Received: 19 June 2023 | Revised: 13 April 2024 | Accepted: 9 May 2024
DOI: 10.1111/coin.12682

ORIGINAL ARTICLE

Computational Intelligence WILEY

Deep learning for personalized health monitoring and prediction: A review

Robertas Damaševičius[1] | Senthil Kumar Jagatheesaperumal[2] | Rajesh N. V. P. S. Kandala[3] | Sadiq Hussain[4] | Roohallah Alizadehsani[5] | Juan M. Gorriz[6]

[1]Department of Applied Informatics, Vytautas Magnus University, Kaunas, Lithuania

[2]Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi, India

[3]School of Electronics Engineering, VIT-AP University, Amaravati, India

[4]Examination Branch, Dibrugarh University, Dibrugarh, India

[5]Institute for Intelligent Systems Research and Innovation (IISRI), Deakin University, Geelong, Victoria, Australia

[6]Data Science and Computational Intelligence Institute, University of Granada, Granada, Spain

Correspondence
Rajesh N. V. P. S. Kandala, School of Electronics Engineering, VIT-AP University, Amaravati 522237, India.
Email: kandala.rajesh2014@gmail.com

Abstract

Personalized health monitoring and prediction are indispensable in advancing healthcare delivery, particularly amidst the escalating prevalence of chronic illnesses and the aging population. Deep learning (DL) stands out as a promising avenue for crafting personalized health monitoring systems adept at forecasting health outcomes with precision and efficiency. As personal health data becomes increasingly accessible, DL-based methodologies offer a compelling strategy for enhancing healthcare provision through accurate and timely prognostications of health conditions. This article offers a comprehensive examination of recent advancements in employing DL for personalized health monitoring and prediction. It summarizes a diverse range of DL architectures and their practical implementations across various realms, such as wearable technologies, electronic health records (EHRs), and data accumulated from social media platforms. Moreover, it elucidates the obstacles encountered and outlines future directions in leveraging DL for personalized health monitoring, thereby furnishing invaluable insights into the immense potential of DL in this domain.

KEYWORDS

deep learning, healthcare, personalized health, telemedicine, wearable devices

1 | INTRODUCTION

Deep learning (DL) models have revolutionized the field of personalized healthcare by providing new avenues for disease diagnosis, In recent years, DL has proven successful in various vertical domains, including internet traffic classification,[1] digital twins for sensor-fault detection and accommodation,[2] and networking and communications, as demonstrated in the application of DL for tasks at the physical layer.[3] Similarly, DL also exhibits significant progress in the clinical field,[4,5] resulting in enhanced precision and rapidity in healthcare applications.[6] By examining enormous datasets, DL models can identify patterns and offer valuable insights that can aid physicians in making informed decisions. As telemedicine and remote patient monitoring become increasingly prevalent,[7–9] personalized health monitoring and prediction using DL can offer a timely, precise, and uninterrupted observation of a patient's health status, allowing for the early identification of possible health problems and averting unfavorable events.[10]

In recent years, significant progress has been made in the field of DL,[4,5] resulting in enhanced precision and rapidity in healthcare applications.[6] By examining enormous datasets, DL models can identify patterns and offer valuable insights that can aid physicians in making informed decisions. As telemedicine and remote patient monitoring become increasingly prevalent,[7–9] personalized health monitoring and prediction using DL can offer a timely, precise, and uninterrupted observation of a patient's health status, allowing for the early identification of possible health problems and averting unfavorable events.[10]

1.1 | Background of personalized health monitoring and prediction

Personalized healthcare monitoring has revolutionized medical services by allowing individuals to track their health in real-time with wearable devices and mobile applications.[11] By doing so, individuals can monitor vital signs, activity levels,[12] and other health parameters, giving them a better understanding of their health status and empowering them to take proactive measures to prevent diseases and manage chronic conditions. An overall framework for DL-based personalized health monitoring is depicted in Figure 1. It shows the integrated supporting technological services for facilitating personalized health prediction.

The growth of personalized healthcare has been made possible through advances in wearable technology and the availability of low-cost sensors that can monitor an extensive range of health metrics.[13] These sensors can be embedded in wearable devices such as smartwatches, fitness trackers, and clothing, enabling individuals to monitor their health seamlessly throughout the day.[14] Chronic diseases such as diabetes, hypertension, and heart disease incur a significant proportion of healthcare costs worldwide. Such healthcare services can help individuals with chronic conditions monitor their health more closely and receive personalized recommendations to manage their condition more effectively, potentially reducing the need for hospitalization and enhancing their quality of life.[15]

Further, personalized healthcare is expected to become increasingly important in the future of healthcare. As wearable technology continues to become more advanced and affordable, more individuals will have access to robust health monitoring tools. Furthermore, advances in DL algorithms and artificial intelligence (AI) are expected to make personalized healthcare systems even more accurate.

FIGURE 1 Overall DL-based personalized health monitoring framework.

1.2 | Motivation: Importance of DL in personalized health monitoring

DL strategies are essential for personalized healthcare services to interpret the vast amounts of data generated by wearable sensors. DL is a type of machine learning that uses artificial neural networks to analyze large amounts of data. Personalized healthcare systems use DL algorithms to learn from the data collected by wearable sensors and generate personalized health recommendations based on an individual's unique health profile.[16,17]

Recent advancements in personalized healthcare using DL strategies have seen the development of algorithms that predict hospital readmissions and mortality risk in heart failure patients using data collected from wearable sensors.[18] Similarly, DL models have been developed to predict the onset of diabetic retinopathy using data collected from eye exams.[19]

1.3 | Objectives, novelty, and contributions of the review paper

The article aims to summarize various DL architectures and their applications for personalized health monitoring, including wearable devices, EHRs, and social media data. The review also explores the challenges and future directions for the application of DL in personalized health monitoring.

The novelty of the review lies in its focus on DL-based approaches for personalized health monitoring and prediction. With the increasing availability of personal health data, DL-based methods have emerged as a promising approach to improve healthcare delivery by providing accurate and timely predictions of health outcomes.[20] The review article provides valuable insights into the potential of DL for personalized health monitoring and prediction.

The significant contribution of this review article can be summarized as follows:

1. To provide a comprehensive summary of the recent developments in the application of DL for personalized health monitoring and prediction.
2. By summarizing the various DL architectures and their applications for personalized health monitoring, the review article provides a valuable resource for researchers and healthcare

providers to develop and implement DL-based approaches for personalized health monitoring and prediction.
3. Additionally, the review article highlights the challenges and future directions for the application of DL in personalized health monitoring, providing useful insights for researchers and policymakers who are interested in advancing personalized healthcare delivery.

1.4 | Research questions

This review article addresses the following research questions:

1. What are the recent developments in the application of DL for personalized health monitoring and prediction?
2. What are the various DL architectures used for personalized health monitoring and prediction, and how do they work?
3. How can DL-based approaches be used to develop personalized health monitoring systems for wearable devices, EHRs, and social media data?
4. What are the challenges associated with the application of DL in personalized health monitoring, and how can they be addressed?
5. What are the future directions for the application of DL in personalized health monitoring and prediction, and what are the potential implications for healthcare delivery?

1.5 | Organization of the article

We organize the rest of the paper as follows: Section 2 outlines our survey describing, including the strategy for including relevant articles. In Section 3, we first furnish an overview of the DL approaches for personalized health monitoring and its architectures, wherein we introduce the premise of our work. Section 4 presents an overview of the issues faced by using DL for personalized health monitoring. Section 5 reiterates the key takeaways from our work, and directs the future scope of EEG.

Finally, Section 6 concludes the overall guide for DL deployment for personalized healthcare. The detailed acronyms and the definitions used in this article are presented in Table 1 for readers' convenience.

2 | METHODOLOGY

This section outlines our approaches in conducting this systematic literature review, including our database selection, search criteria, and inclusion parameters, providing a robust framework for our research process. Figure 2 depicts the phases involved in the literature search and selection process in this study.

2.1 | Search methods

To identify and select relevant studies, we used four databases, including Google Scholar, IEEE Xplore Digital Library, Web of Science (WoS), and Scopus databases. Google Scholar database

TABLE 1 The acronyms and definitions used in the article.

Acronym	Definition
AD	Alzheimer's disease
ADNI	AD neuroimaging initiative
AI	Artificial intelligence
ASD	Autism spectrum disorder
AUC	Area under curve
BiLSTM-CRF	Bidirectional LSTM with a conditional random field
CADD	Computer aided disease diagnosis
CAGR	Compound annual growth rate
CDS	Clinical decision support
CNNs	Convolutional neural networks
COPD	Chronic obstructive pulmonary disease
CT	Computed tomography
CVDs	Cardiovascular diseases
CXR	Chest x-ray
DL	Deep learning
DPD-fVAE	Variational autoencoder with differentially-private decoder
DRIVE	Digital retinal images for vessel extraction
ECG	Electrocardiogram
EHRs	Electronic health records
fMRI	functional magnetic resonance imaging
GANs	Generative adversarial networks
G-BERT	GNN-bidirectional encoder representations from transformers
GCNN	Graph CNN
GDPR	General data protection regulation
GNN	Graphical neural network
GPU	Graphics processing unit
HHOCN	Harris Hawks optimized convolution network
HIPAA	Health insurance portability and accountability act
HRF	High resolution fundus
HRNER	Health-related named entity recognition
ICA	Independent component analysis
ICU	Intensive care unit
IoMT	Internet of medical things
LBP	Local binary pattern

(Continues)

TABLE 1 (Continued)

Acronym	Definition
LSTM	Long-short term memory
MCA	Monte Carlo approach
MCI	Mild cognitive impairment
MRIs	Magnetic resonance images
mTBIs	mild traumatic brain injuries
NLP	Natural language processing
PCA	Principal component analysis
PD	Parkinson's disease
PET	Positron emission tomography
QoL	Quality of life
RNNs	Recurrent neural networks
RTPCR	Reverse transcription polymerase chain reaction
SHAP	Shapley additive explanations
STARE	Structured analysis of the retina
SVM	Support vector machine
TVAE	Transitional VAE
VAEs	Variational autoencoders
WHO	World Health Organization

was chosen due to its large volume of sources available in a single platform. The IEEE database was chosen due to its dedication to technological advancement for the benefit of society. Scopus, a prominent database, was selected for its extensive coverage of abstracts and citations from peer-reviewed literature across a multitude of global publishers. WoS, a comprehensive resource, was included for its wide-ranging access to references and abstracts across all knowledge domains and its array of tools for citation analysis, references, h-index, bibliometric analysis, and access to five distinct database collections. Scopus and WoS were also preferred for their similarities and prominence among other databases, specifically designed to facilitate research citation and bibliometric analysis, making them pivotal references for bibliographic research. To conduct our search, we employed the following set of keywords: "Personalized healthcare," "Wearable," "Internet of Things," "Artificial Intelligence," "Machine Learning," and "Deep Learning."

In shaping the criteria for source selection in this review, we considered several factors. We employed the Boolean logical operator "AND" to merge the search terms "Personalized healthcare" and "Deep Learning," facilitating a focused exploration of articles that encompass both concepts. Furthermore, we utilized the Boolean logical operator "OR" to establish a connection between "Artificial Intelligence" and "Internet of Things," thereby ensuring that articles addressing these interconnected themes were included in our search across the databases. Additionally, we incorporated "Machine Learning" into our search criteria to encompass a broader scope of relevant articles.

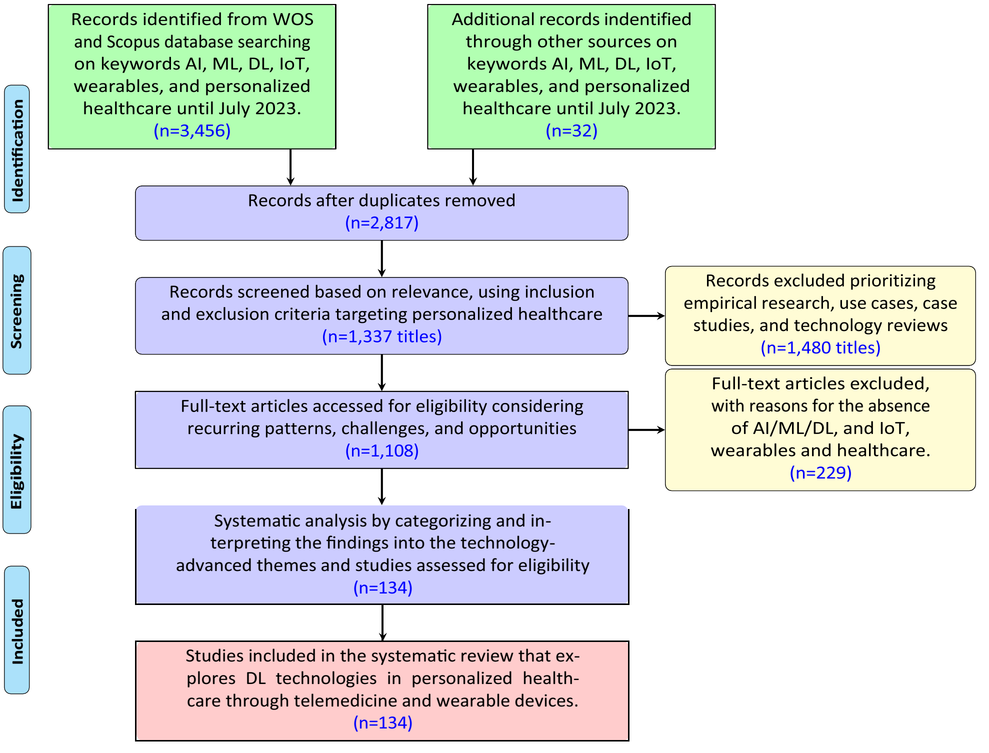

FIGURE 2 Our methodology for systematic review: The PRISMA flowchart for literature search and selection.

2.2 | Inclusion and exclusion criteria

We exclusively considered primary articles in the English language, with further refinement based on specific domains, including Computer Science, Engineering, Medicine, Business, Management, and Health Professions. Notably, we did not impose any restrictions on publication dates, as research related to personalized healthcare and DL has predominantly emerged in recent years, with relevant publications originating within the last 3 years. In this systematic review, the evaluation focused on primary studies addressing specific research inquiries, while excluding secondary studies and other document types, such as books, book chapters, editorials, patent documents, letters, and conference papers, to ensure a comprehensive examination of primary studies relevant to our research question.

2.3 | Data extraction and structured meta-analysis

In the initial screening phase, all titles and abstracts were scrutinized to identify articles potentially pertinent to DL in personalized healthcare. Subsequently, we conducted the initial identification of relevant studies, and full-text screening was then independently performed, with any disparities resolved through peer discussion among all the authors. The data management process was facilitated using Google Sheets, which enabled the recording of reasons for inclusion or exclusion and the storage of extracted data. We used key questions to evaluate the selected studies, including assessing whether they represented primary research, addressed the application of machine learning, smart wearable, and IoT technology in the education domain, and adhered to the specified inclusion and exclusion criteria. Primary insights into the methodological approaches described in the selected studies, with articles lacking a clear definition of their study type or posing ambiguities in their methodology, were excluded. The data extraction strategy primarily entailed tabulation to ensure alignment with the research question and study objectives. All data, along with the final evaluations, were documented in a Google Sheet. The methodological data from the 134 selected articles were meticulously evaluated, analyzed, and subsequently presented in this systematic review.

3 | DL APPROACHES FOR PERSONALIZED HEALTH MONITORING

The use of DL approaches for personalized health monitoring has the potential to revolutionize healthcare by enabling the analysis of large amounts of patient-specific data in real time. In this section, we provide an overview of recent research on DL models for personalized health monitoring and discuss their potential applications in various healthcare domains.

3.1 | Overview of DL models

DL has become a popular approach in various fields for its ability to learn and model complex patterns in data. One of the key advantages of DL models is their ability to learn and generalize from large datasets, which makes them highly useful in applications such as computer vision, natural language processing (NLP), and speech recognition.[21] However, these models can also be computationally expensive and require large amounts of data to train, which can pose challenges for their practical use. In addition, the interpretability of DL models is still an active area of research, as they can be seen as "black boxes" that are challenging to understand and interpret. Despite these challenges, the use of DL models has already led to breakthroughs in many fields, and they hold great promise for the future of AI and machine learning.[22]

In the context of personalized health monitoring and prediction, DL models have the potential to analyze large amounts of data from various sources such as EHRs, wearable devices, and mobile apps.[23] The use of DL can help to uncover important patterns in data that may not be apparent through traditional statistical methods, enabling personalized and precise health monitoring and prediction. The authors in reference 24 reviewed the latest advancements in digital health management using multi-modal signal monitoring, specifically focusing on lower-limb data collection, statistical analysis, and rehabilitation. The use of medical devices that communicate data over a network without human intervention, represented as the Internet of Medical Things (IoMT), is also discussed. A personalized healthcare framework using IoMT is shown in Figure 3, which highlights the layers involved and the incorporation of the DL and visualization aspects involved in the healthcare system.

Various types of DL models can be used in personalized health monitoring and prediction. For instance, convolutional neural networks (CNNs)[25] can be used to process images and signals from wearable devices and sensors to detect patterns and changes in health status. Recurrent neural networks (RNNs) can be used to process sequential data such as time-series data from wearable devices or EHRs to predict health outcomes.[26] Generative models such as variational

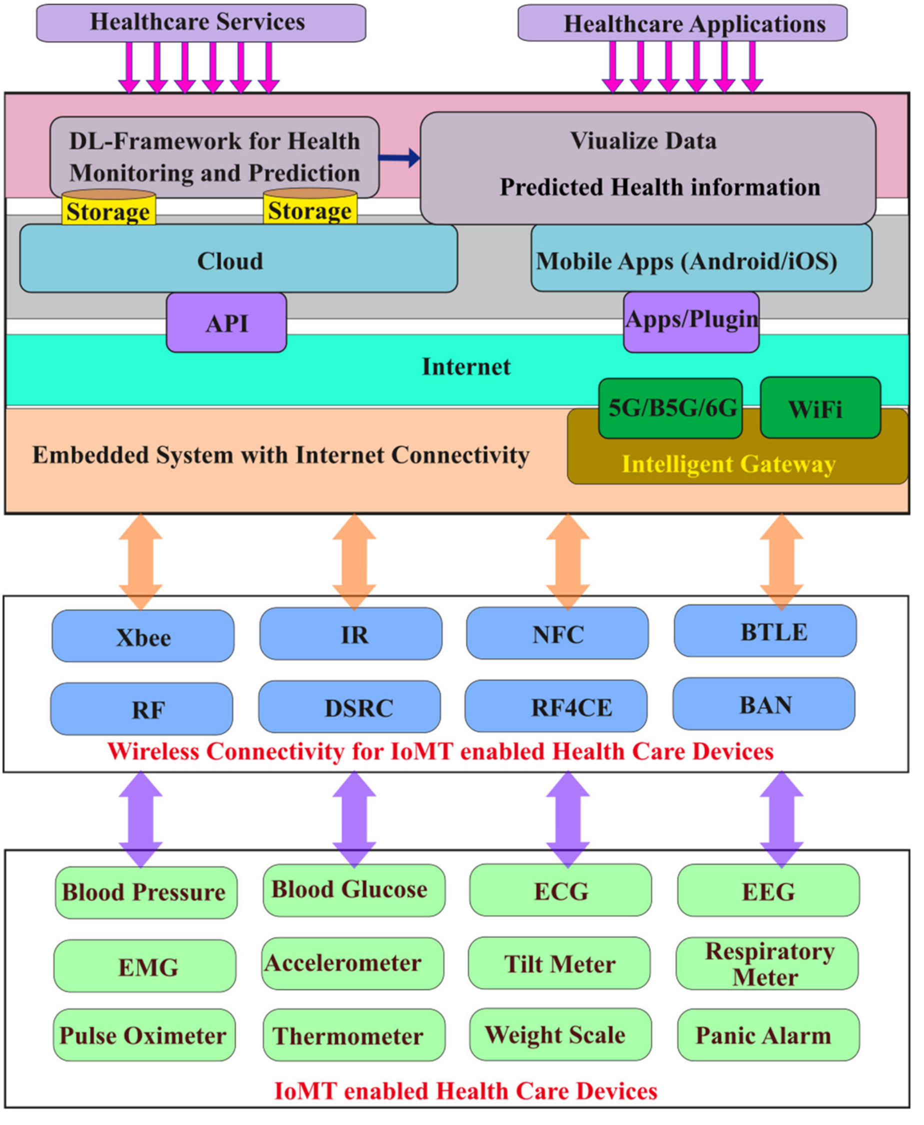

FIGURE 3 IoMT-based personalized health monitoring solution.

autoencoders (VAEs) can be used to generate synthetic data for use in personalized medicine and drug discovery.[27]

To fully comprehend the distinctive contributions of DL applications for individualized health monitoring, specificity is essential. CNNs, for example, are very good at interpreting time-series data from wearables, making it possible to identify irregularities in heart rate or activity levels.[28] Predicting the course of a disease and patient outcomes is made easier by RNNs, particularly LSTM networks, which are excellent at interpreting sequential data from EHRs.[29] Furthermore, real-time monitoring of public health trends is facilitated by the ability of NLP approaches, including transformer models, to extract useful health information from social media posts.[30] These specific examples show how DL techniques are specially designed to take advantage of various data sources for improved health prediction and monitoring.

However, the use of DL models in personalized health monitoring and prediction also presents challenges such as data privacy concerns, the need for large amounts of high-quality data, and the interpretability of the models.[6] Therefore, it is essential to carefully consider the design and implementation of these models, as well as their ethical and legal implications. For promising means of personalized health monitoring and prediction, further research in using DL has the potential to revolutionize the way we approach healthcare.

3.2 | DL for wearable devices and remote monitoring systems

The adoption of DL models in personalized health monitoring and prediction holds immense promise, as highlighted in the section above. However, translating these models into practical solutions for healthcare delivery necessitates overcoming various challenges, including data privacy concerns, data quality, and interpretability issues. Despite these challenges, wearable devices and remote monitoring systems have emerged as a focal point for leveraging DL techniques to revolutionize healthcare.

The field of wearable devices and remote monitoring systems has witnessed a surge in interest in DL techniques. With the help of such techniques, intelligent systems can be developed that analyze and interpret data from multiple sensors. Such systems can offer valuable insights to healthcare professionals for monitoring patients' health conditions and managing diseases. DL techniques have the potential to transform healthcare delivery by enabling personalized and continuous monitoring of patient's health in real time. The study in[31] presents a systematic literature review on smart wearables for detecting and predicting cardiovascular diseases (CVDs), highlighting their effectiveness and the need for DL to enhance their use in healthcare. The systematic literature review in reference 32 focuses on wearable sensors for Parkinson's disease (PD) management, analyzing symptoms, diagnosis, and management techniques. It identifies research gaps and emphasizes the need for DL in wearables, particularly in the management of PD's non-motor symptoms.

The authors in reference 33 developed a wearable respiratory monitoring system using a computational fluid dynamics-assisted on-mask sensor network. The system is also assisted by DL for respiration pattern recognition with classification accuracy. The sensor network is made of permeable and moisture-proof textile triboelectric sensors, which can collect highly accurate respiratory signals with a decent signal-to-noise ratio, response time, and sensitivity. RO-SmartAgeing[34] was developed to address mild cognitive impairment (MCI) in old age. It offers personalized remote monitoring and assistance for the elderly, including predictive models for detecting MCI onset and its progression toward dementia. This system with integrated DL services enables to provision of safe, low-cost, privacy-protected and supports independent living. It also enables continuous monitoring of vital signs, position, and activities, with significant reminders and alarms from remote locations.

The work in reference 35 emphasizes the significance of promptly diagnosing mild traumatic brain injuries (mTBIs) and addresses the shortcomings of current screening methods. It underscores the importance of identifying physiological biomarkers and integrating them with machine learning tools to enhance the diagnostic sensitivity for mTBI, thereby facilitating timely diagnosis and treatment.

The article in reference 36 highlights the increasing demand for wearable devices that can continuously gather high-quality biosignals over long durations to facilitate advanced diagnostics and therapies. It explores the design challenges involved, showcases recent progress in continuous operation and precise biosignal recording, addresses implementation obstacles, and underscores the significance of embedded AI for future autonomous diagnostic, therapeutic, and assistive healthcare tools.

The authors in reference 37 introduces an autonomous smart toilet designed for long-term health monitoring by analyzing a user's excreta. Utilizing sensors, computer vision, and DL, the toilet evaluates urine composition, flow rate, and stool characteristics, achieving comparable performance to trained medical personnel. The technology's objectives include seamless integration with clinical workflows, secure data storage and analysis, and potential applications in screening, diagnosis, and longitudinal monitoring for specific patient groups.

3.3 | DL for predicting health outcomes

DL has shown great potential in predicting health outcomes by analyzing large amounts of data from EHRs, medical imaging, wearable devices,[38] and other sources.[39–41] Here are some examples of how DL can be used to predict health outcomes:

1. *Disease diagnosis*: DL algorithms can be trained to recognize patterns in medical images, such as X-rays or magnetic resonance images (MRI), to diagnose diseases like diagnose breast cancer,[42] lung cancer,[43] and diabetic retinopathy accurately.[44]
2. *Disease risk prediction*: DL methods can predict the risk of developing certain diseases based on genetics, lifestyle, and medical history.[45] For example, DL has been used to predict the risk of developing Alzheimer's,[46] diabetes,[47] and heart diseases.[48]
3. *Clinical decision support (CDS)*: DL can help healthcare providers make more informed decisions about patient care. For example, DL can analyze EHR data to identify patients at high risk of hospital readmission or who may benefit from specific treatments.[40]
4. *Patient monitoring*: DL can be used to monitor patients remotely and detect changes in health status that may require intervention.[49] For example, DL can analyze data from wearable devices to predict the risk of falls in elderly patients[50] or to monitor patients with chronic diseases such as asthma,[51] and heart failure.[52–56]
5. *Drug discovery*: DL can be used to predict the efficacy and safety of new drugs. For example, DL can analyze molecular structures and predict which drugs are most likely effective against a particular disease.[57]
6. *Treatment pathway prediction*: The work in reference 58 highlights the research community's focus on discovering digital biomarkers using diverse data sources (physiological, psychological, social, and environmental) to enable smart services in clinical trials and eHealth/digital therapeutic settings. It discusses the APACHE trial, which aims to assess the quality of life (QoL) in cervical cancer patients, and introduces a methodology to identify a biomarker that can predict significant QoL variations. The abstract emphasizes the use of real-world data for detecting the cervical cancer QoL biomarker and its potential for innovative treatments. The methodology is implemented by Healthentia eClinical solution and has been employed in multiple clinical studies.
7. *Biomarker discovery*: The work in reference 59 emphasizes that DL techniques, specifically long-short-term memory (LSTM) models, can accurately predict the most suitable treatment paths for hypertension and the likelihood of achieving blood pressure goals using different regimens. These models offer significant value as decision-support tools for developing

personalized and adaptable hypertension treatment strategies, particularly for patients with complex conditions.

DL algorithms possess the potential to significantly improve our ability to predict health outcomes and develop personalized treatments for patients. However, it is essential to ensure that DL models are transparent, interpretable, and ethically sound and used with clinical expertise to provide the best possible care for patients.

3.3.1 | Patient monitoring and disease risk prediction

DL techniques have become increasingly popular in patient monitoring via wearable devices due to their ability to analyze large volumes of complex data and make accurate predictions. In reference 60, the authors presented a DL-based approach for fall risk assessment in elderly individuals using data collected from inertial sensors. They proposed a methodology to extract spatiotemporal gait features from inertial sensor data and then use a CNN to classify fallers and non-fallers. The proposed approach was tested on a dataset of elderly individuals with different fall risk levels and achieved high accuracy in fall risk prediction. The authors conclude that their approach shows great promise for accurate and convenient fall risk assessment, which could ultimately lead to improved quality of life for elderly individuals.

In reference 61, the authors presented a prediction system for acute exacerbation of chronic obstructive pulmonary disease (COPD) using data from wearable devices and DL techniques. They extracted features from physiological signals obtained from wearable devices and utilized machine learning and DL models to predict the occurrence of COPD exacerbation. The proposed approach was evaluated on a cohort of COPD patients and achieved high accuracy in predicting exacerbation events. The authors conclude that their method shows potential for early detection and prevention of COPD exacerbation, which could improve patient outcomes and reduce healthcare costs.

DL is a powerful tool that can predict disease risk based on various factors. Here are some general steps involved in using DL for disease risk prediction[62]:

1. *Collecting and preparing data*: The first step is to collect and prepare the data. It may involve gathering information on patient demographics, medical history, lifestyle factors, and biomarkers. The data must be carefully cleaned and formatted for training the DL model. The quality and diversity of data are critical components in DL-based individualized health monitoring.

   Three important categories of data include unstructured data from social media platforms, clinical data from EHRs, and physiological measures from wearable technology (e.g., heart rate, and activity levels).[63] To guarantee data consistency, preprocessing techniques include normalization and standardization as well as imputation methods for handling missing values. Improving the quality of data can be achieved in several ways, such as using NLP to extract structured information from unstructured social media content, reducing noise in wearable data through signal processing, and rigorously validating EHR data to guarantee accuracy and dependability. Completing these stages is essential to creating strong DL models that can accurately monitor and forecast health.
2. *Defining the problem*: The next step is to define the problem and decide on the outcome we want to predict. For example, we might want to predict the risk of developing heart disease or the likelihood of cancer recurrence.

3. *Selecting a DL model*: Once the problem is defined, we must select a suitable DL model. The choice of model will depend on the nature of the problem and the available data. Many models exist, including feedforward neural networks, CNNs, and recurrent neural networks.
4. *Training the model*: The DL model is then trained on the prepared data. It involves feeding the model input data and comparing the output to the desired outcome. The weights and biases of the model are adjusted during training to improve the accuracy of the predictions.
5. *Evaluating the model*: The trained model is then evaluated using a separate test data set. The model's accuracy is measured using various metrics, such as sensitivity, specificity, and area under the curve (AUC). Alternative measures, including precision, recall, and F1-score, are important to consider when assessing DL models for customized health monitoring, particularly in unbalanced datasets where accuracy alone may be deceptive. Precision illustrates the model's capacity to prevent false positives by calculating the percentage of real positive predictions among all positive predictions. Recall measures how many accurate positive predictions there are among all real positives, highlighting the model's capacity to find all pertinent cases. A more thorough evaluation of the model's performance in certain health monitoring applications is provided by the F1-score, which is the harmonic mean of accuracy and recall and offers a balanced evaluation statistic that takes into account both false positives and false negatives.
6. *Deploying the model*: If it performs well on the test data, it can be used in clinical practice. It may involve integrating the model into a CDS system or a mobile app that patients can use.

DL can be a powerful tool for disease risk prediction, but it requires careful preparation and validation of the data and careful selection and training of the DL model. It is important to remember that DL models are not a replacement for clinical judgment and should be used with other diagnostic tools and expert opinions.

In reference 64, the authors conducted a study on multimodal DL models to predict the stage of Alzheimer's disease (AD) based on data from different imaging modalities. They introduced the concept of multimodal imaging, which combines data from different imaging modalities, such as MRI and positron emission tomography (PET), to improve the accuracy of AD diagnosis. The study analyzed data from the AD neuroimaging initiative (ADNI) cohort and used DL algorithms based on multimodal imaging data to predict the AD stage. They concluded that the use of multimodal DL models could be a promising approach for early AD detection and that this approach could potentially be applied in clinical settings for accurate diagnosis and treatment. However, further research is required to validate these findings and address the study's limitations, such as the relatively small sample size. The study in reference 65 proposed a framework for data generation and heart disease prediction based on efficient DL models. They introduced the concept of data generation, which is the process of creating new data from existing data to improve the performance of machine learning models. The authors evaluated the performance of their framework and compared it to other models that used different machine-learning algorithms. The results showed that the proposed framework achieved high accuracy in predicting heart disease risk, outperforming other models. The authors also found that data generation improved the performance of DL models, particularly in cases where the training data was limited. However, the authors state that further research is needed to validate these findings and address the study's limitations, such as the relatively small sample size and limited scope of the data used.

3.3.2 | Disease diagnosis

DL has been extensively used in disease diagnosis and has shown great promise in improving diagnostic accuracy and efficiency. This section presents how DL algorithms have been exploited for various disease diagnoses.

Breast cancer diagnosis
The authors in reference 42 reviewed several studies using DL algorithms for breast cancer diagnosis, including those using CNNs and other DL techniques. They note that DL algorithms perform superiorly in detecting breast cancer and can sometimes outperform radiologists. However, they also caution that more research is needed to validate these results and to ensure that DL algorithms are robust and reliable in clinical settings. The authors also discussed several challenges and future directions for DL in breast cancer imaging, including the need for large datasets, the importance of interpretability and explainability, and the potential for personalized medicine.

In reference 66, the authors proposed a DL-based capsule neural network model for diagnosing breast cancer using mammogram images. The model uses capsule networks, a type of neural network that can handle spatial relationships between features. The proposed model is trained on a dataset of mammogram images and can classify images as either malignant or benign. The capsule network model has several advantages over traditional CNNs, including the ability to handle spatial relationships between features and generate more informative data representations.

In reference 67, the authors proposed a study in which a deep CNN based on residual learning is developed to classify breast cancer histopathological images. The proposed CNN architecture uses residual connections to alleviate the problem of vanishing gradients in deep networks, and it is trained on a large dataset of breast cancer histopathological images. The study also analyzes the contribution of different components of the proposed CNN to its performance. The results show that the residual connections and the use of batch normalization contribute significantly to the network's performance. Moreover, the study shows that the proposed CNN can capture essential features for breast cancer histopathological image classification, such as the shape and texture of nuclei and the architecture of glandular structures.

Lung cancer diagnosis
In reference 43, the authors proposed a DL-based algorithm for detecting lung cancer on chest radiographs using the segmentation method. The proposed algorithm consists of two stages: lung segmentation and nodule detection. In the first stage, the algorithm uses a U-Net architecture to segment the lungs from the chest radiograph. The segmented lungs are then input for the second stage, nodule detection. The second stage uses a Faster R-CNN architecture to detect nodules in the segmented lung region. The algorithm was trained and evaluated on a dataset of chest radiographs with annotations of lung nodules. The results show that the proposed algorithm achieved high accuracy in lung segmentation and nodule detection, with an overall accuracy of 96.7%. However, the algorithm only analyzes 2D chest radiographs. It does not consider information from other imaging modalities, such as computed tomography (CT) scans, which can provide more detailed information on the location and size of lung nodules. The authors in[68] proposed a modified Alexnet DL framework to detect lung abnormalities using chest X-ray (CXR)and lung CT scan images. The study aimed to improve the accuracy and efficiency of lung abnormality detection, which is critical for the early diagnosis and treatment of lung diseases. The proposed DL was trained on a large CXR and lung CT scan image dataset. The dataset consisted of over 50,000 images, which expert radiologists labeled. They introduced a threshold-based filter to remove the

artifacts in the CT images. The features obtained by the DL framework were then subjected to the support vector machine (SVM) to classify the CT images. The study's results showed that the DL framework was highly effective at detecting lung abnormalities, with an accuracy of over 96% for both CXR and lung CT scan images.

Diabetic retinopathy diagnosis

In reference 44, the authors presented a review of the adoption of DL interpretability techniques for analyzing diabetic retinopathy, a leading cause of blindness in working-age adults. The review focuses on using these techniques to improve the transparency, explainability, and reliability of DL models in diagnosing and treating diabetic retinopathy. The review suggests that DL interpretability techniques enable clinicians to understand the model's decision-making process better. They also help identify the most important features contributing to the model's decision-making process. The review also focused on some demerits of these techniques, like needing technical expertise, limited scalability, and limited robustness.

The study in reference 69 aims to address the challenge of limited training data in glaucoma detection and to evaluate the effectiveness of different data augmentation techniques in improving the performance of a DL classifier. The authors developed several local descriptor-based data augmentation techniques and are compared for glaucoma detection using retinal fundus images. The local binary pattern (LBP) based-augmentation with Alexnet provided superior classification performance with an accuracy of 96.7%. Maqsood et al.[70] proposed a method that focuses on precise and early detection of hemorrhages in retinal fundus images for diabetic retinopathy diagnosis. The method incorporates contrast enhancement, a unique CNN architecture, feature extraction, fusion using sparse image decomposition, and feature selection techniques. Evaluation on various databases showcases superior accuracy of 97.71% compared to prior works, offering improved visual quality, quantitative analysis, and outperforming existing methods in hemorrhage detection for diabetic retinopathy.

Brain cancer diagnosis

The challenge of brain tumor classification for radiologists and the potential of DL-based methods to aid in diagnostic analysis are reviewed in reference 71. It focuses on the key steps involved in DL-based brain tumor classification methods, encompassing preprocessing, feature extraction, and classification. The abstract further investigates CNN models, benchmark datasets, and emphasizes the importance of future research directions, particularly in the realm of personalized and smart healthcare. To enhance the accuracy and reliability of brain tumor diagnosis in radiology through the development of an advanced DL algorithm is carried out in reference 72. By integrating DL and radiometric technologies and leveraging a transfer learning model through AlexNet's CNN, the proposed method achieves exceptional accuracy of 99.62%. Furthermore, the algorithm automates the diagnostic process and demonstrates the ability to detect and classify tumors at various stages and sizes, thereby improving robustness, efficiency, and accuracy in the healthcare field.

Computer aided disease diagnosis (CADD)[73] system aimed at improving the accuracy of brain tumor classification (Glioblas- toma/Glioma) using 2D MRI slices. The proposed CADD system integrates CNN-based segmentation and classification methods, combining automated tumor segmentation, deep-feature extraction, handcrafted feature extraction, feature selection using the firefly algorithm, and binary classification. The results demonstrate the effectiveness of the CADD system, with SVM-Cubic achieving superior accuracy >98%, confirming the enhanced disease detection achieved through the combination of CNN-assisted segmentation and classification.

The proposed method of tumor dection in reference 74 consists of several steps, including edge determination, deep neural network-based segmentation, feature extraction with transfer learning, feature selection using an entropy-based controlled method, and classification using a multiclass support vector machine. Experimental findings on BraTS 2018 and the Figshare datasets demonstrate the superior performance of the proposed method in both visual and quantitative assessments, achieving impressive accuracy rates of 97.47% and 98.92%, respectively.

While DL has shown promise in disease diagnosis, there are several demerits to consider:

- *Limited interpretability*: DL models can be complex and difficult to interpret, making it challenging to understand how the model arrives at its predictions. It can limit the model's usefulness in understanding the disease's underlying biological mechanisms.
- *Dependence on large amounts of data*: DL models require massive high-quality training data to achieve optimal performance. In some cases, collecting and labeling this data can be time-consuming and resource-intensive.
- *Potential biases in the training data*: If the data is biased, the DL model may learn these biases and perpetuate them in its predictions. It can lead to discrepancies in diagnosis and treatment.
- *Limited generalizability*: DL models trained on one dataset may not generalize to other datasets or populations. It can limit the model's usefulness in real-world settings where the prevalence and presentation of the disease may differ.
- *Ethical considerations*: Using DL models in disease diagnosis raises ethical considerations, such as privacy concerns, informed consent, and potential biases in the model. Above all, DL can potentially improve disease diagnosis. It is essential to consider and address these demerits to ensure the models are effective, equitable, and ethical.

3.3.3 | Clinical decision support

DL has shown great potential in CDS systems. CDS systems are designed to help healthcare providers make informed decisions about patient care by providing them with timely, accurate, and relevant information. DL algorithms can be used in CDS systems to analyze large amounts of patient data and identify patterns and correlations that might not be apparent to human clinicians. This can help improve patient outcomes, reduce errors, and save time and money. An overview of the use of DL approaches for predicting clinical outcomes from EHRs is presented in reference 40. The article discusses the benefits and challenges of using DL for this purpose and reviews several studies that have applied DL to predict outcomes such as mortality, readmissions, and disease progression. DL's main advantage for outcome prediction is its ability to learn from complex and heterogeneous EHR data, including a wide range of clinical variables such as lab values, medications, and demographics. DL can also capture complex relationships between variables that might not be apparent using traditional statistical models. The authors conducted several studies that have used DL to predict outcomes, including a study that used a CNN to predict mortality in intensive care unit (ICU) patients, a study that used a recurrent neural network to predict 30-day readmissions for heart failure patients, and a study that used a deep autoencoder to predict disease progression in patients with Parkinson's disease.

3.3.4 | Drug discovery

Conventional approaches to drug discovery, known for their arduous and time-intensive nature, have historically required sub-stantial manpower and resources, often prolonging the journey from inception to market by several years or even decades.[75] This process typically involves sequential phases such as target identification, validation, lead compound identification, optimization, and clinical trials, but has been plagued by high rates of failure. Many potential drug candidates encounter setbacks at various stages of development, particularly during clinical trials, primarily due to issues related to efficacy or safety.[76] Furthermore, these methods have been hindered by their limited capacity for data analysis, relying predominantly on empirical data and linear models. This reliance has severely restricted the ability to accurately forecast drug interactions, side effects, and efficacy, owing to the intricate nature of biological data, thereby exacerbating the challenges inherent in traditional drug discovery.[75]

A pivotal achievement facilitated by AI in drug discovery lies in its capacity to sift through extensive volumes of biological data, encompassing genomic, proteomic, and pharmacological datasets, intending to pinpoint potential drug targets.[76] Moreover, AI algorithms can be harnessed to sift through virtual libraries of chemical compounds, pinpointing promising drug candidates that align with predefined criteria. Another notable accomplishment involves AI's capability to forecast drug toxicity and safety with heightened precision in comparison to conventional methods.[57] By scrutinizing vast datasets on chemical compounds and their interactions with biological systems, AI models furnish a more holistic comprehension of potential side effects. Furthermore, AI holds promise in optimizing lead compounds to enhance their effectiveness, pharmacokinetics, and drug-like attributes, thereby facilitating the development of superior medications with reduced adverse effects.[76]

The significant impact of graphics processing unit (GPU) computing and DL on the drug discovery process is explained in reference 57. The authors discussed how the increased computing power provided by GPUs has enabled the development of DL models capable of accurately predicting the properties of small molecules, such as their bioactivity and pharmacokinetics. These models have the potential to greatly accelerate drug discovery and reduce the cost of developing new drugs. The authors also discuss some of the challenges facing the adoption of DL models in drug discovery, such as the need for high-quality data and the interpretability of the models. The article highlights the transformative potential of GPU computing and DL in the field of drug discovery.

3.4 | DL for integrating diverse health data sources

To support the integration of diverse health data sources, DL techniques are widely used for analyzing and integrating large and diverse health data sources. With the increasing availability of data generated from different sources such as EHRs, wearables, and genomics, traditional methods of analyzing health data have become limited.[77] Table 2 presents various known open datasets that are used for health monitoring and prediction applications. The DL-based framework can integrate and analyze diverse health data sources to enable personalized healthcare solutions. The framework employs a deep neural network architecture that can handle both structured and unstructured data, enabling it to integrate and analyze various health data sources.[78] The potential of this framework is demonstrated through examples such as predicting the risk of adverse health outcomes and identifying personalized treatment plans for patients.[79] The following are a

TABLE 2 The open-dataset information used for personalized health monitoring.

References	Year	Disease Diagnosis	Dataset(s) information	Weblink(s)
67	2020	Breast cancer	Breast cancer histopathological image classification: BreakHis: 9109 microscopic images of breast tumor tissues; 2480 benign, and 5429 malignant samples.	https://www.kaggle.com/datasets/ambarish/breakhis
68	2020	Lung abnormality	i. ChestX-ray8 (CXR data): This database contains 108,948 CXR images. ii. LIDC-IDR (Lung CT images): This database has 1018 slices of 1010 cases of lung CT images with different nodule sizes.	i. https://nihcc.app.box.com/v/ChestXray-NIHCC ii. https://wiki.cancerimagingarchive.net/
69	2022	Glaucoma detection	RIM-ONE r2 glaucoma dataset: The dataset has 455 retinal fundus images: 255 normal, and 200 glaucoma.	https://medimrg.webs.ull.es/ This link contains different glaucoma datasets also.
70	2021	Retinal abnormality	i. High-resolution fundus (HRF) images: This data contains, 15 healthy images, 15 images of patients with diabetic retinopathy, and 15 images of glaucomatous patients. ii. Digital retinal images for vessel extraction (DRIVE): This dataset contains 40 retinal images with 7 pathological images. iii. Structured analysis of the retina (STARE): Out of 40 images 20 are pathological images. iv. MESSIDOR: This dataset has 1200 color images with various labels. v. DIARETDB0: It has 130 images vi. DIARETDB1: This dataset has 89 images.	i. https://www5.cs.fau.de/research/data/fundus-images/ ii. https://www.isi.uu.nl/Research/Databases/DRIVE/ or https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=1282003 iii. http://cecas.clemson.edu/~ahoover/stare/ iv. https://www.adcis.net/en/third-party/messidor/ v. http://www.it.lut.fi/project/imageret/diaretdb0/ vi. http://www.it.lut.fi/project/imageret
72	2022	Brain tumor detection	BraTS2020 Dataset (MRI): This dataset consists of 3929 MR images: 2756 are tumor affected, and 1173 are healthy.	https://www.kaggle.com/datasets/awsaf49/brats20-dataset-training-validation
73	2021	Brain tumor detection	The cancer imaging archive: It is a large archive of different types of medical images.	https://www.cancerimagingarchive.net
74	2022	Brain tumor detection	i. BraTS 2018: This dataset consists of 461 MRI scans. ii. Figshare datasets: This dataset consists of 3064 T1- weighted pathological MRI scans.	i. https://www.med.upenn.edu/sbia/brats2018/data.html ii. https://figshare.com/articles/dataset/datasets/5472970
64	2021	AD	ADNI dataset: It is a large repository of imaging, genetic, and clinical data over 2220 patients for ADNI.	https://adni.loni.usc.edu/
65	2022	Heart disease	i. University of California, Irvine (UCI) ML repository: It is a huge repository of many types of data, and it also contains various health-related datasets. ii. The Cleveland and Statlog datasets: This dataset contains 1190 instances of various heart diseases.	i. https://archive.ics.uci.edu/dataset/45/heart+disease ii. https://www.kaggle.com/datasets/sid321axn/heart-statlog-cleveland-hungary-final

few of the most popular deep-learning frameworks that are commonly used for integrating and interpreting meaningful insights from health data sources.

3.4.1 | Convolutional neural networks (CNNs)

CNNs are widely used for medical image analysis, such as identifying tumors or detecting anomalies in X-rays or MRI scans. These models have shown impressive accuracy in detecting diseases from medical images, making them valuable for radiologists and clinicians. The authors in reference 80 overcome the direct Monte Carlo approach for personalized dosimetry as the limitation of excessive computational cost and time in the Monte Carlo approach for personalized dosimetry using CNN. They proposed a voxel dose prediction tool using PET and CT image patches with ground truth from direct Monte Carlo. The CNN-based dosimetry method showed improved accuracy and speed compared to conventional dosimetry approaches and had results comparable to direct Monte Carlo simulation with significantly lower calculation time. In reference 81, the authors ensured to provide clinical decision-making for personalized treatment using CNN, big data through a quadratic phenotypic optimization platform. The Harris Hawks optimized convolution network (HHOCNN)[82] in medical image processing for brain tumor classification has shown an significant impact. It uses pre-processing, candidate region process, feature extraction, and classification by applying a CNN. The use of the HHOCNN system improves the overall tumor recognition accuracy to 98%. The use of precision medicine in oncology relies on obtaining accurate data from various sources to develop personalized treatments. Next-generation sequencing has generated a vast amount of gene-expression data, but existing public gene-expression databases have an unfavorable imbalance between the number of genes and samples available. The study in reference 83 proposes a methodology to rearrange RNA-seq data into gene-expression images, allowing CNNs to extract high-level features to predict lung cancer progression, and investigate if information from other tumor types can improve predictions.

The study in reference 84 proposes a deep graph CNN (GCN) model for diagnosing autism spectrum disorder (ASD) using multi-site data, as the current shallow GCN models are insufficient in handling the variability in data from different sites. The proposed model, integrated with ResNet units and DropEdge strategy, achieves a mean accuracy of 73.7% for ASD classification, outperforming well-established models based on the same subjects, and provides a new perspective for studying biological markers for early diagnosis of ASD.

3.4.2 | Recurrent neural networks (RNNs)

RNNs are commonly used for sequence data analysis, such as time-series data from sensors or patient records. RNNs can learn from past observations to predict future outcomes, making them useful for predicting disease progression or treatment outcomes. The authors in reference 85 discuss how the use of RNN can help capture the dynamic information of time sequences in functional magnetic resonance imaging (fMRI) data for mental disorder classification. Here, the multi-scale RNN model uses fMRI-independent components directly and achieves high accuracy in classifying schizophrenia and healthy controls. The study also identifies the top contributing time courses from specific brain components.

The study in reference 86 suggests a system for recognizing human behavior using body sensors that integrates data from various sensors like electrocardiogram (ECG), accelerometer, and magnetometer, and uses deep RNN. It surpasses traditional methods on standard datasets and has potential practical applications such as smart healthcare systems. The system can support patient rehabilitation and help prolong their independent life. The article in reference 87 presents a health-related named entity recognition (HNER) task to recognize health-related entities in Twitter messages, utilizing DL architecture and healthcare-domain ontology. The bidirectional LSTM with a conditional random field (BiLSTM-CRF) model demonstrated excellent precision, recall, and F1-score for identifying disease, sign or symptom, and pharmacologic substance-named entities, signifying its potential for diverse healthcare applications.

Chovatiya et al.[88] presents a system that employs RNN to forecast the likelihood of a dengue epidemic in India by utilizing data on climatic conditions, pollution, and previous patient statistics. The system intends to aid the public health sector in arranging essential resources in advance and minimizing the fatality rate by utilizing Google heatmaps to indicate the areas where dengue is expected to occur. The authors in reference 89 suggested an optimized LSTM method, to interpret genome sequencing for personalized cancer treatment. Its primary focus is to detect new disease-related variants and genes, and it has shown superior accuracy performance than conventional hybrid classifiers.

The study in reference 90 evaluated the efficacy of machine learning models in predicting suicide risk using data on 3548 suicide deaths and 35,480 non-suicide deaths. Here, the RRN-based gradient-boosted tree model outperformed other models in discrimination and calibration, but additional research is necessary to develop models suitable for clinical implementation. Jelodar et al.[91] utilized NLP and LSTM recurrent neural networks to analyze COVID-19-related discussions from social media and determine their sentiment. The research highlights the significance of employing public opinions and computational methods for decision-making and attained a higher accuracy rate compared to other machine learning algorithms for COVID-19 sentiment classification.

3.4.3 | Variational autoencoders (VAEs)

VAEs are generative models that can learn to generate new data samples that resemble the training data. They have shown great potential in drug discovery by generating new molecules with specific properties, thus reducing the time and cost of developing new drugs. Baucum et al.[92] suggested using transitional VAE, as a neural network architecture that can learn the direct mapping between clinical measurements at adjacent time points, to train reinforcement learning agents with an “environment model” for developing personalized treatment regimens from healthcare data. This approach produces more realistic patient trajectories and can help in learning effective treatment policies.[93] An extension to the Variational Autoencoder is introduced in reference 94 to address the problem of imputing missing values with a single sample. The method outperforms existing imputation strategies in 71% of medical datasets and improves 50% of classifiers in a heart failure data case study.

Biswal et al.[95] proposes a solution for the conflict between timely access to real-world longitudinal EHRs and patient privacy and data security in health systems. The proposed EHR VAE can synthesize realistic EHR sequences that account for individual differences and can be conditioned on specific disease conditions, resulting in improved predictive performance when used to augment real data. EHR VAE[96] synthesizes realistic EHR sequences while considering individual differences and specific disease conditions, allowing for timely access to real-world longitudinal EHRs while maintaining patient privacy and data security. The synthetic EHRs produced by VAE can be used to improve predictive performance when combined with real data. The article in reference 97 presents a self-learning algorithm that utilizes generative variational autoencoder models and LSTM for precise identification and analysis of tumors in MRI images. The proposed model in reference 97 shows 89.7% accuracy, making it a resource-efficient and computationally efficient alternative for tumor identification and analysis, evaluated through benchmark metrics. VAE has been utilized for visualizing big data in the healthcare industry to manage medical files, patient data, and clinical reports. The study in reference 98 shows that VAE outperforms traditional methods like principal component analysis (PCA), independent component analysis (ICA), non-negative matrix factorization, and latent Dirichlet allocation in terms of prediction performance and feature analysis. Variational autoencoder with differentially-private decoder (DPD-fVAE),[99] is a federated VAE that generates synthetic data while preserving privacy. The study demonstrates the competitive performance of DPD-fVAE through an evaluation of MNIST, Fashion-MNIST, and CelebA datasets, reporting benefits over related work in terms of Fréchet Inception Distance and classifier accuracy.

3.4.4 | Generative adversarial networks (GANs)

GANs are also generative models that can generate new data samples. In healthcare, GANs have been used to generate synthetic medical images, which can be used for training other models or to augment small datasets. The survey in reference 100 provides an overview of the potential applications of GANs in the healthcare sector, along with their advantages and disadvantages. The study emphasizes the increasing popularity of GANs in the medical community and concludes with future scope and conclusions. Another similar survey in reference 101 provides an overview of the recent progress in GANs for EHRs applications and proposes new methodologies to generate synthetic EHR data. The study also compiles a list of metrics and datasets used as benchmarks for future research and discusses the challenges and recommended practices for developing GANs in EHRs. To address the privacy challenges associated with creating DL models using EHR data, a new framework called CorGAN[102] has been proposed by combining Convolutional GAN and Convolutional Autoencoders, CorGAN captures correlations between adjacent medical features to generate synthetic healthcare records that perform similarly to real data in classification and prediction tasks. Gonzalez et al.[103] presented a solution to limited data availability and confidentiality concerns in health care by introducing the use of GANs to generate synthetic data of lung cancer patients. The synthetic patients are validated using statistical methods and indirect mortality rates, proving to be a valuable tool for doctors in treatment decisions and procedures.

The study in reference 104 suggests an unsupervised framework using GANs to identify healthcare fraud by detecting anomalies in healthcare provider data sets. The GAN-AD model demonstrates good performance in classification using logistic regression and extreme gradient boosting models, and shapley additive explanations (SHAP) analysis confirms the explanation of predictors for anomalous healthcare providers. The work in reference 105 demonstrated a DL solution that uses deep convolutional generative adversarial networks to produce synthetic hyperspectral images for epidermal lesions. The framework addresses the challenge of training DL architectures with small-sized datasets and demonstrates the effective generation of synthetic data for training DL classifiers to diagnose skin cancer.

The work in reference 106 proposes a model for healthcare data clustering and classification using fuzzy c-means clustering and generative adversarial network-based approaches. The model aims to provide effective medication and precautions based on patient history and exhibits improved accuracy of 97.8% and 98.6% for lung cancer and Arrhythmia datasets, respectively, outperforming existing techniques like support vector machine, decision tree, and random forest algorithms. The proposed research in reference 107 suggests using GANs to generate realistic synthetic data for EHRs that address privacy challenges. The study introduces a novel approach that utilizes 1-D CNN and convolutional autoencoders to capture the correlation between diagnosis records and to measure the similarity between real and synthetic data.

3.4.5 | Transformers

Transformers are a type of DL model that has been used for NLP tasks, such as medical record analysis. Transformers can learn to extract relevant information from unstructured text data, which can be useful for predicting disease risk or patient outcomes. With the potential to transform personalized healthcare, and by enabling the development of personalized treatments the aforementioned DL models can improve patient outcomes. Despite the potential of DL models in personalized healthcare, some challenges need to be addressed. These include concerns about data privacy and security, the need for interpretability and explainability of models, and the potential for biases in the data that could result in unequal access to care. However, it is crucial to ensure that these models are used ethically and responsibly to benefit all patients. Moreover, there are also challenges and limitations associated with using DL for health data integration, such as the need for high-quality data and the interpretability of models.

An attention-based feature learning approach, utilizing Vision Transformers as a new backbone architecture for medical imaging,[108] constructs dependable AI models for healthcare. The study examines the generalization abilities of Vision Trans- formers in categorizing chest radiographs for COVID-19 and establishes that the feature learning approach based on the attention mechanism is a hopeful avenue to create trustworthy DL models in the healthcare sector. The vision transformers for detecting COVID-19 in reference 109 use CXR images as an alternative to the primary screening test with a long turnaround time, reverse transcrip- tion polymerase chain reaction (RT-PCR). The research demonstrates superior performance, achieving an AUC of 0.99 for multiclass classification and a sensitivity of 0.99 for the COVID-19 class, outperforming existing CNN models. Additionally, attention maps show the proposed model's efficient capability to identify COVID-19 signs.

The study in reference 110 investigates the potential of transformers and language models in predicting the prognosis of immunotherapy with the help of clinical data and molecular profiles of real-world patients. The research indicates that transformers offer substantial enhancements in accuracy and possess the ability to advance early detection and intervention for various diseases. SANS formers,[111] a new attention-free sequential model that incorporates inductive biases for predicting healthcare utilization, with a focus on rare diseases. The model is pre-trained on a large health registry and fine-tuned for specific subgroups and shows better performance than LSTM and Transformer models in most cases. A mathematical framework with feature transformers in reference 112 allows for lifelong learning in medical imaging applications while preserving data privacy. The study shows superior results on the iCIFAR100 dataset and demonstrates the framework's effectiveness in the classification of X-ray Pneumothorax and Ultrasound cardiac views.

A Transformer-based EHR embedding pipeline[113] was introduced as a predictive model framework that takes advantage of healthcare-specific data attributes. The framework accurately predicts clinical outcomes in the ICU, demonstrating its feasibility in a case study. Shavit et al.[114] introduced an activity recognition model using Transformers that surpasses current learning-based methods for inertial sensor data. The model demonstrates better accuracy and generalization across various user activity scenarios, as evidenced by evaluations on multiple datasets, with the codebase accessible for public use. Graphical neural network (GNN)-bidirectional encoder representations from transformers (G-BERT),[115] is a novel model that integrates GNN and BERT to improve medication recommendation by exploiting the hierarchical structure of medical codes. The model surpasses previous works by achieving the highest performance on this task using EHRs of patients with only one visit.

3.4.6 | Summary

With the potential to transform personalized healthcare, and by enabling the development of personalized treatments the aforementioned DL models can improve patient outcomes. Despite the potential of DL models in personalized healthcare, some challenges need to be addressed. These include concerns about data privacy and security, the need for interpretability and explainability of models, and the potential for biases in the data that could result in unequal access to care. However, it is crucial to ensure that these models are used ethically and responsibly to benefit all patients. Moreover, there are also challenges and limitations associated with using DL for health data integration, such as the need for high-quality data and the interpretability of models. Table 3 shows a few of the most popular deep-learning approaches from literature used for personalized health monitoring in various disease diagnoses.

4 | CHALLENGES AND LIMITATIONS OF DL FOR PERSONALIZED HEALTH MONITORING

4.1 | Technical challenges

Technical challenges and limitations in using DL for personalized health monitoring have been widely recognized and addressed in the recent literature. Some of the most significant challenges and limitations are discussed below.

1. *Data quality and quantity*: DL algorithms rely heavily on the quality and quantity of data. In personal health monitoring, data collected from wearable devices and health sensors are often noisy, unstructured, and incomplete. This leads to difficulties in data pre-processing and representation, which affects the performance of DL models.
2. *Model complexity and overfitting*: DL models are often very complex and can have millions of parameters, leading to the risk of overfitting. Overfitting occurs when a model fits too closely to the training data, which can result in poor generalization to unseen data. This is a particular challenge in personalized health monitoring, where data is unique to each individual and requires individualized models.
3. *Lack of interpretability*: DL algorithms are often considered as “blue box” models, which makes it difficult to understand the underlying reasoning behind the predictions. This is a major

TABLE 3 DL for personalized health monitoring: Summary.

References	Year	Disease Diagnosis	Methodology	Advantage	Limitation/Future scope
116	2023	Breast cancer	DL algorithms on different medical imaging techniques	The DL methods outperformed the machine learning approaches.	Need for enormous datasets for good precision in real-time diagnosis.
117	2021	Breast cancer	Optimal multilevel thresholding-based segmentation with capsule network (OMLT-CNDL).	Yielded satisfactory performance on Mini-MIAS and DDSM datasets.	Accuracy of segmentation needs improvement.
118	2022	Breast cancer	ResHist, on histopathological images to extract features.	Better results for the 200× magnification factor.	Needs validation on a massive dataset for real-time implementation.
43	2022	Lung cancer	Built DL model for chest radiographs.	Low mean false positive indicators (MFPI) per image was achieved.	The sensitivity values are less, since match pulmonary apices, pulmonary hila, and so forth.
119	2021	Lung cancer	A modified Alexnet (MAN) and its features were used for the classification.	Outperform the other pretrained algorithms.	Add features from the local binary patterns to the proposed model.
120	2021	Diabetic retinopathy	DL method in analyzing fundus images.	Exploited the interpretability techniques for DL for the detection of diabetic retinopathy.	Requires technical expertise, limited scalability, and limited robustness.
121	2021	Diabetic retinopathy	Local-descriptors-based data augmentation with AlexNet for Glaucoma detection.	Local binary pattern (LBP) and local variance-based methods for the data augmentation scheme.	Diversity in the data collection needed for superior online performance.
122	2021	AD	Data fusion for detecting AD and mild cognitive disorders (MCI).	Deep models have outperformed the shallow ones	Limited by the minimal size of the data.
65	2022	Heart disease	Utilized various biomarkers and GAN-1D-CNN and GAN-Bi-LSTM for the heart disease prediction.	PCA has secured the highest accuracy with less time complexity.	Relatively small sample size and limited scope of the data used.
60	2019	Fall risk prediction	LSTM method for assessing the fall risk.	Spatio-tempo gait parameters and then fed them to the DL model for the prediction.	More DL-based approaches could be explored for this objective.
75	2019	Drug discovery	DL methods in discovering new drugs and drug targets.	Neural network architectures and GPUs	Quality of data utilized for learning deep models affect its efficiency.

limitation in the medical domain, where decisions must be transparent and explainable to ensure patient safety.

4. *Privacy concerns*: Personal health monitoring data often contains sensitive information, such as medical history, demographic information, and lifestyle habits. Ensuring the privacy and security of this data is crucial, especially when using cloud-based DL models.
5. *Computational requirements*: DL algorithms require significant computational resources, including high-performance GPUs and large amounts of memory. This is a challenge in personal health monitoring, where data is often collected from wearable devices with limited computational power.
6. *Generalizability*: DL models must be able to generalize well to different populations, health conditions, and data sources. This is a challenge in personalized health monitoring, where data is unique to each individual and requires individualized models.

The technical challenges and limitations in DL for personalized health monitoring are significant and require ongoing research and development to overcome. Despite these challenges, DL has the potential to revolutionize personalized health monitoring and prediction, providing new opportunities for early diagnosis, disease management, and patient-centric healthcare.

4.2 | Ethical considerations

The use of DL in personalized health monitoring presents a range of ethical challenges and considerations. It is important to address these challenges and considerations to ensure that the use of DL in personalized health monitoring is ethical, responsible, and effective. The following are some of the key areas of concern:

1. *Privacy*: The use of personal health data in DL algorithms raises privacy concerns. The data collected for personalized health monitoring may be sensitive and personal, and it is crucial that this data is stored, processed, and shared in an ethical manner. The privacy of patients' health information must be protected, and the data should only be used for the intended purpose, with proper consent from the individuals concerned.
2. *Bias and discrimination*: The use of DL algorithms may introduce bias and discrimination into the results. This can occur if the algorithms are trained on biased data sets or if the algorithms are not designed to be fair and impartial. For example, a DL model trained on a predominantly white population may not perform as well for individuals from other ethnic groups. It is important to ensure that DL models for personalized health monitoring are trained on diverse data sets to reduce the risk of bias and discrimination.
3. *Responsibility and accountability*: The use of DL algorithms in personalized health monitoring may lead to incorrect or misleading results. For example, a DL algorithm may predict a health outcome that is not supported by the available data. In such cases, it is important to determine who is responsible for the incorrect result and what steps should be taken to correct it. There should be clear mechanisms in place to hold those responsible accountable for their actions.
4. *Data quality*: The quality of the data used to train DL algorithms is critical. If the data is incorrect or of poor quality, the results of the algorithm may also be incorrect. It is important to ensure that the data used to train DL algorithms is accurate and reliable.

5. *Interpreting results*: The results of DL algorithms for personalized health monitoring may be difficult to interpret. This can make it challenging for healthcare providers and patients to understand the results and make informed decisions based on them. It is important to develop methods to make the results of DL algorithms more interpretable and understandable.

4.3 | Privacy concerns

The use of DL for personalized health monitoring raises several privacy concerns that must be considered to ensure the responsible use of this technology. The challenges related to data collection and storage, data sharing, bias in algorithms, algorithm transparency, and data security and privacy regulations must be addressed to ensure the responsible use of DL for personalized health monitoring. This section presents a discussion on the key privacy concerns related to the use of DL for personalized health monitoring.

1. *Data collection and storage*: The first privacy concern is related to the collection and storage of personal health data, which is a sensitive type of information. The data collected for health monitoring purposes can be used for malicious purposes if it falls into the wrong hands. Therefore, it is essential to ensure that the data collected and stored is protected using secure methods, such as encryption and access control mechanisms.
2. *Data sharing*: Another privacy concern is related to the sharing of personal health data. This data can be shared with third parties, such as healthcare providers, researchers, or insurance companies. The sharing of personal health data can lead to privacy breaches and can also result in discrimination or prejudice based on the individual's health status.
3. *Bias in algorithms*: DL algorithms can also introduce biases that can result in discrimination and prejudice. For example, if the training data used to develop the algorithm contains biased samples, the algorithm will also be biased. This can result in discriminatory predictions and can also have a negative impact on individual privacy.
4. *Algorithm transparency*: Another challenge related to the use of DL for personalized health monitoring is the lack of transparency in the decision-making process of the algorithms. The lack of transparency makes it difficult to understand how the algorithms are making predictions and also makes it difficult to detect and correct any biases that may exist in the algorithms.
5. *Data security and privacy regulations*: Personal health data is protected by privacy regulations, such as the general data protection regulation (GDPR) in Europe and the Health Insurance Portability and accountability act (HIPAA) in the United States. The use of DL for personalized health monitoring must comply with these regulations to ensure the privacy of personal health data.

Given the sensitive nature of personal health data, privacy concerns are a crucial component of DL-based customized health monitoring. The DL architectures support strong data anonymization methods, safe data storage procedures, and stringent access control mechanisms to address crucial issues in healthcare data. Differential privacy techniques are also used predominantly to protect individual data privacy while allowing aggregate data analysis. Ongoing research and development aim to improve these privacy-preserving strategies to foster confidence and guarantee adherence to legal requirements.

5 | DISCUSSION

5.1 | Answers to research questions

5.1.1 | What are the recent developments in the application of DL for personalized health monitoring and prediction?

Recent developments in the application of DL for personalized health monitoring and prediction include real-time monitoring and prediction, multi-modal data integration, and the ability to analyze large amounts of data from various sources such as EHRs, wearable devices, and mobile apps. Various types of DL models can be used, such as CNNs for processing images and signals from wearable devices and sensors, RNNs for processing sequential data such as time-series data from wearable devices or EHRs, and generative models such as VAEs for generating synthetic data for use in personalized medicine and drug discovery. DL models have revolutionized the field of personalized healthcare by providing new avenues for disease diagnosis, exploring treatment options, and drug discovery.

5.1.2 | What are the various DL architectures used for personalized health monitoring and prediction, and how do they work?

Various DL architectures are used for personalized health monitoring and prediction, including CNNs, recurrent neural networks (RNNs), and generative models such as variational autoencoders (VAEs). CNNs are commonly used for processing images and signals from wearable devices and sensors, while RNNs are used for processing sequential data such as time-series data from wearable devices or EHRs. VAEs are used for generating synthetic data for use in personalized medicine and drug discovery. CNNs work by using multiple layers of filters to extract features from images or signals. The filters are learned through backpropagation, and the output of each layer is fed into the next layer. RNNs work by processing sequential data through a series of hidden states, with each state being a function of the previous state and the current input. This allows RNNs to capture temporal dependencies in the data. VAEs work by learning a low-dimensional representation of the data, which can be used to generate new data points that are similar to the original data. Overall, DL architectures are used to process large amounts of data from various sources such as EHRs, wearable devices, and mobile apps, and to provide accurate and timely predictions of health outcomes.

5.1.3 | How can DL-based approaches be used to develop personalized health monitoring systems for wearable devices, EHRs, and social media data?

DL-based approaches can be used to develop personalized health monitoring systems for wearable devices, EHRs, and social media data by analyzing large amounts of data from these sources and providing personalized insights and recommendations to patients. For wearable devices, DL algorithms can be used to process data from sensors and provide real-time monitoring of vital signs, activity levels, and other health-related metrics. DL models can also be used to predict health outcomes based on this data, such as the risk of falls or the likelihood of developing a particular disease. For EHRs, DL algorithms can be used to analyze large amounts of patient data and identify patterns and correlations that might not be apparent to human clinicians. This can help improve patient outcomes, reduce errors, and save time and money. DL models can be used to predict outcomes such as mortality, readmissions, and disease progression, and can capture complex relationships between variables that might not be apparent using traditional statistical models. For social media data, DL algorithms can be used to analyze user-generated content and identify patterns and trends related to health behaviors and attitudes. This can help identify at-risk populations and provide targeted interventions to improve health outcomes. DL models can also be used to predict health outcomes based on social media data, such as the likelihood of developing a particular disease or the risk of relapse for individuals with substance use disorders. Such DL-based approaches can be used to develop personalized health monitoring systems that provide timely, accurate, and relevant information to patients, healthcare providers, and researchers. These systems have the potential to improve health outcomes, reduce healthcare costs, and advance our understanding of health and disease.

Real-time health trend analysis and early health issue diagnosis are made possible by incorporating social media data into DL health monitoring applications. Social media data may be used to monitor issues related to public health, spot new health trends, and make context-sensitive health forecasts. attitude analysis aids in comprehending public attitudes about health-related events, while advanced natural language processing (NLP) techniques are utilized to extract pertinent health information from social media posts.[123] Personalized health monitoring systems become more accurate and comprehensive when this data is integrated with other health sources.

5.1.4 | What are the challenges associated with the application of DL in personalized health monitoring, and how can they be addressed?

There are several challenges associated with the application of DL in personalized health monitoring, including data quality and quantity, model complexity and overfitting, generalizability, data privacy and security, and data availability. Data quality and quantity are significant challenges in personalized health monitoring, as data collected from wearable devices and health sensors is often noisy, unstructured, and incomplete. This leads to difficulties in data pre-processing and representation, which affects the performance of DL models. To address this challenge, researchers can explore new methods for data cleaning, feature extraction, and data augmentation. Model complexity and overfitting are also significant challenges in personalized health monitoring, as DL models are often very complex and can have millions of parameters, leading to the risk of overfitting. To address this challenge, researchers can explore new methods for regularization, early stopping, and model selection. Generalizability is a challenge in personalized health monitoring, as DL models must be able to generalize well to different populations, health conditions, and data sources. To address this challenge, researchers can explore new methods for transfer learning, domain adaptation, and model interpretability. Data privacy and security are also significant challenges in personalized health monitoring, as personal health data is particularly vulnerable to breaches, theft, or misuse. To address this challenge, researchers can explore new methods for privacy-preserving data analysis, secure data sharing, and data anonymization. Data availability is another challenge in personalized health monitoring, as the accuracy and performance of DL models depend on the quality and quantity of data available for training and testing. To address this challenge, researchers can explore new methods for data collection, data sharing, and data integration. Overall, addressing these challenges requires ongoing research and development in the field of DL for personalized health monitoring. By developing new methods and techniques, researchers can overcome these challenges and realize the full potential of DL for personalized health monitoring and prediction.

5.1.5 | What are the future directions for the application of DL in personalized health monitoring and prediction, and what are the potential implications for healthcare delivery?

The future directions for the application of DL in personalized health monitoring and prediction include the integration of DL models with EHRs, the development of personalized interventions, and the use of DL models for drug discovery and precision medicine. Integrating DL models with EHRs can provide more comprehensive and accurate health information for more effective predictions and treatment. This can lead to improved patient outcomes, reduced healthcare costs, and more efficient healthcare delivery. Personalized interventions can be developed using DL algorithms to provide targeted and individualized treatment plans for patients. This can lead to more effective treatment outcomes and improved patient satisfaction. DL models can also be used for drug discovery and precision medicine by analyzing large amounts of data from various sources such as genomics, proteomics, and metabolomics. This can lead to the development of more effective and personalized treatments for a wide range of diseases. The potential implications for healthcare delivery include improved patient outcomes, reduced healthcare costs, and more efficient healthcare delivery. DL-based approaches can provide accurate and timely predictions of health outcomes, leading to more effective treatment plans and improved patient satisfaction. Additionally, DL-based approaches can help identify at-risk populations and provide targeted interventions to improve health outcomes. Overall, the future directions for the application of DL in personalized health monitoring and prediction are promising, and have the potential to revolutionize the way we approach healthcare delivery.

5.2 | Guidelines for DL deployment for personalized healthcare are as follows

1. *Data quality and quantity*: Ensure that the data used for training and testing DL models is of high quality and quantity. This includes ensuring that the data is accurate, complete, and representative of the population being studied.
2. *Model selection and validation*: Select appropriate DL models for the specific healthcare application and validate the models using appropriate metrics and techniques.
3. *Interpretability and transparency*: Ensure that the DL models used for personalized healthcare are interpretable and transparent so that healthcare providers and patients can understand how the models arrived at their predictions.
4. *Privacy and security*: Ensure that the privacy and security of patient data are protected throughout the entire process of DL deployment, from data collection to model training and testing.
5. *Ethical considerations*: Consider the ethical implications of using DL for personalized healthcare, including issues related to bias, fairness, and informed consent.
6. *Integration with EHRs*: Integrate DL models with EHRs to provide more comprehensive and accurate health information for more effective predictions and treatment.

7. *Personalized interventions*: Use DL algorithms to develop personalized interventions for patients, based on their unique health profiles and needs.
8. *Generalizability*: Ensure that DL models can generalize well to different populations, health conditions, and data sources.
9. *Ongoing research and development*: Continue to invest in research and development to overcome technical, ethical, and privacy challenges associated with DL deployment for personalized healthcare.

By following these guidelines, DL can be leveraged to revolutionize personalized healthcare, providing new opportunities for early diagnosis, disease management, and patient-centric healthcare.

5.3 | Limitations of this review

This review article provides a comprehensive overview of DL methods for personalized health monitoring. However, it is important to keep in mind its limitations and to further advance research in this field.

1. *Scoped to DL*: The review is focused on DL methods, ignoring other machine learning or non-machine learning-based methods, which might have their own limitations, strengths, and applications in personalized health monitoring.
2. *Data availability*: The accuracy and performance of DL models depend on the quality and quantity of data available for training and testing. This review does not take into consideration the limitations of data availability and quality, which may affect the performance of DL models for personalized health monitoring.
3. *Personalization*: Personalized health monitoring requires the collection and use of personal information such as medical history, genetic information, lifestyle habits, and so forth. This review does not cover the ethical, legal, and technical issues related to the collection, storage, and usage of such personal information.
4. *Diversity*: This review does not take into consideration the diversity of individuals and populations, which may affect the performance of DL models for personalized health monitoring. This diversity includes differences in age, gender, ethnicity, and socioeconomic status, which can impact the accuracy of deep-learning models.
5. *Performance evaluation*: The evaluation of DL models for personalized health monitoring is a challenging task, as it requires the collection of large and diverse data sets, proper selection of evaluation metrics, and fair comparison of different models. This review does not address the limitations and challenges of performance evaluation in this field.

5.4 | Open research challenges

Despite the promising advancements in DL for personalized health monitoring, there are still several open research challenges that need to be addressed in order to fully realize the potential of these methods. These challenges highlight the need for continued research and development in the field of DL for personalized health monitoring, in order to fully realize its potential and overcome its limitations as follows:

1. *Data privacy and security*: One of the biggest concerns with the use of DL for personalized health monitoring is the privacy and security of sensitive medical information. This information is particularly vulnerable to breaches, theft, or misuse, and there is a need for robust privacy-preserving methods to protect this data.
2. *Data quality and availability*: Another challenge is the quality and availability of data, as the accuracy of DL models is highly dependent on the quality and diversity of the data they are trained on. Additionally, many health monitoring systems rely on wearable devices and self-reported data, which may not always be reliable or accurate.
3. *Explainability and interpretability*: DL models are often considered black boxes, making it difficult to understand how they arrive at a particular prediction. This lack of transparency can limit the trust that patients, doctors, and regulatory bodies have in these systems, and there is a need for more interpretable models that can be more easily understood.
4. *Generalization*: Another challenge is a generalization, as DL models may not always perform well on new or unseen data. This can be particularly problematic in the health monitoring context, where the performance of the model may have significant consequences for patients.
5. *Integration with existing healthcare systems*: Finally, there is a need for the integration of DL-based personalized health monitoring systems with existing healthcare systems. This will allow for seamless data transfer and collaboration between healthcare providers, and will also help to ensure that these systems are used in the most effective and efficient manner.

5.5 | Future directions

The future of DL in personalized health monitoring and prediction is bright, but many technical, ethical, and privacy challenges need to be addressed. With continued investment and development, these challenges can be overcome and DL can be leveraged to revolutionize the way that we monitor and predict health outcomes. Future directions for DL in personalized health monitoring and prediction could include the following:

1. *Integration with EHRs*: Currently, DL models for personalized health monitoring rely on data collected from wearable devices and self-reported health metrics. Integrating these models with EHRs can provide more comprehensive and accurate health information for more effective predictions and treatment.
2. *Personalized interventions*: DL algorithms can be used to develop personalized interventions that can be adapted to the specific health needs of each individual. This could include targeted treatment plans, tailored lifestyle recommendations, and personalized medication regimes.
3. *Improved model generalizability*: Despite the progress made in DL for personalized health monitoring, many models have limited generalizability and can only be applied to specific populations or health conditions. Future research should aim to develop models that can be applied more broadly to a wider range of populations and health conditions.
4. *Model explainability*: Despite the accuracy of DL models, they can be difficult to interpret and understand, leading to questions about their transparency and accountability.[124] Future research should aim to develop models that are more interpretable and transparent so that the reasoning behind their predictions can be better understood. However, there are a few works in health care that follow this explainable AI to reveal the model's role in health monitoring.[125]
5. *Real-time monitoring and prediction*: DL algorithms can be used to provide real-time health monitoring and predictions. This could involve incorporating data from wearable devices,

sensors, and other sources in real time to provide more accurate and up-to-date health information.

6. *Multi-modal data integration*: DL algorithms can be used to integrate and analyze data from multiple sources, including medical imaging, genomics, and other health data. This can provide a more comprehensive view of an individual's health status and improve the accuracy of predictions.

6 | CONCLUSIONS

This article has provided a comprehensive review of the recent developments in the application of DL for personalized health monitoring and prediction. As personalized healthcare becomes increasingly important in managing chronic diseases and addressing the needs of an aging population, DL has emerged as a promising approach for accurate and efficient health outcomes. DL architectures and their applications in personalized health monitoring, including its utilization through wearable devices, EHRs, and social media data. By leveraging these diverse health data sources, DL-based methods have demonstrated their potential to improve healthcare delivery by providing timely and accurate predictions of health outcomes. Through the exploration of these topics, the article has provided valuable insights into the potential of DL by addressing the challenges and limitations. Through this, future researchers can focus on overcoming technical barriers, addressing ethical concerns, and ensuring privacy protection.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

ORCID

Senthil Kumar Jagatheesaperumal https://orcid.org/0000-0002-9516-0327
Rajesh N. V. P. S. Kandala https://orcid.org/0000-0003-3751-0453

REFERENCES

1. Aceto G, Ciuonzo D, Montieri A, Persico V, Pescape A. AI-powered internet traffic classification: past, present, and future. *IEEE Commun Mag*. 2023;1-7.
2. Darvishi H, Ciuonzo D, Eide ER, Rossi PS. Sensor-fault detection, isolation and accommodation for digital twins via modular data-driven architecture. *IEEE Sens J*. 2020;21(4):4827-4838.
3. O'shea T, Hoydis J. An introduction to deep learning for the physical layer. *IEEE Trans Cogn Commun Netw*. 2017;3(4):563-575.
4. Giordano C, Brennan M, Mohamed B, Rashidi P, Modave F, Tighe P. Accessing artificial intelligence for clinical decision-making. *Front Digit Health*. 2021;3:645232.
5. Cohoon TJ, Bhavnani SP. Toward precision health: applying artificial intelligence analytics to digital health biometric datasets. *Pers Med*. 2020;17(4):307-316.
6. Ahmed Z, Mohamed K, Zeeshan S, Dong X. Artificial intelligence with multi-functional machine learning platform development for better healthcare and precision medicine. *Database*. 2020;2020:1-35.
7. Busnatu SS, Niculescu AG, Bolocan A, et al. A review of digital health and biotelemetry: modern approaches towards personalized medicine and remote health assessment. *J Pers Med*. 2022;12(10):1656.
8. Pap IA, Oniga S. A review of converging technologies in eHealth pertaining to artificial intelligence. *Int J Environ Res Public Health*. 2022;19(18):11413.
9. Vanagas G, Engelbrecht R, Damaševˇius R, Suomi R, Solanas A. eHealth solutions for the integrated healthcare. *J Healthc Eng*. 2018;2018:1-3.

10. Perera MS, Halgamuge MN, Samarakody R, Mohammad A. Internet of things in healthcare: a survey of telemedicine systems used for elderly people. *IoT in Healthcare and Ambient Assisted Living*. Springer; 2021:69-88.
11. Del Caño R, Saha T, Moonla C, De la Paz E, Wang J. Ketone bodies detection: wearable and mobile sensors for personalized medicine and nutrition. *TrAC Trends Anal Chem*. 2023;159:116938.
12. Gholamiangonabadi D, Grolinger K. Personalized models for human activity recognition with wearable sensors: deep neural networks and signal processing. *Appl Intell*. 2023;53(5):6041-6061.
13. Huang JD, Wang J, Ramsey E, Leavey G, Chico TJ, Condell J. Applying artificial intelligence to wearable sensor data to diagnose and predict cardiovascular disease: a review. *Sensors*. 2022;22(20):8002.
14. Hyysalo J, Dasanayake S, Hannu J, et al. Smart mask–wearable IoT solution for improved protection and personal health. *Internet Things*. 2022;18:100511.
15. Fan K, Zhao Y. Mobile health technology: a novel tool in chronic disease management. *Intell Med*. 2022;2(1):41-47.
16. Busnatu T, Niculescu AG, Bolocan A, et al. Clinical applications of artificial intelligence—an updated overview. *J Clin Med*. 2022;11(8):2265.
17. Swapna M, Viswanadhula UM, Aluvalu R, Vardharajan V, Kotecha K. Bio-signals in medical applications and challenges using artificial intelligence. *J Sens Actuator Netw*. 2022;11(1):17.
18. Wang P, Lin Z, Yan X, et al. A wearable ECG monitor for deep learning based real-time cardiovascular disease detection. arXiv preprint arXiv:2201.10083. 2022.
19. Atwany MZ, Sahyoun AH, Yaqub M. Deep learning techniques for diabetic retinopathy classification: a survey. *IEEE Access*. 2022;10:28642-28655.
20. Sevakula RK, Au-Yeung WTM, Singh JP, Heist EK, Isselbacher EM, Armoundas AA. State-of-the-art machine learning techniques aiming to improve patient outcomes pertaining to the cardiovascular system. *J Am Heart Assoc*. 2020;9(4):e013924.
21. Bhatt C, Kumar I, Vijayakumar V, Singh KU, Kumar A. The state of the art of deep learning models in medical science and their challenges. *Multimed Syst*. 2021;27(4):599-613.
22. Bianchi V, Bassoli M, Lombardo G, Fornacciari P, Mordonini M, De Munari I. IoT wearable sensor and deep learning: an integrated approach for personalized human activity recognition in a smart home environment. *IEEE Internet Things J*. 2019;6(5):8553-8562.
23. Sawyer J. Wearable Internet of Medical Things sensor devices, artificial intelligence-driven smart healthcare services, and personalized clinical care in COVID-19 telemedicine. *Am J Med Res*. 2020;7(2):71-77.
24. Fu J, Wang H, Na R, Jisaihan A, Wang Z, Yuko O. Recent advancements in digital health management using multi-modal signal monitoring. *Math Biosci Eng*. 2023;20(3):5194-5222.
25. Wu Q, Chen X, Zhou Z, Zhang J. Fedhome: cloud-edge based personalized federated learning for in-home health monitoring. *IEEE Trans Mob Comput*. 2020;21(8):2818-2832.
26. Guo L, Sim G, Matuszewski B. Inter-patient ECG classification with convolutional and recurrent neural networks. *Biocybern Biomed Eng*. 2019;39(3):868-879.
27. Garoufis C, Zlatintsi A, Filntisis P, et al. Towards unsupervised subject-independent speech-based relapse detection in patients with psychosis using variational autoencoders. In: IEEE; 2022:175–179.
28. Paganelli AI, Mondéjar AG, da Silva AC, et al. Real-time data analysis in health monitoring systems: a comprehensive systematic literature review. *J Biomed Inform*. 2022;127:104009.
29. Men L, Ilk N, Tang X, Liu Y. Multi-disease prediction using LSTM recurrent neural networks. *Expert Syst Appl*. 2021;177:114905.
30. Zhou B, Yang G, Shi Z, Ma S. Natural language processing for smart healthcare. *IEEE Rev Biomed Eng*. 2022;17:4–18.
31. Moshawrab M, Adda M, Bouzouane A, Ibrahim H, Raad A. Smart wearables for the detection of cardiovascular diseases: a systematic literature review. *Sensors*. 2023;23(2):828.
32. Mughal H, Javed AR, Rizwan M, Almadhor AS, Kryvinska N. Parkinson's disease management via wearable sensors: a systematic review. *IEEE Access*. 2022;10:35219-35237.
33. Fang Y, Xu J, Xiao X, et al. A deep-learning-assisted on-mask sensor network for adaptive respiratory monitoring. *Adv Mater*. 2022;34(24):2200252.
34. Ianculescu M, Paraschiv EA, Alexandru A. Addressing mild cognitive impairment and boosting wellness for the elderly through personalized remote monitoring. *Healthcare*. 2022;10:1214.

35. Schmid W, Fan Y, Chi T, et al. Review of wearable technologies and machine learning methodologies for systematic detection of mild traumatic brain injuries. *J Neural Eng*. 2021;18(4):041006.
36. Stuart T, Hanna J, Gutruf P. Wearable devices for continuous monitoring of biosignals: challenges and opportunities. *APL Bioeng*. 2022;6(2):021502.
37. Sm P, Won DD, Lee BJ, et al. A mountable toilet system for personalized health monitoring via the analysis of excreta. *Nat Biomed Eng*. 2020;4(6):624-635.
38. Ibrahim NFA, Sabani N, Johari S, et al. A comprehensive review of the recent developments in wearable sweat-sensing devices. *Sensors*. 2022;22(19):7670.
39. Olsen CR, Mentz RJ, Anstrom KJ, Page D, Patel PA. Clinical applications of machine learning in the diagnosis, classification, and prediction of heart failure. *Am Heart J*. 2020;229:1-17.
40. La Cava W, Bauer C, Moore JH, Pendergrass SA. Interpretation of machine learning predictions for patient outcomes in electronic health records. In: 2019. American Medical Informatics Association; 2019: 572.
41. Tekkeşin Aİ. Artificial intelligence in healthcare: past, present and future. *Anatol J Cardiol*. 2019;22(Suppl 2):8-9.
42. Balkenende L, Teuwen J, Mann RM. Application of deep learning in breast cancer imaging. *Seminars in Nuclear Medicine*. Elsevier; 2022.
43. Shimazaki A, Ueda D, Choppin A, et al. Deep learning-based algorithm for lung cancer detection on chest radiographs using the segmentation method. *Sci Rep*. 2022;12(1):727.
44. Lim WX, Chen Z, Ahmed A. The adoption of deep learning interpretability techniques on diabetic retinopathy analysis: a review. *Med Biol Eng Comput*. 2022;60(3):633-642.
45. Moorman JR. A crossroads in predictive analytics monitoring for clinical medicine. *J Electrocardiol*. 2018;51(6):S52-S55.
46. Shastry KA, Vijayakumar V, Manoj Kumar MV, Manjunatha BA, Chandrashekhar BN. Deep learning techniques for the effective prediction of Alzheimer's disease: a comprehensive review. *Healthcare*. 2022;10:1842.
47. Gupta H, Varshney H, Sharma TK, Pachauri N, Verma OP. Comparative performance analysis of quantum machine learning with deep learning for diabetes prediction. *Complex Intell Syst*. 2022;8(4):3073-3087.
48. Wang J, Rao C, Goh M, Xiao X. Risk assessment of coronary heart disease based on cloud-random forest. *Artif Intell Rev*. 2023;56(1):203-232.
49. Jia Z, Shi Y, Hu J. Personalized neural network for patient-specific health monitoring in IoT: a Metalearning approach. *IEEE Trans Comput Aided Des Integr Circuits Syst*. 2022;41(12):5394-5407.
50. Wang H, Zhao Y, Yu L, et al. A personalized health monitoring system for community-dwelling elderly people in Hong Kong: design, implementation, and evaluation study. *J Med Internet Res*. 2020;22(9):e19223.
51. Tsang KC, Pinnock H, Wilson AM, Shah SA. Application of machine learning algorithms for asthma management with mHealth: a clinical review. *J Asthma Allergy*. 2022;15:855-873.
52. Ma C, Li D, Pan L, et al. Quantitative assessment of essential tremor based on machine learning methods using wearable device. *Biomed Signal Process Control*. 2022;71:103244.
53. Jing X, Min H, Gong Y, et al. A systematic review of ontology-based clinical decision support system rules: usage, management, and interoperability. medRxiv; 2022: 2022–05.
54. Johri A, Bhadula S, Sharma S, Shukla AS. Assessment of factors affecting implementation of IoT based smart skin monitoring systems. *Technol Soc*. 2022;68:101908.
55. Sujith A, Sajja GS, Mahalakshmi V, Nuhmani S, Prasanalakshmi B. Systematic review of smart health monitoring using deep learning and artificial intelligence. *Neurosci Inform*. 2022;2(3):100028.
56. Jaber MM, Alameri T, Ali MH, et al. Remotely monitoring COVID-19 patient health condition using metaheuristics convolute networks from IoT-based wearable device health data. *Sensors*. 2022;22(3):1205.
57. Pandey M, Fernandez M, Gentile F, et al. The transformational role of GPU computing and deep learning in drug discovery. *Nat Mach Intell*. 2022;4(3):211-221.
58. Kyriazakos S, Pnevmatikakis A, Cesario A, et al. Discovering composite lifestyle biomarkers with artificial intelligence from clinical studies to enable smart ehealth and digital therapeutic services. *Front Digit Health*. 2021;3:648190.
59. Ye X, Zeng QT, Facelli JC, Brixner DI, Conway M, Bray BE. Predicting optimal hypertension treatment pathways using recurrent neural networks. *Int J Med Inform*. 2020;139:104122.
60. Tunca C, Salur G, Ersoy C. Deep learning for fall risk assessment with inertial sensors: utilizing domain knowledge in spatio-temporal gait parameters. *IEEE J Biomed Health Inform*. 2019;24(7):1994-2005.

61. Wu CT, Li GH, Huang CT, et al. Acute exacerbation of a chronic obstructive pulmonary disease prediction system using wearable device data, machine learning, and deep learning: development and cohort study. *JMIR mHealth uHealth*. 2021;9(5):e22591.
62. Esteva A, Robicquet A, Ramsundar B, et al. A guide to deep learning in healthcare. *Nat Med*. 2019;25(1):24-29.
63. Dunn J, Kidzinski L, Runge R, et al. Wearable sensors enable personalized predictions of clinical laboratory measurements. *Nat Med*. 2021;27(6):1105-1112.
64. Venugopalan J, Tong L, Hassanzadeh HR, Wang MD. Multimodal deep learning models for early detection of Alzheimer's disease stage. *Sci Rep*. 2021;11(1):3254.
65. Sarra RR, Dinar AM, Mohammed MA, Ghani MKA, Albahar MA. A robust framework for data generative and heart disease prediction based on efficient deep learning models. *Diagnostics*. 2022;12(12):2899.
66. Kavitha T, Mathai PP, Karthikeyan C, et al. Deep learning based capsule neural network model for breast cancer diagnosis using mammogram images. *Interdiscip Sci Comput Life Sci*. 2021;14:1-17.
67. Gour M, Jain S, Sunil KT. Residual learning based CNN for breast cancer histopathological image classification. *Int J Imaging Syst Technol*. 2020;30(3):621-635.
68. Bhandary A, Prabhu GA, Rajinikanth V, et al. Deep-learning framework to detect lung abnormality–a study with chest X-ray and lung CT scan images. *Pattern Recognit Lett*. 2020;129:271-278.
69. Maheshwari S, Kumar TS. A comparison of local descriptor-based data augmentation techniques for glaucoma detection using retinal fundus images. In: IEEE; 2022: 1–4.
70. Maqsood S, Damaševičius R, Maskeliūnas R. Hemorrhage detection based on 3D CNN deep learning framework and feature fusion for evaluating retinal abnormality in diabetic patients. *Sensors*. 2021;21(11):3865.
71. Muhammad K, Khan S, Del Ser J, De Albuquerque VHC. Deep learning for multigrade brain tumor classification in smart healthcare systems: a prospective survey. *IEEE Trans Neural Netw Learn Syst*. 2020;32(2):507-522.
72. Badjie B, Ülker ED. A deep transfer learning based architecture for brain tumor classification using MR images. *Inf Technol Control*. 2022;51(2):332-344.
73. Rajinikanth V, Kadry S, Nam Y. Convolutional-neural-network assisted segmentation and SVM classification of brain tumor in clinical MRI slices. *Inf Technol Control*. 2021;50(2):342-356.
74. Maqsood S, Damaševičius R, Maskeliūnas R. Multi-modal brain tumor detection using deep neural network and multiclass SVM. *Medicina*. 2022;58(8):1090.
75. Vamathevan J, Clark D, Czodrowski P, et al. Applications of machine learning in drug discovery and development. *Nat Rev Drug Discov*. 2019;18(6):463-477.
76. Alizadehsani R, Oyelere SS, Hussain S, et al. Explainable artificial intelligence for drug discovery and development-a comprehensive survey. *IEEE Access*. 2024;12:35796-35812.
77. Miotto R, Wang F, Wang S, Jiang X, Dudley JT. Deep learning for healthcare: review, opportunities and challenges. *Brief Bioinform*. 2018;19(6):1236-1246.
78. Agarwal P, Hassan SI, Mustafa SK, Ahmad J. An effective diagnostic model for personalized healthcare using deep learning techniques. In: IGI Global; 2020: 70–88.
79. Zhang S, Bamakan SMH, Qu Q, Li S. Learning for personalized medicine: a comprehensive review from a deep learning perspective. *IEEE Rev Biomed Eng*. 2018;12:194-208.
80. Lee MS, Hwang D, Kim JH, Lee JS. Deep-dose: a voxel dose estimation method using deep convolutional neural network for personalized internal dosimetry. *Sci Rep*. 2019;9(1):1-9.
81. Blasiak A, Khong J, Kee T. CURATE. AI: optimizing personalized medicine with artificial intelligence. *SLAS Technol*. 2020;25(2):95-105.
82. Kurdi SZ, Ali MH, Jaber MM, Saba T, Rehman A, Damasevicˇius R. Brain tumor classification using meta-heuristic optimized convolutional neural networks. *J Pers Med*. 2023;13(2):181.
83. Lopez-Garcia G, Jerez JM, Franco L, Veredas FJ. Transfer learning with convolutional neural networks for cancer survival prediction using gene-expression data. *PLoS One*. 2020;15(3):e0230536.
84. Cao M, Yang M, Qin C, et al. Using DeepGCN to identify the autism spectrum disorder from multi-site resting-state data. *Biomed Signal Process Control*. 2021;70:103015.
85. Yan W, Calhoun V, Song M, et al. Discriminating schizophrenia using recurrent neural network applied on time courses of multi-site FMRI data. *EBioMedicine*. 2019;47:543-552.
86. Uddin MZ, Hassan MM, Alsanad A, Savaglio C. A body sensor data fusion and deep recurrent neural network-based behavior recognition approach for robust healthcare. *Inf Fusion*. 2020;55:105-115.

87. Batbaatar E, Ryu KH. Ontology-based healthcare named entity recognition from twitter messages using a recurrent neural network approach. *Int J Environ Res Public Health*. 2019;16(19):3628.
88. Chovatiya M, Dhameliya A, Deokar J, Gonsalves J, Mathur A. Prediction of dengue using recurrent neural network. In: IEEE; 2019: 926–929.
89. Suresh A, Nair RR, Neeba E, Kumar SA. Recurrent neural network for genome sequencing for personalized cancer treatment in precision healthcare. *Neural Process Lett*. 2021;55:1-10.
90. Sanderson M, Bulloch AG, Wang J, Williamson T, Patten SB. Predicting death by suicide using administrative health care system data: can recurrent neural network, one-dimensional convolutional neural network, and gradient boosted trees models improve prediction performance? *J Affect Disord*. 2020;264:107-114.
91. Jelodar H, Wang Y, Orji R, Huang S. Deep sentiment classification and topic discovery on novel coronavirus or COVID-19 online discussions: NLP using LSTM recurrent neural network approach. *IEEE J Biomed Health Inform*. 2020;24(10):2733-2742.
92. Baucum M, Khojandi A, Vasudevan R. Improving deep reinforcement learning with transitional variational autoencoders: a healthcare application. *IEEE J Biomed Health Inform*. 2020;25(6):2273-2280.
93. Jagatheesaperumal SK, Mishra P, Moustafa N, Chauhan R. A holistic survey on the use of emerging technologies to provision secure healthcare solutions. *Comput Electr Eng*. 2022;99:107691.
94. Boquet G, Vicario JL, Morell A, Serrano J. Missing data in traffic estimation: a variational autoencoder imputation method. *Proceedings of the 2019 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP) (ICASSP 2019)*. IEEE; 2019:2882-2886.
95. Biswal S, Ghosh S, Duke J, et al. EVA: generating longitudinal electronic health records using conditional variational autoencoders. In: PMLR; 2021: 260–282.
96. Naga Srinivasu P, Krishna TB, Ahmed S, Almusallam N, Khaled Alarfaj F, Allheeib N. Variational autoencoders-BasedSelf-learning model for tumor identification and impact analysis from 2-D MRI images. *J Healthc Eng*. 2023;2023:1-17.
97. Madhukar Rao G, Ramesh D. A novel approach for visualizing medical big data using Variational autoencoders. In: Springer; 2023: 337–346.
98. Pfitzner B, Arnrich B. DPD-fVAE: synthetic data generation using federated Variational autoencoders with differentially-private decoder. arXiv preprint arXiv:2211.11591; 2022.
99. Ahmad B, Sun J, You Q, Palade V, Mao Z. Brain tumor classification using a combination of variational autoencoders and generative adversarial networks. *Biomedicines*. 2022;10(2):223.
100. Saaran V, Kushwaha V, Gupta S, Agarwal G. A literature review on generative adversarial networks with its applications in healthcare. In: Springer; 2021: 215–225.
101. Ghosheh G, Li J, Zhu T. A review of generative adversarial networks for electronic health records: applications, evaluation measures and data sources. arXiv preprint arXiv:2203.07018. 2022.
102. Torfi A, Fox EA. CorGAN: correlation-capturing convolutional generative adversarial networks for generating synthetic healthcare records. arXiv preprint arXiv:2001.09346. 2020.
103. Gonzalez-Abril L, Angulo C, Ortega JA, Lopez-Guerra JL. Generative adversarial networks for anonymized healthcare of lung cancer patients. *Electronics*. 2021;10(18):2220.
104. Naidoo K, Marivate V. Unsupervised anomaly detection of healthcare providers using generative adversarial networks. In: Springer; 2020: 419–430.
105. La Salvia M, Torti E, Leon R, et al. Deep convolutional generative adversarial networks to enhance artificial intelligence in healthcare: a skin cancer application. *Sensors*. 2022;22(16):6145.
106. Purandhar N, Ayyasamy S, Siva KP. Classification of clustered health care data analysis using generative adversarial networks (GAN). *Soft Comput*. 2022;26(12):5511-5521.
107. Torfi A, Beyki M. Generating Synthetic Healthcare Records Using Convolutional Generative Adversarial Networks; 2019.
108. Ma K, Xi P, Habashy K, Ebadi A, Tremblay S, Wong A. Towards trustworthy healthcare AI: attention-based feature learning for COVID-19 screening with chest radiography. arXiv preprint arXiv:2207.09312; 2022.
109. Chetoui M, Akhloufi MA. Explainable vision transformers and radiomics for covid-19 detection in chest x-rays. *J Clin Med*. 2022;11(11):3013.
110. Chen Z, Balan MM, Brown K. Boosting transformers and language models for clinical prediction in immunotherapy. arXiv Preprint arXiv:2302.12692; 2023.

111. Kumar Y, Ilin A, Salo H, Kulathinal S, Leinonen MK, Marttinen P. Medical SANSformers: training self-supervised transformers without attention for electronic medical records. arXiv preprint arXiv:2108.13672; 2021.
112. Ravishankar H, Venkataramani R, Anamandra S, Sudhakar P, Annangi P. Feature transformers: privacy preserving lifelong learners for medical imaging. In: Springer; 2019: 347–355.
113. Shickel B, Tighe PJ, Bihorac A, Rashidi P. Multi-task prediction of clinical outcomes in the intensive care unit using flexible multimodal transformers. arXiv preprint arXiv:2111.05431; 2021.
114. Shavit Y, Klein I. Boosting inertial-based human activity recognition with transformers. *IEEE Access*. 2021;9:53540-53547.
115. Shang J, Ma T, Xiao C, Sun J. Pre-training of graph augmented transformers for medication recommendation. arXiv preprint arXiv:1906.00346; 2019.
116. Atrey K, Singh BK, Bodhey NK, Pachori RB. Mammography and ultrasound based dual modality classification of breast cancer using a hybrid deep learning approach. *Biomed Signal Process Control*. 2023;86:104919.
117. Zebari DA, Ibrahim DA, Zeebaree DQ, et al. Breast cancer detection using mammogram images with improved multi-fractal dimension approach and feature fusion. *Appl Sci*. 2021;11(24):12122.
118. Ukwuoma CC, Hossain MA, Jackson JK, Nneji GU, Monday HN, Qin Z. Multi-classification of breast cancer lesions in histopathological images using DEEP_Pachi: multiple self-attention head. *Diagnostics*. 2022;12(5):1152.
119. Subramaniam U, Subashini MM, Almakhles D, Karthick A, Manoharan S. An expert system for COVID-19 infection tracking in lungs using image processing and deep learning techniques. *Biomed Res Int*. 2021;2021:1-17.
120. Tsiknakis N, Theodoropoulos D, Manikis G, et al. Deep learning for diabetic retinopathy detection and classification based on fundus images: a review. *Comput Biol Med*. 2021;135:104599.
121. Sikder N, Masud M, Bairagi AK, Arif ASM, Nahid AA, Alhumyani HA. Severity classification of diabetic retinopathy using an ensemble learning algorithm through analyzing retinal images. *Symmetry*. 2021;13(4):670.
122. Zhang L, Wang L, Gao J, et al. Deep fusion of brain structure–function in mild cognitive impairment. *Med Image Anal*. 2021;72:102082.
123. Senthil Kumar J, Sivasankar G, Selva NS. An artificial intelligence approach for enhancing trust between social IoT devices in a network. *Toward Social Internet of Things (SIoT): Enabling Technologies, Architectures and Applications: Emerging Technologies for Connected and Smart Social Objects*. Springer; 2020:183-196.
124. Roy B, Gupta R. MoDTRAP: improved heart rate tracking and preprocessing of motion-corrupted photoplethysmographic data for personalized healthcare. *Biomed Signal Process Control*. 2020;56:101676.
125. Chaddad A, Peng J, Xu J, Bouridane A. Survey of explainable AI techniques in healthcare. *Sensors*. 2023;23(2):634.

How to cite this article: Damaševičius R, Jagatheesaperumal SK, Kandala RNVPS, Hussain S, Alizadehsani R, Gorriz JM. Deep learning for personalized health monitoring and prediction: A review. *Computational Intelligence*. 2024;40(3):e12682. doi: 10.1111/coin.12682