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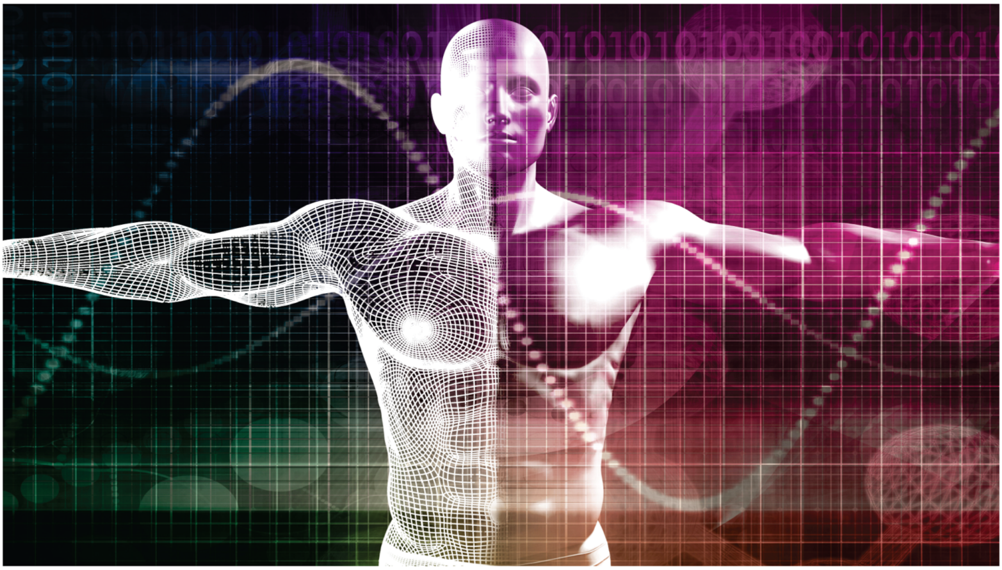
Handbook of Deep Learning in Biomedical Engineering and Health Informatics



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E. Golden Julie | Y. Harold Robinson | S. M. Jaisakthi

CRC Press
Taylor & Francis Group
APPLE ACADEMIC PRESS

HANDBOOK OF DEEP LEARNING IN BIOMEDICAL ENGINEERING AND HEALTH INFORMATICS

Biomedical Engineering: Techniques and Applications

HANDBOOK OF DEEP LEARNING IN BIOMEDICAL ENGINEERING AND HEALTH INFORMATICS

Edited by

E. Golden Julie, PhD

Y. Harold Robinson, PhD

S. M. Jaisakthi, PhD

APPLE ACADEMIC PRESS

First edition published 2022

Apple Academic Press Inc.
1265 Goldenrod Circle, NE,
Palm Bay, FL 32905 USA

4164 Lakeshore Road, Burlington,
ON, L7L 1A4 Canada

CRC Press
6000 Broken Sound Parkway NW,
Suite 300, Boca Raton, FL 33487-2742 USA

2 Park Square, Milton Park,
Abingdon, Oxon, OX14 4RN UK

Library and Archives Canada Cataloguing in Publication

Title: Handbook of deep learning in biomedical engineering and health informatics / edited by E. Golden Julie, PhD, Y. Harold Robinson, PhD, S.M. Jaisakthi, PhD.

Names: Julie, E. Golden, 1984- editor. | Robinson, Y. Harold, editor | Jaisakthi, S. M., editor.

Series: Biomedical engineering (Apple Academic Press)

Description: First edition. | Series statement: Biomedical engineering: techniques and applications | Includes bibliographical references and index.

Identifiers: Canadiana (print) 20210143177 | Canadiana (ebook) 20210143479 | ISBN 9781771889988 (hardcover) | ISBN 9781774638170 (softcover) | ISBN 9781003144694 (ebook)

Subjects: LCSH: Diagnostic imaging. | LCSH: Artificial intelligence. | LCSH: Medical informatics. | LCSH: Biomedical engineering.

Classification: LCC RC78.7.D53 H36 2021 | DDC 616.07/54—dc23

Library of Congress Cataloging-in-Publication Data

Names: Julie, E. Golden, 1984- editor. | Robinson, Y. Harold, editor | Jaisakthi, S. M., editor.

Title: Handbook of deep learning in biomedical engineering and health informatics / edited by E. Golden Julie, Y Harold Robinson, S. M. Jaisakthi

Other titles: Biomedical engineering (Apple Academic Press)

Description: First edition. | Palm Bay, FL : Apple Academic Press, 2021. | Series: Biomedical engineering: techniques and applications | Includes bibliographical references and index. | Summary: "This new volume discusses state-of-the-art deep learning techniques and approaches that can be applied in biomedical systems and health informatics. Deep learning in the biomedical field is an effective method of collecting and analyzing data that can be used for the accurate diagnosis of disease. This volume delves into a variety of applications, techniques, algorithms, platforms, and tools used in this area, such as image segmentation, classification, registration, and computer-aided analysis. The editors proceed on the principle that accurate diagnosis of disease depends on image acquisition and interpretation. There are many methods to get high resolution radiological images, but we are still lacking in automated image interpretation. Currently deep learning techniques are providing a feasible solution for automatic diagnosis of disease with good accuracy. Analyzing clinical data using deep learning techniques enables clinicians to diagnose diseases at an early stage and treat the patients more effectively. Chapters explore such approaches as deep learning algorithms, convolutional neural networks and recurrent neural network architecture, image stitching techniques, deep RNN architectures, and more. The volume also depicts how deep learning techniques can be applied for medical diagnostics of several specific health scenarios, such as cancer, COVID-19, acute neurocutaneous syndrome, cardiovascular and neuro diseases, skin lesions and skin cancer, etc. Key features: Introduces important recent technological advancements in the field Describes the various techniques, platforms, and tools used in biomedical deep learning systems Includes informative case studies that help to explain the new technologies Handbook of Deep Learning in Biomedical Engineering and Health Informatics provides a thorough exploration of biomedical systems applied with deep learning techniques and will provide valuable information for researchers, medical and industry practitioners, academicians, and students"-- Provided by publisher.

Identifiers: LCCN 2021008116 (print) | LCCN 2021008117 (ebook) | ISBN 9781771889988 (hbk) | ISBN 9781774638170 (pbk) | ISBN 9781003144694 (ebk)

Subjects: MESH: Medical Informatics | Deep Learning | Biomedical Engineering

Classification: LCC R855.3 (print) | LCC R855.3 (ebook) | NLM W 26.5 | DDC 610.285--dc23

LC record available at https://lccn.loc.gov/2021008116

LC ebook record available at https://lccn.loc.gov/2021008117

ISBN: 978-1-77188-998-8 (hbk)
ISBN: 978-1-77463-817-0 (pbk)
ISBN: 978-1-00314-469-4 (ebk)
DOI: 10.1201/9781003144694

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ABBREVIATIONS

AAM	active accurate model
ABCD	asymmetric, border structure, color difference, and diameter
AD	Alzheimer's disease
ADHD	attention deficit hyperactivity disorder
ADNI	Alzheimer's disease neuroimaging initiative
AE	autoencoder
AG-CNN	attention guided convolution neural networks
AI	artificial intelligence
AIC	Akaike's information criterion
ALU	arithmetic logic unit
ANN	artificial neural network
AP	Antero-posterior
ASM	active shape model
ASPP	atrous spatial pyramid pooling
A-T	ataxia-telangiectasia
BCDCNN	breast cancer detection using CNN
BGRU	bidirectional gated recurrent unit
BN	batch normalization
BreCaHAD	breast cancer histopathological annotation and diagnosis dataset
BRIEF	binary robust independent elementary features
CAD	computer-aided design
CAD	computer-aided diagnosis
CAE	convolutional autoencoders
CCNN	cloud-based convolution neural network
CCTA	cardiac computed tomography angiography
CE	capsule endoscopy
CECT	contrast-enhanced computed tomography
CN	cognitive normal
CNN	convolutional neural network
CNNI-BCC	CNN improvement for breast cancer classification
CPH	Cox proportional hazard
CRF	conditional random field
CT	computed tomography

CVDL	cooperative variational profound learning
CVDs	cardiovascular diseases
CXR	chest x-ray
DAN	deep autoencoders
DaT	dopamine transporters
DB	database
DBN	deep belief networks
DBS	deep brain stimulation
DCT	discrete cosine transform
DG	disease group
DL	deep learning
DLA	deep learning analyzer
DNN	deep neural networks
DOG	difference of Gaussian
DR	diabetic retinopathy
DTI	diffusion tensor imaging
DTI	dynamic thermal imaging
DV	dorso-ventral
DWT	discrete wavelet transforms
ECG	electrocardiogram
EHR	electronic health record
EMD	experimental mode decay
FAST	features from accelerated segment test
FC Layer	fully connected layer
FDG	fluorodeoxyglucose
FFDM	full-field digital mammography
FFT	fast Fourier transform
FLANN	fast library for approximate nearest neighbors
FLOPs	floating-point operation
FNN	forward neural network
GANs	generative adversarial networks
GDWDL	greedy deep weighted dictionary learning model
GL	generative learning
GM	grey matter
GMM	Gaussian Markov model
GPi	globus pallidus
GRU	gated recurrent unit
HAM	human against machine
HCA	hierarchical clustering algorithm

HCI	human-computer interaction
HG	health group
HPF	high-power magnetic field
HRCT	high-resolution computed tomography
ICSS	intracranial self-activation
ILD	interstitial lung disease
KDD	knowledge discovery/data mining
KNN	K-nearest neighbor
LESH	local energy-based shape histogram
LR	learning rate
LRN	local response normalization
LSH	locality-sensitive hashing
LSTM	long short-term memory
LTP	local ternary pattern
MCCNN	mammogram classification using CNN
MCI	mild cognitive impairment
MIAS	Mammographic Image Analysis Society
ML	medio-lateral
MLP	multi-layer perceptron
MLPNN	multi-layer perceptron neural network
MMSE	mini-mental state examination
MNIST	Modified National Institute of Standards and Technology
MPSD	multiple patches in a single decision
MSOP	multi scale-oriented patches
NORB	NYU object recognition benchmark
OA	osteoarthritis
OCD	obsessive-compulsive disorder
PBC	patch-based classifier
PCA	principal component analysis
PD	Parkinson disorder
PET	positron emission tomography
PMF	probabilistic MF
PSF	point spread function
PSO	particle swarm optimization
RANSAC	random sample consensus
RBM	restricted Boltzmann machine
ReLU	rectified linear unit
ResNet	residual network
RNN	recurrent neural system

ROC	receiver operating characteristic
RPN	region proposal network
RTPCR	reverse transcription-polymerase chain reaction
SARS-CoV-2	syndrome coronavirus 2
SGD	stochastic gradient descent
SGRU	stacked bidirectional gated recurrent unit
SIFT	scale-invariant feature transform
SMOTE	synthetic minority oversampling technique
SNN	shallow neural networks
SN-VTA	substantia Nigra-ventral tegmental areas
SPSD	single patch in a single decision
SS	self-stimulation
STN	subthalamic nucleus
SURF	speed up robust feature
SVD	Saarbrucken voice database
SVM	support vector machine
SWS	Sturge-Weber syndrome
TB	tuberculosis
TDM	topological data mining
TDSN	tensor deep stacking network
TDV	total dermatoscopic values
UV	ultraviolet
VAE	variational autoencoder
VDM	visual data mining
VHL	von Hippel-Lindau
WCE	wireless capsule endoscopy
WHO	World Health Organization
WM	white matter

ACKNOWLEDGMENTS

This edited book's successful completion is made possible with the help and guidance received from various quarters. I would like to avail myself this opportunity to express my sincere thanks and gratitude to all of them.

I am deeply indebted to Almighty God for giving us this opportunity. I extend my deep sense of gratitude to our son, Master H. Jubin, and our parents for their moral support and encouragement at all stages of this book.

I extend my deep sense of gratitude to my scholars and friends for writing the chapters in time to complete this book. I sincerely thank my friends and family member for providing necessary prayer support.

Finally, I would like to take this opportunity to especially thank the Apple Academic Press for their kind help, encouragement, and moral support.

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I express my sincere thanks to the management of Vellore Institute of Technology, Vellore, India, and NVIDIA for providing a GPU granting support of her research work. Also, I would like to thank the Apple Academic Press for giving me the opportunity to edit this book.

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PREFACE

Deep learning (DL) is the most attractive technique in the field of biomedical engineering and health informatics during recent years because it provides an accurate diagnosis of disease. Accurate diagnoses of disease depend on image acquisition and interpretation. There are many methods to get high-resolution radiological images, but we still lack automated image interpretation. Currently, deep learning techniques are providing a good solution for the automatic diagnosis of disease with good accuracy. This book provides a clear understanding of how deep learning architecture can be applied in medical image analysis for providing automatic interpretations such as image segmentation, classification, registration, and computer-aided analysis in a wide variety of areas.

Chapter 1 reviews a variety of methods and techniques in the healthcare system using deep learning. The authors have used a number of deep learning tools such as K-nearest neighbor (KNN) algorithm, AlexNet, VGG-16, GoogLeNet, and vice versa for implementation. This chapter focuses on breast cancer analysis, lung tumor differentiation, pathology detection, and patient-learning using numerous methods.

Chapter 2 gives an overview of convolutional neural network architectures and their variants in medical diagnostics of cancer and COVID-19. The convolutional network is the basic architecture: based on these different variants like YOLO (you look only once), Faster RCNN, RCNN, AlexNet, and GoogLeNet are developed. Fast RCNN is based on region proposal network (RPN) for medical imagining. CNN variants have the ability to classify the images and detect the risk of diseases.

Chapter 3 discusses the technical assessment of various image stitching techniques in a deep learning approach. This chapter presents various image-stitching techniques based on different feature extraction methods. Image stitching can be regarded as a process of assembling more than one image of the same scene having an overlapping area in between them to make them into a single high-resolution image. The experimental results have revealed that ORB outperforms other methods in terms of rotation and scale invariance and execution time.

In Chapter 4, a deep learning approach for an acute neurocutaneous syndrome via cloud-based MRI images is discussed. A decision tree classification is an added advantage in CNN, which gives solutions for many different types of symptoms other than the MRI images. A set of pre-trained GoogLeNet libraries is used for the analysis of MRI images for this work. This chapter provides a more innovative cloud convolutional neural network for neurocutaneous syndrome in the biomedical field, which is under serious research.

Chapter 5, titled "Critical Investigation and Prototype Study on Deep Brain Stimulations: An Application of Biomedical Engineering in Healthcare," focuses on stimulating brain activities to the extent that is considered desirable to boost performance and be a productive human resource. This will be a promising product that can be viewed as a cure for various diseases closely related to brain activity. This includes conditions like epilepsy, Parkinson's disease, chronic pain, Dystonia, and even for normal people.

Chapter 6 gives an insight into various algorithms for medical image analysis using convolutional neural networks (deep learning). This chapter is aimed at the early prediction of Alzheimer's disease (AD). An algorithm that discriminates the mild cognitive impairment (MCI) and cognitive normal (CN) is casted-off, which shows better results in its analysis.

Chapter 7 deals with exploration of deep RNN architectures: LSTM and GRU in medical diagnostics of cardiovascular and neuro diseases. This chapter is delivers specific indispensable material about RNN-based deep learning and its solicitations in the pitch of biomedical engineering. This chapter will inspire young scientists and experts pioneering in the biomedical domain to swiftly comprehend the best-performing methods.

Chapter 8, titled "Medical Image Classification and Manifold Disease Identification through Convolutional Neural Networks: A Research Perspective," discusses a comprehensive analysis of various medical image classification approaches using convolutional neural networks (CNN). Here a short-term explanation of numerous datasets of medical images along with the approaches for facilitating the major diseases with CNN is discussed. All current progress in the image classification using CNN is analyzed and discoursed.

Chapter 9 discusses melanoma detection on skin lesion images using K-means algorithm and SVM classifier for detecting skin cancer in earlier stages. The proposed algorithm includes Sobel's process, Otsu's method, ABCD, and K-means with SVM classifier for getting the accuracy at 92%.

Chapter 10, titled “Role of Deep Learning Techniques in Detecting Skin Cancer: A Review,” deals with automatic detection of skin cancer in the dermoscopic image that are required for detecting melanoma at an early stage. It deals with state-of-the-art deep learning from the foundation of machine learning as it provides better accuracy for medical images.

Chapter 11 explains deep learning and its applications in biomedical image processing. In this chapter, various blocks of DL are clearly discussed. Currently, DBN has evolved and proved to be the best when compared to the other networks. It may be noted that a particular network’s accuracy entirely depends on the type of application and the features.

CHAPTER 1

REVIEW OF EXISTING SYSTEMS IN BIOMEDICAL USING DEEP LEARNING ALGORITHMS

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ABSTRACT

In recent days, many researchers focus on interdisciplinary research work to solve various research problems. One such interdisciplinary research work is the implementation of deep learning (DL) in biomedical engineering and health informatics. It is mandatory to review various research works by various authors, which are implemented using DL in the above fields in order to understand the problem domain, different DL methods/techniques/theorems for prediction and analysis. The main intention of this chapter is to review a variety of methods and techniques in the healthcare system using DL. Authors have used a number of DL tools such as K-nearest neighbor (KNN) algorithm, AlexNet, VGG-16, GoogLeNet, and vice versa for implementation. It has been noticed that DL architecture has been formulated for

medical analysis, such as various cancer prediction, in order to predict the accuracy of results. This DL architecture has three basic layers that help to train and test the model, which are the input layer, multiple hidden layers, and the output layer. The output of various medical analyzes depends on the DL architecture that is used along with a number of convolutional hidden layers. In this chapter, breast cancer analysis, lung tumor differentiation, pathology detection, patient-learning using numerous methods such as similarity learning, predictive similarity learning, and adaptive learning using the DL approach has been described.

1.1 INTRODUCTION

The medicinal industry multiplies because of the headway of remote correspondence innovation and AI applications. The quantity of maturing individuals in the world advances, though the proportion of particular specialists to patients diminishes. Individuals become incredibly involved, and traffic blockage increases. Late advances in remote correspondence innovation have empowered the improvement of a savvy human service structure that is quick, consistent, and universal. The most recent improvements in AI, for example, deep learning (DL), enhancing the exactness of frameworks before utilizing an extensive measure of information. Remote correspondence innovation and AI calculations can understand this issue to a limited degree. Hence, much research is led to build up a keen human services system utilizing 5G innovation, edge, and distributed computing, and DL.

In the most recent decennary, DL algorithms like recurrent neural system (RNN), convolutional neural system (CNN), and autoencoder (AE) was the most commonly used type of DL models, for example, mechanical structure [20] and picture acknowledgment [21]. Recently, a few works have connected variational autoencoder (VAE) [22] to perform CF task in suggestion, for example, CVAE [23], CAVAE [24], CLVAE [25], and VAECF [26]. VAE has a vulnerability in recommender systems with huge information and the capacity of catching non-linearity, and it is a non-direct probabilistic model. In spite of the adequacy of these VAE-based strategies, there are yet a few disadvantages; for example, to separate the idle vectors, CVAE and CAVAE legitimately employ content data. In essential consideration frameworks, the extra data of patients and specialists are exceptionally well-off, and was not completely used for the betterment of proposal execution, which creates HRS even in their earliest stages concerning dependability and unwavering quality. To take care of those issues above, a CVDL (cooperative variational profound learning) model is devised for HRS in essential consideration, to give personalization into the patient's consideration and to give the understanding by utilizing the patient's inclinations.

CVDL makes both inert client/thing vectors through a different neural system structure, which can viably study things for further CF process and non-direct idle portrayals of clients. EHR (electronic health record) frameworks store information related with every patient experience, including statistical data, analyze, lab tests and results, remedies, radiological pictures, clinical notes, and more [1]. While fundamentally intended for improving human services effectiveness from an operational point of view, numerous investigations have discovered auxiliary use for clinical informatics applications [5, 6]. In this chapter, the particular DL system was utilized for EHR information examination and deduction, and talked about the solid clinical applications empowered by these advances. Dissimilar to other ongoing overviews which audit DL in the expansive setting of wellbeing informatics applications going from genomic examination to biomedical picture investigation, this review is centered solely around profound learning procedures custom-fitted to EHR information. In opposition to the choice of particular, viable applications found in these reviews, EHR-based issue settings are described by the heterogeneity and structure of their information sources and by the assortment of their applications. Tolerant closeness learning is a basic and significant assignment in the human services area, which improves clinical basic leadership without bringing about extra endeavors from doctors. The objective of patient closeness is to get familiar with the important metric unit, which estimates the relational similitudes among patient sets as per patient's wellbeing files.

A legitimate closeness value empowers different downstream applications, for example, customized prescription [1, 2], medicinal conclusions [3], direction investigation [4], and accomplice study. The pervasiveness and developing electronic volume wellbeing records (EHRs) gives phenomenal chances to get better medical choice help. The EHR information, which provides the patient's longitudinal electronic record, is a profitable hotspot for prescient demonstrating, which will help the healthcare industry. The records of wellbeings are transiently ordered using victim encounters spoke to as many advanced clinical occasions (for example, restorative codes). Mining EHRs is particularly testing contrasted with standard information mining assignments, because of its loud, unpredictable, and heterogeneous nature for the wellbeing's record information, the computation of physically affected person visits differs to a great extent, because of patients' unpredictable visits and inadequate chronicles. The previously mentioned learning measurements can't be straightforwardly connected to the longitudinal information, as the chronicled files of every patient don't normally frame a practically identical vector. Accordingly, one of the key difficulties in estimating persistent likeness is to determine a successful portrayal for every patient without the loss of his/her authentic data.

The first depends on triplet misfortune work, which learns an edge to isolate the separation of negative and positive examples. Thusly, it is good to get a separation worth demonstrating the general comparability between patients. Secondly, is to perform characterization over scholarly portrayals with the plus mark for comparative combines and minus mark for different sets. In addition, the closeness likelihood among couples of patients demonstrates the level of risk between two patients building up a similar illness; it is used as the point to evaluate the likeness over patients. Subsequent to acquiring the closeness data, two undertakings are performed: ailment forecast and patient grouping, which are application regions of customized human services, so as to approve the educated measurements.

1.2 BREAST CANCER ANALYSIS USING DEEP LEARNING (DL)

Zhang et al. [13] stated the concept of selection of features and separation models in DL, which is used for predicting breast cancer. The flowchart for unsupervised and supervised learning methods for breast cancer was demonstrated by the authors. Authors implemented the concept, which includes data alignment, the objective function for feature extraction that consists of nonlinear transformation and reconstruction loss, activation function in autoencoder, optimization with ADAM, normalized initialization, and Adaboost algorithm for classifier learning.

Sellami et al. [28] elaborated sequence exploration on breast cancer ultrasound pictures by using BI-RADS characteristic extraction. The authors discussed the preprocessing and segmentation process, which includes digital image processing for spot removal and picture segmentation. Morphological features were classified according to the BI-RADS lexicon, which includes three classes such as the pattern, pattern position, and orientation. Texture features were extracted using three classes of the lexicon, such as boundary classification of the lesion, classification of echo pattern, and posterior acoustic feature classification of logical methods of posterior acoustic characteristic.

Gubern-Merida et al. [31] defined a completely automatic framework for breast partition and density estimation. The authors provided a general overview of dense tissue segmentation. There are three preprocessing algorithms applied, such as the N3 bias field correction algorithm, detection of the sternum, and normalization of intensities of MR images. Breast body segmentation has been elaborated. Breast density segmentation has been carried out and evaluated as programed bosom division and thickness division utilizing EM.

Li et al. [32] stated the concept of selective element mining for breast cancer for which histopathology picture categorization was performed using completely convolutional AE. Breast cancer biopsy image dataset was collected to create the likelihood guide of harmful cells. Authors used a patch-based learning solution, which is depicted in Figure 1.1. First-order statistics of true-normal patches were given as the input during the training phase using one-class SVM (support vector machine) for malignant patch detection. SVM's mapping functions were given as the input for training phase 3, which uses the 1-layer neural system for Platt's score and produced patch posterior probability as output.

FIGURE 1.1 Selective element mining for breast cancer.

Athreya et al. [33] used the concept of ML, which guides distinguish drug mechanism in breast cancer. Bosom malignancy tissue comprising cancer cells was done using a human genome of 24,000 genes. Gene expression matrix was constructed using 192 cells of 24,000 × 192. Metformin has been applied to ensure whether it affects gene expression of few cells or many cells. Machine learning approaches were introduced to identify a list of candidate genes using unsupervised learning methods and pathway analysis. From unsupervised learning, it is noticed that cells, which are exposed to the drug, may tend to represent differences in their gene expression that are found in molecular interactions. Data characteristics and preprocessing were performed, which states that 80% of the qualities were latent in the information while preprocessing in which only 5% of genes have shown with changes using metformin.

1.3 LIVER TUMOR ANALYSIS USING DEEP LEARNING (DL)

Trivizakis et al. [34] has extended the DL concept for liver tumor differentiation. MRI is treated to be a powerful tool for detecting small lesions that leads to malignancy in the liver tumor. The authors depicted a 3D convolutional neural network (CNN). Data augmentation is also considered to be important in original patch analysis using image deformation, 270° rotation, and so on. Tissue classification was performed using SVM with various evaluation parameters such as accuracy, sensitivity or recall, and precision, an overall analysis of 2D and 3D.

1.4 DEVELOP 3D PET FOR RADIONICS EXAMINATION AND OUTCOME PROGNOSIS

Amyar et al. [41] have collected data of 97 patients having esophageal cancer for which they have applied PET with CT during the initial stage. Two 3D convolutional layers were used to define 3D RPET-NET, for which image preprocessing was done on the dataset using the K-nearest neighbor (KNN) interpolation algorithm. Visualization of a 2-D cut of a divided tumor of 1S-CNN architecture has been demonstrated by the authors. Three analyzes were accomplished to assess and assess 3D RPET-NET. The outcomes were contrasted with 3 RF-based methodologies. Cross-validation has been performed by splitting the entire data into two groups, which will be used for training and testing. The first group was intended for training the models with 77 patients, and the second group was used for testing the model with 20 patients. Alternatively, training samples, such as 77 patients, were divided into two groups. Fifty-five patients details are used to train the set, and the remaining 22 patients are used for the validation set.

1.5 A GREEDY DEEP LEARNING (DL) METHOD FOR MEDICAL DIAGNOSIS

Greedy deep, weighted dictionary learning [42] which is used for medical disease analysis to overcome over-fitting problem while classifying and training patient data. Internet of Things, together with the healthcare system, has been utilized to enhance the dependability in the analysis of portable media, which is intended for medicinal services to anticipate the sicknesses and for medical diagnosis. ADHD-200 (attention deficit hyperactivity disorder) database (DB) were used to extract 30 datasets of depression as a training set. Authors have defined a Boltzmann machine with three hidden layers which involves unsupervised learning model to carry out the processing along with feedback mechanism. Dictionary learning was done using sparse coding from matrix decomposition.

Greedy deep weighted dictionary learning model (GDWDL) was proposed by the authors for performing clinical data preprocessing, which is followed by extracting data information was done using type series analysis. Two groups were formed by the authors such as health group (HG) and the disease group (DG) in order to segregate the patient details. The optimization process was carried out in the single-layer neural network by using shallow dictionary learning, which is said to be a non-convex optimization method. The algorithm was provided by the authors to find out the objective function to achieve the optimal solution. Comparison has been made by the authors with different dictionary size for various sensitivity of algorithms such as FDDL, DFDDL, and GDWDL.

1.6 MULTI-ARRANGE PROFOUND LEARNING FOR MEDICAL DIAGNOSIS

Yan et al. [43] stated the concept on multi-instance DL, which is used to discover discriminative local anatomies in medical diagnosis. Body part identification was indicated by local image information. The authors designed a DL framework which contains multiple stages in order to recognize body parts of a patient by applying image classification. CNN was used to determine the local regions of a human body that are sensitive. Authors applied cut-based body part identification, which is usually a multi-class picture arrangement technique which includes four kinds of geometry components, for example, square, circle, triangle, and diamond are utilized. Classification accuracy with respect to various classes for triangle and square and then diamond and circle as far as review, accuracy, and F1 score in percentage were tabulated by the authors.

1.7 SKIN LESION GROUPING UTILIZING PROFOUND LEARNING

Marwan [44] used a convolutional neural system with a novel regularizer for skin injury arrangement. The authors used CNN along with the regularization technique in order to control the complexity of the classifier. Regularization process involves assigning weight matrics along with the regularization parameter, which will work in a convolution filter. In addition, 5600 images were used for training, and 2400 images were used for validation. Out of which 4533 were malignant and 19,373 benign skin lesion images were found out.

1.8 STAIN-INVARIANT CONVOLUTIONAL NETWORKS

David et al. [45] trained refined stain-invariant arrangement for entire slide mitosis discovery for which PHH3 was utilized as a source of perspective in H&E bosom histology. Mitotic activity utilizing PHH3 stained slides consists of a whole-slide image, which is used for candidate detection using blue and brown channels. Then PHH3 whole-slide images with candidates were used for sampling and manual annotation, which will be given for training using CNN. H&E Mark: Preparing a Mitosis indicator includes assembling a training data set; stain augmentation, which consists of three invariances such as morphology, stain, and artifact invariance, then ensemble and network distillation, which is followed by the outcome at the whole-slide level.

1.9 HCI-KDD APPROACH

The work proposes an HCI-KDD approach [46], which combines various methodological approaches of DL for the healthcare sector. The approach is a mere combination of HCI (human-computer interaction) and KDD (knowledge discovery/data mining). The former emphasis on cognitive science and the later on machine learning. HCI focuses on specific experimental methodologies and KDD on computational learning problems.

The main task in HI is the data ecosystem identification. Mainly four types of data pools are made based on the context of data origin. The four data pools are: biomedical research data, clinical data, health business data, and primitive patient data. Data preprocessing step is followed by a data integration step. The information integration can overcome the drawbacks laid among medical and biological research points and issues.

The information reconciliation procedure joins information from different sources and gives a brought together view about the information. Similar concept is data interpretation, which matches various data which points one object into a single consistent representation. It is found that fused data is having much better information than the original large collection of data.

Current trend of machine learning is towards the automated machine learning (aML) algorithms, which completely expels the human interventions so that the process becomes completely automated. Voice identification and processing, recommendation systems, automated vehicles are examples of the above mentioned. Another area of ML is the interactive machine learning (iML), which can associate with both statistical assistants and human assistants and they have optimized experiencing via such methods of collaborations. However, the iML algorithms face certain issues-much more difficult, time consuming, hard to replicate, and robustness.

Discovering the associations among data items and to map the necessary data structures, graph theory can be used. Graph theoretical algorithms help us to map the concepts of computer networks, network analysis, and data mining and cluster analysis to the HI concepts. Complexity occurring in the graphical representation of data makes it more difficult to go with Graph theory algorithms. Topological data mining methods (TDM) are similar and related to graph theory-based methods. Homology and persistence are the popular techniques of TDM. The cycles of each space determines its connectivity. The groups which are formed from such sequences are called homology aggregations, which can be computed with the help of linear algebra using an explicit description of the space. A notable measure that could be utilized to quantity the proximity is Cosine uniformity measure. Entropy of an information accounts for the uncertainty which persists in the data. In the graph theory concept, graph entropy is described to measure the structural information of the graph data.

Another important concern in the area of study is the visualization of the data. Visual data mining (VDM) bolsters intuitive and adaptable system representation and the examination of information. Clustering helps us in data visualization-it recognizes homogeneous gatherings of information dependent on the provided measurements.

1.10 PROFOUND NEURAL MODELS FOR FORECAST IN HUMAN SERVICES

This work [47] proposes deep neural architectures that can accept raw data as input and can provide desired outputs. The work primarily concentrates on neurodegenerative maladies-Parkinson's infection. The system is to support nurses and doctors to provide advanced and authentic prognostic and analysis about the disease.

They created public data set with 55 patients having Parkinson's disease and 23 with the interrelated complaints. MRI scan data can show the extent to which the brain has degenerated. So the MRI data is analyzed to identify the lentiform nucleus and capita of caudate nucleus. The image sequences are processed in batches to get the volume information of these interest points.

Dopamine transporters (DaT) scan is another imaging technique used to populate the DB. The degree of dopaminergic innervations to Striatum from Substantia Nigra can be easily identified. From the series of images available via DaT scan, the doctor identifies the most representative one. He then marks the areas corresponding to the most representative scan image. These corresponding spots are compared with the neutral points by using an automated system and produce the ratios which can be used for comparing purposes.

In addition to MRI scan data and DaT scan data, clinical data of a patient is taken to get an idea about the motor/non-motor experiences, motor examinations, and complications of daily experience of the subject. For the training purpose of the proposed model, an annotated representation of MRI data and DaT data is considered. They proposed a deep neural architecture for the diagnosis and prediction of the disease. The components of the proposed model are: Deep CNN, Transfer learning, and recurrent neural networks.

The deep CNN exploits the spatial information of the input. The learning failures which occur due to over fitting when training is done with complex CNN's with small data can be avoided to an extent by using the concept of transfer learning. The concept of transfer learning is that, we will use the previously used networks which are trained with bulky image datasets which are fine-tuned as per our needs or part of the network for the training purpose using the tiny dataset. Sequential data can be processed with the help of a recurrent neural network (RNN). Experiments show that among the various RNNs, gated recurrent units (GRUs) have better performance, and it would be utilized for the prediction and assessment of Parkinson's disorder. CNN's consist of enormous internal representation of the input data. The

CNN under study have 50 layers. In addition to these layers, there are three numbers of fully connected layers (FC layer)-rectified linear units (ReLU).

The MRI and DaT scan data are given as input to the network. If our area of interest is with epidemiological and clinical data inputs, those inputs are given directly to the FC1 layer. In the CNN, the linear FC3 layer performs the estimation of clinical data. The input to the RNN part is F1, F2, F3, …, FN, and the corresponding expected outputs are O(1), …, O(N). A single input to the architecture is a set of four images out of which three consecutive images are grayscale from the MRI data and one color image from DaT scan.

The implementation of the architecture starts with the transfer learning of weights of the ResNet network. Tensor Flow platform is the tool which they have used for implementing the software part of the architecture. The architecture can be enhanced for prediction and assessment of degenerative diseases.

1.11 PATHOLOGY DETECTION USING DEEP LEARNING (DL)

Voice pathology [37] can be extreme if there should arise an occurrence of disappointment in early identification and appropriate administration. This pathology is especially predominant among experts, for example, instructors, vocalists, and legal advisors, who too much utilize their voice. In this chapter, another versatile human services structure has been elaborated that contains a programmed voice pathology recognition framework. The system comprises of brilliant sensors, distributed computing, and correspondence among patients and partners, for example, emergency clinics, specialists, and medical caretakers. The proposed voice pathology recognition framework utilizes convolutional neural system (CNN). A few tests were performed utilizing an openly accessible DB known as SVD (Saarbrucken voice database). A few frameworks utilize acoustic highlights [6], for example, Mel recurrence cepstral coefficients [14], coefficients of perceptual direct forecast, and straight prescient cepstral. The highlights are embedded from speaker and discourse acknowledgment applications which are additionally utilized unitedly with understood classifiers, for example, concealed Markov systems, Gaussian blend system, bolster vector system [7], and counterfeit neural system [10].

Tang et al. [35] stated the concept for survival analysis using DL CNN. There are three stages in data preprocessing, which consists of inspecting from WSIs, characteristic extrication, and bunching then finally choosing groups. This structure includes the image size of 128×128, which is given as the input for a convolutional layer that performs dynamic routing. A survival cap, which includes long term and short term, produces the output, which is linked with survival loss that includes margin loss, cox loss, and reconstruction loss.

Amin et al. [7] explained the concept of a cognitive smart healthcare system, which is for pathology detection and monitoring. The authors described the cognitive smart healthcare system scenario, which includes IoT smart sensors, cognitive engine and DL server and other interconnecting devices, which is depicted in Figure 1.2.

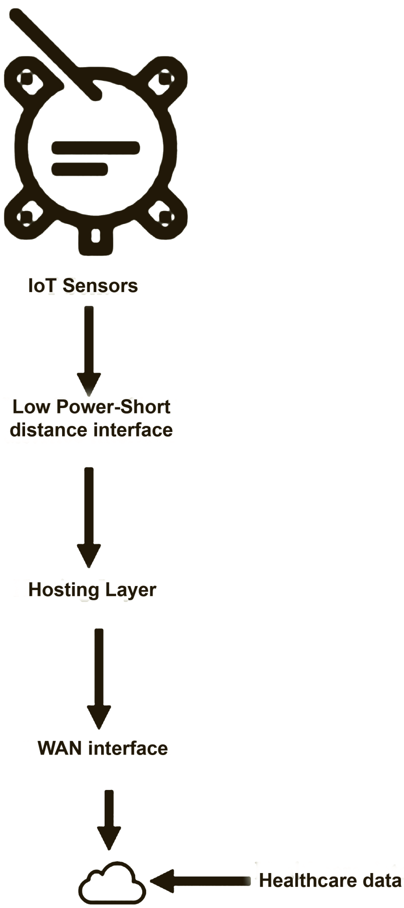

FIGURE 1.2 Cognitive smart healthcare system.

Different EEG preprocessing and representation techniques were used for pathology detection and classification. The authors used DL tools such as VGG-16 and AlexNet to simulate the results.

Alhussein and Muhammad [59] elaborated voice pathology identification utilizing profound learning on portable human services systems. Exemplification of the same is given in Figure 1.3, which includes the required mobile healthcare system and the interaction among them. This mobile healthcare framework and the corresponding voice signal processing used for pathology detection.

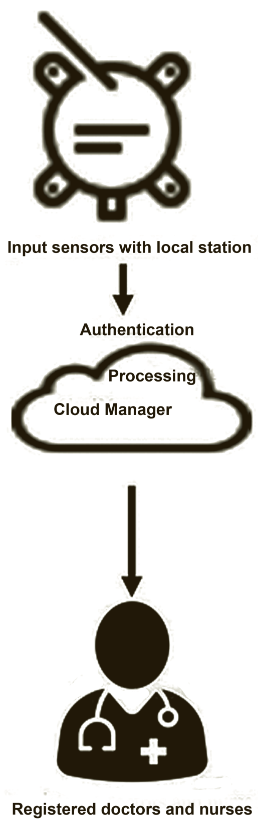

FIGURE 1.3 The mobile healthcare framework.

The authors also depicted the architecture of the VGG 16 DL network and the architecture of CaffeNet for processing the voice signal.

Voice pathology might be surveyed in two different methods: subjective and objective. In subjective evaluation, a professional physician assesses voice pathology through hearing or through the use of tools, including a stroboscope or laryngoscope. In positive activities, more than one medical doctor examines a similar case to accomplish an accord. As anticipated, a particular wellbeing specialist will settle on the last decision with respect to voice pathology [8]. Goal evaluation is directed through a PC method, which examines the voice example and settles on a preference dependent on the assessment outcomes. This method of evaluation is fair-minded against subjects. In objective evaluation, the influenced individual transfers his voice sign to an enlisted human services structure in the wake of paying the enrolment charge. In this chapter, it is extraordinarily engaged in the concerned appraisal of voice pathology identification. To this point, various writing offers many voice pathology identification structures. The early frameworks utilized voice parameters, including gleam, jitter, sign-to-noise proportion, commotion symphonious proportion, and glottal-to-clamor proportion [11]. Parameters are measurements of voice top notch. A solitary parameter demonstrates deficient to identify pathology consequently, in a few structures; numerous parameters are mixed to harvest higher results [12].

Numerous systems use acoustic features [6] inclusive of Mel frequency cepstral coefficients [14], direct prescient cepstral coefficients, and perceptual straight expectation coefficients. Those highlights are imported from discourse and speaker acknowledgment bundles. These highlights likewise are utilized aggregately with a popular classifier, which incorporates concealed Markov models, Gaussian blend model, guide vector machine [10], and synthetic neural community [10].

Recently, deep getting to know primarily voice pathology recognition frameworks carried out with enhancing the accuracy [17, 19]. Specific models of deep studying [18] had been determined from picture preparing packages. The structures, as a rule, transform time-space voice signals into spectrograms that might be considered as photos. The fashions that have been utilized in voice pathology exploration consist of VGG-sixteen [20], AlexNet, and CaffeNet. Those models are pertained using tens of millions of snapshots. However, those deep gaining knowledge of-primarily based structures reject pathology characterization. These days, voice pathology discovery structures are incorporated into a social insurance system which contains the utilization of huge certainties. Various structures use edge processing to offload the transfer speed prerequisite [30]. Nothing unless there are other options noted structures utilizes parallel CNNs to abuse the time-segmental components of voice signals. Twenty-four melanoma sufferers have been enrolled in the observation and CRP degrees have been received.

The CRP estimations [8] were done on weekdays, with certain exemptions where everyday estimations have been made. The utilization of a rotator, plasma progressed toward becoming remote from the total blood assembled, subsequent to evacuating portable and protein flotsam and jetsam; aliquot and put away at 80°C for latter implementation. The stages were chosen through a research facility chemical associated immunosorbent measure (ELISA). The examination is a plate-basically dependent which examines strategy intended for identifying and evaluating peptides, proteins, antibodies, hormones. Sooner than tutoring, a succession of preprocessing tasks are executed, for example, insights institutionalization to increase 0 mean and unit change, and sign destroying utilizing experimental mode decay (EMD). After the investigations, the forecasts are unstandardized the utilization of the parameters determined ahead of time. The RMSE-root-imply-rectangular botches is determined from the unstableness's expectations that needs analyzing the conjecture values with real CRP perceptions, RMSE = $\sqrt{1/N\sum_{i=0}^{N}(x-xi)^2}$ where xi is anticipated value, Oxi speaks to observed value, and N shows the quantity of tests. The RMSE is generally utilized in various studies which includes regression technique. Reality that RMSE punishes a greater divergence from the mean brings us to lease this measurement inside the investigation. CTR employs item content material to improve CF methods and has accomplished encouraging execution by coordinating both individual score and article content. CTR consolidates the benefits of each probabilistic MF (PMF) and theme displaying (LDA) designs, and comprises of the idle variable for balancing the subject extents while demonstrating the client rankings and the balance variable can successfully catch the thing inclination for a specific consumer thinking about their rankings.

CTR doesn't make the most client records and can't look at reliable idle client portrayals. To address this issue, a couple of examines has been introduced utilizing extraordinary versions which accommodates general records into CTR. In addition, CTRSMF [15] and C-CTR-SMF2 [16] included CTR with SMF version the use of a method this is just like SoRec, wherein the social connections are simultaneously factorized with the score lattice. Be that as it may, they don't screen the fundamental relatives among clients because of the deficiency of physical legitimization. In contrast with CTRSMF and C-CTR-SMF2, LACTR, and RCTR legitimately inspect the portion of premium when clients apportion to different clients and use this scholarly impact to soothe spared issue. The strategies depend on that the social cooperation's of clients generally agree to topically practically identical substance, so they might be sensitive to stand-out types of datasets, and the forecast precision may likewise fluctuate with the circulations of datasets. For social suggestion, CTRSTE coordinates client rankings, thing substance and consider troupe into CTR, which is straightforward in the algorithmic statute. However, its portrayal usefulness is obliged on account of LDA model, and the dormant portrayal educated isn't constantly viable enough while the side certainties is scanty.

With the aid of assessment, CTRDAE utilizes DAE and LDA to shopper general portrayal and data exemplification individually, to spare you buyer relationship overfitting under the inadequate social individuals from the family circumstances. However, the content illustration ability of CTRDAE is equivalent to CTR, that's restricted because of subject matter modeling version. Although those works have stepped forward CTR in separate components by the use of either substance or informal community insights, an essential issue stays, i.e., how to correctly integrate article substance, client evaluations and person profiles/family members into CTR [29]. Unlike preceding CTR-primarily based recommendation techniques, this concept develops the propagative techniques of clients and devices using a neural erratic structure that allows this method to catch non-straight inactive portrayals of the two clients and items.

1.12 LEARNING MODELS IN DEEP LEARNING (DL)

1.12.1 SIMILARITY LEARNING

For a new person, figuring out historic facts of sufferers who're identical might support recover comparable recommendations for foreseeing the logical results of the newly affected person. In 2017 [1], mixed affected person comparability and medication closeness evaluation and introduced a contrasting brand proliferation technique to pick out the correct drug compelling for a distressed person. In exercise, distinctive doctors have distinctive realization of affected person similitude dependent on the points of interest. The use of doctor criticism as the supervision [9] introduced a regionally administered metric mastering (LSML) set of rules that attains a comprehensive Mahalanobis distance. For the reason that getting doctors' advice is intense and profoundly estimated in truth, Wang and Sun introduced a pitifully regulated patient similitude acing technique which best utilizes a little amount of supervision data given by the doctors.

1.12.2 PERSONALIZED HEALTHCARE [38]

As of late, the customized expectation in medicinal services projects gets a developing pastime from analysts. It plans to discover the remarkable qualities for individual sufferers, and perform focused on understanding specific forecasts, suggestions, and medications. The vast majority of the works implement customized prediction with the aid of matching scientific comparable sufferers. Authors completed a comparative take a look at worldwide, nearby, and customized modeling, and discovered that altered methods could receive higher overall performance across exceptional bioinformatics class duties.

The aforementioned techniques require the entry of every affected person as a vector. A conventional manner is to acquire Function vectors by means of the usage of the static facts of sufferers consisting of demographic, and facts records (e.g., sum, common, and so forth) within a positive time variety, as the patient illustration. However, these handmade characteristic vectors absolutely ignore the temporal family members throughout go to sequences. To represent the transient actualities, utilized a powerful programming set of guidelines to discover the surest close by arrangements of patient successions [27] advanced two answers for patient closeness contemplating, unaided, and regulated, the utilization of a CNN-based absolutely comparability coordinating structure; and established a second RNN for powerful fleeting coordinating of affected groupings to procure the similitude positioning.

In this segment, first, how to examine a powerful illustration for the longitudinal EHR facts was shown, introduced two techniques to degree the correspondence among pairs of patients. Using discovered equivalence statistics, two tasks were carried out for customized human services: infirmity expectation and patient grouping.

1.12.3 EXEMPLIFICATION LEARNING

1.12.3.1 FUNDAMENTAL ANNOTATIONS

Prosperity documentation of a patient consists of a progression of campaign details, the restorative canon are registered demonstrating the infection or therapy the patient endured or got. The canons can be delineated to the International Classification of Disease (ICD-9).1 It is suggested that all the stand-apart helpful canons from the EHR information as c1, c2. c|C| ∈C, where |C| is the measure of magnificent remedial canons. Expecting that there are N affected people, the n-th affected has various visits Tn. A patient pn can be spoken to by a grouping of visits represented as V1, V2, VTn. Each visit Vi is meant by a high dimensional twofold vector vi ∈ {0, 1}|C|, demonstrating whether Vi contains the canon cj or not.

1.12.4 SIMILARITY LEARNING

Contemplating the comparison between every pair of sufferers is the key advance for customized human services. There are two strategies to gauge the likeness among influenced individual vectors found from Section 1.12.3.1, SoftMax oriented absolutely structure and ternary misfortune system.

1.12.4.1 PREDICTIVE SIMILARITY LEARNING

The likeness among a couple of listing could be estimated with the guide of a bilinear separation: S = hi Mhj, wherein the coordinating lattice M ∈ Rm×m is symmetric. To make sure that the symmetric imperative of M, its miles decayed as M = LT L, where L ∈ Rl×m with l < m to make certain a low-position include.

A symmetric requirement was recalled for listing link and transfer influenced individual listing to avail a similitude vector to guarantee that the request for sufferer has no effect on the likeness score. Initially, convert hello there and hj into separate listing along with the estimation utilizing the framework.

From that point onward, H and S are linked and after that encouraged into a totally related SoftMax layer, to get a yield opportunity y' that takes the path of least resistance cost among 0 and 1. In addition, the floor reality y is set as 1 if two patients have the risk of building up the equivalent sickness, in some other case 0. The higher estimation of y' implies the higher likelihood that pi and pj contain position with a consistent category, or two patients have littler separation and are increasingly like one another. The model can be prepared from start to finish, and every one of the parameters are refreshed at the same time.

Triplet-Loss Metric Learning: Metric learning plans to become familiar with an appropriate separation metric for a specific errand, which is significant to the exhibition of numerous calculations. The possibility of metric learning is utilized to become familiar with the overall separation of sufferers. In the customary measurement method, a straight change L is utilized to delineate crude information into another dimension. Alternative measurement in that dimension can call more likely measure the overall separation of info occasions. The distance between instances x_i and x_j could be generated by applying the Euclidean distance in the alternative dimension.

In profound measurement method, the direct change L is supplanted by a neural system f to become familiar with the convoluted nonlinear connections between crude highlights. In this issue of patient similitude learning, this nonlinear change is found out through the CNN activity. Triplet loss [39] is used as the objective function which carries a hard and fast of triplets, in which each triplet has an anchor, a fantastic, and a poor instance. An effective pattern contains the identical magnificence content because the dependence with bad pattern may contain the distinctive class label.

The one-hot EHR lattice of patient pi is correlated to an implanting framework, and after that sustained into CNN to get a listing portrayal. pi+ and pi− distribute indistinguishable limits from pi. Pairwise separations could be determined depends on the listing portrayals, and ternary misfortune is utilized to refresh every one of the parameters, for example, the separation between stay pi and positive example p+i ought to be nearer than the separation among pi using certain arranged boundary. This measurement picking up learning of layer is expedited top of CNN that considers the listing delineation utilizing the contribution to compute separation among sufferers. The capacity is limited using returned engendering, and the majority of the parameters are forward-thinking at the same time. The educated separation metric demonstrates the comparability among influenced individual sets, with littler separation esteems for better closeness. The system of triplet-misfortune essentially based profound likeness acing is a conclusion to-stop becoming more acquainted with the system.

1.14 CONCLUSION

DL is assumed to be a subset of machine learning, which provides the architecture, algorithm, and methods that are inspired by the structure and function of the human brain. The main functionality of DL is that the designed system will learn and adapt by itself to new data and situation. DL requires a large volume of dataset for training and testing. Hence, DL is a suitable method to apply in most of the interdisciplinary areas such as biomedical engineering and health informatics since they produce huge volumes of data day by day in the healthcare system. In recent days, a huge volume of genetic information, RNA/DNA sequences, amino acid sequences, and other patient-related data are getting generated, which are to be processed effectively by using the DL approaches. This chapter provided a review of various DL techniques in the medical healthcare system for various applications, which include breast cancer analysis, lung tumor differentiation, voice pathology detection, current systems in e-healthcare. This review revealed that DL is found to be an effective method to deal with medical data to enhance performance.

KEYWORDS

- **AlexNet**
- **attention deficit hyperactivity disorder**
- **cancer prediction**
- **convolutional neural system**
- **deep learning**
- **similarity learning**

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