IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 30 July 2024, accepted 25 August 2024, date of publication 28 August 2024, date of current version 10 September 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3450970

TOPICAL REVIEW

Impact of Artificial Intelligence in Nursing for Geriatric Clinical Care for Chronic Diseases: A Systematic Literature Review

MAHDIEH POODINEH MOGHADAM[1], ZABIH ALLAH MOGHADAM[2], MOHAMMAD REZA CHALAK QAZANI[3], PAWEŁ PŁAWIAK[4,5], AND ROOHALLAH ALIZADEHSANI[6], (Member, IEEE)

[1]Department of Nursing, Faculty of Nursing and Midwifery, Zabol University of Medical Sciences, Zabol 98616-15881, Iran
[2]Department of Computer Engineering, School of Technical and Engineering, Birjand Branch, Islamic Azad University, Birjand 14778-93855, Iran
[3]Faculty of Computing and Information Technology, Sohar University, Sohar 311, Oman
[4]Department of Computer Science, Faculty of Computer Science and Telecommunications, Cracow University of Technology, 31-155 Kraków, Poland
[5]Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, 44-100 Gliwice, Poland
[6]Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Waurn Ponds, VIC 3216, Australia

Corresponding author: Paweł Pławiak (pawel.plawiak@pk.edu.pl)

ABSTRACT Nurses are essential in managing the healthcare of older adults, particularly those over 65, who often face multiple chronic conditions. This group requires comprehensive physical, mental, and functional care. Recent advancements in artificial intelligence (AI) have significantly improved nursing capabilities by enabling real-time health monitoring, thus bolstering the early detection and prevention of severe health issues. Despite these advancements, the current systematic literature predominantly focuses on machine learning (ML) applications for a limited set of chronic diseases, often overlooking the extensive capabilities of deep learning (DL) technologies. Additionally, these reviews cover a narrow spectrum of studies, potentially needing broader insights and developments in the field. To address these shortcomings, our study conducts a systematic literature review of ML and DL applications in geriatric care for chronic disease management. We meticulously analyzed peer-reviewed articles published from 2014 to 2024, concentrating on AI technologies in elderly care. This review included 76 selected articles from leading publishers such as Elsevier, Springer, IEEE, MDPI, Wiley, Taylor & Francis, Nature, Cambridge University Press, Oxford University Press, and arXiv, which we categorized into three main groups: Neurological disorders (27 articles), Mental Health disorders (22 articles), and Physical/physiological disorders (27 articles). Our findings reveal that Random Forest, logistic regression, and convolutional neural network (CNN) are the most frequently used AI techniques, typically evaluated by accuracy metrics and the area under the curve (AUC). The findings indicate that although AI applications in geriatric care are promising, they require significant enhancements in technology and methodology to improve accuracy and reliability. Future research should focus on developing advanced AI tools, integrating cutting-edge deep learning models and comprehensive datasets to refine diagnostics and treatment protocols for chronic diseases in the elderly, ultimately enhancing patient outcomes.

INDEX TERMS Nurse, older patients, chronic disease, artificial intelligence, machine learning, deep learning.

I. INTRODUCTION

The United States Census Bureau projects that the population of older adults will reach 88.5 million by 2050 [1], [2]. This demographic frequently faces numerous concurrent health

The associate editor coordinating the review of this manuscript and approving it for publication was Moussa Ayyash.

challenges that can result in deteriorating health outcomes, increased disability, and greater reliance on institutional care. Rapid and accurate diagnosis is challenging due to older patients' complex medical histories and symptoms. Figure 1 illustrates key issues impacting these patients and their caregivers [3].

Comprehensive assessments of older patients require thorough and time-consuming efforts that demand collaboration across various healthcare disciplines. Nurses play a critical role in the ongoing care and monitoring of older patients. However, they often encounter difficulties in fully assessing individuals with multiple health issues during routine visits. These challenges are exacerbated by the increasing burden of clinical paperwork, the use of outdated technologies, and a shortage of nurses specialized in geriatric care, all of which can lead to suboptimal care and possibly missed or incomplete diagnoses [4]. Physicians complement the work of nurses by typically leading the initial assessments and diagnosis. They make key medical decisions using detailed clinical assessments, laboratory results, and diagnostic tools that nurses may not utilize extensively [5]. Nevertheless, there are significant areas of shared responsibilities. For instance, both nurses and physicians are actively involved in the ongoing assessment and management of chronic conditions prevalent among older patients, collaborating to monitor treatment effectiveness and adapt care plans as needed based on changes in patient conditions. This teamwork enables the swift and accurate exchange of patient observations and treatment responses, which is crucial for improving medical outcomes [6].

Artificial intelligence (AI) in healthcare can enhance prevention, diagnosis, and treatment [7], [8], [9]. AI applications are already making strides in areas such as robotic-assisted disease management [10], [11], cancer detection [12], [13], [14], and improving patient safety [15], [16]. Nurses are using AI to guide decision-making, streamline drug development, and monitor patient care more effectively [17]. In some instances, AI has started to exceed human capabilities, especially in handling large datasets and identifying patterns that might elude human observers [18]. For instance, AI systems have shown superior accuracy in diagnosing diseases from imaging data at a faster rate than human radiologists [19]. As another example, AI algorithms have successfully predicted disease outbreaks by analyzing patterns in social media data, which human analysts may miss due to the sheer volume and complexity of information [20].

Recent systematic reviews in chronic disease management have made essential contributions [21], [22] but encounter significant limitations. Firstly, they tend to focus on a narrow range of chronic diseases. Secondly, while they frequently discuss machine learning applications, they often overlook the potential of deep learning techniques. Additionally, these reviews typically analyze a limited selection of articles. To address these issues, our study conducts a comprehensive literature review on applying AI in senior care within a nursing context. We evaluated research published between 2014 and 2024 that utilized AI algorithms to assist in managing chronic conditions in older adults. Our extensive review led us to select 76 articles from renowned publishers such as Elsevier, Springer, IEEE, MDPI, Wiley, Taylor & Francis, Nature, Cambridge University Press, Oxford University Press, and arXiv. We organized these articles into three main categories based on the health issues they address: Neurological disorders (27 articles), Mental Health disorders (22 articles), and Physical/physiological disorders (27 articles). In summary, this systematic review showcases:

- An in-depth analysis of ML and DL methods to evaluate the effectiveness of algorithms across 76 studies spanning the last 11 years.
- We also explore future research directions in automated detection techniques, shedding light on the changing scope of chronic disease management.
- The review highlights research on identifying chronic conditions using various data types, including clinical records, imaging, and biological samples.
- The review identified 18 unique diseases and recognized 9 distinct algorithms.

This study is structured into five key sections. Section II presents related works, while Section III outlines the methodology adopted for the selection of research papers. Section IV provides an overview of current machine learning and deep learning research. Section V offers a discussion of the studies examined. Finally, Section VI concludes the article.

II. LITERATURE REVIEW

A. THREATS TO VALIDITY

This section outlines potential biases and limitations inherent in the reviewed studies within the domain of chronic disease management using AI. Several factors may compromise the validity of these reviews:

- Narrow disease focus: Numerous systematic reviews target a limited array of chronic diseases, potentially introducing bias by failing to represent the broader spectrum of conditions that afflict older adults. This narrow focus restricts the generalizability of the findings and may overlook diseases where AI could have a substantial impact.
- Technological limitations: There is a notable predominance of traditional machine learning techniques in the literature, often at the expense of exploring more advanced deep learning technologies. This technological bias can skew the outcomes of the reviews, leading to an underestimation of the potential benefits that newer, more sophisticated AI models could provide. These advanced models can analyze more complex data sets and identify nuanced patterns that traditional methods might miss, significantly improving diagnosing and managing complex chronic conditions.
- Selective article analysis: Often, these reviews conclude a restricted selection of scholarly articles. Such

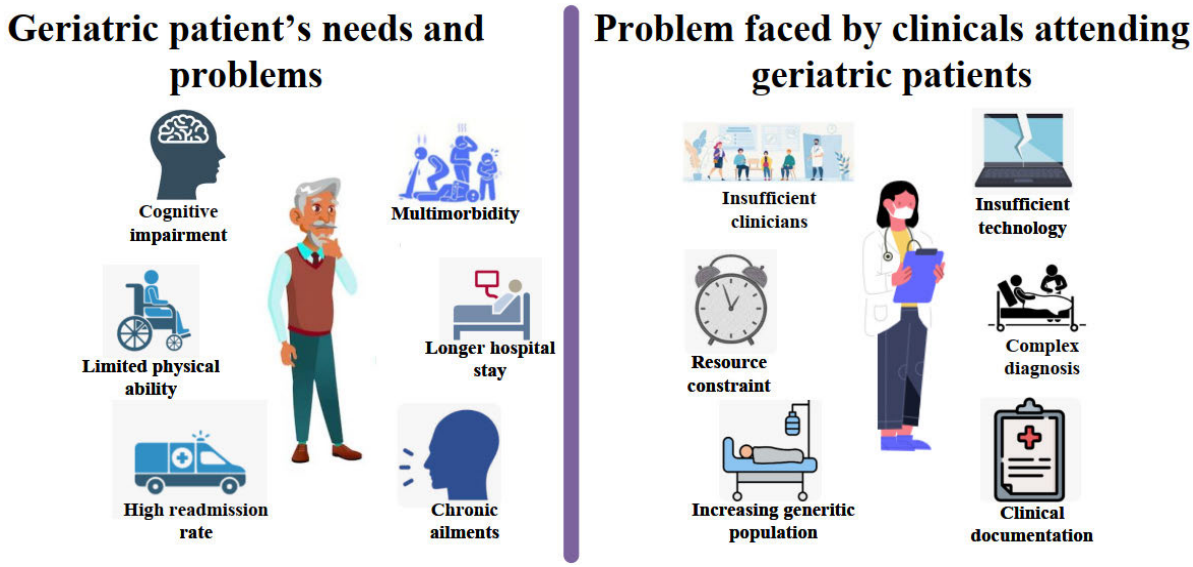

FIGURE 1. Visual representation of the needs of older people and the challenges nurses face.

selection bias can result in an incomplete assessment of the current state of AI in healthcare, potentially missing out on critical studies that offer a more comprehensive understanding of the field's capabilities and limitations. This selective approach may ignore pivotal research that could challenge existing conclusions or highlight new opportunities for AI in healthcare.

- Outdated data: The rapid advancement in AI technologies means that some reviews might incorporate studies that need to be updated at the time of publication. This inclusion can lead to conclusions that may need to accurately reflect the current capabilities and challenges of AI applications in healthcare, rendering some findings obsolete.

To address these threats, a meticulous approach is necessary. It involves systematically selecting and evaluating a wide range of studies that cover various diseases and integrate the latest advancements in AI technology with intense learning. This comprehensive approach ensures a more balanced and current view of the field, promoting a deeper understanding of how AI can effectively contribute to chronic disease management in diverse healthcare settings.

B. COMPREHENSIVE REVIEW OF EXISTING RESEARCH

Chronic diseases are common in the elderly and are characterized by their complex and multifaceted progression. In geriatric care, accurately predicting disease trajectories and potential acute events early on can significantly enhance management strategies. This allows for preventive actions and personalized treatment plans. Researchers have employed various methods to diagnose chronic diseases, focusing primarily on neurological disorders, mental health disorders, and physical disorders [23]. For example, Tawhid et al. [24] developed a computer-aided diagnosis (CAD) system that uses a CNN to analyze spectrogram images from electroencephalography (EEG) data. This system is designed to identify multiple neurological disorders, including autism, epilepsy, Parkinson's disease, and schizophrenia, as well as to differentiate these from healthy controls. Additionally, Mujahid et al. [25] introduced an ensemble method that combines VGG16 and EfficientNet for diagnosing Alzheimer's disease from magnetic resonance imaging (MRI) images. They used an adaptive synthetic oversampling technique to balance the highly imbalanced dataset, thereby enhancing the training of the model and improving diagnostic accuracy by learning complex patterns from the combined outputs of both models.

Several review articles have focused on chronic diseases. Woodman and Mangoni [26] explored the growing role of machine learning in healthcare, driven by increased access to global health data. Their review details the taxonomy of machine learning algorithms, outlining the functions, capabilities, and specific applications in geriatric medicine. They stress the importance of educating clinicians about AI to encourage its adoption. They also discuss the challenges of using clinically approved, yet often less interpretable, machine learning tools in patient care. They also highlight the need to develop explainable machine learning to build trust and utility in clinical settings. Hamaker et al. [27] conducted a systematic review by searching Medline and Embase for studies analyzing the effects of geriatric assessments on treatment decisions, non-oncologic interventions, communication, and outcomes in older cancer patients. Their review assessed the impact of different assessment types on treatment planning, the implementation of interventions, patient-doctor communication, and overall treatment outcomes for this demographic. Cai et al. [28] conducted a comprehensive literature search through databases

such as PubMed, EMBASE, PsycINFO, and Web of Science to explore the global prevalence of depression among older adults and its influencing factors. They utilized a random-effects model to address variances in demographic and clinical characteristics across studies, enabling the calculation of the pooled prevalence of depression and its 95% confidence interval. Correia et al. [29] utilized a systematic review and meta-analysis to assess the content and effectiveness of therapeutic patient education (TPE) programs for chronic disorders. They accessed databases like Web of Science, MEDLINE, CINAHL, PsycINFO, and COCHRANE up to August 2019, employing a rigorously tested search strategy focusing on patient education, chronic diseases, study designs, and outcomes. After a detailed screening process, two reviewers extracted both qualitative and quantitative data from randomized controlled trials concerning TPE interventions. They also created a taxonomy related to curriculum skills and intervention delivery techniques to assist in data extraction. Collado-Mateo et al. [30] performed a systematic review following the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines to investigate adherence to physical exercise among chronic and older adults. They reviewed relevant literature and selected fifty-five articles to identify critical factors commonly suggested to improve exercise adherence. The results were categorized based on the target population and participant characteristics to determine the most prevalent factors affecting adherence. Kumar et al. [31] performed a comprehensive survey on using artificial intelligence techniques, from machine learning to deep learning, in healthcare. This survey included a systematic literature review up to October 2020 from Web of Science, Scopus, Google Scholar, PubMed, Excerpta Medical Database, and Psychology Information. It focused on diagnosing diseases like Alzheimer's, cancer, and diabetes using AI techniques. The review followed Preferred Reporting Items for Systematic Reviews and Meta-Analysis guidelines to select studies that applied AI for early disease prediction, involving medical imaging datasets, feature extraction, and classification processes. Sawad et al. [32] systematically reviewed conversational agents in healthcare, particularly for managing chronic conditions. This review, conducted in February 2021, focused on the agents' communication technologies, evaluation metrics, and AI methods. The researchers used databases such as PubMed Medline, EMBASE, PsycINFO, CINAHL, Web of Science, and ACM Digital Library to gather studies. They included studies where conversational agents were tested with human users in prevention, treatment, or rehabilitation contexts targeting consumers, caregivers, or healthcare professionals. Merabet et al. [33] conducted a systematic literature review using AI-based clinical decision support systems (CDSS) and the internet of medical things (IoMT) to predict multiple diseases. This study highlights the improvements in diagnostics, therapy, and prognosis offered by AI, mainly through ML and DL, enhanced by IoMT technologies that link networked biomedical devices with software applications. The review aims to expand the research focus of medical decision support systems, which have traditionally centered on single disease prediction, by exploring various aspects to encourage future research on predicting multiple diseases. Armand et al. [34] investigated the integration of AI in nutrition as part of the broader automation and digitalization efforts of Industry 4.0. They systematically reviewed the application of AI, ML, and DL in nutrition sciences using a hybrid approach of systematic literature review (SLR) and PRISMA guidelines. The search covered major databases, followed by meticulous study selection and methodological quality assessments. This comprehensive review discusses AI's role in smart nutrition, dietary assessments, food recognition, disease prevention modeling, and monitoring, outlining the current capabilities and future challenges in the field.

Table 1 summarizes the review articles on chronic diseases. To address challenges, including a narrow disease focus, technological limitations, selective article analysis, and outdated data, our study undertakes a systematic literature review of ML and DL applications in geriatric care for managing chronic diseases. We thoroughly examined peer-reviewed articles published from 2014 to 2024, focusing on AI technologies in elderly care. This review includes 76 selected articles from leading publishers, categorized into three main groups: 27 articles on neurological disorders, 22 on mental health disorders, and 27 on physical/physiological disorders. After reviewing the selected articles, we conclude that while AI applications in geriatric care show promise, they still require significant technological and methodological improvements to enhance accuracy and reliability. Future research should aim to develop advanced AI tools and integrate cutting-edge deep learning models and comprehensive datasets to refine diagnostics and treatment protocols for chronic diseases in the elderly, ultimately improving patient outcomes.

III. REVIEW METHOD

To comprehensively select research articles for our study, we meticulously designed a search strategy that utilized highly pertinent keywords, including "chronic disease," "elderly patients," "older adults," "machine learning," and "deep learning." Our goal was to identify papers that specifically address the intersection of these topics. We conducted a thorough search across several well-established digital databases known for their robust collections of academic research. These databases comprised Elsevier, Springer, IEEE, MDPI, and Wiley, Taylor & Francis, Nature, Cambridge University Press, Oxford University Press, and arXiv. We confined our search to works published in English to maintain consistency in our analysis and to ensure that we could accurately assess the quality and relevance of the content.

Figure 2 in our documentation offers an insightful breakdown of the studies related to ML and DL that emerged from our search parameters. This visual representation provides

TABLE 1. Comparison of systematic review studies focusing on AI in the context of healthcare, chronic conditions, and geriatric care.

Authors	Key focus	Main findings	Significance	Limitation
Woodman and Mangoni [26]	ML in geriatric medicine	It discusses the taxonomy of ML algorithms, the challenges of clinical implementation, and the importance of explainable AI	It highlights the need for clinician education in AI to improve adoption and trust in clinical settings	Lacks empirical data; It relies heavily on theoretical and anecdotal evidence, which may not fully represent practical realities
Hamaker et al. [27]	Geriatric assessments in oncology	It analyzes the impact of geriatric assessments on oncologic treatment decisions and outcomes	It emphasizes how geriatric assessments influence treatment planning and patient-doctor communication in older cancer patients	Limited to oncology, may not generalize to other areas of geriatric care; potential publication bias in selected studies
Kumar et al. [31]	AI in diagnosing diseases like Alzheimer's, cancer, diabetes	It explores AI techniques for early disease prediction using medical imaging datasets	It demonstrates AI's potential in early disease diagnosis through advanced feature extraction and classification	It focuses mainly on high-resource settings; underrepresentation of low and middle-income countries in datasets and studies
Sawad et al. [32]	Conversational agents in healthcare for chronic conditions	It investigates communication technologies and AI methods used in conversational agents for chronic disease management	It shows the growing importance of conversational AI in the prevention, treatment, and rehabilitation of chronic diseases	Lacks longitudinal studies to assess the long-term effectiveness and user engagement with AI agents
Merabet et al. [33]	AI-based CDSS and IoMT in disease forecasting	It reviews advancements in ML, DL, and IoMT for diagnostics, therapy, and prognosis of multiple diseases	It broadens the research scope in medical decision support systems, predicting multiple diseases using advanced technologies	Often overly technical, which may hinder understanding and practical implementation by healthcare professionals
Armand et al. [34]	AI in nutrition within Industry 4.0	This research delves into the novel application of AI in nutrition for smart dietary assessments, food recognition, and disease prevention	It highlights the integration of AI in enhancing nutrition science through automation and digitalization	Potential bias in selected studies; lack of real-world application and testing in diverse populations
Cai et al. [28]	Prevalence of depression among older adults	It calculates the pooled prevalence of depression and its influencing factors among older adults	It provides vital epidemiological data on depression in the elderly, aiding in targeted healthcare planning	The methodology may not account for all regional and cultural variations, potentially affecting the generalizability of results

TABLE 1. *(Continued.)* **Comparison of systematic review studies focusing on AI in the context of healthcare, chronic conditions, and geriatric care.**

Correia et al. [29]	Effectiveness of TPE programs for chronic disorders	It assesses the content and effectiveness of TPE programs, creating a taxonomy for curriculum skills	It aids in understanding how TPE can be effectively structured and delivered for chronic disease management	It focuses primarily on randomized controlled trials, which may not represent all types of educational interventions
Collado-Mateo et al. [30]	Adherence to physical exercise among chronic and older adults	It identifies prevalent factors affecting exercise adherence in chronic and older adults	It provides insights into improving physical activity strategies for vulnerable populations	Limited scope in analyzing diverse intervention strategies beyond the selected articles, which might offer broader insights

a clear overview of the distribution and frequency of publications across various databases and categorizations, which is pivotal for understanding the current research landscape in this field. We refined our search methodology multiple times to guarantee a comprehensive and inclusive search result. This iterative process was critical to encompass a broad spectrum of potentially relevant scholarly works and filter out extraneous content that did not meet our specific criteria.

Table 2 presents a concise summary of the findings from our search queries. It enumerates the volume of initially retrieved documents, offering a snapshot of the wealth of literature available on the given subjects. Each of the 1532 documents identified through this process was subjected to a rigorous review. This involved an initial screening based on titles and abstracts, followed by a more in-depth evaluation of the full text where necessary. This meticulous review aimed to ensure that the final selection of articles was highly pertinent to our research objectives, allowing us to draw from a pool of high-caliber. These insightful studies contribute to the understanding of AI applications in geriatric care. Our review process started with evaluating 397 studies from the Elsevier database, focusing on their titles and abstracts. This initial step led us to exclude 216 documents for being off-topic, while 181 were selected for a more detailed full-text examination. Of these, 167 did not meet our criteria upon closer inspection, leaving 14 studies to be included in our review. From the Springer database, we scanned 148 studies' titles and abstracts, which resulted in 98 being discarded as irrelevant and 50 moving forward for full-text review. After a thorough examination, 34 were excluded, and 16 were deemed suitable for inclusion. We looked at 215 studies in the IEEE database, eliminating 136 after the initial screening and taking 79 further for full-text assessment. This process led to 11 studies being included and 68 rejected. The MDPI database presented 104 studies for initial review. Post-screening, 63 were found irrelevant, and 41 underwent full-text review, resulting in 8 studies being included after 33 were rejected. Within the Wiley database, 147 studies were initially considered; 79 were dismissed as unrelated, leaving 68 for full-text review. This step resulted in 12 studies being included after 56 were rejected. For Taylor & Francis, we initially reviewed 151 studies, of which 101 were rejected at the screening stage. The remaining 50 underwent detailed full-text assessment, which resulted in the exclusion of 45 studies, leaving 5 that met our inclusion criteria. Nature provided 125 studies, with 75 discarded during initial screening. Of the 50 that progressed to full-text review, 46 were subsequently excluded, culminating in 4 studies deemed suitable for inclusion. From the Cambridge University Press database, we initially considered 90 studies, rejecting 60 at the screening stage. The 30 reviewed in greater depth resulted in 28 rejections, with 2 studies ultimately included. The Oxford University Press presented 98 studies for review. Initial screening led to the exclusion of 58 studies, and of the remaining 40 that underwent full-text assessment, 38 were rejected, resulting in 2 studies being included. Finally, from arXiv, we screened 57 studies, eliminating 37 initially. The 20 studies that moved to full-text review experienced 18 rejections, with 2 studies meeting our inclusion criteria.

TABLE 2. **Overview of research articles found in the explored databases.**

Database	Number of Research Articles
Elsevier	397
Springer	148
IEEE	215
MDPI	104
Wiley	147
Taylor & Francis	151
Nature	125
Cambridge University Press	90
Oxford University Press	98
arXiv	57
Total	1532

While reviewing titles and abstracts, we first assessed each study's relevance to the predefined themes of our research, which focus on the application of ML and DL in geriatric

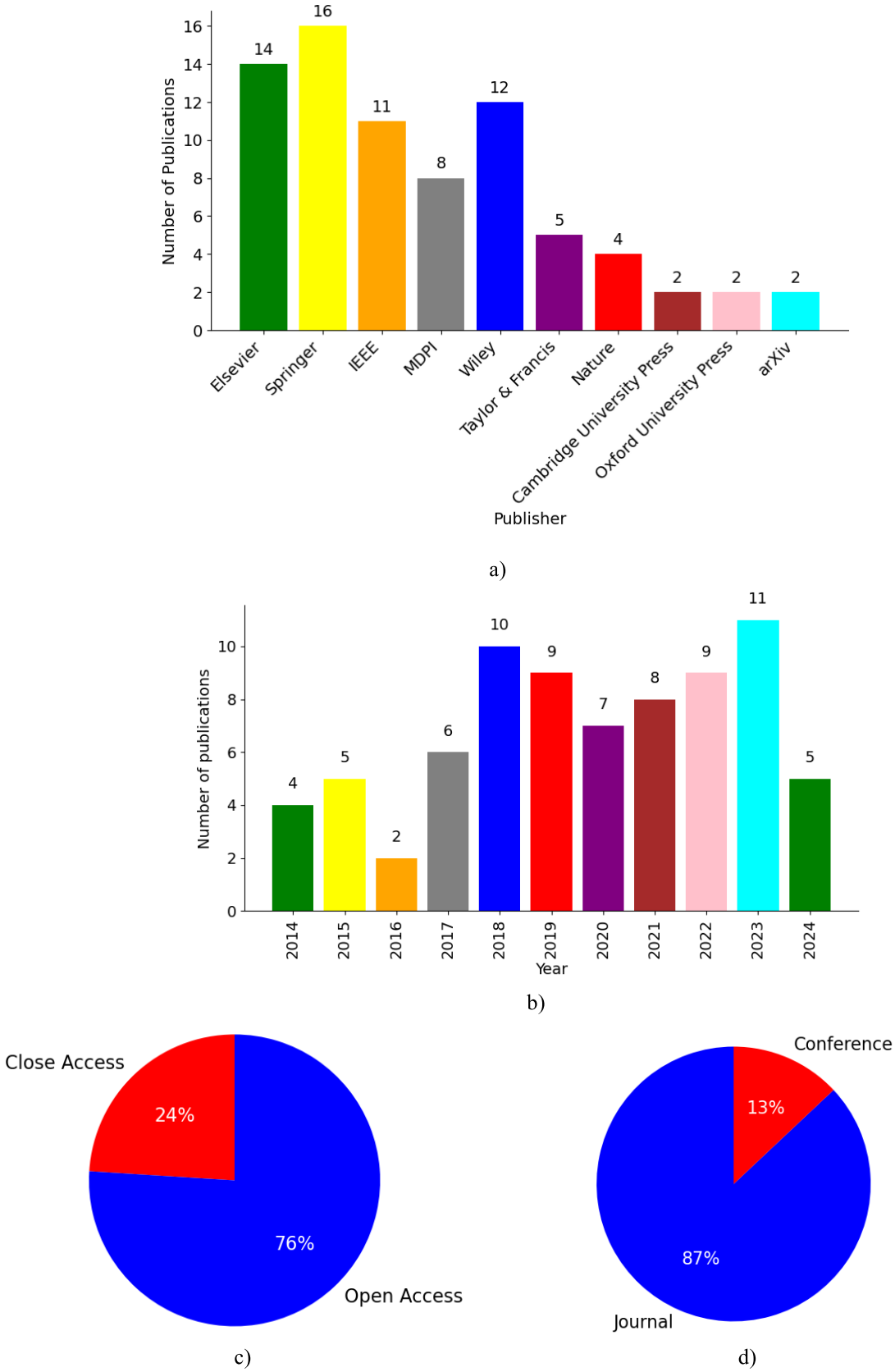

FIGURE 2. Data on ML and DL studies. a) Number of publications by each database, b), Number of publications by year, c) Proportion of open access vs. close access publications, c) Publication types classified as articles and conference papers.

care for managing chronic diseases in older adults. Studies that did not align with these themes were immediately considered off-topic. Additionally, we evaluated the clarity and completeness of the abstracts to determine if they provided enough information to justify a full review. In the review of the complete texts, we outlined our criteria for inclusion in more detail. This process involved assessing the robustness of the study's methodology, the significance of its findings, and its overall contribution to the field. We stipulated that, at a minimum, a manuscript must demonstrate a sound methodological framework and present relevant, clearly articulated results to be considered for inclusion. This thorough approach ensures that only studies of substantial merit and relevance are included in our review, thus maintaining the integrity and depth of our research analysis.

In all, 76 studies were identified in the explored databases. Figure 3 presents the outcomes of the search for research articles.

IV. OVERVIEW OF ML AND DL METHODS

The potential application of ML techniques in diagnosing chronic diseases has garnered significant interest due to their ability to uncover complex patterns in medical data. This has led to a more nuanced understanding of disease progression and patient outcomes. As ML algorithms become more sophisticated, their predictive accuracy and diagnostic capabilities improve, offering a promising toolset for healthcare professionals. These advancements could lead to earlier detection of chronic conditions, personalized treatment plans, and better management strategies tailored to individual patient profiles, ultimately enhancing patient care and potentially reducing the burden of chronic diseases on healthcare systems. Below is a list of renowned ML algorithms extensively used in diagnosing chronic conditions. Their inclusion reflects their widespread adoption and proven success across numerous studies. We discussed these specific algorithms due to their prevalence and effectiveness in the field, as detailed in our literature survey (refer to Table 3).

- Support Vector Machine (SVM) [35]: Beyond establishing a hyperplane, SVM is particularly adept at managing non-linear relationships in data using kernel functions. This allows the algorithm to model complex medical phenomena that are not linearly separable [36], [37]. Its robustness in handling noise and outliers makes it invaluable in clinical settings where data anomalies are shared, thus ensuring reliable biomarker detection and patient categorization even under varied clinical conditions [38].
- Random Forest (RF) [39]: This algorithm reduces overfitting through its ensemble method and provides essential insights into feature importance. In chronic disease applications, understanding which variables most significantly impact disease outcomes can guide clinical practice and research [40], [41]. The ability to perform both classification and regression makes Random Forest versatile for predicting disease presence and progression severity, making it a critical tool in managing and researching chronic conditions [42], [43].
- K-Nearest Neighbor (KNN) [44]: The KNN algorithm classifies data points based on proximity, enabling it to dynamically adjust to changes in input data, which is common in continuous patient monitoring [45]. This flexibility is crucial for tracking disease progression over time or adjusting treatment plans based on new data, offering a direct route to personalized medicine [46].
- Logistic Regression (LR) [47]: While noted for its binary classification capabilities, logistic regression can also be extended to multiclass classification to handle multiple outcomes, which is often necessary for complex chronic diseases manifest in various forms. It can also incorporate interaction terms to explore how different risk factors interact to impact disease likelihood, providing a deeper understanding of disease mechanisms [48], [49].
- Decision Tree (DT) [50]: An added advantage of decision trees in chronic disease management is their interpretability, which is critical for clinical decision-making [51], [52]. Clinicians can follow the paths in the tree to understand the decision process, which aids in patient communication and educational efforts about how lifestyle or demographic factors might influence their health outcomes [53].
- Naive Bayes (NB) [54]: In addition to its efficiency, Naive Bayes handles missing data effectively, an essential feature given the frequent incompleteness of medical records [55], [56]. It can still perform well with partial data, making it particularly useful in real-world clinical environments where perfect datasets are rare [57].
- Extreme Gradient Boosting (XGBoost) [58]: One of XGBoost's notable features is its ability to handle different types of data issues, such as missing values and various types of variable importance. It also allows for fine-tuning of parameters to avoid overfitting, which is particularly beneficial in chronic disease modeling, where the risk of overfitting can skew critical predictions and decision-making [59].

Advancements in hardware capabilities, mainly graphics processing units, along with decreasing costs per unit, are key factors contributing to the surge in the popularity of DL [60], [61]. This growth has been further supported by advancements in machine learning and data processing research [62], [63], [64], [65], coupled with an expansion in the availability of training datasets. DL has been widely adopted across various fields, such as computer vision [9], [61], [63], [66], natural language processing [67], [68], and speech recognition [69], [70], employing diverse deep learning frameworks like ANN, CNN, and RNN:

- ANNs are computational models inspired by the human nervous system, consisting of interconnected layers of neurons, including input, output, and hidden layers.

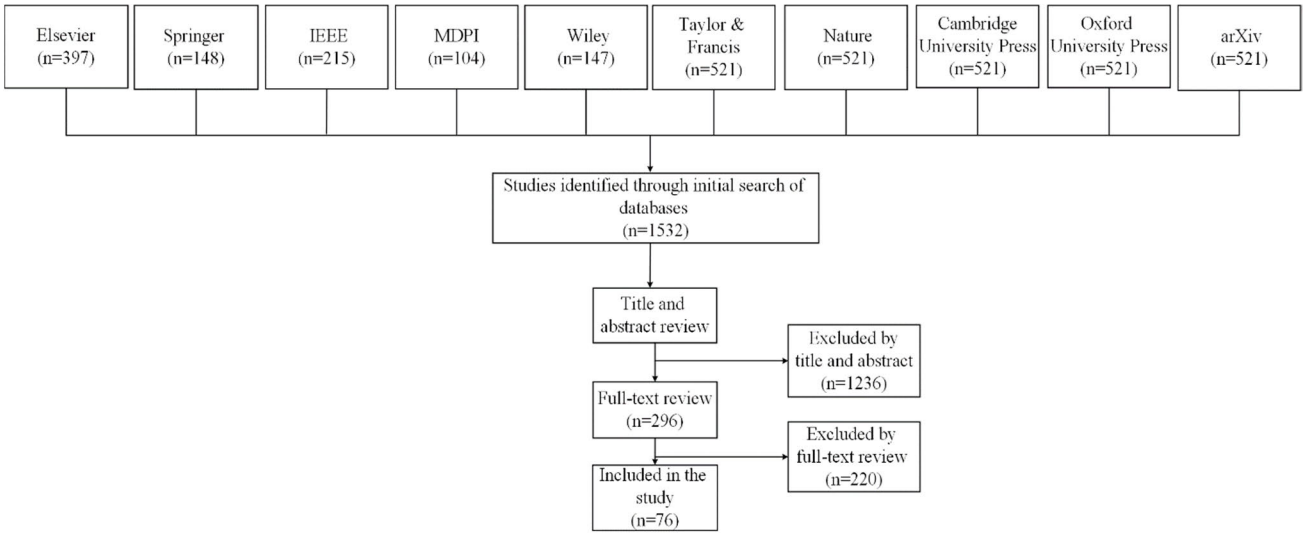

FIGURE 3. Breakdown of the selection process for research articles.

Each layer processes the output of the previous one to identify progressively complex patterns in the data [71], [72]. In chronic illness studies, ANNs can be particularly useful for modeling complex, non-linear relationships between various health indicators, aiding in predicting disease progression and patient outcomes [73], [74].

- CNNs are specialized for processing visual imagery, including videos and images. They consist of distinct layers that perform specific operations, such as convolution, pooling, and activation functions [52], [68], [75]. CNNs are highly effective in medical imaging tasks, such as analyzing X-rays, MRI scans, and CT images, to detect and diagnose chronic conditions like cancer, cardiovascular diseases, and neurological disorders. Their ability to automatically learn spatial hierarchies of features makes them ideal for detecting subtle anomalies in medical images [76], [77].
- RNNs are unique in their ability to consider previous and current inputs, synthesizing information from past and present contexts to generate outputs [78]. This suits them, particularly for time-series analysis and sequential data, which is common in chronic illness monitoring. RNNs can be used to predict disease trajectories, manage patient health records, and analyze longitudinal health data to provide insights into disease progression and the effectiveness of treatment plans [173], [174], [175].

Table 3 presents the ML and DL models for the early identification of chronic illnesses. Most of the research we reviewed approached chronic diseases in older adults fixedly, applying existing algorithms to historical data. These models were neither assessed against a set procedural benchmark (such as a clinical gold standard) nor validated with live data over time. Consequently, while these studies offer valuable insights, they should not be considered fully developed diagnostic or classification systems for age-related disease.

In reviewing the research presented in Table 3, it is evident that e-health and m-Health technologies are integrated into various studies. However, m-Health is featured in a more limited number of studies. For instance, m-Health is employed in research on COPD ([79]), where wearable sensors monitor respiratory rates and activity levels. Similarly, in studies on depression ([89]), mood-tracking apps are used to collect self-reported mood scores and anxiety levels. Research on autism spectrum disorder ([154], [160], [161]) also incorporates m-Health technologies, using behavioral tracking apps to monitor behavioral patterns and social interactions. Additionally, asthma research ([164]) involves using mobile devices and sensors to track respiratory rates and lung function. One reason for the limited use of m-Health technologies in these studies may be the challenges of ensuring data accuracy and reliability. Mobile health technologies often rely on self-reported data or wearable sensors, which can be prone to user error, non-compliance, and variability in sensor accuracy. Additionally, integrating m-Health technologies requires robust data security measures to protect sensitive health information, which can be a significant barrier for some research initiatives. Furthermore, implementing m-Health solutions may necessitate substantial investment in technology and training, limiting their adoption in resource-constrained settings.

On the other hand, e-health technologies are widely utilized across many studies, particularly in the form of clinical data and imaging technologies. Studies on Alzheimer's disease ([82], [87], [93], [102]), heart disease ([90]), schizophrenia ([92], [100]), and multiple sclerosis ([148], [149]) frequently employ e-Health tools such as electronic health records (EHRs) and clinical imaging systems. These e-health tools facilitate collecting, storing, and analyzing vast amounts

TABLE 3. List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.

Reference	Disease	Dataset	Data type	Symptoms collected	Dataset size	Model used	Best results
[79]	COPD	Accelerometers (sensors) and Patient's medical record	Sensor	Respiratory rate, activity levels	52	logarithmic mic regression, NN, SVM	AUC: 90%
[80]	Osteoarthritis	Osteoarthritis Initiative database [81]	Imaging	Joint pain, mobility	-	ANN, RF	AUC: 76.1%
[82]	Alzheimer	Sensing technologies	Imaging	Cognitive decline, brain scans	97	SVM, RF	AUC: 0.97%
[83]	Diabetic retinopathy	DIARETDB 1 [84]	Imaging	Retinal images, vision loss	-	ANN	Acc: 96.6%
[85]	Alzheimer	Japanese Alzheimer's Disease Neuroimaging Initiative [86]	Imaging	Cognitive decline, brain scans	231	SVM	Acc: 84.17%
[87]	Alzheimer	Biobank—(UKSH tertiary referral center) [88]	Clinical	Blood biomarkers, cognitive tests	114	SVM	AUC: 89%
[89]	Depression	Self	Questionnaire/Survey	Mood scores, anxiety levels	40	LR	AUC: 88%
[90]	Heart disease	National Social Life, Health, and Aging Project Wave 2 data [91]	Clinical	Physical health, medication use, cognitive function, emotional health	3377	LR	Acc: 90.48%
[92]	Schizophrenia	Randomized controlled trials	Questionnaire /Survey	Psychotic symptoms, cognitive function	284	XGBoost	AUC: 72%
[93]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	1302	LSN	Acc: 90%, AUC: 96.8%
[95]	Depression	Population Health Metrics Research Consortium Study [96]	Questionnaire /Survey	Mood scores, anxiety levels	1200	Tariff	Acc: 82.6%
[97]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	1618	Multimodal recurrent neural network	Acc: 81%, AUC: 86%
[98]	Glaucoma	Scans of the patient's eyes	Imaging	Eye pressure, vision loss	38	Sparse Cox proportional hazard regression	AUC: 75%
[99]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	202	Multimodal manifold-regularized transfer learning	Acc: 80.1%
[100]	Schizophrenia	Taiwanese mental hospital	Clinical	Psychotic symptoms,	185	DT, KNN, NB, RF, SVM, LR	Acc: 94.5%,

TABLE 3. ***(Continued.)*** **List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.**

				medication use			AUC: 99.3%
[101]	Mild cognitive impairment	Degenerative Diseases at Laboratrio de Biologia Molecular do Centro de Oncohematologia Peditrica	Clinical	Cognitive decline, genetic markers	151	NN, RF, SVM, and stochastic gradient boosting	AUC: 98%
[102]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	275	DBN	Acc: 90%, AUC: 95%
[103]	Depression	Self	Signal	Mood scores, activity levels	27	RF	Acc: 81.5%
[104]	Glaucoma	Diagnostic Innovations in Glaucoma (DIGS) Study [105]	Imaging	Eye pressure, vision loss	121	PCA	AUC: 74%
[106]	Alzheimer	Memory Clinic located at the Institute Claude Pompidou in the Nice University Hospital	Signal	Cognitive decline, speech patterns	60	LR	AUC: 88%
[107]	Alzheimer	Two more extensive studies at Washington State University	Clinical	Cognitive decline, medical history	582	NB, DT, LR	-
[108]	Age-related macular degeneration	Self-captured using Spectralis, Heidelberg Engineering, Heidelberg, Germany	Imaging	Vision loss, retinal images	-	CNN	Acc: 96%
[109]	Hepatitis C virus infection	Self	Clinical	Liver function, viral load	648	Ensemble ML	Acc: 96%
[110]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	100	SVM, RF, NB	Acc: 95.8%
[111]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	113	Multi-kernel SVM	Acc: 78.2 %
[112]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	281	Multi-kernel SVM	Acc: 75%
[113]	Hepatitis C virus infection	GenBank database [114]	Genomic	Genetic sequences	17	linear projection	Acc: 90-95%
[115]	Age-related macular degeneration	HARBOR clinical trial [116]	Clinical	Vision loss, retinal images	1097	Sparse Cox proportional hazard regression	Acc: 80%

TABLE 3. ***(Continued.)*** **List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.**

[117]	Creutzfeldt-Jakob	The Magna Graecia University of Catanzaro and Regional Epilepsy Center, Reggio Calabria; Neurologic Institute "Carlo Besta," Milano; Neurologic Institute, University of Catania	Signal	Cognitive decline, EEG patterns	195	SVM and MLP	Acc: 89%
[118]	Alzheimer	A longitudinal case-control study. Subjects were recruited via posted flyers from the local community	Imaging	Cognitive decline, brain scans	178	LR	AUC: 91.06%
[119]	Alzheimer	National Alzheimer's Coordinating Center (NACC) [120]	Clinical	Cognitive decline, medical history	1096	CNN	Acc: 90.7%
[121]	Age-related macular degeneration	Phase II AVENUE trial (NCT02484690) [122]	Imaging	Vision loss, retinal images	185	RF, XGBoost	AUC: 87%
[123]	Age-related macular degeneration	Self	Imaging	Vision loss, retinal images	-	TransUNet	AUC: 96.9%
[124]	Glaucoma	DRIONS-DB [125]	Imaging	Eye pressure, vision loss	1285	DeepLabV3, CNN	Acc: 90.82%
[126]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	1391	SVM, DT, RF, LR	Acc: 97.58%
[127]	Glaucoma	DRIONS-DB [125]	Imaging	Eye pressure, vision loss	1218	ResNet-50, Bi-LSTM, CNN	Acc: 99.67%
[128]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	1065	LR, SVM, DT, RF, DL	Acc: 98.97%
[129]	Diabetic retinopathy	Shenzhen Aier Hospital's Ultra-Widefield Fundus (UWF) database	Imaging	Vision loss, retinal images	1000	Multi-model fusion-based approach	Acc: 94.29%
[130]	Diabetic retinopathy	Shanghai Diabetes Registry (SDR)	Clinical	Vision loss, blood sugar levels	197	RF, XGBoost	-
[131]	Alzheimer	Alzheimer's Disease Neuroimaging	Imaging	Cognitive decline, brain scans	1391	RF, SVM, LR	Acc: 97.58%

TABLE 3. ***(Continued.)*** **List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.**

		Initiative database [94]					
[132]	Depression	China Health and Retirement Longitudinal Study (CHARLS)	Questionnaire/Survey	Mood scores, anxiety levels	36888	LR, SVM, DT, RF, XGBoost	AUC: 72%
[133]	Alzheimer	Alzheimer's Disease Neuroimaging Initiative database [94]	Imaging	Cognitive decline, brain scans	10000	SVM, DT, RF, NN	Acc: 90%
[134]	Alzheimer	Open Access Series of Imaging Studies (OASIS)	Imaging	Cognitive decline, brain scans	486	DT, RF, SVM, GBT	Acc: 83.0%
[135]	Alzheimer	Open Access Series of Imaging Studies (OASIS)	Imaging	Cognitive decline, brain scans	1570	CNN	Acc: 93.5%
[136]	Depression	Swedish Longitudinal Study of Adult Men (SLSAM)	Questionnaire /Survey	Mood scores, lifestyle factors	15111	RF, GBT, SVM, DT	AUC: 78%
[137]	Depression	Korean Longitudinal Study of Aging (KLoSA)	Questionnaire /Survey	Mood scores, lifestyle factors	7674	Generalized estimating equation	
[138]	Depression	National Health and Nutrition Examination Survey (NHANES) [139]	Questionnaire /Survey	Mood scores, anxiety levels	2546	DT, SVM, LR	AUC: 89.1%
[140]	Depression	Sleep Health Index (SHI) and Clinical Health Measures (CHM) datasets [141]	Questionnaire /Survey	Sleep quality, health markers	1135	SVM, RF, DT	AUC: 82.5%
[142]	Depression	Home-based older adults from the Health and Retirement Study [143]	Questionnaire /Survey	Mood scores, lifestyle factors	3164	RF, GBM, XGBoost	AUC: 76%
[144]	Alzheimer	Taiwan Alzheimer's Disease and Other Dementia (TAAD) study	Signal	Cognitive decline, speech patterns	2422	CNN	AUC: 82.14%
[145]	Depression	2020 Community Health Survey of the Republic of Korea	Questionnaire /Survey	Mood scores, lifestyle factors	97230	DL	AUC: 89.92%
[146]	Osteoarthritis	CMU MoCap Gait Database [147]	Gait	Mobility, joint pain	100	CNN	Acc: 0.95%
[148]	Multiple sclerosis disease	Two large proprietary, multi-scanner, multi-center, clinical trial datasets of patients with Relapsing-Remitting	Imaging	Mobility, cognitive function	465	3D CNN with parallel convolutional pathways	AUC: 74.3%

TABLE 3. ***(Continued.)*** **List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.**

		Multiple Sclerosis (RRMS)					
[149]	Multiple sclerosis disease	University of Pittsburgh Medical Center (UPMC) and the Rocky Mountain MS Clinic (RMMC)	Clinical	Mobility, cognitive function	431	RF, XGBoost, SVM	AUC: 73%
[150]	Multiple sclerosis disease	Multiple Sclerosis Gait Database	Gait	Mobility, gait cycle	-	CNN	Acc: 89.3%
[151]	Osteoarthritis	Instrumented treadmill	Gait	Mobility, joint pain	40	RF, GBM, MLP	Acc:94.3%
[152]	Coronary artery disease	Mayo Clinic Clinical Data Repository	Clinical	Heart function, cholesterol levels	103424	SVM	AUC: 83%
[153]	Coronary artery disease	Mayo Clinic Biorepository	Clinical	Heart function, cholesterol levels	48228	ANN, DT, and SVM	Acc: 90.6%
[154]	Autism spectrum disorder	Self	Questionnaire /Survey	Behavioral patterns, social interactions	60	MLP, DT, KNN, RF, NB	Acc: 97.22%
[155]	Coronary artery disease	Alfred Hospital in Melbourne	Clinical	Heart function, medical history	584	LR	AUC: 79%
[156]	Parkinson	English Longitudinal Study of Ageing (ELSA) [157]	Questionnaire /Survey	Motor function, cognitive decline	-	DT, RF, ANN, NB	AUC: 88.4%
[158]	Autism spectrum disorder	Four specialized ASD outpatient clinics in Germany	Clinical	Behavioral patterns, social interactions	673	SVM	Acc: 87.4%
[159]	Coronary artery disease	De-identified electronic health records	Clinical	Heart function, medical history	6186	RF	-
[160]	Autism spectrum disorder	Self	Questionnaire /Survey	Behavioral patterns, social interactions	433	NB, LR, DT	-
[161]	Autism spectrum disorder	Self	Clinical	Behavioral patterns, social interactions	389	SVM, RF, NB	Acc: 96.52%
[162]	Coronary artery disease	Self	Signal	Heart function, ECG patterns	94	KNN	Acc: 98.94%
[163]	Coronary artery disease	Emergency Department of Penang Hospital, Penang and Pusat Kesihatan, UTM, Malaysia	Signal	Heart function, CO2 waveforms	73	SVM	Acc: 94.52%
[164]	Asthma	Self	Signal	Respiratory rate, lung function	75	KNN, RF	AUC: 91%
[165]	Asthma	Adults with suspected	Signal	Respiratory rate, lung function	-	XGBoost, RF	Acc: 83%,

TABLE 3. *(Continued.)* **List of papers considered for chronic diseases. Self indicates that the data were gathered directly by the researcher or author of the paper rather than being sourced from any external database or previous research.**

		asthma during methacholine challenge test					AUC: 81%
[166]	Asthma	Empirical pulmonology study	Clinical	Respiratory rate, lung function	132	RF	-
[167]	Depression	Self	Clinical	Mood scores, anxiety levels	1381	RF, Deep-insight visible neural network	AUC: 95%
[168]	Depression	Social networking sites	Social media	Mood scores, behavioral patterns	32493	NB	Acc: 94%
[169]	Bipolar disorder	Peking University Health Cohort	Clinical	Mood scores, medical history	10156	SVM, RF, ANN, XGBoost	-
[170]	Autism spectrum disorder	Self	Clinical	Behavioral patterns, social interactions	1409	KNN, RF, LR, DT, SVM, NB	Acc: 83.32%
[171]	Depression	Social networking sites	Social media	Mood scores, behavioral patterns	4996	SVM, KNN	Acc: 77.48%
[172]	Depression	Self	Signal	Mood scores, speech patterns	319	SVM	Acc: 91.12%

of health data, enabling researchers to draw more accurate and comprehensive conclusions. EHRs provide a centralized and standardized way to access patient data, which can improve the efficiency of data collection and reduce the likelihood of errors. Additionally, clinical imaging technologies, such as MRI and CT scans, offer high-resolution and detailed visual data crucial for diagnosing and monitoring disease progression. The widespread use of e-health technologies can be attributed to their established presence in clinical settings and the robust infrastructure supporting their use. Many healthcare institutions already have EHR systems, making it easier for researchers to access and utilize this data. Moreover, the high standardization and regulation of e-health technologies ensures data quality and consistency, which is essential for rigorous scientific research. Integrating e-health tools into clinical workflows also allows for seamless data sharing and collaboration among healthcare professionals, further enhancing their utility in research.

Assistive technologies are also a crucial component in several studies, particularly in managing and assessing chronic diseases. Cognitive assessment tools are prominently featured in Alzheimer's research ([82], [144]), aiding in the evaluation of cognitive decline through digital platforms that can perform complex cognitive testing remotely or in clinical settings. Speech analysis tools are used in studies on cognitive decline ([106]), where they analyze patients' speech patterns to detect changes that may indicate the progression of neurological conditions. Additionally, behavioral tracking apps are employed in autism spectrum disorder research ([154], [160], [161]), allowing continuous monitoring of behavioral patterns and social interactions, which can be challenging to assess in traditional clinical environments. Moreover, wearable devices and sensors are used as assistive technologies to provide continuous health monitoring and support for patients with chronic conditions. For example, in COPD research ([79]), wearable sensors help monitor respiratory rates and physical activity, providing real-time data that can be used to adjust treatment plans dynamically. In asthma studies ([164]), mobile sensors track respiratory function, offering immediate feedback and enabling patients to manage their conditions more effectively.

The software and tools often include advanced machine learning frameworks such as TensorFlow or PyTorch, which facilitate the complex computations required for deep learning applications. For instance, CNNs used for imaging data often leverage these frameworks to process and analyze large datasets efficiently. Data preprocessing, especially in imaging studies where normalization and augmentation are critical, is crucial in preparing data for analysis and significantly impacts the outcomes. Imaging data from sources such as MRI scans and fundus autofluorescence images undergo preprocessing steps like normalization, resizing, and augmentation to enhance the model's robustness and performance. For clinical data, which includes electronic health records and biochemistry data, preprocessing might involve cleaning the data, handling missing values, and standardizing the data format. These steps ensure high consistency in the data fed into machine learning models. Clinical data models often

employ algorithms such as LR, RF, and SVM, implemented using tools like Scikit-learn, a versatile machine learning library in Python. Questionnaire and survey data, common in studies addressing mental health and aging, are processed to convert categorical data into numerical formats suitable for machine learning algorithms. Techniques such as one-hot encoding and normalization are typically applied here. Models like XGBoost and generalized estimating equations are trained on these preprocessed datasets using cross-validation to ensure they generalize well to new, unseen data. Signal data, such as EEG or CO2 waveforms, often requires feature extraction and noise reduction before model training. This preprocessing step can involve Fourier or wavelet transforms to convert signals into a more interpretable format. Tools like MATLAB or Python libraries such as SciPy are commonly used. The extracted features are then used to train models such as SVMs or neural networks. Gait data and genomic data involve unique preprocessing steps as well. Gait data from wearable sensors or instrumented treadmills must often be filtered to remove noise and extract meaningful features such as stride length and gait cycle. Genomic data, like nucleotide sequences, may involve alignment and annotation processes using bioinformatics tools before being fed into machine learning models. Social media data, which includes posts and related metadata, typically undergoes text preprocessing steps such as tokenization, stemming, and removal of stop words. Natural language processing (NLP) libraries like NLTK or SpaCy prepare the data for models such as NB or SVM. The training and validation processes employed rigorous methodologies, utilizing cross-validation and splitting data into distinct training and testing sets to ensure that models are accurate and generalizable. Cross-validation helps to tune hyperparameters and avoid overfitting, ensuring the models perform well on new data. The metrics used for evaluating model performance—predominantly accuracy and AUC—are chosen based on the specific requirements of the health condition being addressed, ensuring that the models provide practical and clinically relevant results. For example, high AUC values are crucial in diagnostic applications where the trade-off between sensitivity and specificity impacts clinical decisions.

Based on Table 3, international contributions to AI in healthcare show significant diversity. The United States leads with 38 articles, underscoring its role in pioneering AI-driven healthcare solutions. Germany and the United Kingdom follow, with seven articles reflecting their deep involvement in developing technologies that could enhance diagnostic accuracy and treatment reliability. Notably, contributions from China and South Korea, with 5 and 4 articles, respectively, indicate a growing interest and capability in AI across Asia. Japan, Taiwan, Sweden, Malaysia, and Italy, each with three articles, demonstrate a wide range of innovative efforts that span from East Asia to Europe.

Regarding collaboration, the most effective partnerships in AI-driven healthcare occur among academic institutions, healthcare providers, and private enterprises in the United States and Europe. For example, collaborative research between American and European universities has led to advances in predictive analytics for patient management. Furthermore, cooperative projects between countries like Germany and the UK drive AI algorithm innovations that enhance diagnostic precision and patient outcomes in elderly care. These international collaborations push the envelope on AI technology development and ensure that these advancements are seamlessly integrated into various healthcare systems, offering scalable and adaptable solutions for a global audience.

A. CHARACTERISTIC OF THE STUDIES

Figure 4 categorizes the research approaches used in the studies examined, focusing on identifying chronic diseases using ML and DL techniques. It highlights that RL is the most frequently studied algorithm within the ML category, which dominates the research with 65 studies, followed by LR, SVM, RF, and NB. This indicates a strong preference for RL in the current research landscape. On the DL front, which is less represented with 11 studies, CNN is the leading method, with RNN, LSTM, and MLP being considerably less explored. While various techniques are being applied to the challenge of detecting chronic diseases, there is a concentration of research on specific algorithms, particularly RL and CNN. This could suggest that these methods are currently seen as more promising or suitable for the complexities of chronic disease identification. However, the lower representation of DL methods might also indicate a potential area for further exploration, as advancements in DL could offer new insights and improvements in the detection and diagnosis of chronic diseases. It also underscores a possible research opportunity to expand the application of less-used methods that might address the problem from different angles or offer improvements over more commonly used techniques.

The distribution of research studies by health condition in Table 4 underscores significant disparities in research focus and funding, influenced by disease prevalence, societal impact, and the potential for medical advancement. Neurological disorders, including Alzheimer's, Parkinson's, and multiple sclerosis, garner a substantial portion of research with 27 publications, indicative of the high level of scientific and medical community interest. This is mainly due to the severe impact these diseases have on quality of life and their generally irreversible progression. The complexity of neurological disorders, coupled with their increasing prevalence in an aging population, necessitates ongoing research into advanced diagnostics and therapeutic strategies. This intense focus also mirrors the urgent need for breakthroughs in treatment options and management practices that can significantly alter disease outcomes and patient quality of life. In contrast, mental health disorders accounted for by 22 publications also reveal a strong research interest driven by the growing recognition of mental health's critical impact on overall health and societal well- being. Disorders such as depression, autism spectrum disorders, and schizophrenia have seen a

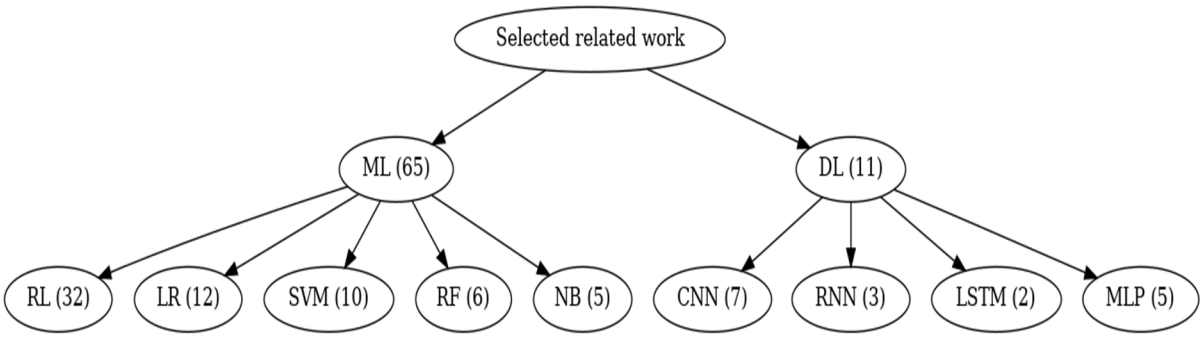

FIGURE 4. The most common methods utilized for identifying chronic diseases in the research surveyed. The numbers enclosed in brackets reflect the number of research papers.

significant rise in global prevalence, prompting a surge in research activities aimed at understanding their complex etiologies and developing more effective, personalized treatment plans. The research in this area reflects a broader shift in healthcare priorities towards mental well-being, acknowledging mental health's profound role in achieving overall health security and social stability. Physical and physiological disorders, a significant research focus with 27 publications, cover a broad spectrum of conditions primarily affecting the aging population and those with substantial lifestyle impacts. Conditions such as coronary artery disease, COPD, and osteoarthritis necessitate extensive research due to their widespread prevalence and the considerable healthcare resources they command. The focus on these diseases is strategic, aimed at enhancing life expectancy and quality of life through improved treatment protocols and preventive measures, highlighting the significant societal and economic impacts these conditions hold. Overall, allocating research across these health conditions illustrates a strategic approach to addressing the most pressing health challenges. The emphasis on diseases with high societal burdens and complex management needs reflects a targeted effort to optimize healthcare outcomes through focused and sustained research investments. This distribution informs about current scientific endeavors in chronic disease management and indicates potential shifts in health priorities and resource allocation essential for future healthcare strategies.

Figure 5 showcases the various data types used in chronic disease research, illustrating the preference for specific methodologies based on their practical application, reliability, and the depth of insights they provide. Imaging data tops the chart at 35.5%, highlighting its indispensable role in the field due to its non-invasive nature and ability to offer precise, real-time visual insights into the body's internal state. Such technologies as MRI and CT scans are crucial for diagnosing and monitoring disease progression and assessing treatment efficacy, making them a cornerstone in chronic disease research. Clinical data, which includes detailed medical records and laboratory test results, represents 26.3% of the usage. This data type is fundamental because it provides a direct insight into the patient's health status, treatment history, and biological markers, all essential for personalized treatment plans and longitudinal studies. Conversely, the relatively lower utilization of sensor data (1.3%) and gait data (1.3%) can be attributed to the niche applications and the specific types of chronic diseases they are relevant for, such as multiple sclerosis, where movement metrics are critical. Additionally, the complexity and the required infrastructure to collect and analyze such data accurately might limit their broader application in the field. Social media and genomic data, accounting for 2.6% and 3.9%, respectively, represent emerging fields in chronic disease research. Social media offers a unique perspective through patient-reported experiences and outcomes, but its subjective nature and potential privacy concerns might hinder its broader acceptance. Genomic data, though increasingly crucial for understanding genetic predispositions and tailoring treatments, requires high-tech equipment and specialized knowledge, contributing to its lesser usage than more traditional data types.

Table 5 outlines the computational demands of various artificial intelligence models utilized in chronic disease research. It categorizes them based on their space complexity and the computational expense involved during the training and prediction phases. In this table, the variable n represents the number of samples in the dataset, which is a common factor in complexity calculations, affecting how algorithms iterate over data points. The variable d denotes the number of features or dimensions in the dataset, influencing operations across data features. For SVM, v indicates the number of support vectors crucial for defining the model's decision boundaries, and s refers to the size of each support vector in memory. In ensemble methods like Random Forest and XGBoost, t signifies the number of trees, which directly impacts both training and prediction complexity due to the ensemble nature of these models. The variable m varies in meaning; in SVMs, it can reflect the output space's dimensionality, while in CNNs, it often pertains to the number of feature maps. The number of neurons or layers in neural networks is captured by q, and h details the number of units

TABLE 4. Distribution of research studies by health condition category.

Disease type	Disease name	Number of publications
Neurological disorders	Alzheimer	27
	Mild Cognitive Impairment	
	Parkinson	
	Creutzfeldt-Jakob	
	Multiple Sclerosis Disease	
Mental Health disorders	Autism Spectrum Disorder	22
	Depression	
	Schizophrenia	
	Bipolar Disorder	
Physical/Physiological Disorders	Age-Related Macular Degeneration	27
	Diabetic Retinopathy	
	Glaucoma	
	Asthma	
	COPD	
	Osteoarthritis	
	Hepatitis C Virus Infection	
	Coronary Artery Disease	
	Heart Disease	

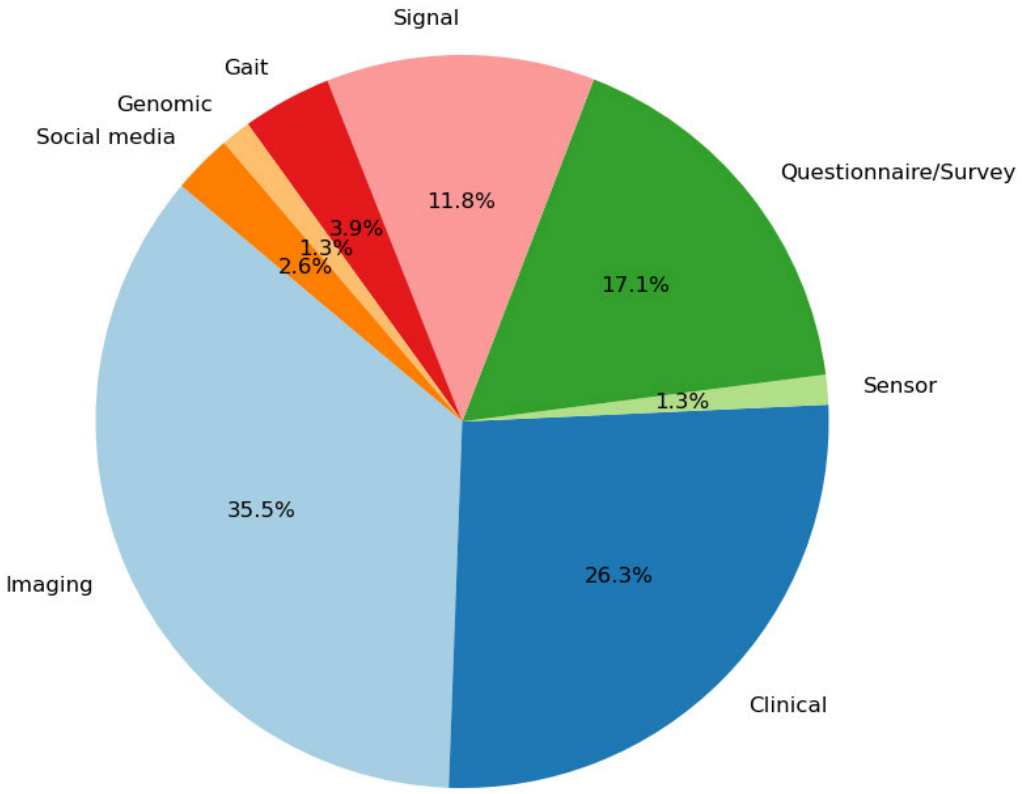

FIGURE 5. Data types used in chronic disease research.

in a hidden layer, which is relevant to both ANNs and RNNs. For CNNs, k represents the number of filters, which is crucial for understanding the processing depth of these networks. The variable f may relate to the storage requirements for feature maps in CNNs, whereas p in RNNs indicates the sequence length, reflecting how many time steps the network processes in each input sequence. Understanding these variables is essential for assessing an algorithm's feasibility and efficiency concerning data size, features, and computational capacity.

The information in Table 5 reveals that SVM demands considerable computational resources. The training time

TABLE 5. Computational complexities of AI models in chronic disease research.

Algorithm	Time complexity (Training)	Time complexity (Prediction)	Space complexity
SVM	$O(n^2 \times d)$ to $O(n^3 \times d)$	$O(v \times m)$	O(n×d+v×s)
RF	$O(t \times d \times n \times log(n))$	$O(t \times d \times \log(n))$	O(t×d×n)
KNN	$O(d)$	$O(n \times d)$	O(t×d×n)
LR	$O(n \times d)$	$O(d)$	O(n×d)
DT	$O(d \times n \times \log(n))$	$O(d)$	O(d)
NB	$O(n \times d)$	$O(d)$	O(d×n)
XGBoost	O (t× d ×log n)	O (t× d × n ×log n)	O(d×n)
ANN	O (d × q × n)	O (d × q)	O(d×q+q×h)
CNN	O (k × m × d × n)	O (k × m × d)	O(k×m×d+f)
RNN	O (p × d × h × n)	O (p × d × h)	O(p×d×h)

complexity can rise exponentially with data size, making SVMs less ideal for large-scale datasets commonly found in chronic disease studies. This is compounded by their space complexity, which is influenced by the number of support vectors and the dimensionality of the data. Despite these challenges, SVMs remain valuable for smaller, well-defined datasets where the high dimensionality needs to be effectively managed. On the other hand, ensemble methods like RF and XGBoost demonstrate their robustness in handling large and complex datasets, a typical scenario in chronic disease research. These models, characterized by their deep integration of multiple decision trees, show a significant computational cost that scales with the number and depth of each tree. However, their ability to improve predictive accuracy and control over-fitting makes them indispensable, especially in scenarios where predictive reliability is critical. KNN and LR present lower prediction complexities, indicating faster operational capabilities during the deployment phase. However, KNN's significant space complexity, due to its need to store the entire dataset, limits its practicality in large-scale applications. While more scalable in its training phase, Logistic Regression offers a balance between computational efficiency and predictive performance, making it a go-to model for baseline assessments in many studies. Furthermore, advanced deep learning models such as ANN, CNN, and RNN exhibit considerable complexities both in space and time. These models require extensive computational resources due to their intricate architectures involving multiple layers and numerous parameters. However, their ability to handle unstructured and complex data types, like medical imaging and sequential patient data, makes them particularly useful in extracting nuanced patterns and delivering high-accuracy predictions crucial for diagnosing and managing chronic diseases.

The selection of evaluation criteria is a critical step in chronic disease research, as it directly impacts the interpretation and applicability of AI model outcomes. Figure 6 describes how frequently various metrics are utilized to assess AI performance in this field. The dominance of accuracy, used in 63 studies, highlights its status as a fundamental metric, suggesting that researchers prioritize the correct classification of the presence or absence of disease. Recall, employed in 14 publications, is acknowledged for its role in minimizing false negatives, which is paramount in a clinical setting where missing a positive case can have serious consequences. Precision, cited in 12 studies, is valued for its measure of result relevancy, ensuring that the identified cases are indeed correct and reducing the rate of false positives. With 68 publications using it, the AUC is the most frequently applied metric. The AUC's significance lies in its comprehensive evaluation of a model's performance at various thresholds, providing a singular measure of effectiveness that encompasses both the true positive and negative rates. The F-measure, employed in 18 publications, offers a balanced view by combining precision and recall into a single metric. This is especially useful in scenarios where both false positives and false negatives carry significant consequences, ensuring a harmonized assessment of the model's accuracy in predicting true positive and actual negative cases. Its utilization in a smaller subset of studies may indicate a more targeted approach where both errors are equally critical to the research outcomes. These metrics together form a multifaceted evaluation framework essential for developing and validating AI tools in diagnosing and managing chronic diseases. The balance of these metrics ensures that AI models are accurate, clinically reliable, and relevant, leading to improvements in patient care and health outcomes.

B. FEATURES

The role of features in the diagnosis of chronic diseases is of paramount importance, particularly within the disciplines of ML and DL. In the case of chronic diseases, features could include a wide array of data points, from basic demographic information like age and gender to complex biological markers such as gene expressions or protein levels. These features are vital because they are the fundamental inputs that feed into predictive models. The quality and relevance of these features directly impact the model's ability to learn from data. For example, in a dataset concerning heart disease, relevant features might include blood pressure readings, cholesterol levels, smoking status, and exercise frequency. Each feature

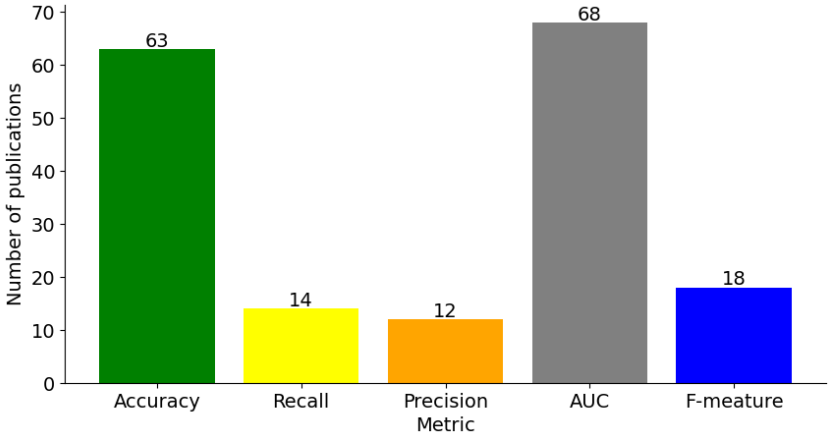

FIGURE 6. Metrics used in chronic disease research.

captures a different aspect of a patient's health profile that could indicate their risk for heart disease.

In ML and DL models, the feature extraction process involves selecting data pieces that are most likely to reveal patterns related to the onset and progression of chronic diseases. The significance of this process lies in its ability to transform raw data into a format that predictive models can use to discern complex relationships within the data that may not be immediately apparent to human observers [176]. Once the features are identified and extracted, ML algorithms can be trained to detect patterns and anomalies that signify the presence of a disease. DL models, which are particularly adept at handling vast amounts of unstructured data, can identify even subtler patterns within complex features, such as those derived from medical imaging. The predictive power of these models hinges on the careful selection and processing of features. High-quality features allow models to achieve greater accuracy, leading to earlier and more reliable detection of chronic diseases. This can inform treatment decisions and lead to better patient outcomes. For instance, early detection of a chronic condition like diabetes can lead to interventions that prevent complications, reduce the burden on healthcare systems, and ultimately save lives [177].

Below, we present the most critical features identified by the studies for the diagnosis of chronic diseases.

- Genetic markers: Genetic markers are specific sequences in the genome indicating an increased likelihood of developing certain diseases [178]. They are critical for conditions with a hereditary component, such as Alzheimer's and Parkinson's disease, as well as many heart conditions. Identifying these markers can lead to preemptive measures and personalized treatment plans [179], [180]. For instance, in Alzheimer's, genetic markers like the APOE $\varepsilon 4$ allele have been associated with a higher risk, and their detection can warrant closer monitoring and early intervention strategies. In Parkinson's, mutations in genes such as LRRK2 and PARK7 are insightful for risk assessment [181]. In cardiology, genetic markers can signal the propensity for conditions like hypertrophic cardiomyopathy [182]. The analysis of genetic markers is a complex field in which machine learning can significantly benefit, as it can handle large datasets and uncover patterns that may not be readily visible to human researchers [63].
- Imaging data: Imaging data from MRI, CT scans, or X-rays provide a non-invasive window into the body's internal structures [9], [183]. In neurological disorders, imaging can reveal the size and volume of brain regions, which may shrink or show lesions in diseases like Multiple Sclerosis (MS) or Alzheimer's. MRI scans can show the plaques and tangles associated with Alzheimer's, while MS is characterized by brain and spinal cord lesions, which can be detected via these imaging techniques. Machine learning models trained on this data can help radiologists and neurologists identify these signs earlier than ever, which is crucial because earlier diagnosis can lead to more effective management of these conditions. They can also monitor changes, providing insight into disease progression and treatment effectiveness [61].
- Speech patterns: Speech pattern analysis is a rich domain within machine learning applications for diagnosing neurological and psychiatric conditions [184]. Subtle changes in speech, such as pauses, intonation, and word selection, can be early indicators of Alzheimer's disease as cognitive decline begins to affect language centers in the brain. In depression and schizophrenia, speech can become monotone or disjointed, reflecting the underlying psychological disturbances. Machine learning algorithms excel at detecting these subtle changes by analyzing large datasets of speech recordings, which can be particularly helpful for tracking disease progression or response to treatment [185].
- Movement data: Regarding diseases like Parkinson's and other motor disorders, movement data is critical to diagnosis and monitoring [186], [187]. Gait patterns, for

example, can reveal much about the severity and type of a motor disorder. Patients with Parkinson's disease often have a shuffling gait with reduced arm swing and sometimes freezing of gait, where they temporarily are unable to move. Tremor analysis is another essential feature, as resting tremors are a hallmark of Parkinson's disease, while intention tremors are more associated with cerebellar diseases [188], [189]. Advanced machine learning algorithms can analyze these movement patterns, often captured by motion sensors or video recordings, to discern subtle differences in motor function that may not be noticeable to the naked eye. This data can be used to track the disease's progression over time, evaluate the efficacy of treatments, and adjust medications or therapy as needed. Moreover, movement data can provide insight into the risk of falls and help develop preventive strategies, which are crucial for maintaining the quality of life in patients with motor impairments [190].

- Blood test results: Blood tests provide a wealth of information through various biomarkers that reflect the functioning of different body systems [191], [192]. In the case of inflammatory diseases like rheumatoid arthritis, markers such as C-reactive protein (CRP) and erythrocyte sedimentation rate (ESR) can indicate the presence and intensity of inflammation [193], [194]. For Hepatitis C virus infection, liver enzymes such as AST, ALT, and viral load measurements are critical. Anemia, elevated inflammatory markers, and nutrient deficiencies may indicate inflammatory bowel diseases like Crohn's disease and ulcerative colitis. Blood markers can also help monitor the effectiveness of treatments, such as reducing inflammation in response to medication. Machine learning models can use these markers to identify patterns that may predict disease flares or remissions. Additionally, by analyzing changes in blood markers over time, machine learning can help predict the course of a disease and tailor personalized treatment plans, which can be vital for chronic conditions that require long-term management.
- Electrophysiological signals: Electrophysiological signals, especially those derived from electroencephalography (EEG), are critical in diagnosing and understanding neurological conditions like epilepsy, characterized by abnormal brain activity that can lead to seizures and other severe symptoms [195]. EEG signals capture the brain's electrical activity and reveal telltale patterns associated with seizure activity. Additionally, EEG features are studied in autism spectrum disorders (ASD), where they may indicate neural connectivity differences, and in depression, where they can reflect altered brain function [196]. By analyzing these signals, machine learning algorithms can learn to recognize the unique electrical patterns associated with these conditions, aiding in early detection and intervention. Moreover, EEG data can be valuable in monitoring treatment response, adjusting medications, and developing neurofeedback therapies to help patients manage their conditions more effectively [197].
- Cognitive test results: Cognitive test results are a rich data source for machine learning models that identify and track the progression of cognitive impairments and mental health issues [198], [199]. These tests often assess various aspects of cognition, including memory, attention, problem-solving skills, and language abilities. For conditions like Alzheimer's disease or mild cognitive impairment, declining scores in memory-related tasks can indicate the progression of the disease. In mental health, cognitive tests can help diagnose conditions such as depression or schizophrenia, where patients may show difficulties in concentration, memory, or executive function. Machine learning can analyze longitudinal test data to predict the trajectory of a disease, monitor changes over time, and evaluate the effectiveness of interventions. The nuanced analysis can also help differentiate between similar cognitive conditions, aiding in more accurate diagnoses and personalized treatment strategies [200].
- Ocular measurements: Ocular measurements, like intraocular pressure (IOP) and optic nerve health, provide quantifiable data crucial for diagnosing and managing eye diseases [201]. In glaucoma, elevated IOP can lead to optic nerve damage and vision loss; therefore, monitoring IOP is essential for early detection and prevention of the disease's progression. Similarly, in diabetic retinopathy, changes in retinal blood vessels can be quantified and monitored [202]. Machine learning algorithms can analyze these ocular parameters to identify patterns that may indicate disease before significant damage occurs. They can also track the effectiveness of treatments like pressure-lowering medications in glaucoma or anti-VEGF injections [203] in diabetic retinopathy. Furthermore, advanced imaging techniques like optical coherence tomography provide detailed images of the retina, enabling the detection of subtle changes that may not be visible during a standard eye exam [204].
- Histopathological data: Histopathological data gathered from tissue samples under a microscope includes cellular morphology, tissue architecture, and the presence of specific markers [205], [206]. This data is pivotal in diagnosing conditions such as cirrhosis, where liver tissue undergoes fibrosis and loses its typical architecture, or cancer, where abnormal cell growth patterns are evident. Machine learning models trained on histopathological images can assist pathologists in detecting disease characteristics that might be too subtle or complex for the human eye to discern consistently [207]. They can also help quantify the extent of disease, which is critical for staging cancer or assessing liver damage. Furthermore, these algorithms can uncover

correlations between histopathological features and patient outcomes, aiding in prognosis and the tailoring of therapy to individual patient profiles [208].

- Patient history: Patient history encompasses a wealth of information vital for personalized healthcare [209]. This includes past medical diagnoses, treatment regimens, medication adherence, and lifestyle choices such as diet, exercise, and smoking status. This historical context can help machine learning systems predict disease progression and potential complications for chronic diseases. Patient history can inform risk stratification and preventive heart disease or asthma strategies [210]. For mental health conditions, historical data on symptom onset, duration, and response to previous treatments can guide therapeutic decisions. Machine learning can analyze these complex, multidimensional data to identify patterns that inform risk prediction models, enhance understanding of disease etiologies, and optimize treatment approaches tailored to individual patient histories [211].

Figure 7 shows the distribution of critical features considered crucial for diagnosing chronic diseases as identified by various studies. The largest segment, at 28.6%, is devoted to imaging data, emphasizing its pivotal role in diagnosing conditions through MRI, CT scans, and X-rays. Genetic markers constitute 14.3%, reflecting the growing recognition of genetics in the development and progression of chronic diseases. Blood test results, capturing 11.4% of the pie, are also significant, likely due to their role in revealing physiological abnormalities. Movement data and cognitive test results each account for 10% and 8.6%, respectively, highlighting their importance in diagnosing diseases that affect motor skills and cognitive functions. Electrophysiological signals, which can indicate various conditions, from heart rhythm disorders to neurological diseases, make up 5.7% of the chart. Speech patterns are considered in 4.3% of the cases, which could be critical in conditions like Parkinson's disease or after a stroke. Patient history and ocular measurements each have 7.1%, signifying the value of comprehensive medical histories and eye-related metrics in chronic disease management. Histopathological data, the analysis of tissue changes caused by disease, accounts for 2.9%, showing its specific but vital role in diagnosing certain conditions.

V. DISCUSSION

This study highlights the application of cutting-edge technology in the automated diagnosis of chronic diseases. Through a thorough analysis of 76 scholarly articles, we have explored various automated methods for chronic disease detection spanning the last decade, from 2014 to 2024. Our investigation has tracked the evolution and development of automated detection systems tailored to chronic illnesses, focusing on ML and DL strategies as documented in references. Our review found that ML was the primary method used in 65 studies for the automatic detection of insomnia, with only 11 studies utilizing DL models, as illustrated in Figure 4. The trend indicates that ML was the dominant approach in automated chronic disease detection until 2019. Post-2019, DL has surged in popularity, recognized for its ability to manage large datasets and achieve enhanced outcomes. DL differs from ML's minimal need for manual feature engineering and selection, offering a more automated process. This automation streamlines the data processing and supports the flexible use of various algorithms, making DL a powerful and increasingly preferred tool in chronic disease diagnosis.

The reliability and success of AI applications in diagnosing chronic diseases are deeply dependent on the integrity of the underlying data. AI systems require a robust dataset—complete, consistent, and accurate—to make precise predictions and diagnoses. The data collection process, which often falls under the purview of nursing staff, is a critical step; any discrepancies, omissions, or inaccuracies at this stage can significantly compromise the effectiveness of AI diagnostic tools. Nurses play a vital role in ensuring the quality of patient data. They are on the front lines, providing care and meticulously documenting various patient metrics and clinical findings. Their contributions to the medical records form the foundation upon which AI algorithms are trained and tested. Therefore, any variation in data quality, whether due to human error or systemic issues, can lead to AI systems making unreliable predictions. Moreover, the volume of data is just as important as its quality. AI models, especially those employing deep learning techniques, require large datasets to learn the complex patterns associated with chronic diseases. Inadequate data can hinder the model's generalization of its findings to broader patient populations. Training AI systems with comprehensive and accurately annotated datasets allows for more sophisticated and nuanced understandings of chronic conditions. This, in turn, can lead to earlier and more accurate identifications of such diseases, potentially improving patient outcomes. Consequently, the healthcare industry must emphasize the critical role of data collection and encourage rigorous training and protocols to minimize errors in data entry and maintenance. This will ensure that AI-assisted diagnostic tools can reach their full potential in the fight against chronic diseases.

The AI models scrutinized in our review reveal specific data-related constraints. The complexity lies in the intricate interplay between the available data and the data processing methods used to extract relevant insights. A notable data challenge is the prevalence imbalance between classes, where data for non-disordered instances outweighs that for disordered cases. For AI models to function without bias, it is crucial to establish a balanced dataset. Data augmentation strategies are frequently employed to rectify this discrepancy, primarily to bolster the representation of the less prevalent, disordered class. This step is vital to counter the issues that arise from such imbalances, ensuring that the AI models can learn to identify disorders with equal precision across varied instances.

Automated methods for chronic disease detection and intense learning models are often described as black boxes because their decision-making processes are not easily

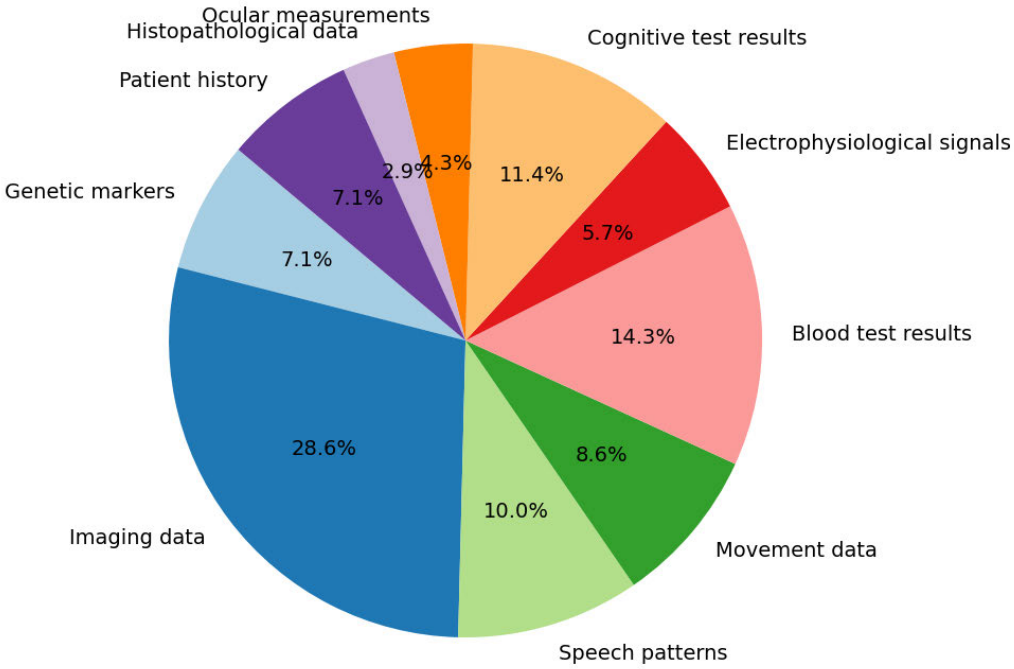

FIGURE 7. Feature types used in chronic disease research.

interpretable by humans. Nurses may need help trusting or acting on AI recommendations if they understand their rationale. This lack of transparency can hinder the effective integration of AI tools into clinical decision-making processes. The inability to interpret AI decisions affects trust and limits the nurse's ability to explain treatment choices to patients, potentially impacting patient satisfaction and adherence to treatment plans. Moreover, the black-box nature of AI models raises significant challenges regarding accountability and error tracing. In cases where an AI-driven diagnosis leads to an adverse outcome, it can be challenging to analyze the decision-making process and identify where errors occurred. This ambiguity complicates efforts to improve AI systems and can lead to legal and ethical dilemmas about responsibility for medical decisions. To address these issues, there is a growing call for developing more interpretable AI models and incorporating explainable AI (XAI) principles into healthcare applications. XAI aims to make AI decision-making processes more transparent and understandable to human users, thereby increasing trust and facilitating more informed decision-making by healthcare professionals. In addition to improving AI interpretability, enhancing nurse education and training regarding AI technologies is crucial. Providing nurses with a better understanding of how AI tools function, their potential benefits, and limitations can empower them to use these technologies more effectively and confidently. Training should focus not only on the technical aspects of AI but also on ethical considerations, data privacy, and the importance of integrating AI assistance with human judgment and patient-centered care. Furthermore, involving nurses and other healthcare professionals in designing and developing AI tools can lead to more user-friendly solutions that are better aligned with clinical workflows and the practical needs of care providers. Collaborative efforts between AI developers, healthcare professionals, and patients are essential to create AI systems that enhance rather than complicate healthcare delivery.

Chronic diseases, characterized by their long-lasting and persistent nature, frequently exhibit a wide range of symptoms that can vary significantly among individuals, particularly in the context of aging. These conditions, such as heart disease, diabetes, arthritis, and Alzheimer's disease, often involve multiple factors, including genetic predisposition, lifestyle choices, and environmental exposures, making their diagnosis and management a challenging task. The progression and manifestation of symptoms in chronic diseases are not linear and can be influenced by the intricate interplay between these factors. For AI models to effectively capture the complexity of chronic diseases, especially in elderly populations, they must be designed to account for the nuanced ways these diseases present and progress. Physiological changes that come with aging, such as decreased organ function, altered metabolism, and reduced physical resilience, can significantly affect the manifestation of diseases. For example, an elderly individual might show atypical symptoms of a heart attack, such as fatigue and shortness of breath, rather than the classic chest pain. Similarly, the response to treatment in older adults can differ from younger individuals due to changes in drug metabolism and increased susceptibility to side effects. Incorporating these complexities into AI models requires a multifaceted approach that includes diverse datasets encompassing various ages, ethnicities, and comor-

bidities. Advanced algorithms capable of processing and learning from these heterogeneous data sources are essential. Moreover, AI systems need to be dynamic and capable of adapting to new information and evolving patterns of disease manifestation. Interdisciplinary collaboration among clinicians, gerontologists, data scientists, and AI experts is crucial to ensure that the models are clinically relevant and capable of handling the intricacies of chronic diseases in the elderly. Furthermore, ethical considerations and biases in AI development must be addressed to ensure equitable and effective healthcare outcomes. Elderly populations are often underrepresented in clinical trials and datasets, leading to potential biases in AI models. Ensuring the inclusion of robust and representative data from older adults in developing AI systems is essential for creating models that accurately capture the complexity of chronic diseases in this demographic.

Future works in chronic disease detection in geriatric care, leveraging AI technologies, could consider several avenues to address the identified gaps and enhance the precision and reliability of current methods. These potential directions include:

- Developing Interpretable AI Models: Future research could focus on creating more interpretable AI models that allow healthcare professionals, particularly nurses, to understand the rationale behind the AI's decisions. This transparency could improve trust in AI-assisted diagnostics and enable nurses to make more informed decisions regarding patient care.
- Expanding Dataset Diversity: To improve the robustness of AI models, future studies should aim to incorporate a broader range of data sources, including electronic health records, imaging data, and wearable device data. Diverse datasets can help train more comprehensive models capable of detecting a wider array of chronic conditions in elderly patients.
- Integrating Multimodal Data Analysis: Combining various data types (e.g., clinical notes, lab results, patient-reported outcomes) through multimodal AI models could provide a more holistic view of the patient's health status. This approach can enhance the early detection of chronic diseases by capturing subtle signs that might be overlooked when analyzing data sources in isolation.
- Personalized AI Models: Future works could explore the development of personalized AI models that take into account the unique characteristics of each patient, such as genetic information, lifestyle factors, and comorbidities. Personalized models could lead to more accurate predictions and tailored interventions, improving patient outcomes.
- Real-time Monitoring and Prediction Systems: Implementing AI systems capable of real-time monitoring and predictive analytics could enable more timely interventions. Future research could focus on creating systems that detect existing conditions and predict the risk of developing new chronic diseases or exacerbations of existing ones.
- Ethical and Privacy Considerations in AI: As AI technologies become more integrated into healthcare, addressing ethical concerns and ensuring patient privacy will be crucial. Future studies should explore frameworks and guidelines for ethical AI use in clinical settings, ensuring that these technologies benefit patients without compromising their rights or autonomy.
- Cross-disciplinary Collaborations: Encouraging collaborations between computer scientists, healthcare professionals, and ethicists could lead to more effective and ethically sound AI solutions. These collaborations can ensure that AI technologies are developed with a deep understanding of clinical needs and ethical standards.
- Longitudinal Studies on AI Implementation: Conducting longitudinal studies to assess the long-term effects of AI integration in geriatric care can provide insights into its efficacy, patient outcomes, and potential challenges. These studies could help refine AI applications for chronic disease management in elderly populations.

VI. CONCLUSION

This systematic literature review emphasizes the transformative impact of AI on geriatric clinical care. Adopting ML and DL technologies, including Random Forest, Logistic Regression, and CNNs, has significantly improved real-time health monitoring and early disease detection. These AI tools play a vital role in addressing the complex health requirements of older adults, who typically contend with various chronic conditions that demand comprehensive care strategies. AI's integration into geriatric care enhances the precision and efficiency of diagnosing and managing neurological, mental health, and physical disorders, which are common among elderly populations. Advanced algorithms that process extensive and intricate datasets boost decision-making effectiveness, leading to prompt and precise interventions. Furthermore, AI supports ongoing monitoring, enabling the early identification of potential health declines to prevent severe complications and enhance overall patient outcomes. This capability is precious in environments like nursing homes or home care, where continuous professional supervision is challenging. Although the benefits of AI in geriatric care are clear, continued research and technological improvement are essential to maximize its effectiveness and ensure dependable integration into daily clinical settings.

To enhance the credibility of our findings and guide future research, it is essential to address the limitations identified in our review. A primary concern is the generalizability of our results, drawn mainly from high-impact journals. This selection may overlook pioneering studies from lesser-known or nascent platforms. Future research should include a wider variety of sources, thereby enriching the diversity and inclusivity of the research examined. Additionally, while our study categorizes articles into three major disorder groups, it needs to adequately investigate the interactions among these disorders or assess the impact of multimorbidity on the effectiveness of AI technologies. A more detailed exploration

of these dynamics would deepen our understanding of how AI can manage complex health scenarios in older adults. Moreover, integrating AI with fields like bioinformatics, pharmacology, and gerontology could spawn more innovative solutions specifically designed for the aging population. Addressing ethical and privacy concerns in the deployment of AI in healthcare is also critical. Developing robust frameworks to safeguard patient data while maximizing the benefits of AI is imperative, especially in sensitive areas like geriatric care. Taking these steps will allow future studies to significantly enhance our comprehension of AI's role in geriatric care, ensuring that technological advancements lead to practical improvements in the management of elderly care.

ABBREVIATIONS

The following abbreviations are used in this study:

NN	Neural network.
SVM	Support vector machine.
ANN	Artificial neural network.
AUC	Area Under the Curve.
MRI	Magnetic Resonance Imaging.
COPD	Chronic Obstructive Pulmonary Disease.
LSN	Siamese neural-network.
XGBoost	Extreme gradient boosting.
DBN	Deep belief network.
KNN	K-nearest neighbors.
MLP	Multilayer neural networks.
ML	Machine learning.
DNN	Deep neural networks.
CNN	Convolution neural network.
LSTM	Long Short-Term Memory.
RF	Random forest.
LR	Logistic regression.
DT	Decision tree.
DL	Deep learning.
GBT	Gradient boosting.
GBM	Gradient boosting machine.
BN	Bayesian network.
PCA	Principal component analysis.
NLP	Natural language processing.

REFERENCES

[1] G. K. Vincent, *The Next Four Decades: The Older Population in the United States: 2010 To 2050*, document 1138, U.S. Dept. Commerce, Econ. Statist. Admin., 2010.

[2] K. E. Miller, R. G. Zylstra, and J. B. Standridge, "The geriatric patient: A systematic approach to maintaining health," *Amer. Family Physician*, vol. 61, no. 4, pp. 1089–1104, 2000.

[3] C. Hawk, M. Schneider, P. Dougherty, B. J. Gleberzon, and L. Z. Killinger, "Best practices recommendations for chiropractic care for older adults: Results of a consensus process," *J. Manipulative Physiological Therapeutics*, vol. 33, no. 6, pp. 464–473, Jul. 2010.

[4] J. Barrio-Cortes, A. Castaño-Reguillo, M. T. Beca-Martínez, M. Bandeira-de Oliveira, C. López-Rodríguez, and M. Á. Jaime-Sisó, "Chronic diseases in the geriatric population: Morbidity and use of primary care services according to risk level," *BMC Geriatrics*, vol. 21, no. 1, pp. 1–11, Dec. 2021.

[5] S. Mancin, M. Sguanci, D. Cattani, F. Soekeland, G. Axiak, B. Mazzoleni, M. G. De Marinis, and M. Piredda, "Nutritional knowledge of nursing students: A systematic literature review," *Nurse Educ. Today*, vol. 126, Jul. 2023, Art. no. 105826.

[6] H. Karabuga Yakar, S. Oguz, B. Bulut, C. Kapusuz, P. Abi, and R. Yavuz, "Compassion fatigue in nurses caring for chronic diseases," *Int. J. Occupational Saf. Ergonom.*, vol. 29, no. 1, pp. 109–114, Jan. 2023.

[7] E. Akleman, "Deep learning," *Computer*, vol. 53, no. 9, pp. 17–17, Sep. 2020.

[8] N. Mavaddat, K. Michailidou, J. Dennis, M. Lush, L. Fachal, and A. Lee, "Polygenic risk scores for prediction of breast cancer and breast cancer subtypes," *Amer. J. Human Genet.*, vol. 104, no. 1, pp. 21–34, 2019.

[9] L. Hong, M. H. Modirrousta, M. H. Nasirpour, M. M. Chargari, F. Mohammadi, S. V. Moravvej, L. Rezvanishad, M. Rezvanishad, I. Bakhshayeshi, R. Alizadehsani, I. Razzak, H. Alinejad-Rokny, and S. Nahavandi, "GAN-LSTM-3D: An efficient method for lung tumour 3D reconstruction enhanced by attention-based LSTM," *CAAI Trans. Intell. Technol.*, vol. 1, pp. 1–24, May 2023.

[10] A. Saeed, A. AlShafea, A. Bin Saeed, M. Nasser, and R. Ali, "Robotics and artificial intelligence and their impact on the diagnosis and treatment of cardiovascular diseases," *Cureus*, vol. 15, no. 7, pp. 1–26, Jul. 2023.

[11] O. Arigbede, T. Amusa, and S. G. Buxbaum, "Exploring the use of artificial intelligence and robotics in prostate cancer management," *Cureus*, vol. 15, no. 9, pp. 1–32, Sep. 2023.

[12] C. Jailin, S. Mohamed, R. Iordache, P. Milioni De Carvalho, S. Y. Ahmed, E. A. Abdel Sattar, A. F. I. Moustafa, M. M. Gomaa, R. M. Kamal, and L. Vancamberg, "AI-based cancer detection model for contrast-enhanced mammography," *Bioengineering*, vol. 10, no. 8, p. 974, Aug. 2023.

[13] H. E. C. D. Silva, G. N. M. Santos, A. F. Leite, C. R. M. Mesquita, P. T. D. S. Figueiredo, C. M. Stefani, and N. S. de Melo, "The use of artificial intelligence tools in cancer detection compared to the traditional diagnostic imaging methods: An overview of the systematic reviews," *PLoS One*, vol. 18, no. 10, Oct. 2023, Art. no. e0292063.

[14] S. K. Bhatt and S. Srinivasan, "Lung cancer detection using AI and different techniques of machine learning," *Int. J. Intell. Syst. Appl. Eng.*, vol. 12, no. 8s, pp. 630–638, 2024.

[15] H. Chen, E. Cohen, D. Wilson, and M. Alfred, "A machine learning approach with human-AI collaboration for automated classification of patient safety event reports: Algorithm development and validation study," *JMIR Hum. Factors*, vol. 11, Jan. 2024, Art. no. e53378.

[16] E. A. Johnson, K. M. Dudding, and J. M. Carrington, "When to ERR is inhuman: An examination of the influence of artificial intelligence-driven nursing care on patient safety," *Nursing Inquiry*, vol. 31, no. 1, Jan. 2024, Art. no. e12583.

[17] M. Bekbolatova, J. Mayer, C. W. Ong, and M. Toma, "Transformative potential of AI in healthcare: Definitions, applications, and navigating the ethical landscape and public perspectives," *Healthcare*, vol. 12, no. 2, p. 125, Jan. 2024.

[18] E. Mosqueira-Rey, E. Hernández-Pereira, D. Alonso-Ríos, J. Bobes-Bascarán, and Á. Fernández-Leal, "Human-in-the-loop machine learning: A state of the art," *Artif. Intell. Rev.*, vol. 56, no. 4, pp. 3005–3054, Apr. 2023.

[19] M. Khalifa and M. Albadawy, "AI in diagnostic imaging: Revolutionising accuracy and efficiency," *Comput. Methods Programs Biomed. Update*, vol. 5, Jun. 2024, Art. no. 100146.

[20] S. Nyholm, "Artificial intelligence and human enhancement: Can AI technologies make us more (artificially) intelligent?" *Cambridge Quart. Healthcare Ethics*, vol. 33, no. 1, pp. 76–88, Jan. 2024.

[21] A. Choudhury, E. Renjilian, and O. Asan, "Use of machine learning in geriatric clinical care for chronic diseases: A systematic literature review," *JAMIA Open*, vol. 3, no. 3, pp. 459–471, Oct. 2020.

[22] A. Das and P. Dhillon, "Application of machine learning in measurement of ageing and geriatric diseases: A systematic review," *BMC Geriatrics*, vol. 23, no. 1, p. 841, Dec. 2023.

[23] A. Husnain, H. K. Hussain, H. M. Shahroz, M. Ali, and Y. Hayat, "A precision health initiative for chronic conditions: Design and cohort study utilizing wearable technology, machine learning, and deep learning," *Int. J. Adv. Eng. Technol. Innov.*, vol. 1, no. 2, pp. 118–139, 2024.

[24] M. N. A. Tawhid, S. Siuly, K. Wang, and H. Wang, "Automatic and efficient framework for identifying multiple neurological disorders from EEG signals," *IEEE Trans. Technol. Soc.*, vol. 4, no. 1, pp. 76–86, Mar. 2023.

[25] M. Mujahid, A. Rehman, T. Alam, F. S. Alamri, S. M. Fati, and T. Saba, "An efficient ensemble approach for Alzheimer's disease detection using an adaptive synthetic technique and deep learning," *Diagnostics*, vol. 13, no. 15, p. 2489, Jul. 2023.

[26] R. J. Woodman and A. A. Mangoni, "A comprehensive review of machine learning algorithms and their application in geriatric medicine: Present and future," *Aging Clin. Experim. Res.*, vol. 35, no. 11, pp. 2363–2397, Sep. 2023.

[27] M. Hamaker, C. Lund, M. T. Molder, P. Soubeyran, H. Wildiers, and L. van Huis, "Geriatric assessment in the management of older patients with cancer-a systematic review (update)," *J. geriatric Oncol.*, vol. 13, no. 6, pp. 761–777, 2022.

[28] H. Cai, Y. Jin, R. Liu, Q. Zhang, Z. Su, G. S. Ungvari, Y.-L. Tang, C. H. Ng, X.-H. Li, and Y.-T. Xiang, "Global prevalence of depression in older adults: A systematic review and meta-analysis of epidemiological surveys," *Asian J. Psychiatry*, vol. 80, Feb. 2023, Art. no. 103417.

[29] J. C. Correia, A. Waqas, J.-P. Assal, M. J. Davies, F. Somers, A. Golay, and Z. Pataky, "Effectiveness of therapeutic patient education interventions for chronic diseases: A systematic review and meta-analyses of randomized controlled trials," *Frontiers Med.*, vol. 9, Jan. 2023, Art. no. 996528.

[30] D. Collado-Mateo, A. M. Lavín-Pérez, C. Peñacoba, J. Del Coso, M. Leyton-Román, A. Luque-Casado, P. Gasque, M. Á. Fernández-del-Olmo, and D. Amado-Alonso, "Key factors associated with adherence to physical exercise in patients with chronic diseases and older adults: An umbrella review," *Int. J. Environ. Res. Public Health*, vol. 18, no. 4, p. 2023, Feb. 2021.

[31] Y. Kumar, A. Koul, R. Singla, and M. F. Ijaz, "Artificial intelligence in disease diagnosis: A systematic literature review, synthesizing framework and future research agenda," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 7, pp. 8459–8486, Jul. 2023.

[32] A. Bin Sawad, B. Narayan, A. Alnefaie, A. Maqbool, I. Mckie, J. Smith, B. Yuksel, D. Puthal, M. Prasad, and A. B. Kocaballi, "A systematic review on healthcare artificial intelligent conversational agents for chronic conditions," *Sensors*, vol. 22, no. 7, p. 2625, Mar. 2022.

[33] A. Merabet, A. Saighi, Z. Laboudi, and M. A. Ferradji, "Multiple diseases forecast through AI and IoMT techniques: Systematic literature review," in *Proc. Int. Conf. Intell. Syst. Pattern Recognit.*, 2024, pp. 189–206.

[34] T. P. Theodore Armand, K. A. Nfor, J.-I. Kim, and H.-C. Kim, "Applications of artificial intelligence, machine learning, and deep learning in nutrition: A systematic review," *Nutrients*, vol. 16, no. 7, p. 1073, Apr. 2024.

[35] C. Cortes and V. Vapnik, "Support-vector networks," *Mach. Learn.*, vol. 20, pp. 273–297, Jul. 1995.

[36] V. C. R, Asha, V, A. Prasad, S. Das, S. Kumar, and S. S. P, "Support vector machine (SVM) and artificial neural networks (ANN) based chronic kidney disease prediction," in *Proc. 7th Int. Conf. Comput. Methodologies Commun. (ICCMC)*, Feb. 2023, pp. 469–474.

[37] P. Ebrahimi, H. Dustmohammadloo, H. Kabiri, P. Bouzari, and M. Fekete-Farkas, "Transformational entrepreneurship and digital platforms: A combination of ISM-MICMAC and unsupervised machine learning algorithms," *Big Data Cognit. Comput.*, vol. 7, no. 2, p. 118, Jun. 2023.

[38] A. S. Shanthakumari and R. Jayakarthik, "Utilizing support vector machines for predictive analytics in chronic kidney diseases," *Mater. Today, Proc.*, vol. 81, pp. 951–956, May 2023.

[39] L. Breiman, "Bagging predictors," *Mach. Learn.*, vol. 24, no. 2, pp. 123–140, Aug. 1996.

[40] H. Dustmohammadloo, A. Nikeghbalzadeh, F. F. Karkaragh, and S. Souri, "Knowledge sharing as a moderator between organizational learning and error management culture in academic staff," *Int. J. Multicultural Educ.*, vol. 25, no. 3, pp. 1–24, 2023.

[41] Z. Ghasemi Kooktapeh, H. Dustmohammadloo, H. Mehrdoost, and F. Fatehi, "In the line of fire: A systematic review and meta-analysis of job burnout among nurses," 2023, *arXiv:2312.14853*.

[42] G. Airlangga, "Comparative analysis of machine learning models for chronic disease indicator classification using U.S. chronic disease indicators dataset," *MALCOM, Indonesian J. Mach. Learn. Comput. Sci.*, vol. 4, no. 3, pp. 1034–1042, 2024.

[43] N. Rankovic, D. Rankovic, I. Lukic, N. Savic, and V. Jovanovic, "Unveiling the comorbidities of chronic diseases in Serbia using ML algorithms and Kohonen self-organizing maps for personalized healthcare frameworks," *J. Personalized Med.*, vol. 13, no. 7, p. 1032, Jun. 2023.

[44] T. Cover and P. Hart, "Nearest neighbor pattern classification," *IEEE Trans. Inf. Theory*, vols. IT13, no. 1, pp. 21–27, 1967.

[45] M. L. Alarcon, U. Roy, A. Kambhampati, N. Nguyen, M. Attari, R. Surya, F. Bunyak, M. Maschmann, K. Palaniappan, and P. Calyam, "Learning-based image analytics in user-AI agent interactions for cyber-enabled manufacturing," in *Proc. IEEE 4th Int. Conf. Hum.-Mach. Syst. (ICHMS)*, May 2024, pp. 1–7.

[46] T. A. Assegie, T. Suresh, R. Purushothaman, S. Ganesan, and N. K. Kumar, "Early prediction of gestational diabetes with parameter-tuned K-nearest neighbor classifier," *J. Robot. Control (JRC)*, vol. 4, no. 4, pp. 452–457, Jul. 2023.

[47] M. Kateri, "Contingency table analysis," *Statist. Ind. Technol.*, vol. 525, pp. 1–24, Sep. 2014.

[48] P. K. Misra, N. Kumar, A. Misra, and A. Khang, "Heart disease prediction using logistic regression and random forest classifier," in *Data-Centric AI Solutions and Emerging Technologies in the Healthcare Ecosystem*. Boca Raton, FL, USA: CRC Press, 2023, pp. 83–112.

[49] A. Das, "Logistic regression," in *Encyclopedia of Quality of Life and Well-Being Research: Springer*. Cham, Switzerland: Springer, 2024, pp. 3985–3986.

[50] R. Bhardwaj and S. Vatta, "Implementation of ID3 algorithm," *Int. J. Adv. Res. Comput. Sci. Softw. Eng.*, vol. 3, no. 6, pp. 1–24, 2013.

[51] E. O. Paul, "Hybrid decision tree-based machine learning models for diabetes prediction," *SCIREA J. Inf. Sci. Syst. Sci.*, vol. 8, pp. 1–30, Jan. 2024.

[52] M. Attari, N. P. Nguyen, K. Palaniappan, and F. Bunyak, "Multi-loss topology-aware deep learning network for segmentation of vessels in microscopy images," in *Proc. IEEE Appl. Imag. Pattern Recognit. Workshop (AIPR)*, Sep. 2023, pp. 1–7.

[53] M. V. N, A. N, and K. S. K, "Decision tree-based explainable AI for diagnosis of chronic kidney disease," in *Proc. 5th Int. Conf. Inventive Res. Comput. Appl. (ICIRCA)*, Aug. 2023, pp. 947–952.

[54] L. Jiang, H. Zhang, and Z. Cai, "A novel Bayes model: Hidden naive Bayes," *IEEE Trans. Knowl. Data Eng.*, vol. 21, no. 10, pp. 1361–1371, Oct. 2009.

[55] S. Halder, S. Kumar, D. P. Acharjya, and S. Dutta, "Forecast of health risk for chronic kidney disease: A comparison between Naïve Bayes (NB) and support vector machine (SVM) models," in *Proc. Comput. Vis. AI-Integr. IoT Technol. Med. Ecosystem*, 2023, pp. 267–287.

[56] H. Gharagozlou, J. Mohammadzadeh, A. Bastanfard, and S. S. Ghidary, "RLAS-BIABC: A reinforcement learning-based answer selection using the BERT model boosted by an improved ABC algorithm," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–21, May 2022, doi: 10.1155/2022/7839840.

[57] S. Reddy, N. Sethi, R. Rajender, and G. Mahesh, "Forecasting diabetes correlated non-alcoholic fatty liver disease by exploiting Naïve Bayes tree," *ICST Trans. Scalable Inf. Syst.*, vol. 10, Jul. 2018, Art. no. 173975.

[58] T. Chen and C. Guestrin, "XGBoost: A scalable tree boosting system," in *Proc. 22nd ACM SIGKDD Int. Conf. Knowl. Discovery Data Mining*, Aug. 2016, pp. 785–794.

[59] H. A. Al-Jamimi, "Synergistic feature engineering and ensemble learning for early chronic disease prediction," *IEEE Access*, vol. 12, pp. 62215–62233, 2024.

[60] S. Danaei, A. Bostani, S. V. Moravvej, F. Mohammadi, R. Alizadehsani, A. Shoeibi, H. Alinejad-Rokny, and S. Nahavandi, "Myocarditis diagnosis: A method using mutual learning-based ABC and reinforcement learning," in *Proc. IEEE 22nd Int. Symp. Comput. Intell. Informat. 8th IEEE Int. Conf. Recent Achievements Mechatronics, Autom., Comput. Sci. Robot. (CINTI-MACRo)*, Nov. 2022, pp. 000265–000270.

[61] H. Zareiamand, A. Darroudi, I. Mohammadi, S. V. Moravvej, S. Danaei, and R. Alizadehsani, "Cardiac magnetic resonance imaging (CMRI) applications in patients with chest pain in the emergency department: A narrative review," *Diagnostics*, vol. 13, no. 16, p. 2667, Aug. 2023.

[62] S. Bhaskar and T. T. M., "LSTM model for visual speech recognition through facial expressions," *Multimedia Tools Appl.*, vol. 82, no. 4, pp. 5455–5472, Feb. 2023.

[63] S. V. Moravvej, R. Alizadehsani, S. Khanam, Z. Sobhaninia, A. Shoeibi, F. Khozeimeh, Z. A. Sani, R.-S. Tan, A. Khosravi, S. Nahavandi, N. A. Kadri, M. M. Azizan, N. Arunkumar, and U. R. Acharya, "RLMD-PA: A reinforcement learning-based myocarditis diagnosis combined with a population-based algorithm for pretraining weights," *Contrast Media Mol. Imag.*, vol. 2022, no. 1, pp. 1–18, Jan. 2022.

[64] M. Roshanzamir, R. Alizadehsani, S. V. Moravvej, J. H. Joloudari, H. Alinejad-Rokny, and J. M. Gorriz, "Enhancing interpretability in machine learning: A focus on genetic network programming, its variants, and applications," in *Proc. Int. Work-Conf. Interplay Between Natural Artif. Comput.*, 2024, pp. 98–107.

[65] M. Esmaeili, S. H. Goki, B. H. K. Masjidi, M. Sameh, H. Gharagozlou, and A. S. Mohammed, "ML-DDoSnet: IoT intrusion detection based on denial-of-service attacks using machine learning methods and NSL-KDD," *Wireless Commun. Mobile Comput.*, vol. 2022, pp. 1–16, Aug. 2022.

[66] A. Mirzaee Moghaddam Kasmaee, A. Ataei, S. V. Moravvej, R. Alizadehsani, J. M. Gorriz, Y.-D. Zhang, R.-S. Tan, and U. R. Acharya, "ELRL-MD: A deep learning approach for myocarditis diagnosis using cardiac magnetic resonance images with ensemble and reinforcement learning integration," *Physiological Meas.*, vol. 45, no. 5, May 2024, Art. no. 055011.

[67] S. V. Moravvej, M. J. M. Kahaki, M. S. Sartakhti, and A. Mirzaei, "A method based on attention mechanism using bidirectional long-short term memory(BLSTM) for question answering," in *Proc. 29th Iranian Conf. Electr. Eng. (ICEE)*, May 2021, pp. 460–464.

[68] S. Vahid Moravvej, A. Mirzaei, and M. Safayani, "Biomedical text summarization using conditional generative adversarial network(CGAN)," 2021, *arXiv:2110.11870*.

[69] C. Hema and F. P. Garcia Marquez, "Emotional speech recognition using CNN and deep learning techniques," *Appl. Acoust.*, vol. 211, Aug. 2023, Art. no. 109492.

[70] M. Rayhan Ahmed, S. Islam, A. K. M. Muzahidul Islam, and S. Shatabda, "An ensemble 1D-CNN-LSTM-GRU model with data augmentation for speech emotion recognition," *Expert Syst. Appl.*, vol. 218, May 2023, Art. no. 119633.

[71] K. Modi, I. Singh, and Y. Kumar, "A comprehensive analysis of artificial intelligence techniques for the prediction and prognosis of lifestyle diseases," *Arch. Comput. Methods Eng.*, vol. 30, no. 8, pp. 4733–4756, Nov. 2023.

[72] P. R. Kotha, M. Attari, M. Maschmann, and F. Bunyak, "Deep style transfer for generation of photo-realistic synthetic images of CNT forests," in *Proc. IEEE Appl. Imag. Pattern Recognit. Workshop (AIPR)*, Sep. 2023, pp. 1–7.

[73] K. Sinha, Z. Uddin, H. I. Kawsar, S. Islam, M. J. Deen, and M. M. R. Howlader, "Analyzing chronic disease biomarkers using electrochemical sensors and artificial neural networks," *TrAC Trends Anal. Chem.*, vol. 158, Jan. 2023, Art. no. 116861.

[74] S. Taherinavid, S. V. Moravvej, Y.-L. Chen, J. Yang, C. S. Ku, and P. L. Yee, "Automatic transportation mode classification using a deep reinforcement learning approach with smartphone sensors," *IEEE Access*, vol. 12, pp. 514–533, 2024.

[75] G. Kim, H. Lim, Y. Kim, O. Kwon, and J.-H. Choi, "Intra-person multi-task learning method for chronic-disease prediction," *Sci. Rep.*, vol. 13, no. 1, p. 1069, Jan. 2023.

[76] A. Chunduru, A. R. Kishore, B. K. Sasapu, and K. Seepana, "Multi chronic disease prediction system using CNN and random forest," *Social Netw. Comput. Sci.*, vol. 5, no. 1, p. 157, Jan. 2024.

[77] A. A. Malibari, "An efficient IoT-artificial intelligence-based disease prediction using lightweight CNN in healthcare system," *Meas., Sensors*, vol. 26, Apr. 2023, Art. no. 100695.

[78] S. Chitra and V. Jayalakshmi, "Heart disease and chronic kidney disease prediction based on Internet of Things using FRNN algorithm," in *Proc. 6th Int. Conf. Comput. Methodologies Commun. (ICCMC)*, Mar. 2022, pp. 467–479.

[79] L. Gorzelniak, K. Schultz, M. Wittmann, J. Rudnik, R. Jörres, A. Horsch, and A. Dias, "Classification of exacerbation episodes in chronic obstructive pulmonary disease patients," *Methods Inf. Med.*, vol. 53, no. 2, pp. 108–114, 2014.

[80] Y. Du, R. Almajalid, J. Shan, and M. Zhang, "A novel method to predict knee osteoarthritis progression on MRI using machine learning methods," *IEEE Trans. Nanobiosci.*, vol. 17, no. 3, pp. 228–236, Jul. 2018.

[81] *Osteoarthritis Initiative Database*. Accessed: Aug. 30, 2024. [Online]. Available: https://nda.nih.gov/oai

[82] A. Akl, B. Taati, and A. Mihailidis, "Autonomous unobtrusive detection of mild cognitive impairment in older adults," *IEEE Trans. Biomed. Eng.*, vol. 62, no. 5, pp. 1383–1394, May 2015.

[83] M. A. Al-Jarrah and H. Shatnawi, "Non-proliferative diabetic retinopathy symptoms detection and classification using neural network," *J. Med. Eng. Technol.*, vol. 41, no. 6, pp. 498–505, Aug. 2017.

[84] *DIARETDB1*. Accessed: Sep. 2, 2024. [Online]. Available: https://www.kaggle.com/datasets/nguyenhung1903/diaretdb1-standard-diabetic-retinopathy-database

[85] I. Beheshti, N. Maikusa, M. Daneshmand, H. Matsuda, H. Demirel, and G. Anbarjafari, "Classification of Alzheimer's disease and prediction of mild cognitive impairment conversion using histogram-based analysis of patient-specific anatomical brain connectivity networks," *J. Alzheimer's Disease*, vol. 60, no. 1, pp. 295–304, Aug. 2017.

[86] *Japanese Alzheimer's Disease Neuroimaging Initiative*. Accessed: Aug. 28, 2024. [Online]. Available: https://humandbs.biosciencedbc.jp/en/hum0043-v1

[87] M. Hubenthal, G. Hemmrich-Stanisak, F. Degenhardt, S. Szymczak, Z. Du, A. Elsharawy, A. Keller, S. Schreiber, and A. Franke, "Sparse modeling reveals MiRNA signatures for diagnostics (don't short) of inflammatory bowel disease," *PLoS One*, vol. 10, no. 10, Oct. 2015, Art. no. e0140155.

[88] *U.K. Biobank*. Accessed: Sep. 3, 2024. [Online]. Available: https://www.ukbiobank.ac.uk

[89] J. A. Andrews, R. F. Harrison, L. J. E. Brown, L. M. MacLean, F. Hwang, T. Smith, E. A. Williams, C. Timon, T. Adlam, H. Khadra, and A. J. Astell, "Using the NANA toolkit at home to predict older adults' future depression," *J. Affect. Disorders*, vol. 213, pp. 187–190, Apr. 2017.

[90] J. Choi, J. Choi, and W. J. Choi, "Predicting depression among community residing older adults: A use of machine learning approch," in *Nursing Informatics 2018*. Amsterdam, The Netherlands: IOS Press, 2018, p. 265.

[91] *National Social Life, Health, and Aging Project*. Accessed: Aug. 29, 2024. [Online]. Available: https://www.icpsr.umich.edu/web/ICPSR/studies/20541

[92] C. M. Hatton, L. W. Paton, D. Mcmillan, J. Cussens, S. Gilbody, and P. A. Tiffin, "Predicting persistent depressive symptoms in older adults: A machine learning approach to personalised mental healthcare," *J. Affect. Disorders*, vol. 246, pp. 857–860, Mar. 2019.

[93] N. Bhagwat, J. D. Viviano, A. N. Voineskos, M. M. Chakravart, and A. D. Initiative, "Modeling and prediction of clinical symptom trajectories in Alzheimer's disease using longitudinal data," *PLoS Comput. Biol.*, vol. 14, no. 9, 2018, Art. no. e1006376.

[94] *Alzheimer's Disease Neuroimaging Initiative*. Accessed: Sep. 2, 2024. [Online]. Available: https://adni.loni.usc.edu

[95] S. L. James, M. Romero, D. Ramírez-Villalobos, S. Gómez, K. Pierce, A. Flaxman, P. Serina, A. Stewart, C. J. Murray, E. Gakidou, R. Lozano, and B. Hernandez, "Validating estimates of prevalence of non-communicable diseases based on household surveys: The symptomatic diagnosis study," *BMC Med.*, vol. 13, no. 1, pp. 1–12, Dec. 2015.

[96] *Population Health Metrics Research Consortium Study*. Accessed: Aug. 20, 2024. [Online]. Available: https://www.georgeinstitute.org.in/projects/population-health-metrics-research-consortium-phmrc-project

[97] G. Lee, K. Nho, B. Kang, K. A. Sohn, and D. Kim, "Predicting Alzheimer's disease progression using multi-modal deep learning approach," *Sci. Rep.*, vol. 9, no. 1, p. 1952, 2019.

[98] H. Bogunovic, A. Montuoro, M. Baratsits, M. G. Karantonis, S. M. Waldstein, F. Schlanitz, and U. Schmidt-Erfurth, "Machine learning of the progression of intermediate age-related macular degeneration based on OCT imaging," *Investigative Opthalmology Vis. Sci.*, vol. 58, no. 6, Jun. 2017, Art. no. BIO141.

[99] B. Cheng, M. Liu, H.-I. Suk, D. Shen, and D. Zhang, "Multimodal manifold-regularized transfer learning for MCI conversion prediction," *Brain Imag. Behav.*, vol. 9, no. 4, pp. 913–926, Dec. 2015.

[100] K. M. Kuo, P. C. Talley, C. H. Huang, and L. C. Cheng, "Predicting hospital-acquired pneumonia among schizophrenic patients: A machine learning approach," *BMC Med. Informat. Decis. Making*, vol. 19, no. 1, pp. 1–8, Dec. 2019.

[101] A. J. C. C. Lins, M. T. C. Muniz, A. N. M. Garcia, A. V. Gomes, R. M. Cabral, and C. J. A. Bastos-Filho, "Using artificial neural networks to select the parameters for the prognostic of mild cognitive impairment and dementia in elderly individuals," *Comput. Methods Programs Biomed.*, vol. 152, pp. 93–104, Dec. 2017.

[102] A. Ortiz, J. Munilla, J. M. Górriz, and J. Ramírez, "Ensembles of deep learning architectures for the early diagnosis of the Alzheimer's disease," *Int. J. Neural Syst.*, vol. 26, no. 7, Nov. 2016, Art. no. 1650025.

[103] Ashraf A and Taati B, "Automated video analysis of handwashing behavior as a potential marker of cognitive health in older adults," *IEEE J. Biomed. Health Informat.*, vol. 20, no. 2, pp. 682–690, Jul. 2015.

[104] M. Christopher, A. Belghith, R. N. Weinreb, C. Bowd, M. H. Goldbaum, L. J. Saunders, F. A. Medeiros, and L. M. Zangwill, "Retinal nerve fiber layer features identified by unsupervised machine learning on optical coherence tomography scans predict glaucoma progression," *Investigative Opthalmology Vis. Sci.*, vol. 59, no. 7, p. 2748, Jun. 2018.

[105] *Diagnostic Innovations in Glaucoma*. Accessed: Jul. 18, 2024. [Online]. Available: https://grantome.com/grant/NIH/R01-EY027510-05

[106] A. König, N. Linz, R. Zeghari, X. Klinge, J. Tröger, J. Alexandersson, and P. Robert, "Detecting apathy in older adults with cognitive disorders using automatic speech analysis," *J. Alzheimer's Disease*, vol. 69, no. 4, pp. 1183–1193, Jun. 2019.

[107] A. Weakley, J. A. Williams, M. Schmitter-Edgecombe, and D. J. Cook, "Neuropsychological test selection for cognitive impairment classification: A machine learning approach," *J. Clin. Experim. Neuropsychology*, vol. 37, no. 9, pp. 899–916, Oct. 2015.

[108] M. Treder, J. L. Lauermann, and N. Eter, "Deep learning-based detection and classification of geographic atrophy using a deep convolutional neural network classifier," *Graefe's Arch. Clin. Experim. Ophthalmology*, vol. 256, no. 11, pp. 2053–2060, Nov. 2018.

[109] S. M. Naushad, T. Hussain, B. Indumathi, K. Samreen, S. A. Alrokayan, and V. K. Kutala, "Machine learning algorithm-based risk prediction model of coronary artery disease," *Mol. Biol. Rep.*, vol. 45, no. 5, pp. 901–910, Oct. 2018.

[110] C. Cabral, P. M. Morgado, D. Campos Costa, and M. Silveira, "Predicting conversion from MCI to AD with FDG-PET brain images at different prodromal stages," *Comput. Biol. Med.*, vol. 58, pp. 101–109, Mar. 2015.

[111] K.-H. Thung, C.-Y. Wee, P.-T. Yap, and D. Shen, "Identification of progressive mild cognitive impairment patients using incomplete longitudinal MRI scans," *Brain Struct. Function*, vol. 221, no. 8, pp. 3979–3995, Nov. 2016.

[112] Y. Zhan, K. Chen, X. Wu, D. Zhang, J. Zhang, L. Yao, and X. Guo, "Identification of conversion from normal elderly cognition to Alzheimer's disease using multimodal support vector machine," *J. Alzheimer's Disease*, vol. 47, no. 4, pp. 1057–1067, Aug. 2015.

[113] J. Lara, F. X. López-Labrador, F. González-Candelas, M. Berenguer, and Y. E. Khudyakov, "Computational models of liver fibrosis progression for hepatitis c virus chronic infection," *BMC Bioinf.*, vol. 15, no. S8, pp. 1–9, Jul. 2014.

[114] *GenBank*. Accessed: Sep. 3, 2024. [Online]. Available: https://www.ncbi.nlm.nih.gov/genbank/

[115] U. Schmidt-Erfurth, S. M. Waldstein, S. Klimscha, A. Sadeghipour, X. Hu, B. S. Gerendas, A. Osborne, and H. Bogunovic, "Prediction of individual disease conversion in early AMD using artificial intelligence," *Investigative Opthalmology Vis. Sci.*, vol. 59, no. 8, p. 3199, Jul. 2018.

[116] *HARBOR*. Accessed: Sep. 3, 2024. [Online]. Available: https://clinicaltrials.gov/study/NCT04910685

[117] F. C. Morabito, M. Campolo, N. Mammone, M. Versaci, S. Franceschetti, F. Tagliavini, V. Sofia, D. Fatuzzo, A. Gambardella, A. Labate, L. Mumoli, G. G. Tripodi, S. Gasparini, V. Cianci, C. Sueri, E. Ferlazzo, and U. Aguglia, "Deep learning representation from electroencephalography of early-stage creutzfeldt-jakob disease and features for differentiation from rapidly progressive dementia," *Int. J. Neural Syst.*, vol. 27, no. 2, Mar. 2017, Art. no. 1650039.

[118] V. Pedoia, J. Haefeli, K. Morioka, H. Teng, L. Nardo, R. B. Souza, A. R. Ferguson, and S. Majumdar, "MRI and biomechanics multidimensional data analysis reveals R_2-$R_1\rho$ as an early predictor of cartilage lesion progression in knee osteoarthritis," *J. Magn. Reson. Imag.*, vol. 47, no. 1, pp. 78–90, Jan. 2018.

[119] J. L. Avila-Jimenez, V. Canton-Habas, M. del Pilar Carrera-Gonzslez, M. Rich-Ruiz, and S. Ventura, "A deep learning model for Alzheimer's disease diagnosis based on patient clinical records," *Comput. Biol. Med.*, vol. 169, Sep. 2024, Art. no. 107814.

[120] *National Alzheimer's Coordinating Center*. Accessed: Sep. 2, 2024.

[121] H. Yao, Z. Wu, S. S. Gao, R. H. Guymer, V. Steffen, H. Chen, M. Hejrati, and M. Zhang, "Deep learning approaches for detecting of nascent geographic atrophy in age-related macular degeneration," *Ophthalmology Sci.*, vol. 4, no. 3, May 2024, Art. no. 100428.

[122] *NCT02484690*. Accessed: Sep. 2, 2024. [Online]. Available: https://clinicaltrials.gov/study/NCT02484690

[123] J. Lu, Y. Cheng, F. E. Hiya, M. Shen, G. Herrera, Q. Zhang, G. Gregori, P. J. Rosenfeld, and R. K. Wang, "Deep-learning-based automated measurement of outer retinal layer thickness for use in the assessment of age-related macular degeneration, applicable to both swept-source and spectral-domain OCT imaging," *Biomed. Opt. Exp.*, vol. 15, no. 1, p. 413, 2024.

[124] M. Elsharkawy, A. Sharafeldeen, F. Khalifa, A. Soliman, A. Elnakib, M. Ghazal, A. Sewelam, A. Thanos, H. S. Sandhu, and A. El-Baz, "A clinically explainable AI-based grading system for age-related macular degeneration using optical coherence tomography," *IEEE J. Biomed. Health Informat.*, vol. 28, no. 4, pp. 2079–2090, Apr. 2024.

[125] *DRIONS-DB*. Accessed: Aug. 31, 2024. [Online]. Available: https://www.idiap.ch/software/bob/docs/bob/bob.db.drionsdb/master/index.html

[126] A. Khan and S. Zubair, "An improved multi-modal based machine learning approach for the prognosis of Alzheimer's disease," *J. King Saud Univ.-Comput. Inf. Sci.*, vol. 34, no. 6, pp. 2688–2706, Jun. 2022.

[127] G. Muni Nagamani and E. Rayachoti, "Deep learning network (DL-Net) based classification and segmentation of multi-class retinal diseases using OCT scans," *Biomed. Signal Process. Control*, vol. 88, Feb. 2024, Art. no. 105619.

[128] I. M. Saied, T. Arslan, and S. Chandran, "Classification of Alzheimer's disease using RF signals and machine learning," *IEEE J. Electromagn., RF Microw. Med. Biol.*, vol. 6, no. 1, pp. 77–85, Mar. 2022.

[129] M. H. Wang, J. Zhou, C. Huang, Z. Tang, X. Yu, G. Hou, J. Yang, Q. Yuan, K. K. Chong, and L. Huang, "Fusion learning methods for the age-related macular degeneration diagnosis based on multiple sources of ophthalmic digital images," in *Proc. 2nd Int. Conf. Electr., Electron., Inf. Eng.*, Jan. 2024, pp. 470–492.

[130] C.-H. Liu, C.-H. Peng, L.-Y. Huang, F.-Y. Chen, C.-H. Kuo, C.-Z. Wu, and Y.-F. Cheng, "Comparison of multiple linear regression and machine learning methods in predicting cognitive function in older Chinese type 2 diabetes patients," *BMC Neurol.*, vol. 24, no. 1, p. 11, Jan. 2024.

[131] G. Battineni, M. A. Hossain, N. Chintalapudi, E. Traini, V. R. Dhulipalla, M. Ramasamy, and F. Amenta, "Improved Alzheimer's disease detection by MRI using multimodal machine learning algorithms," *Diagnostics*, vol. 11, no. 11, p. 2103, Nov. 2021.

[132] S. Hong, B. Lu, S. Wang, and Y. Jiang, "Comparison of logistic regression and machine learning methods for predicting depression risks among disabled elderly individuals: Results from the China health and retirement longitudinal study," Hubei Univ. Med., China, Tech. Rep. 2021WNLOKF020, 2024.

[133] P. Kishore, C. U. Kumari, M. Kumar, and T. Pavani, "Detection and analysis of Alzheimer's disease using various machine learning algorithms," *Mater. Today, Proc.*, vol. 45, pp. 1502–1508, Jun. 2021.

[134] C. Kavitha, V. Mani, S. R. Srividhya, O. I. Khalaf, and C. A. Tavera Romero, "Early-stage Alzheimer's disease prediction using machine learning models," *Frontiers Public Health*, vol. 10, Mar. 2022, Art. no. 853294.

[135] A. Singh and R. Kumar, "Brain MRI image analysis for Alzheimer's disease (AD) prediction using deep learning approaches," *Social Netw. Comput. Sci.*, vol. 5, no. 1, p. 160, Jan. 2024.

[136] C. Montorsi, A. Fusco, P. Van Kerm, and S. P. A. Bordas, "Predicting depression in old age: Combining life course data with machine learning," *Econ. Hum. Biol.*, vol. 52, Jan. 2024, Art. no. 101331.

[137] H. Park, C. Kang, A.-C. Team, W. Lee, I. Song, D. Kwon, J. Oh, J. Moon, J. Park, J. Min, E. Kim, H. Jang, and H. Kim, "Particulate matters ($PM_{2.5}$, PM_{10}) and the risk of depression among middle-aged and older population: Analysis of the Korean longitudinal study of aging (KLoSA), 2016–2020 in South Korea," *Environ. Health*, vol. 23, no. 1, p. 4, Jan. 2024.

[138] Z. Qu, Y. Wang, D. Guo, G. He, C. Sui, Y. Duan, X. Zhang, L. Lan, H. Meng, Y. Wang, and X. Liu, "Identifying depression in the United States veterans using deep learning algorithms, NHANES 2005–2018," *BMC Psychiatry*, vol. 23, no. 1, p. 620, Aug. 2023.

[139] *National Health and Nutrition Examination Survey*. Accessed: Sep. 3, 2024. [Online]. Available: https://www.cdc.gov/nchs/nhanes/index.htm

[140] S. R. B. S. Gomes, M. von Schantz, and M. Leocadio-Miguel, "Predicting depressive symptoms in middle-aged and elderly adults using sleep data and clinical health markers: A machine learning approach," *Sleep Med.*, vol. 102, pp. 123–131, Feb. 2023.

[141] *Sleep Health Index*. Accessed: Aug. 29, 2024. [Online]. Available: https://www.thensf.org/sleep-health-index/

[142] S. Lin, Y. Wu, L. He, and Y. Fang, "Prediction of depressive symptoms onset and long-term trajectories in home-based older adults using machine learning techniques," *Aging Mental Health*, vol. 27, no. 1, pp. 8–17, Jan. 2023.

[143] *Health and Retirement Study*. Accessed: Aug. 30, 2024. [Online]. Available: https://hrs.isr.umich.edu/

[144] Y. Lin, B. N. Liyanage, Y. Sun, T. Lu, Z. Zhu, Y. Liao, Q. Wang, C. Shi, and W. Yue, "A deep learning-based model for detecting depression in senior population," *Frontiers Psychiatry*, vol. 13, Nov. 2022, Art. no. 1016676.

[145] H. V. Nguyen and H. Byeon, "Explainable deep-learning-based depression modeling of elderly community after COVID-19 pandemic," *Mathematics*, vol. 10, no. 23, p. 4408, Nov. 2022.

[146] R. Kaur, R. W. Motl, R. Sowers, and M. E. Hernandez, "A vision-based framework for predicting multiple sclerosis and Parkinson's disease gait dsfunctions—A deep learning approach," *IEEE J. Biomed. Health Informat.*, vol. 27, no. 1, pp. 190–201, Jan. 2023.

[147] *CMU MoCap Gait Database*. Accessed: Aug. 23, 2024. [Online]. Available: https://www.kaggle.com/datasets/dasmehdixtr/cmu-motion-capture-walking-database

[148] A. Tousignant, *Prediction of Future Multiple Sclerosis Disease Progression Using Deep Learning Analysis of MRI Data*. New York, NY, USA: McGraw-Hill, 2022.

[149] W. Zhu, C. Chen, L. Zhang, T. Hoyt, E. Walker, S. Venkatesh, F. Zhang, F. Qureshi, J. F. Foley, and Z. Xia, "Association between serum multi-protein biomarker profile and real-world disability in multiple sclerosis," *Brain Commun.*, vol. 6, no. 1, Dec. 2023, Art. no. fcad300.

[150] B. M. Meyer, L. J. Tulipani, R. D. Gurchiek, D. A. Allen, L. Adamowicz, D. Larie, A. J. Solomon, N. Cheney, and R. S. McGinnis, "Wearables and deep learning classify fall risk from gait in multiple sclerosis," *IEEE J. Biomed. Health Informat.*, vol. 25, no. 5, pp. 1824–1831, May 2021.

[151] R. Kaur, Z. Chen, R. Motl, M. E. Hernandez, and R. Sowers, "Predicting multiple sclerosis from gait dynamics using an instrumented treadmill: A machine learning approach," *IEEE Trans. Biomed. Eng.*, vol. 68, no. 9, pp. 2666–2677, Sep. 2021.

[152] B. G. Rajagopal and M. Arock, "Application of machine learning techniques for study of drug interactions using clinical parameters for creutzfeldt-jakob disease," in *Proc. IEEE-EMBS Conf. Biomed. Eng. Sci. (IECBES)*, Mar. 2021, pp. 415–420.

[153] G. Gimhani, A. C. Aponso, and N. Krishnarajah, "Critical evaluation of different biomarkers and machine-learning-based approaches to identify dementia disease in early stages," in *Proc. 4th Int. Congr. Inf. Commun. Technol.*, vol. 1, 2019, pp. 353–364.

[154] A. Y. Bayahya, W. Alhalabi, and S. H. Alamri, "Older adults get lost in virtual reality: Visuospatial disorder detection in dementia using a voting approach based on machine learning algorithms," *Mathematics*, vol. 10, no. 12, p. 1953, Jun. 2022.

[155] C. Hercus and A.-R. Hudaib, "Delirium misdiagnosis risk in psychiatry: A machine learning-logistic regression predictive algorithm," *BMC Health Services Res.*, vol. 20, no. 1, pp. 1–7, Dec. 2020.

[156] N. Fazakis, O. Kocsis, E. Dritsas, S. Alexiou, N. Fakotakis, and K. Moustakas, "Machine learning tools for long-term type 2 diabetes risk prediction," *IEEE Access*, vol. 9, pp. 103737–103757, 2021.

[157] *English Longitudinal Study of Ageing*. Accessed: Sep. 3, 2024. [Online]. Available: https://www.elsa-project.ac.uk/

[158] C. Kupper, S. Stroth, N. Wolff, F. Hauck, N. Kliewer, T. Schad-Hansjosten, I. Kamp-Becker, L. Poustka, V. Roessner, K. Schultebraucks, and S. Roepke, "Identifying predictive features of autism spectrum disorders in a clinical sample of adolescents and adults using machine learning," *Sci. Rep.*, vol. 10, no. 1, p. 4805, Mar. 2020.

[159] L. Bishop-Fitzpatrick, A. Movaghar, J. S. Greenberg, D. Page, L. S. DaWalt, M. H. Brilliant, and M. R. Mailick, "Using machine learning to identify patterns of lifetime health problems in decedents with autism spectrum disorder," *Autism Res.*, vol. 11, no. 8, pp. 1120–1128, Aug. 2018.

[160] M. B. Usta, K. Karabekiroglu, B. Sahin, M. Aydin, A. Bozkurt, T. Karaosman, A. Aral, C. Cobanoglu, A. D. Kurt, N. Kesim, I. Sahin, and E. Ürer, "Use of machine learning methods in prediction of short-term outcome in autism spectrum disorders," *Psychiatry Clin. Psychopharmacology*, vol. 29, no. 3, pp. 320–325, Jul. 2019.

[161] Md. A. Awal, Md. S. Hossain, K. Debjit, N. Ahmed, R. D. Nath, G. M. M. Habib, Md. S. Khan, Md. A. Islam, and M. A. P. Mahmud, "An early detection of asthma using BOMLA detector," *IEEE Access*, vol. 9, pp. 58403–58420, 2021.

[162] S. Sarkar, S. Bhattacherjee, P. Bhattacharyya, M. Mitra, and S. Pal, "Automatic identification of asthma from ECG derived respiration using complete ensemble empirical mode decomposition with adaptive noise and principal component analysis," *Biomed. Signal Process. Control*, vol. 77, Aug. 2022, Art. no. 103716.

[163] O. P. Singh, R. Palaniappan, and M. Malarvili, "Automatic quantitative analysis of human respired carbon dioxide waveform for asthma and non-asthma classification using support vector machine," *IEEE Access*, vol. 6, pp. 55245–55256, 2018.

[164] J. L. M. Amaral, A. J. Lopes, J. Veiga, A. C. D. Faria, and P. L. Melo, "High-accuracy detection of airway obstruction in asthma using machine learning algorithms and forced oscillation measurements," *Comput. Methods Programs Biomed.*, vol. 144, pp. 113–125, Jun. 2017.

[165] R. Haba, G. Singer, S. Naftali, M. R. Kramer, and A. Ratnovsky, "A remote and personalised novel approach for monitoring asthma severity levels from EEG signals utilizing classification algorithms," *Expert Syst. Appl.*, vol. 223, Aug. 2023, Art. no. 119799.

[166] D. Spathis and P. Vlamos, "Diagnosing asthma and chronic obstructive pulmonary disease with machine learning," *Health Informat. J.*, vol. 25, no. 3, pp. 811–827, Sep. 2019.

[167] S. Susanty, H. Sufriyana, E. C.-Y. Su, and Y.-H. Chuang, "Questionnaire-free machine-learning method to predict depressive symptoms among community-dwelling older adults," *PLoS One*, vol. 18, no. 1, Jan. 2023, Art. no. e0280330.

[168] S. D. Pande, S. K. Hasane Ahammad, M. N. Gurav, O. S. Faragallah, M. M. A. Eid, and A. N. Z. Rashed, "Depression detection based on social networking sites using data mining," *Multimedia Tools Appl.*, vol. 83, no. 9, pp. 25951–25967, Aug. 2023.

[169] M. Du, M. Li, X. Yu, S. Wang, Y. Wang, W. Yan, Q. Liu, M. Liu, and J. Liu, "Development and validation of prediction models for poor sleep quality among older adults in the post-COVID-19 pandemic era," *Ann. Med.*, vol. 55, no. 2, Dec. 2023, Art. no. 2285910.

[170] Z. Sabouri, N. Gherabi, M. Nasri, M. Amnai, H. E. Massari, and I. Moustati, "Prediction of depression via supervised learning models: Performance comparison and analysis," *Int. J. Online Biomed. Eng.*, vol. 19, no. 9, pp. 93–107, Jul. 2023.

[171] V. Adarsh, P. Arun Kumar, V. Lavanya, and G. R. Gangadharan, "Fair and explainable depression detection in social media," *Inf. Process. Manage.*, vol. 60, no. 1, Jan. 2023, Art. no. 103168.

[172] Y. Zhou, X. Yao, W. Han, Y. Li, J. Xue, and Z. Li, "Measurement of neuropsychiatric symptoms in the older adults with mild cognitive impairment based on speech and facial expressions: A cross-sectional observational study," *Aging Mental Health*, vol. 28, no. 5, pp. 828–837, May 2024.

[173] A. Ibrahim, "Leveraging deep learning models for early detection of chronic diseases in healthcare," in *Oral Surgery Innovations: Advancing Dental Procedures for Optim. Outcomes*. China: Inkbound Publishers, 2023, p. 143.

[174] C. Kim, Y. Son, and S. Youm, "Chronic disease prediction using character-recurrent neural network in the presence of missing information," *Appl. Sci.*, vol. 9, no. 10, p. 2170, May 2019.

[175] S. V. Moravvej, M. J. M. Kahaki, M. S. Sartakhti, and M. Joodaki, "Efficient GAN-based method for extractive summarization," *J. Electr. Comput. Eng. Innov. (JECEI)*, vol. 10, no. 2, pp. 287–298, 2022.

[176] M. Zeinolabedini, M. Pazoki, and P. Saeid, "Optimization of parameters that affect biogas production of anaerobic digestion using a particle swarm algorithm," *Int. J. Energy Water Resour.*, vol. 7, no. 1, pp. 29–41, Mar. 2023.

[177] P. Saeid, M. Pazoki, and M. Zeinolabedini, "Optimization of biomass production from sugar bagasse in anaerobic digestion using genetic algorithm," *Model. Earth Syst. Environ.*, vol. 9, no. 2, pp. 2183–2198, Jun. 2023, doi: 10.1007/S40808-022-01598-X.

[178] H. Shukla, J. L. Mason, and A. Sabyah, "Identifying genetic markers associated with susceptibility to cardiovascular diseases," in *Proc. Adv. Med. Biochemistry, Genomics, Physiol., Pathol.*, 2021, pp. 177–200.

[179] N. Peć ina-Šlaus, A. Kafka, I. Salamon, and A. Bukovac, "Mismatch repair pathway, genome stability and cancer," *Frontiers Mol. Biosciences*, vol. 7, p. 122, Jun. 2020.

[180] D. J. M. Crouch and W. F. Bodmer, "Polygenic inheritance, GWAS, polygenic risk scores, and the search for functional variants," *Proc. Nat. Acad. Sci. USA*, vol. 117, no. 32, pp. 18924–18933, Aug. 2020.

[181] C. Blauwendraat, M. A. Nalls, and A. B. Singleton AB, "The genetic architecture of Parkinson's disease," *Lancet Neurol.*, vol. 19, no. 2, pp. 170–178, 2020.

[182] J. Younger, A. Lo, L. McCormack, J. McGaughran, S. Prasad, and J. J. Atherton, "Hypertrophic cardiomyopathy: Challenging the status quo?" *Heart, Lung Circulat.*, vol. 29, no. 4, pp. 556–565, Apr. 2020.

[183] D. Pfeiffer, F. Pfeiffer, and E. Rummeny, "Advanced X-ray imaging technology," *Mol. Imag. Oncol.*, vol. 1, pp. 3–30, Aug. 2020.

[184] K. Dikaios, S. Rempel, S. H. Dumpala, S. Oore, M. Kiefte, and R. Uher, "Applications of speech analysis in psychiatry," *Harvard Rev. Psychiatry*, vol. 31, no. 1, pp. 1–13, 2023.

[185] D. M. Low, K. H. Bentley, and S. S. Ghosh, "Automated assessment of psychiatric disorders using speech: A systematic review," *Laryngoscope Investigative Otolaryngology*, vol. 5, no. 1, pp. 96–116, Feb. 2020.

[186] A. K. Schalkamp, K. J. Peall, N. A. Harrison, and C. Sandor, "Wearable movement-tracking data identify Parkinson's disease years before clinical diagnosis," *Nature Medicine*, vol. 29, no. 8, pp. 2048–2056, 2023.

[187] Z. Ayaz, S. Naz, N. H. Khan, I. Razzak, and M. Imran, "Automated methods for diagnosis of Parkinson's disease and predicting severity level," *Neural Comput. Appl.*, vol. 35, no. 20, pp. 14499–14534, Jul. 2023.

[188] S. Farashi, A. Sarihi, M. Ramezani, S. Shahidi, and M. Mazdeh, "Parkinson's disease tremor prediction using EEG data analysis—A preliminary and feasibility study," *BMC Neurol.*, vol. 23, no. 1, p. 420, Nov. 2023.

[189] Z. Chen, C. He, P. Zhang, X. Cai, W. Huang, X. Chen, M. Xu, L. Wang, and Y. Zhang, "Abnormal cerebellum connectivity patterns related to motor subtypes of Parkinson's disease," *J. Neural Transmiss.*, vol. 130, no. 4, pp. 549–560, Apr. 2023.

[190] C. H. F. Camargo, S. A. Ferreira-Peruzzo, D. I. R Ribas, G. L. Franklin, and H. A. G. Teive, "Imbalance and gait impairment in Parkinson's disease: Discussing postural instability and ataxia," *Neurological Sci.*, vol. 1, pp. 1–12, Apr. 2023.

[191] M. M. Berger, D. Talwar, and A. Shenkin, "Pitfalls in the interpretation of blood tests used to assess and monitor micronutrient nutrition status," *Nutrition Clin. Pract.*, vol. 38, no. 1, pp. 56–69, Feb. 2023.

[192] C. Schulz, B. Kalali, A. Link, M. Gerhard, and P. Malfertheiner, "New rapid Helicobacter Pylori blood test based on dual detection of FliD and CagA antibodies for on-site testing," *Clin. Gastroenterology Hepatology*, vol. 21, no. 1, pp. 229–231, Jan. 2023.

[193] H. Kaplan, G. Cengiz, S. Sas, and Y. Ö. Eldemir, "Is the C-reactive protein-to-albumin ratio the most remarkable simple inflammatory marker showing active disease in patients with axial spondyloarthritis, psoriatic arthritis, and rheumatoid arthritis?" *Clin. Rheumatology*, vol. 42, no. 11, pp. 2959–2969, Nov. 2023.

[194] W. Shi, Y. Jiang, H. Tian, Y. Wang, Y. Zhang, T. Yu, and T. Li, "C-reactive protein-to-albumin ratio (CAR) and C-reactive protein-to-lymphocyte ratio (CLR) are valuable inflammatory biomarker combination for the accurate prediction of periprosthetic joint infection," *Infection Drug Resistance*, vol. 1, pp. 477–486, Jan. 2023.

[195] H. Altaheri, G. Muhammad, M. Alsulaiman, S. U. Amin, G. A. Altuwaijri, W. Abdul, M. A. Bencherif, and M. Faisal, "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: A review," *Neural Comput. Appl.*, vol. 35, no. 20, pp. 14681–14722, Jul. 2023.

[196] I. Lambert and L. Peter-Derex, "Spotlight on sleep stage classification based on EEG," *Nature Sci. Sleep*, vol. 1, pp. 479–490, Jun. 2023.

[197] J. Dong, Y. Peng, Y. Zhang, Y. Chai, J. Long, Y. Zhang, Y. Zhao, Y. Huang, and T. Liu, "Superelastic radiative cooling metafabric for comfortable epidermal electrophysiological monitoring," *Nano-Micro Lett.*, vol. 15, no. 1, p. 181, Dec. 2023.

[198] S. S. Mukerji, K. J. Petersen, K. M. Pohl, R. M. Dastgheyb, H. S. Fox, R. M. Bilder, M.-J. Brouillette, A. L. Gross, L. A. J. Scott-Sheldon, R. H. Paul, and D. Gabuzda, "Machine learning approaches to understand cognitive phenotypes in people with HIV," *J. Infectious Diseases*, vol. 227, no. 1, pp. S48–S57, Mar. 2023.

[199] A. K. Bowe, G. Lightbody, A. Staines, and D. M. Murray, "Big data, machine learning, and population health: Predicting cognitive outcomes in childhood," *Pediatric Res.*, vol. 93, no. 2, pp. 300–307, Jan. 2023.

[200] F. de Arriba-Pérez, S. García-Méndez, F. J. González-Castaño, and E. Costa-Montenegro, "Automatic detection of cognitive impairment in elderly people using an entertainment chatbot with natural language processing capabilities," *J. Ambient Intell. Humanized Comput.*, vol. 14, no. 12, pp. 16283–16298, Dec. 2023.

[201] R. H. Somogye, C. J. Roberts, E. Spoerl, K. R. Pillunat, L. E. Pillunat, and R. H. Small, "Estimating pulsatile ocular blood volume from intraocular pressure, ocular pulse amplitude, and axial length," *PLoS One*, vol. 18, no. 3, Mar. 2023, Art. no. e0283387.

[202] Y. Yang, X. Zhang, Z. Chen, Y. Wei, Q. Ye, Y. Fan, N. Nathwani, G. Gazzard, and M. Yu, "Intraocular pressure and diurnal fluctuation of open-angle glaucoma and ocular hypertension: A baseline report from the LiGHT China trial cohort," *Brit. J. Ophthalmology*, vol. 107, no. 6, pp. 823–827, Jun. 2023.

[203] Q. Daka, N. Špegel, M. Atanasovska Velkovska, T. Steblovnik, M. Kolko, B. Neziri, and B. Cvenkel, "Exploring the relationship between anti-VEGF therapy and glaucoma: Implications for management strategies," *J. Clin. Med.*, vol. 12, no. 14, p. 4674, Jul. 2023.

[204] J. J. O. N. van den Bosch, V. Pennisi, K. Mansouri, R. N. Weinreb, H. Thieme, M. B. Hoffmann, and L. Choritz, "Effect of eyelid muscle action and rubbing on telemetrically obtained intraocular pressure in patients with glaucoma with an IOP sensor implant," *Brit. J. Ophthalmology*, vol. 107, no. 10, pp. 1425–1431, Oct. 2023.

[205] M. Moscalu, R. Moscalu, C. G. Dascau, V. Trca, E. Cojocaru, I. M. Costin, E. Trca, and I. L. serban, "Histopathological images analysis and predictive modeling implemented in digital pthology—Current affairs and perspectives," *Diagnostics*, vol. 13, no. 14, p. 2379, Jul. 2023.

[206] A. Palladino, A. Salerno, A. Crasto, C. Lucini, L. Maruccio, L. D'Angelo, P. A. Netti, P. de Girolamo, A. Cacchioli, C. Attanasio, and F. Ravanetti, "Integration of micro-CT and histology data for vasculature morpho-functional analysis in tissue regeneration," *Ann. Anatomy-Anatomischer Anzeiger*, vol. 245, Jan. 2023, Art. no. 152019.

[207] D. A. Naik, R. M. Mohana, G. Ramu, Y. S. Lalitha, M. SureshKumar, and K. V. Raghavender, "Analyzing histopathological images by using machine learning techniques," *Appl. Nanoscience*, vol. 13, no. 3, pp. 2507–2513, Mar. 2023.

[208] M. Cooper, Z. Ji, and R. G. Krishnan, "Machine learning in computational histopathology: Challenges and opportunities," in *Genes, Chromosomes and Cancer*. Hoboken, NJ, USA: Wiley, 2023.

[209] J.-P. Calbimonte, O. Aidonopoulos, F. Dubosson, B. Pocklington, I. Kebets, P.-M. Legris, and M. Schumacher, "Decentralized semantic provision of personal health streams," *J. Web Semantics*, vol. 76, Apr. 2023, Art. no. 100774.

[210] A. Carnevale, E. A. Tangari, A. Iannone, and E. Sartini, "Will big data and personalized medicine do the gender dimension justice?" *AI Soc.*, vol. 38, no. 2, pp. 829–841, Apr. 2023.

[211] A. E. W. Johnson, L. Bulgarelli, L. Shen, A. Gayles, A. Shammout, S. Horng, T. J. Pollard, S. Hao, B. Moody, B. Gow, L.-W.-H. Lehman, L. A. Celi, and R. G. Mark, "MIMIC-IV, a freely accessible electronic health record dataset," *Sci. Data*, vol. 10, no. 1, p. 1, Jan. 2023.

MAHDIEH POODINEH MOGHADAM is currently pursuing the Ph.D. degree in nursing with Zabol University of Medical Sciences, extensive expertise in computer and nursing. She is an Esteemed Scholar with Zabol University of Medical Sciences. Her research enriched by her passion for artificial intelligence, is focused on groundbreaking applications in nursing.

ZABIH ALLAH MOGHADAM is currently pursuing the Ph.D. degree in computer software engineering with Birjand Branch, Islamic Azad University, Birjand, Iran, known for his extensive expertise in computer. He is an Esteemed Scholar with Birjand Branch, Islamic Azad University. He is deeply involved in cutting-edge research, particularly in the areas of machine learning, deep learning, and computer sciences.

MOHAMMAD REZA CHALAK QAZANI received the B.Eng. degree in manufacturing and production from the University of Tabriz, Tabriz, Iran, in 2010, the master's degree in robotic and mechanical engineering from Tarbiat Modares University, Tehran, Iran, in 2013, and the Ph.D. degree in modeling and simulation of a motion cueing algorithm using prediction and computational intelligence techniques from the Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Australia, in 2021. He was an Alfred Deakin Postdoctoral Research Fellow with IISRI for two years working in the areas of model predictive control, motion cueing algorithms, and soft computing controllers. He is currently an Assistant Professor with the Faculty of Computing and Information Technology (FoCIT), Sohar University, Sohar, Oman. His teaching and research interests include data structure and algorithms, enterprise resource planning modeling and implementation, modeling and visualization, computer architecture, introduction to artificial intelligence, and advanced machine learning.

PAWEŁ PŁAWIAK was born in Ostrowiec, Poland, in 1984. He received the B.Eng. and M.Sc. degrees in electronics and telecommunications and the Ph.D. degree (Hons.) in biocybernetics and biomedical engineering from the AGH University of Science and Technology, Kraków, Poland, in 2012 and 2016, respectively, and the D.Sc. degree in technical computer science and telecommunications from the Silesian University of Technology, Gliwice, Poland, in 2020. He is currently the Dean of the Faculty of Computer Science and Telecommunications and an Associate Professor with Cracow University of Technology, Kraków, the Deputy Director of Research with the National Institute of Telecommunications, Warsaw, and an Associate Professor with the Institute of Theoretical and Applied Informatics, Polish Academy of Sciences, Gliwice. He has published more than 90 articles in refereed international SCI-IF journals. His research interests include machine learning and computational intelligence (e.g., artificial neural networks, genetic algorithms, fuzzy systems, support vector machines, k-nearest neighbors, and hybrid systems), ensemble learning, deep learning, evolutionary computation, classification, pattern recognition, signal processing and analysis, data analysis and data mining, sensor techniques, medicine, biocybernetics, biomedical engineering, and telecommunications. He is an academic editor and a reviewer of many prestigious and reputed journals.

ROOHALLAH ALIZADEHSANI (Member, IEEE) received the Bachelor of Science and Master of Science degrees in computer engineering-software from Sharif University of Technology. He is currently a Research Fellow with Deakin University, Australia. His research interests include data mining, machine learning, bioinformatics, heart disease, skin disease, diabetes disease, hepatitis disease, and cancer disease.