no longer owned.

A total of 11 articles were selected, more than half of which were dominated by Caucasian ethnicity (80.90%) and white race (72.95%), but only 1 article was represented by Caucasian ethnicity, while white race was almost in every article. African-American and Black racial groups were in the middle position at 29.95% and 17.50%. The racial representation with the least percentage below 10% was Hispanic and Asian (6.10% and 2.17%).

Number of samples

Of the 11 articles selected, the average number of patients in the interquartile range was 28,124 patients out of a total of 281,244 patients. There is one article for which the number of patients is not available or is not specific in number. This number includes the inclusion and exclusion criteria that have been set.

Quality Assessment

From the results of the case series study assessment related to publication quality, we selected 11 publications with a "good" rating level in the range of scores 7 - 9 (Table 1).

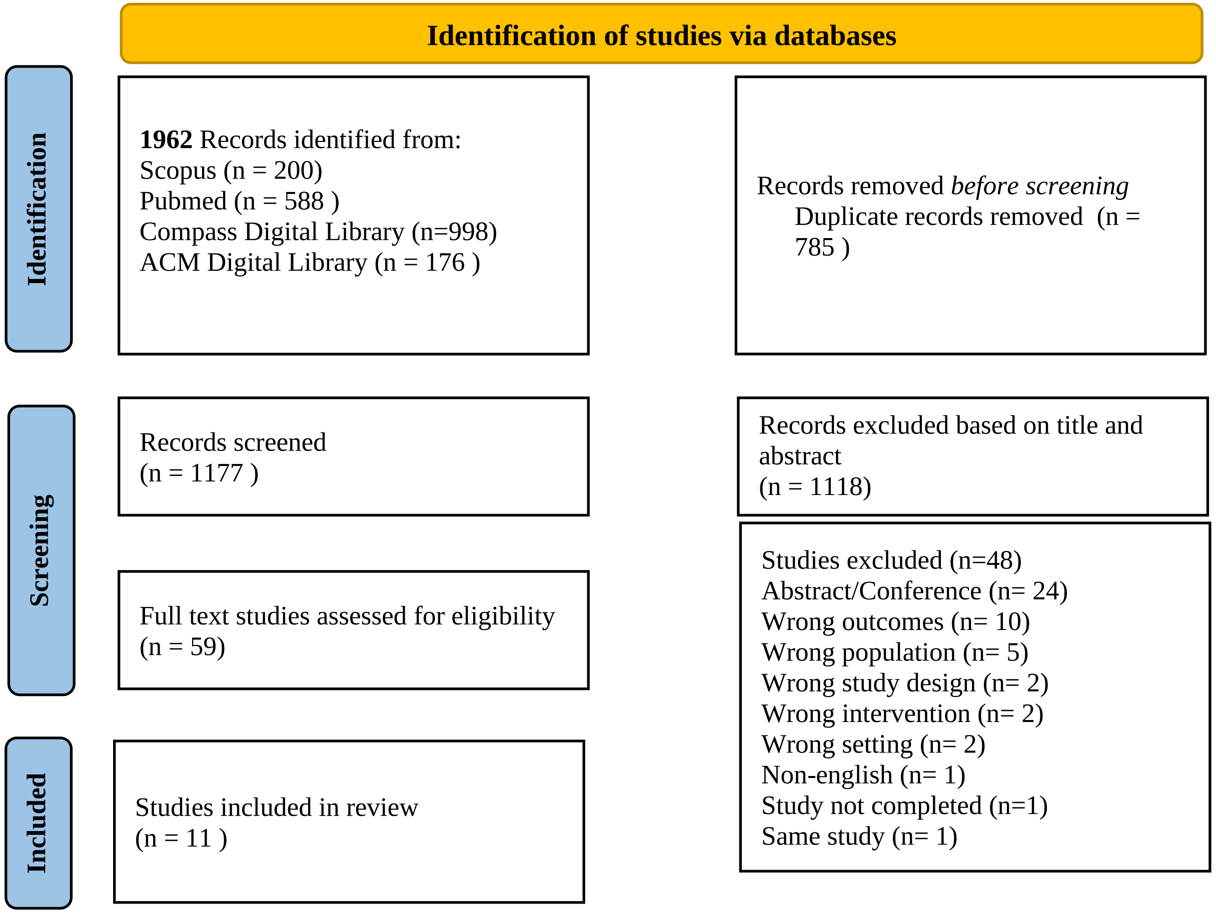

Figure 1. Flow diagram of included and excluded studies.

Table 1. Study quality ranking according to NIH quality assessment tool for case study series[15]

Quality Assessment Tool	Study										
	Ginestra [16]	Levy et al. [17]	Baxt et al. [18]	Li et al. [19]	Jorge et al. [20]	Corey et al [21]	Danford et al. [22]	Sahli et al [23]	Antohi et al. [24]	Danford et al. [25]	Nataraja n et al. [26]
1.Was the study question or objective clearly stated?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
2.Was the study population clearly and fully described, including a case	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

definition?											
3.Were the cases consecutive?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
4.Were the subjects comparable?	CD	CD	Yes	Yes	Yes	Yes	Yes	Yes	CD	Yes	Yes
5.Was the intervention clearly described?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
6.Were the outcome measures clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
7.Was the length of follow-up adequate?	CD	CD	CD	CD	CD	CD	CD	CD	CD	CD	CD
8.Were the statistical methods well-described?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
9.Were the results well-described?	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quality rating consensus (GOOD, FAIR, POOR)	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good	Good

*Abbreviations: **CD**, cannot determine; **NIH,** National Institutes of Health*

Data Extraction and Synthesis

Table 2. Study Characteristics

Reference	Publication year	Author	Institution	Disease or condition	Number of patients	Race ratio
16	2019	Ginestra	Hospital of University of Pennsylvania	Severe Sepsis and Septic Shock	724	N/A
17	2017	Levy et al.	Stanford University, USA	Autism Spectrum Disorder (ASD)	4532	N/A
18	2002	Baxt et al.	Hospital of University of Pennsylvania USA	Cardiac Ischemia	2204	Asian 1.4 %, African American 54.6%, Hispanic 0.8% White 40.7%
19	2020	Li et al.	Ping An Technology, Beijing, China	Sepsis	24819	N/A
20	2019	Jorge et al.	Harvard Medical School	Systemic lupus erythematosus (SLE)	1322	White 73.9% Black 13.8% Asian 3.52% Hispanic 5,8%
21	2018	Corey et al	Duke Institute for Health Innovation,	high-risk surgical	245359	White 72.0%, Black or African American 21.2%, Asian 1.6%

			USA			2 or more races 0.8%, merican Indian or Alaska Native 0.4% Other 4.0%
23	2021	Danford et al.	Université Lyon, Francis	Cancer	1600	N/A
24	2013	Sahli et al	Biochemistry Laboratory, Tunisia	Thalassemia	384	N/A
25	2019	Antohi et al.	University of Medicine Carol Davila, Romania	Acute decompensated Heart Failure	N/A	N/A
23	2021	Danford et al.	Division of Gastroenterology and Hepatology, Israel	Steatohepatitis Cirrhosis	300	Caucasian 80.9%, African American 5.3%, Hispanic 11.7%, Asian 2.1%
26	2023	Natarajan et al.	Philips Research North America	Low Birthweight Neonates	1348	White 64% Black 11% Other 25%

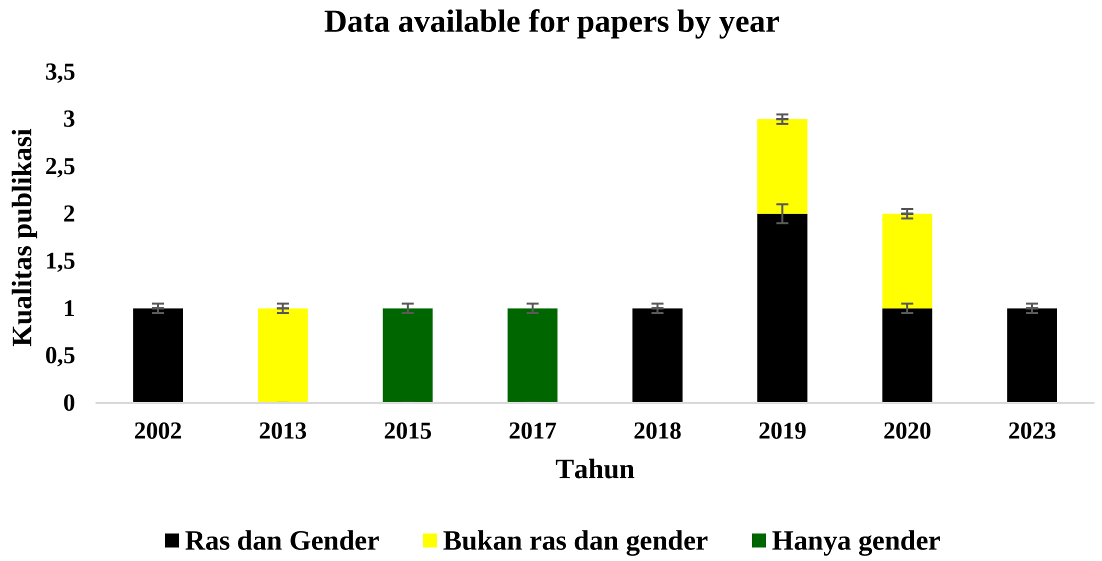

Figure 2. A paper applying text-based machine learning to diagnosis, with data available and published 2002 through 2023.

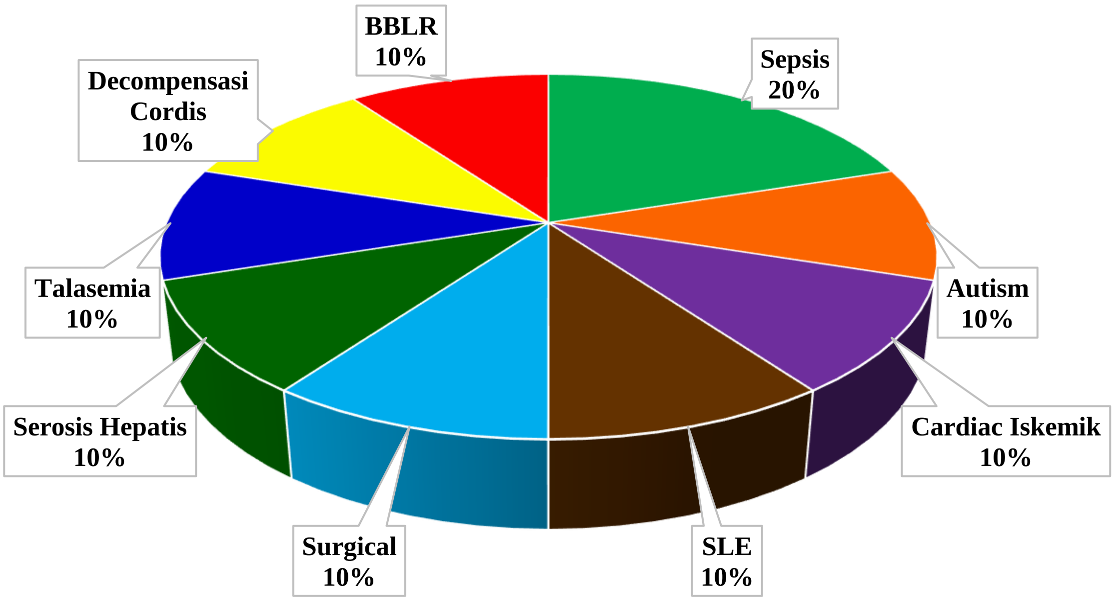

Figure 3. Diseases and conditions are studied in several papers

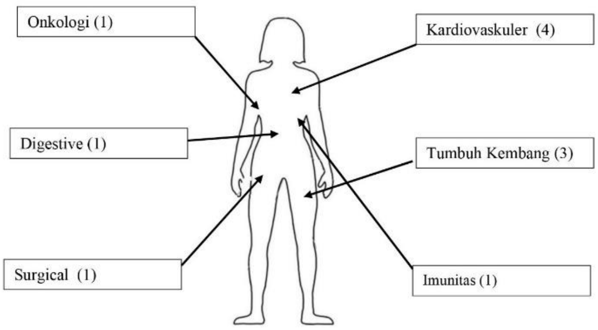

Figure 4. The number of papers studying diseases in each body system.

DISCUSSION

Literature studies on test-based health analysis of basic health information with the use of machine learning show significant improvement.

Our literature search proved that EMRs are an appropriate instrument and widely used today, so that this can facilitate the formulation of diagnoses relevant to the patient's clinical condition[27].

The process of reporting patient demographic information must be correct by matching electronic medical record data with clnis data in the field. The categorization of data sources should be clear and specific and sorted according to alphabetical collection format. Demographic diversity on the characteristics of larger populations will make it easier to generalize machine learning models. Generalizing to unrepresented population groups will widen the gap and potentially bias the results[28,29].

The genome-wide association study found a number of problems related to long-term genetic testing, and the end result was that they found that the disease was dominated by whites, even though they were not classified as a vulnerable group. Fragmentation of health data in various body systems is experienced by vulnerable populations with low socioeconomic status and they regularly visit health care centers . Models that rely on quantity and programmed testing processes will have adverse implications for vulnerable groups. Despite the negative impacts, proper documentation is still carried out, while still being guided by demographic characteristics and representative samples, available racial categories and subcategories, especially in articles that provide white race data[30]. The availability of racial/ethnic data is critical because it is an early stage of natural machine learning that requires a diverse study population to achieve successful diagnosis of complex patients. The concept of comparison to be made is to include a racial component in population studies, descriptive statistics, and a menu of features that will be the basic components of machine learning algorithms. The idea that genetic differences are due to race and trying to formulate an outcome algorithm based on race is risky to widen the racial gap that has been previously available in medical catalogs [31,32]. But race should not be completely ignored in decision-making. Although the genetics component k, race, sex and sos ial become faktor determinants of health that impact the experience of patients experiencing disease. To ensure that the evaluation of machine learning algo ritma goes well, it is very important to consider the overall representativeness of the population including some of the components mentioned above[32].

Understanding and skills of accessing diagnostic tools are essential for both a researcher and practitioner. Therefore, dissertation recommendations with detailed and clear explanations will help to accurately establish the clinical diagnosis by the doctor. In addition, the application of good machine learning models will help improve clinical decision making through fast and accurate diagnosis. Conversely, a lack of understanding and skill in machine learning models will reduce the level of accuracy in determining basic clinical diagnoses through deep learning applications [33].

This review is limited to inclusion criteria that may not represent the whole breath of machine learning integration into healthcare. By excluding image-based applications, their scope is narrowed; However, by focusing first on diagnostics, research can be applied to additional areas. We do not look beyond peer-reviewed literature, it is possible that studies from relevant conferences or congresses are missed. Because conferences typically report incomplete work, abstracts may have no impact on results. The evidence in the review is limited by the availability of information. By contacting the authors to provide additional data, other factors such as how responsive a researcher is or if an email address is up to date come into play. Factors like these should be understood when considering calculated statistics for gender, race, and race information.

Understanding and skills of accessing diagnostic tools are essential for both a researcher and practitioner. Therefore, dissertation recommendations with detailed and clear explanations will help to accurately establish the clinical diagnosis by the doctor. In addition, the application of good machine learning models will help improve clinical decision making through fast and accurate diagnosis. Conversely, a lack of understanding and skill of machine learning models will decrease the level of accuracy in determining basic clinical diagnoses through deep learning applications [1,7].

Our study offers the advantage of providing a comprehensive picture of the current state of machine learning applications in basic diagnostic testing, synthesizing insights from a wide range of studies. This broad scope allows the identification of general patterns, emerging trends, and overarching themes in the literature. By combining findings from different disciplines and methodologies, the review takes a holistic approach, increasing the richness and depth of understanding in this rapidly evolving field. In addition, the integrative nature of the review enables the identification of practical implications, guiding practitioners and researchers in the effective deployment and advancement of machine learning technologies in diagnostic contexts. The synthesis of existing knowledge, when executed well, can serve as a valuable resource for professionals seeking evidence-based insights in this dynamic and transformative domain.

The study's potential weakness lies in the inherent risk of bias stemming from the selectivity of the included studies. If a review favors a specific database, time period, or journal, it may introduce skewed representations of the literature, which has the effect of generalizing findings. In addition, the quality of individual studies integrated into the review is critical, and limitations in their methodology or data collection procedures may compromise the overall reliability of the synthesized conclusions. The dynamic nature of machine learning technology poses another challenge, as literature reviews may not capture the latest advances or emerging trends, potentially making parts of the analysis outdated. It is critical for the review to transparently address these limitations to ensure a nuanced interpretation of its findings and to guide future research efforts in addressing these gaps.

Our review of studies limited only to inclusion criteria and generally did not represent channels for integrating machine learning into healthcare systems. We also exclude reviews that are image-based. However, we focused more on the study of machine learning literature based on basic clinical diagnostic tests that were added with additional software supporting the program. In this literature review we also narrow the search to the original article only. It is based on the aspect of variable homogeneity to access information more quickly and accurately and reduce bias.

We recognize that the diversity of machine learning application models for health serviceshas been widely applied in healthcare facilities[34], However, we focus on basicclinical diagnostic applications [35,36]. Articles that are text-based and diagnosedwith data or demographic characteristics are not reviewed.

Overall, this information synthesis underscores that the utilization of EMRs and machine learning in the context of early detection of clinic baseline diagnosis is a potential step forward to improve the quality of health care. However, ongoing efforts to address privacy, data security, and bias related challenges are integral to the development of these technologies to ensure their application provides maximum benefit to patients and healthcare practitioners [7,8].

Our findings proved to be consistently very precise with the chosen topic. The process of inputting and storing medical record data by EMRs greatly accelerates access to the application of informatics, especially assisting doctors in establishing diagnostics quickly, precisely and accurately, thus obtaining several benefits, including; The health service process becomes fast, patient satisfaction increases, public trust in hospitals or clinics increases, treatment duration is shorter, patient care and treatment costs are more efficient, effective and efficient

Research Limitations

An Integrative Literature Review only focuses on text-based artists, so the scope of electronic medical records (EMRs) applications has not been comprehensively reviewed. Therefore, reviewers need careful analysis to get maximum review results. These studies are limited by the inclusion of selective studies, potentially introducing bias if a particular database, journal, or time period is preferred. The quality of included studies may vary, with some pointing out limitations in their methodology or sample size, impacting the overall reliability of the findings synthesized. The rapidly evolving nature of machine learning technology and the dynamic landscape of the field can result in the omission of recent advances or emerging trends. Potential publication bias, language bias, and exclusion of primary research can also affect the completeness of a review. These limitations underscore the need for a nuanced interpretation of the review's findings and highlight avenues for future research to address these gaps in understanding.

CONCLUSION

The increasing trend of using machine learning applications for clinic basic diagnostic tests reflects the huge potential of technology in improving the quality of healthcare. Further development in this area can contribute significantly to efficiency and accuracy in establishing clinical diagnosis. However, keep in mind that these advances must be accompanied by strict ethical and data security considerations, especially when handling sensitive patient information. Careful measures in considering the demographic characteristics of populations are key to generating relevant and effective applications, given variations in disease presentation and response to treatment among specific demographic groups.

In this context, it is important to encourage collaboration between health experts, data scientists, and technology developers to achieve optimal alignment between technological innovation and medical needs. Continued efforts in research and development of machine learning applications for clinical diagnosis will bring long-term benefits in improving diagnosis precision, speeding up the treatment process, and ultimately, improving clinical outcomes for patients. Thus, while the digital age opens the door to positive transformation in the world of healthcare, the sustainability of multidisciplinary approaches and concern for ethical aspects become key in portraying a successful future for these applications.

ACKNOWLEDGEMENTS

The reviewers expressed their gratitude to the Academic Supervisor of the Faculty of Informatics Engineering Education, Makassar State University.

CONFLICTS OF INTEREST

There is no conflict of interest in this integrative literature review.

REFERENCE

1. Spano IL, Sulis S, Serpi A, Marongiu I,

Gatto G. EMC Characterization of Implantable Cardiac Medical Devices in an anechoic chamber. In: 2014 International Symposium on Electromagnetic Compatibility. IEEE; 2014. p. 872–7.
2. Parasrampuria S, Henry J. Hospitals' use of electronic health records data, 2015–2017. ONC Data Br. 2019;46:1–13.
3. Murdoch TB, Detsky AS. The inevitable application of big data to health care. Jama. 2013;309(13):1351–2.
4. Kononenko I. Machine learning for medical diagnosis: history, state of the art and perspective. Artif Intell Med. 2001;23(1):89–109.
5. Maity NG, Das S. Machine learning for improved diagnosis and prognosis in healthcare. In: 2017 IEEE aerospace conference. IEEE; 2017. p. 1–9.
6. Shah M, Shu D, Prasath VBS, Ni Y, Schapiro AH, Dufendach KR. Machine learning for detection of correct peripherally inserted central catheter tip position from radiology reports in infants. Appl Clin Inform. 2021;12(04):856–63.
7. Liberati A, Altman DG, Tetzlaff J, Mulrow C, Gøtzsche PC, Ioannidis JPA, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate healthcare interventions: explanation and elaboration. BMJ. 2009 Jul;339:b2700.
8. Scopus. Scopus [Internet]. Scopus preview. 2023 [cited 2023 Sep 10]. Available from: https://www.scopus.com/home.uri
9. NCBI. Pubmed [Internet]. MeSH - NCBI. 2023 [cited 2023 Sep 10]. Available from: https://www.ncbi.nlm.nih.gov/mesh/
10. Compass. Compass Digital Library [Internet]. University Libraries. 2023 [cited 2023 Oct 9]. Available from: https://du.primo.exlibrisgroup.com/discovery/search?vid=01UODE_INST:01UODE_MAIN&mode=advanced&tab=Everything&offset=0&sortby=rank&search_scope=MyInst_and_CI&lang=en
11. ACM. ACM Digital Library [Internet]. Association for Computing Machinery. 2023 [cited 2023 Sep 10]. Available from: https://dl.acm.org/search/advanced
12. Schnatter AR, Rooseboom M, Kocabas NA, North CM, Dalzell A, Twisk J, et al. Derivation of an occupational exposure limit for benzene using epidemiological study quality assessment tools. Toxicol Lett. 2020;334:117–44.
13. National Heart, Lung and BI. Study quality assessment tool [Internet]. NIH. 2021 [cited 2023 Aug 31]. Available from: https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools
14. Pestian JP, Sorter M, Connolly B, Bretonnel Cohen K, McCullumsmith C, Gee JT, et al. A Machine Learning Approach to Identifying the Thought Markers of Suicidal Subjects: A Prospective Multicenter Trial. Suicide Life Threat Behav. 2017 Feb;47(1):112–21.
15. NHLBI. Study Quality Assessment Tools [Internet]. NIH. 2013 [cited 2023 Oct 9]. Available from: https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools
16. Ginestra JC. Clinician Perception of a Machine Learning–Based Early Warning System Designed to Predict Severe Sepsis and Septic Shock. Crit Care Med. 2019;47(11):1477–84.
17. Levy S, Duda M, Haber N, Wall DP. Sparsifying machine learning models identify stable subsets of predictive features for behavioral detection of autism. Mol Autism. 2017;8:65.
18. Baxt WG, Shofer FS, Sites FD, Hollander JE. A neural network aid for the early diagnosis of cardiac ischemia in patients presenting to the emergency department with chest pain. Ann Emerg Med. 2002 Dec;40(6):575–83.
19. Li X, Xu X, Xie F, Xu X, Sun Y, Liu X, et al. A Time-Phased Machine Learning Model for Real-Time Prediction of Sepsis in Critical Care. Crit Care Med. 2020 Oct;48(10):e884–8.
20. Jorge A, Castro VM, Barnado A, Gainer V, Hong C, Cai T, et al. Identifying lupus patients in electronic health records: Development and

validation of machine learning algorithms and application of rule-based algorithms. Semin Arthritis Rheum. 2019 Aug;49(1):84–90.
21. Corey KM, Kashyap S, Lorenzi E, Lagoo-Deenadayalan SA, Heller K, Whalen K, et al. Development and validation of machine learning models to identify high-risk surgical patients using automatically curated electronic health record data (Pythia): A retrospective, single-site study. PLoS Med. 2018 Nov;15(11):e1002701.
22. Gicquel Q, Tvardik N, Bouvry C, Kergourlay I, Bittar A, Segond F, et al. Annotation methods to develop and evaluate an expert system based on natural language processing in electronic medical records. Stud Health Technol Inform. 2015;216:1067.
23. Danford CJ, Lee JY, Strohbehn IA, Corey KE, Lai M. Development of an Algorithm to Identify Cases of Nonalcoholic Steatohepatitis Cirrhosis in the Electronic Health Record. Dig Dis Sci. 2021 May;66(5):1452–60.
24. Sahli CA, Bibi A, Ouali F, Fredj SH, Dakhlaoui B, Othmani R, et al. Red cell indices: differentiation between β-thalassemia trait and iron deficiency anemia and application to sickle-cell disease and sickle-cell thalassemia. Clin Chem Lab Med. 2013 Nov;51(11):2115–24.
25. Antohi EL, Ambrosy AP, Collins SP, Ahmed A, Iliescu VA, Cotter G, et al. Therapeutic Advances in the Management of Acute Decompensated Heart Failure. Am J Ther. 2019;26(2):e222–33.
26. Natarajan A, Lam G, Liu J, Beam AL, Beam KS, Levin JC. Prediction of extubation failure among low birthweight neonates using machine learning. J Perinatol. 2023 Feb;43(2):209–14.
27. Elkin PL, Froehling DA, Wahner-Roedler DL, Brown SH, Bailey KR. Comparison of natural language processing biosurveillance methods for identifying influenza from encounter notes. Ann Intern Med. 2012 Jan;156(1 Pt 1):11–8.
28. Parikh RB, Teeple S, Navathe AS. Addressing Bias in Artificial Intelligence in Health Care. JAMA. 2019 Dec;322(24):2377–8.
29. Gijsberts CM, Groenewegen KA, Hoefer IE, Eijkemans MJC, Asselbergs FW, Anderson TJ, et al. Race/Ethnic Differences in the Associations of the Framingham Risk Factors with Carotid IMT and Cardiovascular Events. PLoS One. 2015;10(7):e0132321.
30. Zemore SE, Gilbert PA, Pinedo M, Tsutsumi S, McGeough B, Dickerson DL. Racial/Ethnic Disparities in Mutual Help Group Participation for Substance Use Problems. Alcohol Res. 2021;41(1):3.
31. Gianfrancesco MA, Tamang S, Yazdany J, Schmajuk G. Potential Biases in Machine Learning Algorithms Using Electronic Health Record Data. JAMA Intern Med. 2018 Nov;178(11):1544–7.
32. Vyas DA, Eisenstein LG, Jones DS. Hidden in Plain Sight - Reconsidering the Use of Race Correction in Clinical Algorithms. N Engl J Med. 2020 Aug;383(9):874–82.
33. Holzinger A, Langs G, Denk H, Zatloukal K, Müller H. Causability and explainability of artificial intelligence in medicine. Wiley Interdiscip Rev Data Min Knowl Discov. 2019;9(4):e1312.
34. Thomsen K, Iversen L, Titlestad TL, Winther O. Systematic review of machine learning for diagnosis and prognosis in dermatology. J Dermatolog Treat. 2020 Aug;31(5):496–510.
35. de Filippis R, Carbone EA, Gaetano R, Bruni A, Pugliese V, Segura-Garcia C, et al. Machine learning techniques in a structural and functional MRI diagnostic approach in schizophrenia: a systematic review. Neuropsychiatr Dis Treat. 2019;15:1605–27.
36. Kassem MA, Hosny KM, Damaševičius R, Eltoukhy MM. Machine Learning and Deep Learning Methods for Skin Lesion Classification and Diagnosis: A Systematic Review. Diagnostics (Basel, Switzerland). 2021 Jul;11(8).