COMPUTATIONAL INTELLIGENCE AND MACHINE LEARNING APPROACHES IN BIOMEDICAL ENGINEERING AND HEALTHCARE SYSTEMS

Editors:

P. Naga Srinivasu

Norita Md Norwawi

Sheng Lung Peng

Azuraliza Abu Bakar

Bentham Books

Computational Intelligence and Machine Learning Approaches in Biomedical Engineering and Health Care Systems

Edited by

Parvathaneni Naga Srinivasu
Department of Computer Science and Engineering,
Prasad V. Potluri Siddartha Institute of Technology,
Vijayawada, India

Norita Md Norwawi
Faculty of Science and Technology Universiti Sains Islam
Malaysia,
Nailai, Malaysia

Sheng Lung Peng
National Dong Hwa University, Taiwan
Beijing Information Science and Technology University,
China
Ningxia Institute of Science and Technology, China
Mandsaur University, India

&

Azuraliza Abu Bakar
Center for Artificial Intelligence Technology Universiti
Kebangsaan,
Malaysia

Computational Intelligence and Machine Learning Approaches in Biomedical Engineering and Health Care Systems

Editors: Parvathaneni Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng & Azuraliza Abu Bakar

ISBN (Online): 978-1-68108-955-3

ISBN (Print): 978-1-68108-956-0

ISBN (Paperback): 978-1-68108-957-7

First published in 2022.

Bentham Science Publishers Pte. Ltd.
80 Robinson Road #02-00
Singapore 068898
Singapore
Email: subscriptions@benthamscience.net

CONTENTS

FOREWORD

Biomedical engineering and healthcare systems must transform using computational intelligence as a future idea to viewing it as a practical tool that can be used immediately. If machine learning plays a role in healthcare, a gradual approach is required. There is a great necessity to identify unique cases in which machine learning capabilities provide value to a particular technical application. This would be a regular process for developing analytics, artificial intelligence, and modeling techniques in clinical settings. Additionally, computational intelligence models may simplify physician usage of healthcare management systems by offering clinical decision assistance, automating imaging techniques, and incorporating telehealth technology. Health professionals are implementing machine intelligence-based frameworks and diagnostic tools to optimize the utility of such gathered data. Machine intelligence is essentially the potential of computers to mimic human cognition to rapidly extract data published by different datasets, allowing healthcare professionals to navigate vast quantities of data and conduct complex statistical analyses more efficiently and accurately.

Recently, technology like remote patient monitoring through the Internet of Things is mainly in demand. Machine learning is crucial in technologies like Healthcare Information Exchange through electronic healthcare record management and analytics. Emerging technologies like telemedicine and teleconsultation rely on machine learning for the effective treatment of patients. Such evolution has prompted researchers and healthcare service professionals to invest in application development to optimize their healthcare needs and improve patient health care. Advancement in innovative phone technology for disease identification and classification through machine learning models has paved a new dimension in the healthcare industry.

Advanced machine learning technologies like neural networks and deep learning models are extensively used in biomedical engineering and healthcare. Deep learning is a kind of technology that incorporates hidden layers of comparable functions into the network. It can gather insights from an enormous volume of healthcare records and diagnosis data. With light-weight neural network models, current transformation accelerators toward customized health care delivery will be feasible. The deep learning models have mainly influenced the health care domain and applications that need robust frameworks that can learn from sparsely labeled samples and deal with noisy and incorrect annotations. The frameworks are capable of adjusting continuously to novel information without losing prior knowledge.

In deep learning models, input is processed through a hierarchy of layers, with each successive layer informing its findings with the output from the preceding layer. Deep learning models may improve accuracy as more data is processed, basically by learning from past results to enhance their capacity to identify relationships and associations. Computational intelligence technologies improve efficiency and recognize valuable insights from massive volumes of complex medical imaging data through effective feature extraction techniques.

Emerging ecosystems in the biomedical engineering and healthcare industry will need to strike the right balance between doctors' and patients' usage and perceptions of machine intelligence. Researchers should design and implement hybrid models that include machine learning. It can be seen as a supplement to or accelerator for medical knowledge but not as a substitute for physicians. While machine intelligence should be utilized and viewed as assisting in diagnosis, treatment planning, and risk factor identification, doctors should maintain ultimate responsibility for the patient's care. The hybrid approach will increase healthcare professionals' use of machine intelligence while also providing quantifiable and sustainable benefits in health outcomes.

Prof. Dr. Hiroyuki Lida
Vice-President, Professor,
School of Information Science,
Entertainment Technology Area,
Japan Advanced Institute of Science and Technology,
Japan

PREFACE

Biomedical engineering and healthcare systems are rapidly developing through computational intelligence and machine learning-based techniques for smart medical diagnosis and analysis. Biomedical engineering disciplines have been greatly assisted by advancements in deep learning and soft computing techniques, which lead to improved accuracy in diagnosis, smart treatment, and therapy. Moreover, with multidisciplinary strategies in biomedical research, the physician can deal with critical health issues like cardiac-related issues, high blood pressure, stroke, and liver diseases. Medical illnesses can be treated effectively by recognizing them in much earlier stages using sophisticated medical imaging technologies, including X-Ray, CT, MRI, PET scan, and Electronic Healthcare Records (EHR). Computational intelligence models are extensively used in several phases in medical imaging and medical data analysis, which include the initial rendering of images, image enhancement, complex hidden extraction of features, the segmentation of images, the post-processing of images for the identification of abnormalities, and the incorporation of evolutionary computations. EHRs are analyzed through machine learning techniques, and patients are regularly monitored to assist them in a better lifestyle that would reduce the chances of future illness.

Computational intelligence is the study, design, prototype, implementation, and development of computational paradigms inspired by biological and semantic principles. The intelligent computational models include various advanced technologies like Neural Networks, Ensemble models, Bioinspired models, evolutionary models, swarm intelligence, fuzzy technology, and data-centric knowledge-driven models. The computational intelligence models are proven to be robust in precisely predicting the future illness and diagnosis of the disease at the earlier stages of the abnormality that will assist the physician in providing better treatment and guide the individual in better living habits and lifestyle that are less likely to result in predicted future illness. Artificial intelligence and machine learning would keep improving in the healthcare sector, improving illness prevention and diagnosis, extracting deeper insight from data from many clinical trials, and assisting in developing individualized medicines.

This book encompasses path-breaking and remarkable contributions in the field of computer-aided diagnosis and biomedical analytics that can benefit a wide range of biomedical engineering disciplines, including medical imaging to computational medicine, smart diagnosis, healthcare informatics, ambient assisted living, managing and monitoring wearable medical devices, and even effective systems engineering. The book covers a broad range of machine learning techniques and deep neural network-based methodologies in the healthcare domain. The next horizon in image analysis, multimodal imaging mechanisms, assistive technology, telemedicine, and interdisciplinary applications is emphasized practically.

Parvathaneni Naga Srinivasu
Department of Computer Science and Engineering,
Prasad V. Potluri Siddartha Institute of Technology,
Vijayawada, India

Norita Md Norwawi
Faculty of Science and Technology
Universiti Sains Islam Malaysia
Nailai, Malaysia

Sheng Lung Peng
Department of Creative Technologies and Product Design
National Taipei University of Business
Taiwan

&

Azuraliza Abu Bakar
Center for Artificial Intelligence Technology, Universiti Kebangsaan
Malaysia

List of Contributors

B. Hemapriya	Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India
B.Roja Reddy	Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India
B.S. Maya	Bangalore Institute of Technology, Bangalore, Karnataka, India
B.S. Premananda	Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India
Bhimavarapu Usharani	Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India
Fauziah Abdul Wahid	Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
Ganapati Bhavana	ANITS, India
Harshavardhini Parthiban	Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India
Jackson Durairaj Selvan Christyraj	Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India
Johnson Retnaraj Samuel Selvan Christyraj	Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India
K. Abirami	Department of Computer Science and Engineering, Fatima Michael College of Engineering and Technology, Madurai, Tamil Nadu 625020, India
K. Aswarth	Department of Computer Science & Engineering, VR Siddhartha Engineering College, Vijayawada, India
Karthikeyan Subbiahanadar Chelladurai	Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India
Mohd Helmy Abd Wahab	Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia
Muhammad Mahadi Abdul Jamil	Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia

Noor Anita Khairi	Farmasi Aiman, Sri Ehsan Pharmahealth, No 25 Jalan Besar Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
Norita Md Norwawi	Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
P. Deepalakshmi	Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamilnadu - 626126, India
P. Prajwal	Bangalore Institute of Technology, Bangalore, Karnataka, India
P.N. Revanth	Bangalore Institute of Technology, Bangalore, Karnataka, India
Pratik R Pailwan	Bangalore Institute of Technology, Bangalore, Karnataka, India
Radzi Ambar	Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia
Rafidah Hanim Mokhtar	Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
Rahul Kumar Gupta	Bangalore Institute of Technology, Bangalore, Karnataka, India
Ranjitha Vijay Anand	Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India
Reddy K. Viswavardhan	Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India
Roesnita Ismail	Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
S. Naganandhini	Department of Computer Science, G.T. N Arts College, Tamil Nadu, India
S. Vasavi	Department of Computer Science & Engineering, VR Siddhartha Engineering College, Vijayawada, India
Shanmuk Srinivas Amiripalli	Department of Computer Science and Engineering, GITAM Institute of Technology, GITAM Deemed to be University, Visakhapatnam, AP, India
Sheik Khadar Ahmad Manoj	Raghu Engineering College, Visakhapatnam, India
Siti Aishah Muhammed Suzuki	Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia
Sruthi Mohan	Department of M.Sc. Computer Science, G.T. N Arts College, Tamil Nadu, India
T. Asha	Bangalore Institute of Technology, Bangalore, Karnataka, India
Y.V Nagesh Meesala	Raghu Engineering College, Visakhapatnam, India

Zakarya Farea Shaaf Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia

CHAPTER 1

Convolutional Neural Network for Denoising Left Ventricle Magnetic Resonance Images

Zakarya Farea Shaaf[1], **Muhammad Mahadi Abdul Jamil**[1,*], **Radzi Ambar**[1] and **Mohd Helmy Abd Wahab**[1]

[1] *Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia*

Abstract: Medical image processing is critical in disease detection and prediction. For example, they locate lesions and measure an organ's morphological structures. Currently, cardiac magnetic resonance imaging (CMRI) plays an essential role in cardiac motion tracking and analyzing regional and global heart functions with high accuracy and reproducibility. Cardiac MRI datasets are images taken during the heart's cardiac cycles. These datasets require expert labeling to accurately recognize features and train neural networks to predict cardiac disease. Any erroneous prediction caused by image impairment will impact patients' diagnostic decisions. As a result, image preprocessing is used, including enhancement tools such as filtering and denoising. This paper introduces a denoising algorithm that uses a convolution neural network (CNN) to delineate left ventricle (LV) contours (endocardium and epicardium borders) from MRI images. With only a small amount of training data from the EMIDEC database, this network performs well for MRI image denoising.

Keywords: Deep learning, Image denoising, Image processing, Left ventricle, Neural network.

INTRODUCTION

Medical image analysis in radiology is critical in the healthcare system for detecting and diagnosing the disease at an early stage. Computed tomography (CT), ultrasound (US), positron emission tomography (PET), and Magnetic resonance imaging (MRI) are the most commonly used medical imaging tools. Because of its advantages over other imaging techniques, the MRI tool is widely used in clinical imaging. The MRI imaging technique uses contrast to create

* **Corresponding author Muhammad Mahadi Abdul Jamil:** Biomedical Engineering Modelling and Simulation Research Group, Department Of Electronic Engineering, Faculty of Electrical And Electronic Engineering, Universiti Tun Hussein Onn Malaysia, 86400 Parit Raja, Batu Pahat, Johor, Malaysia; E-mail: mahadi@uthm.edu.my

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

diagnostic images by combining many pulse sequences. MRI also has distinct parameters such as a strong magnetic field, imaging planes, and dimensions [1]. Furthermore, cardiac MRI is one of the most effective techniques for estimating clinical parameters such as myocardium mass, ventricular volumes, stroke volume, and ejection fraction [2].

Medical image quality is still noised due to the imaging condition process and various patients, resulting in a lower resolution. As a result, improving image quality is critical for disease detection and prediction, particularly in the early stages of cardiovascular disease. There are two important factors. Image reconstruction, which is based on an algorithm that creates 2D and 3D images of an object, and image processing, which uses algorithms to improve image quality, remove noise, and detect regions of interest (ROIs), are both used in medical imaging [3, 4].

Many methods for denoising MRI images have been proposed in the literature, including spatial domain approaches, statistical techniques, transform domain methods, and filtering techniques [5]. Currently, a conventional denoising method, such as the block matching 3D (BM3D) filter, is being introduced [6]. The BM4D technique was developed by Foi *et al*. [7], who extended the BM3D filter to volumetric data. However, neither the BM3D nor the BM4D filters can be applied to varying image contents [8]. Several novel learning methods, such as neural network-based techniques [9 - 11], have recently been proposed to over come this limitation. With the current development in deep learning architecture, several models, including convolutional denoising autoencoder (CNN-DAE) [12], residual learning (RL) of deep convolutional neural network (DnCNN) [13], and generative adversarial network (GAN), have shown promising results for medical image denoising.

DENOISING MRI IMAGES USING CONVOLUTIONAL NEURAL NETWORKS

A significant amount of work has been done in the medical image analysis field to denoise images. Denoising is essential in image processing to improve segmentation and classification accuracy. Rician and Gaussian noise is the most common types of noise in MRI images [14]. An efficient algorithm for denoising MR images aims to minimize noise while retaining the image's useful features. The most important metric in processing a diagnostic image is edge preservation. As a result, the denoising algorithms must be robust to reduce noise effectively.

For denoising MRI images, various filters are proposed. A median filter [15] is a non-linear low pass filter that reduces unpredictable noise. Weiner filters [16] are used to reduce the gap between filtered and preferred output. The Gaussian filter [17] is used to remove blur noise. In contrast, the mean filter [18] replaces each pixel with pixels' calculated mean to reduce the intensity variation between two pixels using a convolution process. The wavelet filter uses an energy compaction feature to denoise the image. Also, filtering MRI images can be done through noise reduction, re-sampling, and interpolation. The selection of the applied filter is based on the type and amount of noise.

Linear and non-linear image filters are the two types of image filters. Linear filters have been used to eliminate spatial noise but without retaining image textures [19]. Mean filters have been proposed for reducing Gaussian noise, but they over-smooth images with high noise. A Wiener filter was used to address this issue, but it still blurs sharp edges [20]. Non-linear filters such as median and weighted median filters are used to eliminate noise.

Convolutional neural networks (CNNs) have recently demonstrated remarkable performance in image processing tasks such as image denoising [21] and image super-resolution [22]. Zhang *et al*. [21] created a noise removal model called fast flexible denoising CNN (FFDNet) that can handle white Gaussian noise. Recently, Jiang *et al*. [23] used the VGG [24] network with ten layers of CNN for MRI denoising. Tripathi and Bag [25] developed a CNN for MRI denoising, with the network employing an encoder-decoder structure to retain important image features while excluding unwanted ones. Furthermore, several methods for denoising medical images using CNN have recently been developed, as shown in Table **1**. Also, the review paper [26] summarized numerous methods for using CNN in image filtering.

Table 1. Previous related works for denoising medical images using CNNs.

References	Methods	Applications	Specification
Wang *et al*. [27]	CNN	Gaussian image denoising	Image denoising using CNN with dilated convolutions and BN
Jiang *et al*. [23]	CNN	Gaussian image denoising	Multi-channel CNN model
Abbasi *et al*. [28]	NN	3D MRI image denoising	Generative adversarial network (GAN) and residual learning (RL)
Tian *et al*. [29]	CNN	Real noisy image, Gaussian and blind image denoising	A sparse method with two CNNs
Xie *et al*. [30]	CNN	Denoising arterial spin labeling perfusion MRI	Dilated convolution and residual blocks
Zhang *et al*. [13]	CNN	Gaussian image denoising	Residual learning with CNN
Jifara *et al*. [31]	CNN	Medical image restoration	U-Net for image restoration

CHAPTER 2

Early Diabetic Retinopathy Detection Using Elevated Continuous Particle Swarm Optimization Clustering With Raspberry PI

Bhimavarapu Usharani[1,*]

[1] *Department of Computer Science and Engineering Koneru Lakshmaiah Education Foundation Vaddeswaram, AP, India*

Abstract: Diabetic retinopathy is a disease in an eye caused due to the diabetic condition present in the person, resulting in blindness. Early diagnosis of the disease prevents the progression of blindness. Microaneurysms are the significant symptoms of the early detection of diabetic retinopathy and are initiated by dilating the thin blood vessels. Microaneurysms are red lesions, which may be round and sometimes irregular in shape. Generally, microaneurysms appear near the macula or close to the blood vessel. The present study concentrates on detecting microaneurysms to detect diabetic retinopathy in the early stage. This chapter utilizes the Particle Swarm Optimization (PSO) algorithm to effectively segment the microaneurysms. The segmented microaneurysm is analyzed using the measures of Entropy, Skewness, and Kurtosis. The elevated PSO clustering gives high performance irrespective of image contrast. The elevated continuous PSO clustering successfully detects microaneurysms and helps diagnose diabetic retinopathy in the early stage in an efficient way. This work uses digital image processing techniques and mainly concentrates on the effective detection of microaneurysms. The results proved that the proposed approach improves performance in the early detection of diabetic retinopathy.

Keywords: Diabetic retinopathy, Microaneurysms, Particle Swarm Optimization, PSO Clustering, Raspberry PI, *etc*.

INTRODUCTION

Diabetes is a problem that arises because of the glitch of the pancreas, which impedes the overall recovery of patients in certain illnesses. Diabetes influences the fundamental organs of the body like the eye [1], heart [2], kidney [3], nerves [4] and so on. The resulting segments talk about a concise outline of diabetes and its effect on various human body organs.

[*] **Corresponding authors Bhimavarapu Usharani:** Department of Computer Science and Engineering Koneru Lakshmaiah Education Foundation Vaddeswaram, AP, India; E-mail: ushafdp1122@gmail.com

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

Heart

The studies based on distinguished cardiovascular breakdown caused due to diabetes are expounded and affirmed [5, 6]. Around 19% to 30% of diabetic patients may have cardiovascular breakdown [7]. A cardiovascular breakdown in diabetic-influenced people is more likely than in nondiabetic patients. The chance of cardiovascular breakdown in type-1 diabetes is over 30% more, and type-2 diabetes is more than 10% contrasted with the risk of cardiovascular breakdown because of teething or other coronary infections [8].

Kidney

Diabetes likewise harms the kidney prompting a constant condition called diabetic nephropathy [9]. Diabetes assumes a critical part and a quicker movement of diabetic nephropathy. Diabetic nephropathy occurs in about 20% to 40% of diabetic patients [10]. Kidney illnesses with type 1 diabetes were more than 12.6% [11] and, with type2 diabetes, it was more than 2.0% [12].

Eye

Diabetes influences the retina part of the eye [13]. Diabetes is the essential driver of visual impairment [14], and practically 80% of the deficiency of sight is because of diabetes [15]. Diabetic retinopathy is the point at which the retina of the diabetic patient was harmed because the blood spills from the retina's veins. Around 75% of individuals experiencing diabetes will have diabetic retinopathy [16]. The diabetic retinopathy is ordered as 2 stages: (a) Non-Proliferative Diabetic Retinopathy (NPDR) (b) Proliferative Diabetic Retinopathy (PDR) [17]. Table **1** presents the seriousness levels of diabetic retinopathy [1].

Table 1. Diabetic Retinopathy (DR) Severity Levels [18-20].

Severity Level	Description
No NPDR	No Anomalies
Mild NPDR	Microaneurysms only
Moderate NPDR	More Microaneurysms and Exudates
Severe NPDR	Intraretinal Microvascular anomalies, Intraretinal hemorrhage, abnormal blood vessel growth
PDR	Neovascularisation, preretinal hemorrhage
Gestational DR	The newborn child has type-II diabetes

Detection of diabetic retinopathy is vital at the initial stage to avert loss of sight with the correct treatment. The initial hint of diabetic retinopathy is red grazes called Microaneurysms [21]. Microaneurysms are the first sign of diabetic retinopathy.

In this chapter, the pivotal focus is on the concept of detecting diabetic retinopathy in the early stage to lessen the possibility of vision loss. In the pre-processing phase, the image is resized to 250x250 pixels. Then, the resized image was subjected to contrast enhancement by utilizing the Contrast Limited Adaptive Histogram Equalization algorithm to identify the lesions in the image. In the next step, we perform the segmentation to extract useful lesion information from the image. Then, feature extraction is applied to distinguish the candidate regions as microaneurysms or non-microaneurysm. This work utilized the Particle Swarm Optimization clustering variants model applied to diabetic retinopathy databases such as MESSIDOR, DIARETDBO and E-OPTHA.

The contribution is summarized as follows:

- To diagnose the early detection of the non-proliferative diabetic retinopathy, utilizing the PSO clustering for the segmentation of fundus images improves the accuracy of the non-proliferative diabetic retinopathy with raspberry PI.
- They performed pre-processing to improve the image's contrast by applying image enhancement techniques.
- Elevated continuous Particle Swarm Optimization clustering algorithms are applied in the segmentation phase.
- Seven different features are extracted to distinguish the candidate regions as Microaneurysms or non- Microaneurysms.
- Extensive Experiments were conducted using MESSIDOR, DIARETDBO, E-OPTHA diabetic retinopathy datasets.

The rest of the paper is organized as follows. Section 2 gives an overview of the Particle Swarm Optimization clustering, fitness measures, and Particle Swarm Optimization terminology. Section 3 summarizes the literature survey of the contributions made by several researchers in the early detection of diabetic retinopathy and microaneurysms detection. The proposed technology is discussed in Section 4. Finally, the paper concludes with the conclusion section.

BACKGROUND

Particle Swarm Optimization Clustering

Clustering is an innovation that bunches comparative information focuses into a

CHAPTER 3

E-Health System and Telemedicine: An Overview and its Applications in Health Care and Medicine

Ranjitha Vijay Anand[1], Harshavardhini Parthiban[1], Karthikeyan Subbiahanadar Chelladurai[1], Jackson Durairaj Selvan Christyraj[1,*] and Johnson Retnaraj Samuel Selvan Christyraj[1,*]

[1] *Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India*

Abstract: E-Health and telemedicine deliver health care and health-related services using medical informatics, telecommunication, and exchange of health care data across distant places. This is one small leap of information technology that allows all to access good health care. The key fact of telemedicine is electronic signals to transfer knowledge from one computer to another through videoconferencing among health care experts to provide better treatment and care. Since many indoor and outdoor patients require referral for specialized care in remote areas, telemedicine can deliver a better solution. In addition to that, it also provides quality, low-cost health care to the poorest individuals and the rural population, thereby it bridges the rural-urban health divide. It will help avoid unnecessary transportation and the potential to chop back health care prices by reducing the burden of ill health, the danger of complications, hospitalizations, continual events, and premature death and boosting the quality of life. Through this, the public can easily get medical consultation, diagnosis, and monitoring of their health records to get proper treatment, and also it is possible to get robotic surgery. Telemedicine and E-health alternatives are widely popularized in COVID-19 pandemics and will aid future public health crisis management. However, there is a need to educate and make awareness among the people, develop policies and infrastructure in the E-health system, and telemedicine to provide equal health care access to all and improve public health and medical care. Overall, this chapter discusses detailed information about the E-health system and telemedicine and its applications in the healthcare system.

Keywords: E-health, Health Care, Information technology, Remote areas, Telemedicine, Treatment, Video-conference.

* **Corresponding authors Jackson Durairaj Selvan Christyraj and Johnson Retnaraj Samuel Selvan Christyraj:** Regeneration and Stem Cell Biology Lab, Centre for Molecular and Nanomedical Sciences, International Research Centre, Sathyabama Institute of Science & Technology (Deemed to be University), Chennai, Tamilnadu, India; E-mails: jacksondurairaj@sathyabama.ac.in & johnnbt@sathyabama.ac.in

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

INTRODUCTION

E-health system uses modern information technology and electronic communication in the health sector [1]. It plays a wide role in electronic health records, electronic medication overview, and telemedicine-related services (Fig. **1**). An E-health system helps store clinical data in an electronic format where it is digitally stored, transmitted, and retrieved electrically for various health-related purposes. It can be accessed whenever needed for different clinicians from different places. One of the components is telemedicine, which plays a major role in delivering health care. This web-based health care system helps both patients and clinicians interact face-to-face through real-time video conferencing and the exchange of patients' medical history for enhanced quality in diagnosis and treatment.

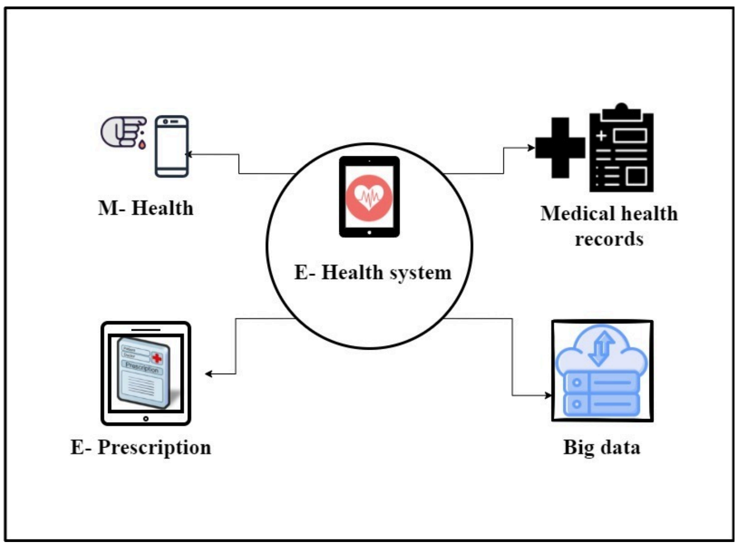

Fig. (1). Illustrates the complete framework of the E-health system, allowing patients and consumers to easily communicate with health care professionals over the internet. E-health system uses integrated telehealth data and stores it in medical health records for various health care applications.

Besides, E-health provides advantages in improving medical care efficacy, quality, privacy, reduced transportation, reduced medical errors, convenience, and cost-effectiveness.

E-Health

E-Health system integrates electronic communication, clinical data, information storage, and management. This E-Health system uses more than data, information technologies, and electronic communication in the health sector where the clinical data is digitally stored, transmitted, retrieved directly for various purposes like clinical, educational, administrative purpose, health literature, health surveillance, *etc.*This informative and interactive method provides easy accessibility, higher effectiveness, and increased quality of life. Efficiency enhances quality, evidence-based scientific evaluation, empowerment, encouragement, education, enabling, extending, ethics, and equity are the ten e's in the electronic healthcare system. It provides information for patients or clinicians *via* the internet or medical databases like PubMed. Importantly, communication in E-Health is the exchange of data and information between patient to doctor, doctor's interaction between communication partners involved in telesurgery, electronic handling of the complete treatment process, and integration.

This E-Health system provides the most significant benefits for public health, clinicians, healthcare workers, *etc.*This provides the higher efficacy through electronic medical records, virtual healthcare teams, video conferencing, consumer health informatics, health knowledge virtual healthcare teams, video conferencing, consumer health informatics, health knowledge management, which play a major role in telehealth, telemedicine, and telecare as shown in Fig. (**2**).

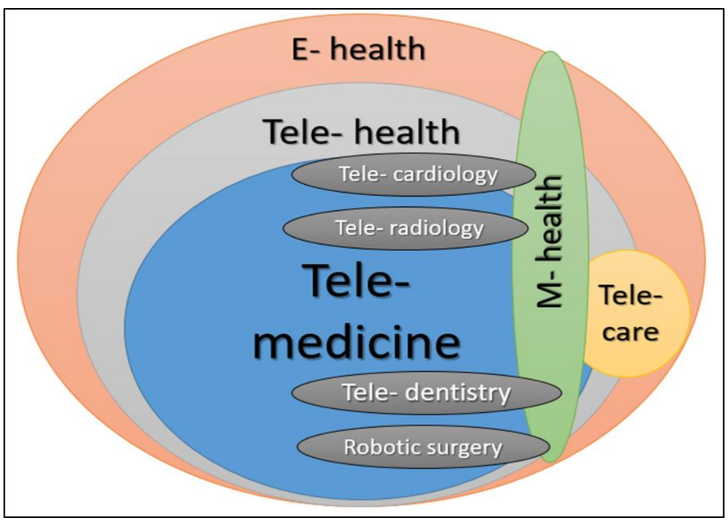

Fig. (2). Illustration of the application of E-health system in medicine (telecardiology, teleradiology, telepsychiatry). Telehealth, telemedicine, and telecare are part of it.

Electronic Health System

An electronic health system, which is also known as E-shealth care includes electronic health records (EHR), Electronic medical records (EMR), software systems like EPIC uses digital technologies and telecommunications like computers, the internet, mobile devices, m-health applications to ease health

CHAPTER 4

Fuzzy Logic Implementation in Patient Monitoring System for Lymphatic Treatment of Leg Pain

Fauziah Abdul Wahid[1], **Noor Anita Khairi**[2], **Siti Aishah Muhammed Suzuki**[1,*], **Rafidah Hanim Mokhtar**[1], **Norita Md Norwawi**[1] and **Roesnita Ismail**[1]

[1] *Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia*

[2] *Farmasi Aiman, Sri Ehsan Pharmahealth, No 25 Jalan Besar Nilai, 71800 Nilai, Negeri Sembilan, Malaysia*

Abstract: Leg pain occurs in many people nowadays due to today's lifestyle. This leads to various treatments for leg pain with an unprecedented monitoring system. However, there are some issues regarding the existing leg pain treatments concerning a suitable monitoring procedure. The first issue is the treatment method, where most treatments for leg pain use compression. Still, they are costly, time-consuming, and cumbersome, requiring patients to visit hospitals regularly and affecting patients' compliance to continue with treatments. The second issue is the treatment period for leg pain within a short time frame, whereby it is difficult to see the major effect of a certain treatment. The third issue is the lack of a system to monitor patient's rehabilitation progress to increase patients' confidence to continue treatment consistently to cure their leg pain. Therefore, a patient monitoring system needs to be developed to cover existing research issues under the main area of health informatics. This system will apply the double-loop feedback theory that includes the agile framework to continue the process. The double-loop framework will ensure all the problems and preferred modifications will undergo a simultaneous fixation once each development segment is completed. This patient monitoring system is a computational intelligence system that focuses on fuzzy logic, producing a decision-making outcome based on collected data. This process aims to perform a valid treatment analysis as accurately as possible. Its development is significant for the national agenda as it falls under the national research priority area of health and medicine. The expected outcome would be introducing a computational intelligence inpatient monitoring system for lymphatic treatment of leg pain based on double-loop feedback theory.

* **Corresponding author Siti Aishah Muhammed Suzuki:** Department of Information Security and Assurance, Faculty of Science and Technology, Universiti Sains Islam Malaysia (USIM), Bandar Baru Nilai, 71800 Nilai, Negeri Sembilan, Malaysia; E-mail: baishah.fst@gmail.com

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

Keywords: Computational intelligence, Double-loop, E-health, Lymphatic treatment, Patient-monitoring system.

INTRODUCTION

Leg pain occurs in many people of all ages, leading them to experience years of pain. The research conducted is to counter the upcoming problems from previous treatment monitoring through a computational intelligence system. Leg pain occurs due to today's lifestyle. As a result, numerous leg pain therapies have been developed. However, there are some limitations to the existing leg pain treatment.

The issue is the short treatment period for leg pain. For example, a study [1] tested lymphedema in the patient leg with inelastic multicomponent compression (ICM) bandages for 2 hours and another 24 hours with adjustable compression wraps (ACW) to obtain results for analysis. Meanwhile, patients with leg ulcers using sequential pneumatic compression (SPC) for a single treatment before generating results using near-infrared fluorescence lymphatic imaging (NIRFLI) for non-invasive, real-time assessment of lymphatic contribution, were tested [2].

The next issue is the lack of interactive converge-based smart healthcare service as a patient remote monitoring system. One example of an intelligent healthcare service for leg pain is a self-management program called telerehabilitation (TR) for chronic lower limb swelling and mobility problems. For this purpose, a viable method has been developed in the United States of America (USA) [3]. In this regard, establishing a method for providing smart healthcare using convergence technologies is urgently required. Novel methods, architectures, algorithms, and interactions of multimedia technologies and business resources should all be considered. Telemedicine, e-health, and home care practices are some fields that need attention [4, 5]. More studies need to be conducted to determine the medical community and patients' acceptance of remote patient monitoring technology-based methods. Furthermore, there is still a lack of a patient monitoring system with double-loop feedback theory, where this approach is one of the successful methods in human monitoring. Another study has tested a double feedback loop in the education process, and it was a success [6].

The research questions for this project are how to design and develop a patient monitoring system based on a double-loop feedback theory and how to evaluate the proposed model for leg pain resolution through the patient monitoring system. Hence, the main research objective is to propose and develop a patient monitoring system based on the double-loop feedback theory and evaluate the lymphatic treatment model for leg pain resolution through the patient monitoring system.

Therefore, this research covers all two gaps mentioned above: the treatment period and the patient monitoring system. All these issues are covered under health informatics. This system is compulsory to assist patients in resolving leg pain using the lymphatic treatment model. This study is essential for the national agenda since it falls under the Health and Medicine national research priority sector. The expected outcome of this study is a new idea for a systemic patient management system based on the double-loop feedback theory for the lymphatic treatment of leg pain.

LITERATURE REVIEW

Definition of Computational Intelligence

According to another study [7], computational intelligence is a subset of machine learning techniques in which algorithms are designed to copy human information processing and reasoning processes for complex and unknown data sources. A study [8] describes that it is not limited to rule-following but includes rule-making. Computer intelligence techniques are a set of nature-inspired computational methodologies and techniques designed to solve complex real-world data-driven problems. These are used when mathematical and traditional modeling fails due to high complexity, uncertainty, and computational complexity. Fuzzy Logic (FL), Evolutionary Algorithms (EA), and Artificial Neural Networks (ANN) are the three main CI methods that have been developed to address this growing class of real-world problems. The fuzzy logic approach is the tolerable framework for developing the process in this system. It is a well-known method for dealing with ambiguous and imprecise data. Fuzzy logic is a method for approximating reasoning, qualitative modeling data, and adaptive control.

Definition of Lymphatic System

The lymph system is a network of lymph vessels, organs, and specialized cells throughout the body. It is an essential part of the body's defense against invading microorganisms. The lymphatic system, which works in tandem with the cardiovascular system to move a fluid called lymph throughout the body, is a lesser-known component of the circulatory system [9]. It has been reported that the lymphatic system plays an important role in the body's disease protection.

Lymphatic Treatment for Leg Pain

There are many causes of leg pain, but the focus is on lymphatic system treatment. Various research studies on leg pain treatment have reported lymphatic system involvement. However, all these treatments involve cost and the need to

CHAPTER 5

Safe Distance and Face Mask Detection using OpenCV and MobileNetV2

B.S. Maya[1,*], T. Asha[1], P. Prajwal[1], P.N. Revanth[1], Pratik R Pailwan[1] and **Rahul Kumar Gupta[1]**

[1] *Bangalore Institute of Technology, Bangalore, Karnataka, India*

Abstract: The COVID-19 epidemic affects humans irrespective of race, religion, standing, and caste. It has affected more than 20 million people worldwide. Wearing face masks and taking public safety measures are two advanced safety measures that need to be taken in open areas to prevent the spread of the disease. To create a secure environment that contributes to public safety, we propose a computer-based method that focuses on automatic real-time surveillance to identify safe general distance and face masks in public places using a model to monitor movement and detect camera violations. We achieve 97.6% specificity with the help of OpenCV and MobileNetV2 strategies.

Keywords: Coronavirus, Covid-19, Deep learning, Face-mask-detection, MobileNetV2, OpenCV, Safe-distancing, Transfer learning, YOLO-V3.

INTRODUCTION

It is believed that the novel coronavirus originated from bats in Wuhan, China, on the 17th of November 2019 and spread from one country to another in no time. The prevalent symptoms of COVID-19 are fever, tiredness, dry cough, anosmia, sore throat, headache, *etc*. This virus has affected the world due to its severity and adverse effects on humans [1]. For a person having mild symptoms, the recovery time is a fortnight. The recovery period for patients with critical symptoms depends on the severity. It is advisable for a person to stay quarantined or be in self-isolation if affected by coronavirus. RTPCR is a standard method that is currently being implemented to detect the presence of the virus in an individual's body.

* **Corresponding author Maya B S:** Bangalore Institute of Technology, Bangalore, Karnataka, India; E-mail: mayabs@bit-bangalore.edu.in

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

In December 2019, the deadly coronavirus 2, a modern preventable disease, infected about 8,612 people in China. Coronavirus was declared a global pandemic worldwide, named COVID-19. According to research, the current COVID-19 explosion affected more than 14,028,753 people. It affected more than 562,549 individuals in more than 180 countries worldwide, carrying about a 3.6% mortality rate, which is less than 2% of the flu. Now, the WHO recommends that people wear face masks to maintain the strategic distance from infection and a small community distance of 2m [2] should be kept between individuals to contain the spread of the virus. In addition, many benefit providers require customers to wear masks and follow the safe public distance. Since then, face detection and secure public-level testing have become an important computer science concept [3] to help the international community. This chapter shows how to anticipate the spread of the disease by looking in real-time if a person takes a strong social position and wears masks in public places.

COVID-19 has significantly affected the lives of individuals and their families. The spread of the COVID-19 [4] virus and the subsequent massive closure worldwide have created an alarming situation. We must play our part to prevent the spread of coronavirus. Studies have shown that maintaining a social distance between colleagues and wearing face masks compelled them to reduce this risk. As a result, we have developed plans that may test these activities by providing photo or video feeds.

The face mask detector system presents three classification classes: if a person is wearing a mask properly, wearing it improperly, or not wearing a mask. First, we are implementing our model with still image datasets, and secondly, we are using the live video streams shown in Fig. (**1**). Previously, binary classification [5] has been performed to detect face masks. We use a three-class classification [6], which is not common. A Retina face mask has been proposed by Jiang [7], which uses the models like ResNet and MobileNet. Wang [8] has made a face mask-related project by providing three samples of masked face datasets, which comprise MFDD, RMFRD, and SMFRD. G. Jignesh Chowdary and his team, in their research [9] have demonstrated a method using transfer learning to detect face masks.

To comply with the Safe Distancing constraint, governments adopt many restrictions over the minimum interpersonal distance of at least 2 meters between people. To this end, a few studies [10, 11] rely on Visual Social Distancing to analyze the proximal behavior of people, the VSD problem, which automatically detects the interpersonal distance from an image.

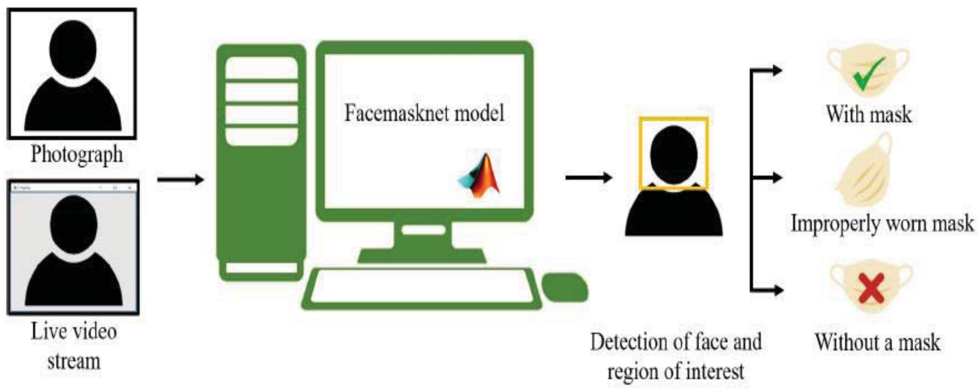

Fig. (1). Image or live video stream for Facemasknet detection model. Classification of an image occurs as with a mask, improperly worn mask, or without a mask.

This chapter incorporates a lightweight neural arrange MobileNetV2 [12, 13] with a transfer learning strategy to achieve the adjustment of asset impediments and recognition precision so that it can be used on real-time video surveillance to monitor public places to identify if people are wearing a face mask and keeping up secure social distancing. Our solution employments neural organizing models to analyze video streams utilizing OpenCV and MobileNet V2.

We blend the approach of modern-day deep learning and classic projective geometry strategies, which do not, as it were, makes a difference in meeting the real-time prerequisites but, moreover, keep tall expectation precision. In case the individual is recognized as not taking after the covid-19 security rules, violation cautions will be sent to police for taking encouraging activity. It permits mechanizing the arrangement, implements the wearing of the mask, and takes after the rules of social distancing.

The rest of the paper is divided into sections and is as follows. Section 2 deals with the literature review of related works, and Section 3 describes the dataset used to develop the model. Section 4 describes the proposed architecture. In section 5, we discuss the proposed methodology. Section 6 presents the experimental analysis of the proposed model. Finally, Section 7 tells about the conclusion and future work that can be taken up to improve the model.

LITERATURE REVIEW

S. Ge and co-workers [14] proposed a model using LLE-CNNs (Locally Linear Embedding - Convolutional Neural Network) for masked face detection, detecting masked faces in different orientations. The model detects masked faces in

CHAPTER 6

Performance Evaluation of ML Algorithms for Disease Prediction Using DWT and EMD Techniques

Reddy K. Viswavardhan[1,*], **B. Hemapriya**[1], **B. Roja Reddy**[1] and **B.S. Premananda**[1]

[1] *Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India*

Abstract: Information and communication technology usage in the healthcare sector is not perceptible due to various challenges with increased healthcare needs. With the outburst of COVID-19, when the different countries announced lockdown and social distancing rules, it is crucial to predict a person's symptoms, which will help in the early diagnosis. In such situations, there is a tremendous growth seen in the usage of various technologies, such as remote health monitoring, Wireless Body Area Networks (WBANs), Machine Learning (ML), and Decision Support system (DSS). Hence, the chapter focuses on detecting diseases and associated symptoms using various ML algorithms. A total of 3073 patient data (heartbeat, snore, and body temperature) has been collected. The collected data were preprocessed to remove empty cells and zero values by replacing the mean of the cells. Later, the extracted features were used in Empirical Mode Decomposition (EWD) and Discrete Wavelet Transformation (DWT). Then, the optimized algorithms with the threshold values were identified by consulting doctors for accurate disease prediction. With the testing performance of various ML algorithms, such as Decision Tree Classifier (DTC), K-Nearest Neighbor (KNN), Gradient Descent (SGD), Naive Bayes (NB), Multilayer perceptron (MLP), Support Vector Machine (SVM), and Random Forest (RF), was compared. Performance evaluation parameters are accuracy, precision, F1 score, and recall. The results showed an average of 100% accuracy with SGD and SVM with DWT, whereas EMD, SVM, and MLP outperformed the state-of-the-art algorithms with 99.83% accuracy.

Keywords: Classification, Disease prediction performance, Feature extraction, Preprocessing, Threshold, Wireless Body Area Networks (WBANs).

* **Corresponding authors Viswavardhan Reddy K.:** Department of Electronics and Telecommunication Engineering, RV College of Engineering, Bengaluru, India ; E-mail: viswavardhank@rvce.edu.in

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

INTRODUCTION

With the continuous increase in the world's population, considerable pressure is mounted on the healthcare system to provide valuable treatment and healthcare services. Moreover, with the outburst of COVID-19, many people are exposed to various diseases, and detecting time plays a major role in the healthcare system.

Hence, it is time to tackle the potential benefits present in the data with Machine Learning (ML) models. ML is one such area seeing continuous acceptance in the healthcare industry. ML applications in healthcare range from identifying diseases and diagnosis to medical image diagnosing to intelligent health records. With such techniques, one can provide high-quality information to doctors to better understand their patients. Furthermore, it has been found that giving some extra information to clinicians will help provide better prescriptions or medications for patient diagnoses and treatments. The main idea in the usage of ML in the healthcare sector is to process the huge amounts of medical data and provide some relevant patterns that will help physicians provide better outcomes, low-cost care, and increased patient satisfaction. With the recent technological advances in microelectronics, wireless communication, ML, and the decision-making process, Wireless Body Area Network (WBAN) has become the most promising technology.

A review on skin disease image detection using a deep learning approach was conducted [1]. Furthermore, the authors suggested research on AI-based treatments to diagnose skin diseases early. A framework for diagnosing chronic kidney disease (CKD) is developed [2] by focusing on filling the missing values using the k^{th} Nearest Neighbor (KNN). Moreover, a hybrid model is developed using Logistic Regression (LR) and Random Forest (RF) for predicting such diseases. The developed algorithm prediction performance was found to be 99.75% compared to other existing algorithms. Using various indicators, a novel deep learning model is developed to predict Parkinson's disease (PD) [3]. A total of 584 datasets from the Parkinson's Progression Markers Initiative (PPMI) were performed on the developed model. From the results, it is observed that an average of 96.45% accuracy has been achieved.

A Hybrid RF with Linear Model (HRFLM) [4] was developed for predicting accurate cardiovascular diseases by finding compelling features with the help of various ML techniques. The predictive accuracy of the developed model was found to be 88.7%. Prediction of heart disease with ML models, such as Artificial Neural Network (ANN), LR, KNN, Support Vector Machine (SVM), Decision Tree (DT), and Naive Bayes (NB), was carried out in another study [5]. Moreover, the Leave-one-subject-out cross-validation (LOSO) algorithm selected the best hyper-parameters for better model selection. The approach has been tested on the Cleveland HD dataset and obtained an accuracy of 92.37% incused to predict CKD with various feature selection approaches to find the best algorithm to extract features. Finally, we compared the performance evaluation of various ML algorithms and achieved an accuracy of 99.6% using deep learning models. A few studies [7 - 9] reported disease prediction using ML algorithms.

Datasets Preparation

The database consists of 3073 user details stored in an Excel file. The Excel consists of ECG signals with symptoms like chest pain, anxiety, body temperature symptoms like nausea, snore detector with symptoms like high blood pressure and drowsiness, and Skin Conductivity Response (SCR) symptoms with a symptom like excessive sweating. The diseases like Tachycardia and Bradycardia are predicted based on the heart rate, mild sleep apnea and moderate sleep hypopnea on Apnea-Hypopnea Index (AHI) value, hyperthermia based on body temperature, and endocarditis based on SCR. The strong signal values are extracted from PhysioNet. The platform provides authentically replicated datasets for the medical domain. The threshold values for each vital signal are identified after consulting doctors and practitioners. Additionally, one major symptom experienced by the person is also considered for the classification. These features will improve the model accuracy.

Pre-processing

Pre-processing involves creating a dummy variable for “characters/alphabets' present in the database and filling in missing values, if any, with the mean of the respective feature. The creation of a dummy variable for categorical data is based on Symone. Updated excel file with one of the symptoms and 0 if the symptom is absent.

Feature Extraction Techniques

Discrete Wavelet Transformation (DWT) [10] and Empirical Mode Decomposition (EMD) [11] are applied to the biomedical signals for the extraction of features. DWT provides extensive research on how to use this transform in time series. Feature selection before classification plays a vital role. In DWT, the results are represented as approximation coefficient array and complex coefficient array. EMD is an adaptive approach to decomposing non-stationary and nonlinear signals into Intrinsic Mode Functions (IMF).

CHAPTER 7

Cardiovascular Disease Preventive Prediction and Medication (CVDPPM) - A Model Based on AI Techniques for Prediction and Timely Medical Assistance

Y.V. Nagesh Meesala[1,*], **Sheik Khadar Ahmad Manoj**[1] and **Ganapati Bhavana**[2]

[1] *Raghu Engineering College, Visakhapatnam, India*

[2] *ANITS, India*

Abstract: Cardiovascular diseases (CVDs) are the primary cause of death worldwide. If these are not detected early and are not treated on time, one may lose a life. Despite using various measures and standards by doctors, the disease is unpredictable and has a significant death toll. Artificial intelligence (AI) techniques have been introduced to predict the outcome and utilization of machine learning (ML) techniques in diversified areas, showing promising results to make it more sophisticated for both medical professionals and patients. In this chapter, a cardiovascular disease preventive prediction and medication (CVDPPM) model has been developed, which utilizes various communication models for assisting the patients through constant monitoring of heart rate and blood pressure. The main focus of CVDPPM is to predict the early occurrences of artery disease, stroke, and heart failure. It helps notify the nearest cardiologist and medical team with all needed reports for immediate and appropriate medical treatment to save the patient's life. The proposed model fastens the medical procedure by alerting the regular consulted doctor and the family about the patient's condition and medical reports immediately.

Keywords: AI, Cardiologist, Cardiovascular diseases, Cloud storage, CVDPPM, Modeling and training.

INTRODUCTION

In light of the overall measurable information introduced by the World Health Organization (WHO), cardiovascular infections are the major cause of death. It is further estimated that 23.3 million people will die by 2030 due to CVDs globally [1]. Many researchers have conducted significant studies and identified the CVD

[*] **Corresponding author Vasilis Y V Nagesh Meesala:** Raghu Engineering College, Visakhapatnam, India; E-mail: nagesh.myv@raghuenggcollege.in

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

causing factors like hereditary, stress levels, living standards, dietary habits, and other physiological factors [2].

Coronary heart disease, cardiomyopathy, angina, congestive coronary failure, congenital heart condition, arrhythmias, and myocarditis are different heart conditions.

To minimize the risk rate of people dying from CVD, automated techniques can assist in CVD research and examine the attributes and symptoms of CVD that lead to early prediction and prevention of the disease. The advent of digital technology in medical diagnosis has increased the dimensions to detect the pre-existence of the disease [3]. Over the last few decades, there have been efforts to train machines to replicate the human brain, giving rise to machine learning (ML) [4]. The AI and ML algorithms have shown their potential ability to determine the existence of CVD by accurate data mining on the health records and medical history of families of the patients [5].

The recent developments in ML algorithms based on neural networks (NN) have given accurate results regarding CVDs [6]. These algorithms also utilize the internet of things (IoT) and cloud storage support for faster diagnosis and communication purposes. The ML algorithms and techniques, along with the assistance of medical experts, generate reliable reports.

However, there are incidences of the ML calculations giving false positives (FP) and false negatives (FN). Errors in the generated report are not unusual, even in manual checkups and diagnoses. Still, since the prediction is related to CVD, there is a higher level of risk and possibility of the patient ending up with a serious complication and may also have heart failure. This happens because the medication is not prescribed for the FN cases, and the patient's next visit is not known as one may feel that he is safe and may take a longer time for the next diagnosis.

A model of Cardiovascular Disease Preventive Prediction and Medication (CVDPPM) has been proposed to overcome the risk level associated with FN and assist CVD patients. The CVDPPM model predicts the CVD and has a mechanism to monitor the positive and negative cases for a pre-determined period. The observations are made by attaching the electric sensors to the patient's body for examination. In that phase, checkups are conducted again to confirm positivity if any abnormalities are found. The primitive goal of CVDPPM is to increase the accuracy of TP and minimize the risks associated with the FNs. In an emergency, the TP cases are also continuously monitored and immediately assigned to the nearby medical team.

The proposed CVDPPM model is designed to incorporate the latest techniques for prediction and utilize the internet of things (IoT) concepts and the cloud platform for storing and sharing the patient's health records. The model has collected relevant data for the prediction purpose, and the same data set is used to convert an FN to TP. It also maintains the details of cardiologists and related medical teams for assisting the patient in opting for immediate help. In emergencies, the model itself will assign medical support to the patient.

LITERATURE SURVEY

J. Mishra *et al.* [7] have used machine learning methods to forecast chronic diseases in patients and then used Adam as an optimizer to review the growing popularity of AI and ML algorithms in medical sciences, especially in predicting diseases. F. Z. Abdeldjouad *et al.* [8] developed a hybrid method with Weka and Keela programming for CVD prediction by utilizing diverse AI procedures and implementing machine learning algorithms. The resulted accuracy of each classifier was also compared.

M. Tarawneh *et al.* [9] urged the need for an expert system to be served as an analysis tool for discovering the information and patterns in heart diseases. They proposed a prediction system for heart disease by combining techniques that involved data mining in an algorithm for prediction and claimed to give more accurate results. C. B. C. Latha *et al.* [10] has investigated a classification method that improves the accuracy of weak algorithms. Experimentation is carried out on a heart disease dataset. According to the paper, the results indicate improved prediction accuracy, *i.e.*, 7% accuracy with ensemble classification.

M. Ashraf *et al.* [11] used individual learning calculations and outfit approaches like J48, random tree, KNN, multi-facet perceptron, Bayes Net, Naïve Bayes, and irregular timberland for forecast purposes. After investigation, they guaranteed that J48 had a precision of 70.77% in correlation with different classifiers. They utilized procedures, such as TensorFlow, PyTorch, and KERAS, which gave 80% precision. F.Miao *et al.* [12] built up a thorough danger model utilizing improved arbitrary endurance woodland (iRSF) to foresee mortality due to cardiovascular complications. Results from an investigation involving clinical data set of 8059 patients, 32 danger factors, including meds, socioeconomics, and clinical lab data, help in creating the danger model. A few cases support that the trial consequences of the danger model created help in choosing a significant instrument by specialists for the forecast of mortality due to cardiovascular complications.

D. Mienye *et al.* [13] proposed an expectation model which includes the mean-based parting strategy, relapse, tree, and characterization, where more modest subsets are shaped by irregular parceling of the dataset. Afterward, a homogenous

CHAPTER 8

Personalized Smart Diabetic System Using Hybrid Models of Neural Network Algorithms

K. Abirami[1], **P. Deepalakshmi**[2,*] and **Shanmuk Srinivas Amiripalli**[3]

[1] *Department of Computer Science and Engineering, Fatima Michael College of Engineering and Technology, Madurai, Tamil Nadu 625020, India*

[2] *Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Krishnankoil, Tamilnadu - 626126, India*

[3] *Department of Computer Science and Engineering, GITAM Institute of Technology, GITAM Deemed to be University, Visakhapatnam, AP, India*

Abstract: The healthcare sector is rapidly evolving due to the exponential growth of the digital space and emerging technologies. Maintaining and effectively handling large quantities of data has become difficult in all industries. Furthermore, collecting helpful knowledge from extensive data collection is a daunting challenge. There would be an immense amount of data that continues to grow, making it harder and harder to find some helpful information. In the healthcare industry, big data analytics offers a variety of tools and strategies for detecting or predicting illnesses faster and delivering better healthcare facilities to the right patient at the right time to increase the quality of life. It is not as simple as one would imagine, given the myriad functional challenges that need to be addressed within current health data analytics systems that offer procedural frameworks for data collection, aggregation, processing, review, simulation, and interpretation. This chapter aims to design a long-term, commercially viable, and intelligent diabetes diagnosis approach with tailored care. Due to a lack of systematic studies in the previous literature, this chapter describes the different computational methods used in big data analytical techniques and the various phases and modules that transform the healthcare economy from data collection to knowledge distribution. The investigation findings indicate that the suggested framework will effectively offer adapted evaluation and care advice to patients, emphasizing a knowledge exchange approach and adapted data processing model for the smart diabetic system.

Keywords: Big Data in Healthcare, Convolution Neural Network, Deep Learning, Hybrid Model of Neural Network, Personalized Diagnosis System, Real-Time Analytics, Smart Diabetics System.

* **Corresponding author P. Deepalakshmi:** Department of Computer Science and Engineering, Kalasalingam Academy of Research and Education, Krishnanoil, Tamilnadu – 626126, India; E-mail: deepa.kumar@klu.ac.in

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

INTRODUCTION

The lifestyle of people and metabolic changes in healthcare pave the way for the invention of new diseases and even sometimes deadly infections.

A lack of skills and ability in gaining and managing healthcare-related information from health centers is also a challenging issue. Diabetes is an exceedingly common chronic disease from which about 8.5 percent of the planet's populace endures, and 422 million individuals worldwide have to battle diabetes [1]. Much obliged to the exceptionally reality that diabetes is considered a global disease, it is necessary to improve strategies for evasion and treatment of diabetes. The high treatment amount and lifelong medication involved in the treatment method are bitter for diabetics patients. So their concern is about whether the disease cannot be predicted early or any predictive analysis method is not available to detect it. The proposed system is a boon for them and helps the health care organization provide services to patients effectively. In this chapter, the main focus is on Type 2 diabetes patients because 90% of patients are diagnosed with it. Only 10% are detected with type 1 diabetes, which is very difficult to predict since it depends on diet and other factors. Deep learning is a form of machine learning, but it is also one of the methods for implementing machine learning. It is based on Artificial Neural Networks, which are based on the biological neural networks of humans. It would be instrumental in making choices and will outperform deep learning algorithms. The hidden layer indirectly trains itself and produces predictive effects, so no external researchers are needed to train the model repeatedly. Machine learning calculations are useful for identifying hybrid designs within large amounts of data. This capability is well-suited to therapeutic applications, especially for people who depend on complicated proteomic and genomic estimates.

Consequently, computer learning has been used to diagnose and treat various illnesses. Machine learning calculations can help patients make better medical decisions by providing efficient healthcare structures in clinical settings. Machine learning is effective and can even work with lesser data [2].

The primary focus area of this chapter is summarized as follows:

- To make a clear view of the pros and cons of the analytical method in the health care industry.
- To explore the different hybrid models of neural network systems available and how they can be evaluated and applied in the system.
- To display the different levels and steps involved in analytical methods with their key components.

- To clarify the open investigation challenges confronted in data collection, analyzing, and storing methods with future directions.

The critical goal of healthcare facilities is to gain the confidence and credit of their patients. They will devise a system that divides the patients' data into categories based on their disease complications, allowing them to determine if they ought to see them daily or whether drugs will suffice. The healthcare sector has progressed significantly over the last five years in efficiently processing a large amount of data. This big data breakthrough paves the way for improved outcomes by processing and tolerating knowledge with unique dimensions. Big data technology has spawned a slew of cutting-edge strategies for delivering treatments and saving lives at a lower cost in healthcare. Many health care industries' storage facilities are now mainly used to store, pre-process, process, identify, search, handle, and recover vast volumes of data to make it readily accessible to the general public. As a result, it is clear that it is not just about offering instruction to understand the condition, disorder, or medications but rather about educating patients on how to detect disease at an early stage and making the best choices [2]. This chapter aims to explain the significance of big data and the different steps involved in conventional machine learning algorithms and their hybrid model of applications in healthcare. Even though the new scheme has various tools for making more statistical assessments, it also needs a lot of work, and healthcare sectors' effective procedures need to be developed. Since patients are the end consumers of these schemes, the focus should be on making more accurate choices to protect them. While the healthcare industry has a large volume of data, the tools we use to collect knowledge are in short supply. As a result, it is critical to invest in computer-based solutions or decision-making processes that assist doctors in recommending less costly therapeutically equivalent options. However, it is not as simple as we had hoped; many studies and techniques experiments are needed to achieve the best results.

In the healthcare sector, disease prediction with high precision is critical. Data sets with a large number and complexity can be computationally processed for patterns, instances, and connections. Organized, unstructured, and semi-structured data can all be mined for learning. To use machine learning and artificial intelligence successfully, a large dataset is required. Big data is not only used in healthcare sectors but also in various areas and contexts. For instance, multiple air-quality surveillance systems could be set up to estimate air emissions using Big Data. Data on air quality and observations from current control stations may be combined with other considerations, such as meteorology, human mobility, road networks, and traffic flow.

CHAPTER 9

A Framework of Smart Mobile Application for Vehicle Health Monitoring

K. Aswarth[1] and **S. Vasavi**[1,*]

[1] *Department of Computer Science & Engineering, V.R. Siddhartha Engineering College, Vijayawada, India*

Abstract: The smart system integrates cloud computing and mobile computing, also known as mobile cloud computing. This smart system helps monitor the vehicle's health condition on any device, *i.e*., platform-independent. Using machine learning algorithms, the smart system helps predict vehicle health and maintain the vehicle's and the driving person's safety. The cloud computing used to deploy this smart system for monitoring the vehicle condition is the Google Cloud Platform. Google Cloud Platform provides various services like Computing and Hosting, Networking, Storage, *etc*., which help deploy and host web applications on Google Cloud using multiple services. One of the best securities is achieved using the Google Cloud Platform. Several layers are encrypted with specially designed algorithms for the safety of the customer data and applications. Google Cloud Platform helps provide data integrity, making it better for storing all the data. It also provides Denial of Service protection which helps real-time protection of servers for hosting the data. The smart system is deployed to only authenticated users eligible to monitor the vehicle's health condition. The health of the car may be tracked in the cloud and on every device with an internet connection and communication services. The mobile application is deployed from the webserver, facilitating secure and safe data browsing. The smart system is developed for displaying vehicle conditions dynamically, Google Maps for tracking the present vehicle location, and manual testing of the vehicle health by entering the values in the portal, which helps notification of risk, medium risk, and no risk of the vehicle condition using machine learning algorithm, which runs at the backend of the application.

Keywords: Cloud computing, Mobile computing, Machine learning algorithms, Security, Vehicle health.

* **Corresponding author S. Vasavi:** Department of Computer Science & Engineering, VR Siddhartha Engineering College, Vijayawada, India; E-mail: vasavi.movva@gmail.com

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

INTRODUCTION

The smart system assists the driving person with vehicle health status on a mobile device similar to Google's Android Auto or Apple's CarPlay, promoting the Internet of Vehicles (IoV) [1]. The application can also be accessed from the cloud server. To view the application, the user must sign in with his google account to view the status or condition of the vehicle. The permission for viewing the applications will only be given to limited users. The users only have permission to read, so they cannot modify the software. They only have written access to provide the inputs of the sensors for manual assistance for vehicle health monitoring. Risk details are displayed through a mobile application in notifications and a dashboard at the terminal [10]. The application's security is maintained at its best because it uses Google Platform and accounts for signing in to access the application. The proposed system uses a machine learning model at the backend for risk factoring of the vehicle with 98% accuracy.

The services delivered to the users will be high because maximum services are provided like computation and hosting, storing data, databases for backup, networking for connectivity, and Big Data, and Machine Learning for prediction. The application is developed in a cost-efficient way. It can be used by any person and has great features that provide platform independence and can be accessed and used by any device from the old generation to today's modernized systems. The application's downtime is less as it uses the Google Cloud Platform. The services are delivered without downtime as they are deployed in different regions. Hence, latency for deploying the application is reduced as we present the data in the nearest location.

An automated system provides predictions on the health of the vehicle using various sensor data that enables cloud-based health monitoring, analyzes vehicle risk factors dynamically over the cloud, and displays the result on a mobile device. Preventive maintenance is based on an android application and an onboard vehicle diagnostic system for the vehicle's health remote monitoring. The driver will notify in case of any alarming conditions.

LITERATURE SURVEY

The reported work [2] consists of a VMMS architecture that acts as a central part of the system. This approach uses an OBD2 port to gather the DTC codes of the various sensors. Classification algorithms are applied, and exciting patterns are learned, which can cause the system to fail [3].

This work has the advantage of providing a basic architecture of the health monitoring system.

Challenges in VMMS Architecture System

- It does not provide a user interface like a mobile application or a webpage.
- In this architecture, Bluetooth transmits data from the OBD scanner to the phone, which is inadequate.
- This approach uses DTC codes that vary from vehicle to vehicle.
- The OBD scanner is not compatible with different types of cars.

Work reported previously [4] uses DTC codes from the collected cards and stored in a server through the network. The processing of the data is done at the server. The data collected consists of vehicle operational data, user data, and vehicle service info. The DTC codes match the previously available codes, and the vehicle's condition is predicted. This approach uses an unsupervised machine learning approach.

Challenges in the DTC Coding System

- This approach uses DTC codes, which require further processing and increase the overhead time.
- It also imposes confusion on the operating person or the vehicle user.
- This architecture requires a different set of software for decoding the DTC codes.
- Furthermore, these DTC codes are vehicle-dependent, differing from one set of vehicles to the other vehicles.

Several authors [5] discussed that the “Automotive Diagnostic Command Set” is structured into three layers of functionality.

Challenges in Automotive Diagnostic Command Set

- Use of outdated technology.
- It does not provide feasibility to interact with remote people.
- It applies to only a system point of view.
- This architecture does not use server or cloud technologies for computations.

A study on moto monitoring system for vehicle [6] uses a sound recorder to monitor the engine. The microcontroller collects the electrical signals from all the sensors. The microcontroller locally processes the data and converts them to JSON objects to be sent over the internet. This JSON object contains the Id of the vehicle, the Id of the sensor, and an array of data with a timestamp. The collected data through sound analysis and other sensors will be incorporated into machine learning techniques, such as linear regression, to monitor various components and logistic regression to anticipate engine system failure in percentages in the near future [6].

CHAPTER 10

Progression Prediction and Classification of Alzheimer's Disease using MRI

Sruthi Mohan[1,*] and **S. Naganandhini**[2]

[1] *Department of M.Sc. Computer Science, G.T. N Arts College, Tamil Nadu, India*

[2] *Department of Computer Science , G.T. N Arts College, Tamil Nadu, India*

Abstract: Alzheimer's disease (AD) is one of the most common neurodegenerative diseases (dementia) among the aged population. In this paper, we propose a unique machine learning-based framework to discriminate subjects with the first classification of AD. The training data, preprocessing, feature selection, and classifiers all affect the output of machine-learning-based methods for AD classification. This chapter discusses a new comprehensive scheme called Progression Prediction and Classification of Alzheimer's Disease using MRI (PPC-AD-MRI). Considering the data gathered with T1-weighted MRI clinical OASIS progressive information, the consequences have been evaluated in terms of precision, recall, F1 score, and accuracy. This recommended model with enhanced accuracy confirms its suitability for use in AD classification. Other methods can also be used successfully in the disease's early detection and diagnosis in medicine and healthcare.

Keywords: Confusion metrics, OASIS dataset, Random Forest Classifier, SGD Gradient Classifier.

INTRODUCTION

Alzheimer's disease (AD) is a progressive brain disease that impairs thinking and can result in death in its advanced stages. As a result, early detection of Alzheimer's disease is essential for effective treatment.

Machine learning (ML) is a neural network that detects post-concussion syndrome (PCS) from massive, multipart datasets using various predictive and performance analyses. As a result, several researchers are focusing on using machine learning for the early diagnosis of Alzheimer's disease. Many variables, including data for preparation, feature selection for preprocessing, and classifiers, influence the production of machine learning-based classification methods for AD. In this

* **Corresponding author Sruthi Mohan:** Department of M.Sc. Computer Science, G.T. N Arts College, Tamil Nadu; E-mail: sruthimohan.gtn @gmail.com

P. Naga Srinivasu, Norita Md Norwawi, Sheng Lung Peng and Azuraliza Abu Bakar (Eds.)

chapter, the proposed model combines mining principles to provide a solution for neurodegenerative disease diagnosis, which involves preprocessing, attribute selection, and classification.

According to the American National Institutes of Health-National Institutes of Aging (NIH-NIA), Alzheimer's disease (AD) is a gradual degeneration of brain function that leads to cognitive and physical dysfunction, particularly in the elderly. Today, AD ranks third among the world's common disabilities, alongside cardiovascular and cancer diseases. It is also the sixth most significant cause of death in the United States [1]. No visual analysis of radiologists can directly detect the development of neurodegenerative diseases. Neuroimaging is a crucial method for detecting neurosensory disorders by deriving objective patterns and structural relationships from MR images. In Magnetic Resonance images (MR), detecting abnormality is challenging, as noted by Reuda *et al.* [2].

Alzheimer's disease is the most recent sort of dementedness and one of the most common disorders in the world. It is critical to detect Alzheimer's disease early to provide patients with the best possible care. Structural Magnetic Resonance Imaging (SMRI) is a powerfully diagnostic tool for high tissue contrast and high-resolution images. Generally, there are three AD phases: mild, moderate, and severe. AD is a characteristic disease. This chapter presents four methods of AD classification using an Open Access series image data set of T1 _weighted MRI images (OASIS).

This chapter provides a new prediction and recommendation scheme called "Progression Prediction and Classification of Alzheimer’s Disease using MRI" (PPC-AD-MRI). This system uses MRI's clinical temporal data for experimental analysis and validation. The proposed model is intended for the early stage of AD to be classified and anticipated.

REVIEW OF THE LITERATURE

Automated diagnosis of brain injury using magnetic resonance images is becoming increasingly relevant in the medical field. The following is a list of research works on the AD classification.

Freund *et al.* [3] described a diagnostic model and its application. In the light of algorithms and learning functions, they introduced a process to update the capacity of this modified method.

Chaplote *et al.* [4] used MR brain images, which have been transformed into waves, to classify as normal and abnormal in an SVM and Self Organizing Map

(SOM). This study found that SOM outperforms SVM to achieve greater accuracy in classification.

El-Dahshan *et al.* [5] introduced the three-phase AD Classifier for MRIs combined with feature extraction, dimensional reduction, and AD classification. They applied DWT for extraction of the features, PCA for function reduction, and FP-ANN (artificial neural network) and nearest neighbor (k-NN) feed backward propagation for classification. The classification accuracy was found to be 97 percent or higher by those methods.

Sandhya Joshi *et al.* [6] developed a range of models using various AD grading machine learning methods, namely multilayer perception, bagging, decision book, and genetic algorithm. The accuracy of the CANFIS method classification was 99.55%. To detect brain atrophy patterns and predict Alzheimer's disease, Claudia Plant *et al.* [7] developed a hybrid model with a support vector machine (SVM) and a Bayesian classifier. A pattern-matching index of 92% was used for their method.

Suhuai Luo *et al.* [8] developed an automatic AD method using a profound learning model. It uses 3D brain images for CNN-based classification. The innovation has been qualified and experienced based on the ADNI dataset. The results have shown 100% higher AD accuracy sensitivity and 93% specificity.

The new Deep Neural Network class approach for Alzheimer’s disorder detection has been demonstrated by Kajal Kiran Gulhare *et al.* [9]. The data section and the feature choice image processing technique were employed in this research for non-demented or demented older person data. Finally, the AD detection system implements deep neural networks (DNN) classification. AD with 96.6% accuracy and minimal error rates were identified correctly by the DNN.

METHODOLOGY OF PPC-AD-MRI

Classifiers are models that allocate appropriate class labeling to test samples represented as feature vectors (from a set of known class labels).

PPC-AD-MRI uses statistical loading, single encoding, and normalization when creating the training dataset. One of the most common and standard methods is hot coding, which can work well if you do not have many classification attributes. This code creates raw data values in the new (binary) column. Each level with the reference variable for that category is compared. As shown in Fig. (**1**), codes with dichotomous values of 0 and 1 can conveniently encode gender and hands.

SUBJECT INDEX

A

B

C

D

E

F

I

J

K

L

M

N

O

P

R

S

T