Soft Computing Techniques for Medical Diagnosis, Prognosis and Treatment

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Abstract With the rapid advancement in the fields of computation and deep learning, the use cases of artificial intelligence in healthcare are blooming more than any time in history. In past years, it was supposed that only doctors and medical practitioners should handle the decisions in healthcare systems. With the rise of machine learning, the tables have turned and dependency on algorithms to make support systems for healthcare has increased. Various AI predictive models have been built for the prediction of diseases at an early stage. Not only this, but data science is also used in a lot of areas of healthcare ranging from summarization of clinical data to intelligent predictive models. However, the work in developing a decision-support system for healthcare is still in the infancy state. Most of the conventional decision-support systems are based on hard computing which requires exactly state analytic models and does not have any place for approximation and uncertainty. Soft computing, being an approach that imitates the human mind to reason and learns in an environment of uncertainty and impression, helps to provide an optimal solution through its nature of adaptivity and knowledge. Various studies have shown that models which extensively used soft computing methodologies, for example, fuzzy logic, ANN, Genetic Algorithms, etc. were able to present clinical observations and inferences in a way that better helped doctors in decision making. There are various applications in the medical field like summarization of clinical text, activity monitoring, development of adaptive disease management systems where soft computing can be used. The book chapter can discuss the prevailing practices, comparative analysis of the necessity of soft computing over more prevalent hard computing techniques, and future directions for the application of soft computing in the healthcare decision-support system.

Keywords Soft-computing · Health care systems · Fuzzy logic · Artificial neural networks · Probabilistic reasoning · Computer-aided diagnosis

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1 Introduction

Artificial intelligence is broadly defined as the programming of machines to enable them to perform tasks like humans. It is an area where machines learn to solve problems mimicking human cognition. Artificial intelligence simulates human intelligence in learning, perceiving, planning, and decision making [1]. Artificial intelligence devices are made to learn the surroundings and act accordingly that also improves their performance with experiences. The main implementations of artificial intelligence and the closely related subfields include computer vision, natural language processing, human-computer interaction, and human-agent interaction. These fields have been leveraged in various sectors such as biomedicine, environment, education, social sciences, finance and economics, cybersecurity, automotive industry, government, law, and most importantly healthcare to improve their domains extensively. Artificial intelligence includes hardware and software both to give human-like decisions on problems related to several fields. With regard to software, artificial intelligence extensively uses algorithms, such as the Artificial Neural Network (ANN) that mimics the human brain cells. The neuron is activated by stimuli, which in AI is the weighted channels and activated functions that work together to form predictions accordingly. These neural networks generate outputs according to the environmental stimulus. Various learning algorithms are present for all sorts of tasks, such as supervised learning, unsupervised learning, reinforcement learning, ensemble learning, and deep learning. Similarly, from a hardware perspective, Artificial intelligence mostly deals with devices that implement the mentioned algorithms on a physical platform to optimize the performance measures and automate problem-solving and decision-making tasks.

As the digital and technological advancements are culminating to reach their zenith, a lot of data is being produced. Data is ubiquitous. Data is produced and consumed at the same time on a very large scale. Data is massively present in the form of text, images, videos, numbers, etc. that can be exploited to reach conclusions, and again the knowledge obtained can be transferred to other tasks. Big data is thus produced and utilized for human development and enhancing human society making human lives easier.

1.1 Healthcare Data

Healthcare data comprises any data that is related with the patient's medical history, drugs given to patients, progression or impedance of the disease, presence of a benign or malignant microorganism in the body, choice of lifestyle, and any other details giving information on the physical or mental state of people. Healthcare data can broadly be divided into two categories, structured and unstructured data. Structured data contains well-ordered data such as the name of the patient along with their medical records including various parameters. For example, in a tumor patient, the size of the tumor, spread rate of the tumor, the amount of drugs taken, can be structured data. Unstructured data, on the other hand, give patients' medical history or records in a not-so-well organized manner. These include clinical notes of doctors, medical prescriptions, audio recordings of the patients, etc. Broadly speaking, healthcare data is enormously present in the form of clinical text, images, and electronic records.

These data can be appropriately utilized for clinical diagnosis, medical history analysis, and prognosis of various diseases. Although utilizing these data and building predictive AI models does not replace real doctors, it is seen that they give significant assistance to the doctors in the entire process. Various learning methods and artificial intelligence techniques can be utilized to deal with the specific type of data. Apart from the regular disease identification and analyzing medical history, AI can also be exploited to bring advances in biomedicine and bioinformation to gain a deeper understanding of different microorganisms, their evolution, and their impacts on the human body. Since, it is a monotonous task for humans to analyze such a large amount of data, with the help of AI, the process becomes a lot easier and saves a significant amount of time. Biomedical literature can be well exploited taking help from AI to get a better understanding of the present scenarios and past developments in biomedicine and healthcare.

1.2 Types of AI in Healthcare

The healthcare data can, thus, be exploited by using supervised learning, unsupervised learning, natural language processing, and deep learning to reach a decision with regard to biomedicine and healthcare. This section gives insights into using different techniques to solve problems in healthcare.

1.2.1 Machine Learning

Machine learning is the most common form of AI used in several fields. Machine learning usually involves supervised and unsupervised learning to make predictions and classifications to data. It usually involves training a large dataset containing several features to come into a conclusion. This can broadly be said as supervised learning. Unsupervised learning, on the other hand, does not take labeled data. It tries to find a distinction between data and finds a correct group for the data. Both supervised and unsupervised learning are utilized in healthcare systems for effective health services to the patients.

The most widely used field in healthcare where machine learning is used is precision medicine. It involves which drug effectively works on a patient given the context and treatment methodologies in a patient. Supervised learning techniques use labeled data to come to conclusions such as the presence of a disease, or if a person will get the disease in the future. It helps clinicians and doctors in the prediction of a disease or other features of a potentially harmful disease by utilizing the past history of the patients.

Unsupervised learning, on the other hand, that majorly involves clustering and principal component analysis (PCA), is used to group patients with similar symptoms or traits. It doesn't conclude into an outcome such as the prediction of a disease or onset of any ailment. But it groups patients and hence the analysis of several patients' medical history becomes easier. Mostly, K-means clustering is used for this purpose. On the other hand, PCA is mostly used for dimensionality reduction. When the features of the patients are recorded in larger dimensions, like the gene history or the number of genes, PCA is used to project the data to only a few components preserving the necessary information about the subject. Usually, in healthcare, PCA is used initially to reduce the data to smaller dimensions, and later clustering is used for grouping them into relevant groups.

Machine learning involves hand-crafted features for analyzing the medical data. Since healthcare is a very vast field and data with delicate handcrafted features are not available all the time. Hence, to deal with this limitation, deep learning is widely used in the healthcare sector.

1.2.2 Deep Learning

Deep learning is a more complex form of machine learning that mostly deals with neural network models. They are being extensively used in health care to deal with data that have many levels of features and outcomes to predict a clinical event. Deep learning can be utilized majorly for analyzing medical images. It can be used extensively for dealing with images that even the human eye may miss out. Deep learning is hence a significant way of providing radiologists, cardiologists, and neurologists in dealing with brain images, heart images, and other images of delicate organs and finding if they contain any lesions. Thus, its use in radiomics is expanding to make a clinically relevant distinction in the medical images of the patients [2]. In the past, computer-aided detection (CAD) had been widely used to exploit the features in medical images. Their combination with deep learning models has proved to give very high accuracy, especially in oncology-oriented image analysis [3]. As a significant amount of medical data is in the form of images, deep learning can essentially be used to gain valuable insights of these images for better diagnosis that eventually leads to better healthcare services to the patients.

1.2.3 Natural Language Processing

Natural Language Processing is the field of AI that deals with enabling computers to understand the natural language of humans and interpret them to gain better insights on text data. Natural language processing, which mainly involves speech synthesis, translation, text data analysis, and information extraction, has been widely used in healthcare systems to enable a better understanding of the natural language used by clinicians as well as patients.

NLP can be used to exploit clinical notes of doctors, and any other unstructured medical text data to be able to make decisions accordingly. NLP can be used in biomedical literature as well to understand the relationships of various biomedical components such as proteins, genes, etc. with the human body. NLP can be used to analyze patients' speech and necessary conclusions can be drawn regarding the progression of any neuropsychological disorder. For example, NLP is extensively studied for Alzheimer's disease (AD) patients and their disorders in the speech which is directly associated with the degeneration of speech. NLP can also be used for conversational AI that converses with patients and hence their speech data can be recorded and analyzed for prediction and diagnosis of clinical events, such as depression or neuropsychological ailments like AD or any other forms of dementia that have an effect in a patient's speech. For example, Alexa, developed by Amazon, is providing assistance to elderly people in their daily activities, and hence has become easier to deal with dementia for them.

Similarly, NLP can also be used in the biomedical literature to extract necessary information. Due to the availability of enormous amounts of information in the literature, it is not feasible for researchers and clinicians to go through such a large amount of data. It is, therefore, necessary to exploit NLP tools to be able to extract only the relevant information from medical journals and help in clinical decision making. Named-entity recognition (NER) has been widely used for this purpose. Similarly, NLP is used in biomedical question answering to help gain fast and accurate answers for questions regarding health and medicine [4].

1.2.4 Physical Robots

Physical robots were initially trained to lift, weld, and do other manual jobs in industries and warehouses. They learn easily and perform accurately in their given surrounding environments. In healthcare, physical robots have done essentially amazing tasks in providing assistance to healthcare professionals in hospitals. Sanitization of medical tools, moving beds, cleaning, can be a few examples of several things that are directly linked with enhancing healthcare services.

Due to blooming advancements in AI, robots have been trained to perform surgery on patients. They assist surgeons and nurses in operating a patient. These surgical robots give significant assistance to surgeons in improving the ability to see, form precision incisions, stitch wounds, etc. [5]. Although the important and sensitive decisions are made by human surgeons, robotic surgery such as head and neck surgery, gynaecologic surgery, etc. have widely been practiced.

1.2.5 Examples of AI in Healthcare

Disease diagnosis and treatment has always been a major goal of AI employed in healthcare. Initially, although AI was developing, it wasn't better than human diagnostics. MYCIN, which was among the first AI technology to have been used in healthcare, was developed at Stanford that was used in diagnosing blood-borne diseases [6]. Since then, a lot of institutions and organizations have been actively using AI tools for prediction, diagnosis, and treatment of diseases.

IBM's Watson is used for cancer detection and necessary treatments. It uses a hybrid of cognitive services through vision, speech and language, and machine learning-based data-analysis programs. Similarly, Google Health has been partnering with a lot of health organizations to come up with solutions regarding various health-related issues. Open-source programs, such as TensorFlow, have been widely used in developing several predictive models to help come up with clinical decisions. PathAI is helping pathologists to help employ machine-learning models for cancer diagnosis and develop methods for individualized treatment by using proper drugs.

2 Intelligent Systems for Healthcare Decisions

Intelligence can be defined as the ability to perceive, reason, analyze, calculate, understand natural language, and compare relationships and analogies between several aspects of the surrounding. The findings and knowledge gained can then be used for solving complex problems, comprehending ideas, and making decisions. Intelligence is a combination of reasoning, learning, problem-solving, perception, and linguistic intelligence. Human intelligence is considered the most supreme form of intelligence due to its remarkable potential for complex decision making, analyzing, interpersonal skills, and outstanding aptitude. Humans are thus distinguished as marvellous beings. Due to the amazing progress, humans have made because of their intelligence, such intelligence is being searched for tremendously. Machines are programmed to mimic this human intelligence to enable them to perform tasks like humans. Although it might take several years to be able to replace human intelligence or even come in par with it, technological advancements in intelligence have become notable in this era. Intelligent systems are being developed massively to enhance human intelligence and assist them in various tasks. Intelligent systems are so vast that they have been deployed gigantly in several fields such as meteorology, e-commerce, businesses, finance, and healthcare. Intelligent systems tend to assist humans in complex decision-making tasks to optimize the use of resources available. Intelligent systems are complex and use a wide range of combinations of technologies—artificial intelligence, wireless networking, computer graphics, cybersecurity, natural language processing, embedded and distributed systems, deep learning, etc.

Intelligence systems can broadly be thought of as computer-based approaches for decision making. Intelligent systems are extensively used in transportation to automate the driving process. The way this is done is by learning the surrounding environment as massive data and being able to make decisions accordingly. Intelligent systems, although, is a very vast field with magnificent advances in technology, when utilizing them, they make sure of the proper amount of energy used so they can be utilized sustainably. Intelligent systems use machine learning to learn from the massive amount of data present. Due to ease of storage and communications at high speeds, intelligent systems can be trained to enable them to make decisions accurately as humans do.

Intelligent systems can be used to manage large amounts of prevalent data in the healthcare domain. This enables healthcare professionals to look into the best medical practices and come up with solutions for treating and diagnosing a wide range of rare diseases. Intelligent systems provide sophisticated approaches to visualize the healthcare data and explore AI techniques in decision-making processes in several processes, such as drug development, patients' recovery, and prognosis. Due to human-like accuracy in decision making in clinical fields, Intelligent systems have proved to become an efficient and significant way of providing healthcare services and care delivery to the patients.

Below, we discuss a few intelligent systems currently in practice in healthcare.

2.1 Virtual Assistants in Drug Development

A remarkable advancement in the clinical field is the ability of AI-informed virtual assistants to automate and speed up the drug discovery process. In the drug development process, clinical trials more specifically randomized control trials (RCT) and control trials are conducted and the effects of a specific drug are recorded with time. This medical report is then analyzed to reach a specific conclusion regarding the relationship of the drug with a specific disease. The clinical trials produce a massive amount of data, and analyzing them manually is a very costly process. Through virtual assistants, these data can be accurately explored to come up with drug development ideas within a lesser amount of time than through manual data handling.

These virtual assistants further help healthcare professionals in finding key answers related to their research. Since they are trained on a specific task, virtual assistants excavate through only the necessary data to come up with answers a researcher wants to know. These can further lessen the time a researcher uses to go through several sources and medical journals in order to come up with a specific finding. Hence, virtual assistants are intelligent enough to comprehend the drug effectiveness in a subject, and furthermore, they are able to extract just the right amount of information from the vast medical literature.

2.2 Intelligent Medical Devices

Medical devices provide significant assistance to healthcare professionals as well as patients. Patients, more specifically, are aided in their daily activities to live an easier and better life. There have been developments of several wearable devices, smart recorders, clinical devices, etc. to automate and ease the process of treatment. Examples include intelligent wheelchairs to aid people with disabilities in their mobility. Speech-based wheelchairs that work on instructions given in the form of speech, help people ease their mobility to a much greater extent. Similarly, ADAMM Intelligent Asthma monitoring can be an example of a wearable technology that assists asthma patients by notifying them if they are approaching an asthma attack. It records the symptoms, past data, use of drugs by patients and hence is able to make such decisions. Similarly, for diabetic patients, by use of an AI-powered insulin pump, they are able to have an insight into how much insulin they need in their blood and when they would need it. Sugar spikes in the blood cause rupture of vital organs in the body, hence diabetic patients need to be extra careful, and AI-powered insulin pumps help them in maintaining the records and eventually giving significant predictions. Moreover, several smartwatches have been developed that effectively keep records of the amount of calories burnt, distance walked, etc. to assist people in decision making regarding their health.

2.3 Ambient Healthcare Monitoring System

Ambient healthcare has been essentially important to comprehend the patients' behaviour in several environments such as hospitals, homes, or parks. It is necessary to observe the patients' reactions in different situations. Sensors such as temperature sensors, Carbon monoxide sensor (CO), Carbon dioxide (CO_2) sensor, and oxygen sensors collectively determine a patient's reaction to certain environments [7]. Similarly, monitoring systems for the patients such as their body temperature, heartbeat rate, body weight, blood sugar level, and several other features need to be recorded to aid PA's (Physician's assistants) as a part of their treatment. These sensors, directly connected with mobile devices can help medical professionals in continuous monitoring of the patients' daily activities as well as their ability to adapt with changes. Banerjee and Roy [8] developed a pulse rate detection system. This used a plethysmography process and displayed the output digitally and hence was able to detect the pulse rate in real-time. Gregoski [9] proposed a smartphone-based heart rate monitoring system. Since heart rate and body temperature are significant indicators of the prevalence of any disease in the body, it is essentially important to monitor them to be able to detect any clinical event at any time, and eventually make decisions accordingly.

3 Use Cases of Soft Computing in Basic Sciences and Diagnostics

Soft computing approaches have found to be working greatly with imprecise data [10]. As it is based on approximate models, they are also able to adapt according to problem domains. Their potential to exploit meaningful and significant relationships set in a data set can further be utilized in the diagnosis, prediction, and treatment of many clinical events. Due to imprecise test measurements, uncertainty and randomness on the normal range of test results, incomplete knowledge on biological mechanisms, and missing information in a large number of cases, imperfect data forms a major part of medical data. Because of this reason, it becomes difficult to find out the best mathematical model or direct computational algorithm to manage this imperfect, incomplete, partially true, or approximate data [11]. Soft computing techniques, thus, are becoming extremely popular in the healthcare industry because of their ability to find a good balance by correctly exploring the randomness in bioinformatics and healthcare data. This makes soft computing powerful, reliable, and efficient in a number of medical tasks such as, drug development, understanding the intricate biology, physiology, and life cycles of microorganisms and their effects in human bodies, interaction of biological molecules in diseases, and finding biomarkers.

The use of soft computing techniques in healthcare can be found in areas like basic sciences, clinical disciplines, and diagnostics measures. The use of soft computing techniques and current works in these areas are discussed below.

3.1 Soft Computing in Basic Sciences

Basic sciences can broadly be defined as the study of biology, chemistry, pathology, or bacteriology that are closely related with life and medicine. Biochemistry, for example, requires the study of complex reactions, proteins, nucleotides, and genes' effect on the enzyme activities of each other, which becomes extremely difficult to analyze. Moreover, conventional mathematical models fail to capture the intricacies of these phenomena. For this reason, Neural Networks, Fuzzy Logic, and Genetic Algorithms have been applied in a number of fields [12]. These include pathology, genetics, biochemistry, cytology, biostatistics, histology, etc.

Genomics is another important field in the basic sciences of medicine. Genomic and proteomic data analysis is important for the knowledge of the fundamental factors of human illness problems. Futschik et al. [13] and Catto et al. [14] used a combination of Fuzzy Logic and Neural Network to identify cancer tissue from gene expression data. Statistical analysis did not perform well in this case. Futschik studied fuzzy rules to detect genes that are associated with particular types of cancer. In understanding hereditary diseases, genomics plays a pivotal role. With this regard, Villmann et al. [15] proposed a soft computing technique of fuzzy labeled neural Gas for the classification of patients suffering from a genetic disease, Wilson's disease. A discrete

Fuzzy logic and neural network model along with the Gaussian variant was applied in the study. Microarray gene expression profiling is another field in genomics that studies the clinical diagnosis of diseases. Their cellular states and biological networks are significant in gene expression data. Ho et al. [16] proposed a Fuzzy logic model tuned by Genetic Algorithms to develop an interpretable gene expression classifier by creating a fuzzy rule base for microarray data analysis. This served as a very easy tool for analyzing gene expression profiles.

Similarly, pharmacology, the area of drug development seems to use soft computing in many of its applications. The field involves in detecting any medicinal or therapeutic substance, their composition, along with toxicology and medical applications. Agatonovic-Kustrin et al. [17] proposed a combination of artificial neural network and genetic algorithms for the prediction of corneal permeability of drugs that have structural differences. This model was able to identify the corneal permeability of the given drugs by analyzing their molecular structure. Furthermore, Agatonovic-Kustrin [17] utilized this model for measuring the plasma concentration in breast milk. It is seen that several kinds of drugs are excreted into breast milk in some quantity. In the study, genetic algorithms were used for finding the subset of descriptors that were found best for transferring the drug to breast milk by studying only the molecular structure of the drug.

Cytology, or cellular biology, is another field in biological life sciences that involves cell studies. The cellular structure, interactions with the environment, their life cycle, division, organelles are studied extensively in this field. Ma et al. [18] proposed a cell slice image segmentation. The complex structure of cells and their sliced images, it becomes an extremely strenuous task for segmenting any biological cell slice image. Fuzzy algorithms and artificial neural networks were used for the segmentation of the image morphologically. This is able to detect edges, regional segments, and wavelet transforms that make it very easy for the cytologists in finding the characteristics of a cell and their impact on any environment.

3.2 Soft Computing in Medical Diagnosis

Medical diagnosis is the recognition or identification of an illness or a disease by examining the symptoms and clinical events in a person. Medical diagnosis can closely be connected with anomaly detection. It is one of the important and delicate issues in healthcare. The correct identification of symptoms leads to a correct diagnosis leading to proper treatments. For this reason, computer-aided diagnosis is becoming extremely popular in the healthcare industry. Soft computing techniques are assisting doctors in identifying subtle changes in the body that may be difficult for human doctors to notice. A few use cases in the medical diagnosis using soft computing techniques have been discussed below.

With regard to medical diagnosis, it is seen that soft computing techniques are majorly used in medical images of the human body. Radiology, hence, seems to be the most popular field where soft computing techniques have taken a significant role.

The medical image study mostly involves ultrasound (US), angiography, magnetic resonance imaging (MRI), and computed tomography (CT). MR images are very prone to excessive noise due to equipment or operator performance, or environment. This leads to a major inaccuracy in the segmentation of such images. Shen et al. [19], Meyer-Baese et al. [20], and Wismuller et al. [21] have used neural-fuzzy systems to address MRI related problems. Similarly, Lee et al. [22] have proposed a multimodal contextual neural network and spatial fuzzy rules for automatically identifying abdominal organs from CT scans slices. This helped solve a major difficulty in this domain due to gray-level similarities of adjacent organs.

Similarly, Shitong et al. [23] proposed an advanced fuzzy cellular neural network (AFCNN) for the identification of liver images with better accuracies. It gave greater accuracy than the cellular neural network by including the fuzzy logic enabling strong endurance to handle the uncertainties in the images. Raja et al. [24] proposed a neuro-fuzzy hybrid system for analyzing ultrasound kidney images. This method is successful in classifying kidney diseases and also helps physicians in forecasting any future aberrance in the kidney in present normal subjects. N-Benamrane et al. [25] proposed a neuro-fuzzy method in identifying tumors in medical images. Along with the neuro-fuzzy model, the proposed system also uses an expert system. The architecture was tested in MRI images of the brain. Similarly, Andre et al. [26] developed a fuzzy system tuned by genetic algorithms to detect breast cancer. The model was used for testing the Wisconsin breast cancer diagnosis and was able to achieve an accuracy of 97%. Verma et al. [27] proposed a combination of neural networks and genetic algorithms to study digital mammograms. It is seen that it is extremely difficult to recognize a breast tumor as malignant or benign from the mammography images. Hence, it is extremely necessary for a computer aided system to help doctors in this purpose. The model proposed by Verma et al. [27] extracts features and the genetic algorithms select the most relevant ones.

4 Soft Computing Techniques in Healthcare Decision Systems

Soft Computing uses approximate models instead of deterministic models to solve real-world computing problems. Many real-world problems are impossible to be defined by exact deterministic mathematical models. This is where soft computing comes to the rescue. Using soft computing we can solve complex problems by modeling the problem using approximation logic and variables. Soft computing is not a single technique, rather it is an umbrella for a group of techniques and ensembles of various techniques. It consists of Artificial Neural Networks, Genetic Algorithms, Evolutionary Computing, Fuzzy Logic, Expert Systems, etc.

The main objective of healthcare can be loosely identified as the diagnosis of a disease and eventually curing the disease in a human patient. Since healthcare problems are tremendously complicated, the correct diagnosis and cure for a particular disease and anything in between most definitely require the attention of a human mind i.e. a doctor. It is near impossible for a deterministic system to solve healthcare problems, primarily because of the large amount of variables and logic that need to be accounted for. Soft computing seems to be the only way out for computational systems to be able to efficiently solve the issues of health care decision systems. Soft computing derives its inspiration from nature, particularly the human mind and it makes utter sense that if soft computing techniques are able to mimic the human mind to a certain extent, we can have computational systems that can proficiently solve healthcare problems and perhaps even completely replace a clinical doctor.

There are various soft computing techniques currently used in the healthcare industry and they are discussed below.

4.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) derive their inspiration from the human mind and closely resembles the learning pattern of the human mind. ANN is considered to be a universal approximator and it learns a function that maps input to output given the training data. ANNs consist of layers of nodes and each layer of the node has weighted connections to the next layer. The first layer of nodes is the input layer and the last layer of nodes is the output layer. The ANNs learn by approximating the weights of the connection from layer to layer using backpropagation and gradient descent (Fig. 1).

The Value at every node is going to be equal to X = activation ($\sum w_{ji,}\ x_j$). Here activation function can be the sigmoid function or the Relu function. Nowadays mostly the Relu function is used as the activation function. The learning happens in the backpropagation step.

ANNs are intensively used in healthcare systems. Biswas et al. [28] has proposed an ANN-based classification algorithm for the diagnosis of swine flu. Their algorithm gives an accuracy of 94% on their test set. Their ANN consists of 10 input nodes i.e. the feature set they have used has a cardinality of 10. The feature set consists of Fast breathing, sore throat, chills, temperature, runny nose, nausea, cough, fatigue, headache, body aches, and the values that they can attain is in the range of (0–4) i.e. none (0) to severe (4). The ANN consists of 1 output layer which says whether the patient with the given feature set has swine flu or not (Yes/No). There is one hidden layer and the number of nodes in the hidden layer is 14. The activation function used by this ANN is the sigmoid function, and it uses backpropagation as the learning algorithm.

Abdalla et al. [29] propose the use of artificial neural networks for the detection of brain tumor given MRI (Magnetic Resonance Imaging) scans of the brains of patients. Their algorithm gives an accuracy of 99% and sensitivity of 98% which is incredibly good. Their Algorithm consists of six steps.

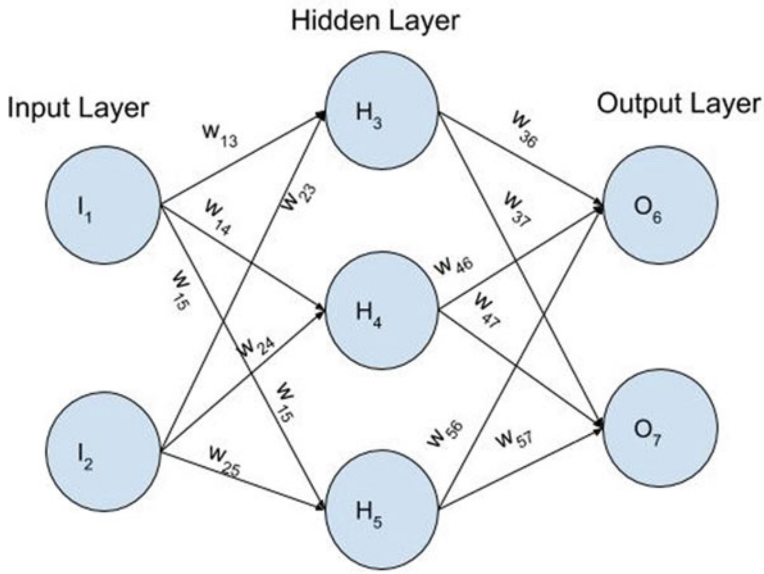

Fig. 1 Artificial neural network

- Database preparation: The data was collected from whole-brain atlas website and the MRI scans were from people above 20 years of age.
- Preprocessing steps: This step consists of reducing the noise in the image and smoothening and sharpening the edges of the MRI image so that there is better feature extraction.
- Image segmentation: The MRI image is then segmented using the threshold method.
- Morphological operations: Then the morphological operations known as erosion and dilation is applied to the MRI image.
- Feature Extraction: This is arguably the most important part of the algorithm. This step used the statistical feature analysis to extract features from the MRI images. The equations of Haralick's features based on the spatial gray level dependence matrix (SGLD) of images computed the features.
- ANN: The features were then put into the ANN. The ANN used the sigmoid function as the activation function.

The above are some examples where ANN has been used to solve healthcare problems. There are many cases in the real world where ANNs have been successfully used to save the life of a human being.

4.2 Fuzzy Logic

A binary logic system is a system in which each variable can have a value of either 0 or 1. A fuzzy logic system can have variables with values ranging from 0 to 1, e.g. 0.67. Using fuzzy logic, we can better approximate real-world problems and solve them accordingly. Fuzzy Logic is extensively used to solve problems in health care. A typical fuzzy logic-based system consists of a fuzzification module, inference system module, knowledge base, and defuzzification module (Fig. 2).

The fuzzification module is responsible for fuzzifying the input i.e. changing the input variables into a range from 0 to 1 accordingly, the inference system and knowledge base consists of a set of rules that work on the fuzzy variables. The defuzzification module defuzzifies the fuzzy variables into a human understandable output which can be further worked with.

Fatima [30] proposes an algorithm based on fuzzy logic for the diagnosis of skin cancer given images of patches on the skin. It uses various image processing techniques and feature extraction techniques to extract information from the image and the classifier used is based on fuzzy logic. The algorithm consists of five steps.

- **Preprocessing**: In this step, the colored image is changed into a grayscale image.
- **Segmentation Image**: In this step, the skin patch is extracted from the rest of the skin.
- **Feature Extraction by using GLCM**: The features are then extracted using the Gray level Dependence Matrix.
- **Diagnostic by using fuzzy logic**: The fuzzy logic in this algorithm uses 9 inputs, and Mamdani's fuzzy logic inference rules.

Simple fuzzy-based logics don't give as high accuracy as neural networks or neural fuzzy systems.

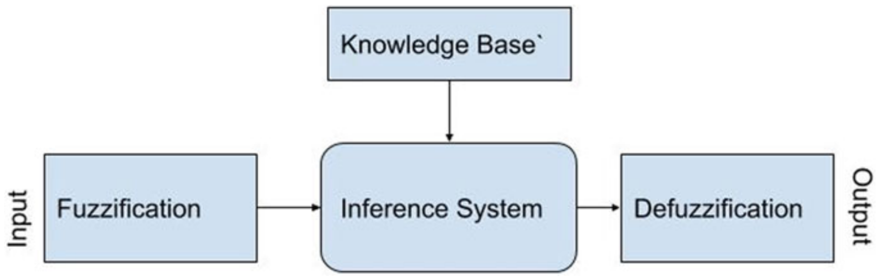

Fig. 2 Working of a fuzzy system

4.3 Genetic Algorithms

Genetic Algorithms are a class of algorithms that gets its inspiration from natural selection and evolution. Genetic Algorithms are mainly used to solve optimization problems. The basic processes of genetic algorithms are as follows:

- **Initialization**: In this step, the initial population is randomly created.
- **Evaluation**: In this step every member of the population is estimated and the performance of the individuals are assessed based on how well they solve the required problem
- **Selection**: In this step, the ones that solve the problem to the greatest extent efficiently is chosen.
- **Crossover**: In this step new offspring are created by incorporating the aspects of the current individuals. After all these processes are over it is expected to create systems that are closer to the requirements that are able to solve the problem. The process is repeated from the second step until a converging point is reached [31].

A breast cancer diagnosis that used neural networks and genetic algorithms was proposed by Khaled et al. [32]. In this model genetic algorithm is used to optimize the weights of the neural network for the highest level of efficiency and accuracy.

5 Further Applications of Soft Computing in Healthcare Decision Making

The usage of soft computing in healthcare is not just limited to medical diagnosis. We can also use Soft Computing techniques for well-being assessment, and health risk assessments like the risk of getting cancer given medical data of a patient, etc. We can also use soft computing for the diagnosis of depression. The diagnosis of depression is a bit different from the diagnosis of other diseases as it is a mental disease and the changes in a brain structure are not so prevalent that depression can be seen in MRI images or other scans of the brain. Yet, we can use soft computing to analyze clinical and questionnaire data of the patient to diagnose depression, as soft computing models are reliable and can be used to solve a lot of real-world problems. Soft computing can also be used to determine the chances of a disease being cured if a patient has a particular disease.

5.1 Fuzzy Logic in Remote Healthcare Monitoring

Hamid et al. [33] propose a method for the healthcare monitoring of the elderly using fuzzy logic. They set up a bunch of sensors and attach it to the person to be monitored or the environment of the person to be monitored. The sensors gather data and then the data goes through a fuzzy logic inference system that outputs the activity that the person is doing. The output includes but not limited to sleeping, washing hands, cleaning, watching TV, bathing, walking, running. This system can be used in elderly people and when abnormal activity is occurring in the monitored person the concerned authorities can be notified.

In the Hamid et al. [33] system there are primarily 3 types of sensors. The first type is a set of microphones that monitors the acoustical environments i.e. the sounds coming from the environment. It also monitors the sounds being produced by the person being monitored. The second type of sensors are wearable sensors that monitor the physiological activities of the person e.g. heart rate, breathing rate, temperature, etc. The third type of sensors are infrared sensors that monitor the environment of the person. This includes smoke detectors etc. Then a master system gathers all the data and uses fuzzy logic to get an output. The data gathered from all these sensors can be imprecise and uncertain and we know that fuzzy systems are able to handle such types of data and give high accuracy results. The advantage of using fuzzy logic for such a system also includes simplicity of design and its ability to deal with complex data from tall these sensors. The data from all the sensors are first analyzed and a correct description is made and the description is numeralized. E.g. If from the first sensor a medium pitched constant sound is coming then the description becomes a vacuum sound and the numerical value for it can be 5. There are different independent algorithms that each of the sensors uses to come up with the description given the raw data. All the inputs are then processed by the fuzzy logic system which uses Mamdani's rules. E.g. If (Sensor 1 has a snoring sound) and (Activity is None) and (heart rate is low) and (Pulse Rate is Low) and (breathing rate is low) Then the Person is (Sleeping).

5.2 Risk Assessment of Cervical Cancer in Women-Based on Convolutional Neural Network

Zahras et al. [34] have used a convolutional neural network to perform the cervical cancer risk assessment. There is a device known as Hinselman's device that magnifies the doctor's view of the cervix using an intense light source and a set of lenses. This acts as the image in the model. The feature set also consists of 32 factors like age, number of sexual partners, number of pregnancies, etc. And there are 4 target variables mentioned in their paper i.e. Biopsy, Schiller, Hinselmann, Cytology. For the Hinselmann target variable, the accuracy is 95.99%. For the Schiller target variable, the accuracy is 95.71%. For the cytology target variable, the accuracy is 97.41% and for the biopsy target variable, the accuracy is 92.69%. Here we can see that researchers have successfully used soft computing techniques risk assessment of cancer.

5.3 Diagnosis of Depression Using Neuro-fuzzy Model of Soft Computing

Subhagata et al. [35] proposed a soft computing model that uses a neural fuzzy hybrid system for the diagnosis of depression in a patient. The feature set used by Subhagata et al. has a cardinality of 14 i.e. there are 14 features that are being considered by this algorithm. Some of the features are loss of appetite, insomnia, indecisiveness, lack of thinking. The output consists of a binary value i.e. Yes/No. Yes if the algorithm diagnoses the input feature set as depressive and No if the algorithm doesn't diagnose the input feature set as depressive (Fig. 3).

The methodology proposed by Subhagata et al. consists of five steps. They are:

- **Data accumulation**: The data is gathered from various hospitals.
- **Principal Component Analysis**: This step uses PCA to extract highly important features so that the data dimension is reduced and then the model can run faster. This is similar to how a real doctor identifies key symptoms first.
- Creating an input vector matrix that comprises significant symptoms as features
- **Fuzzy neural Hybrid Model**: In this part, there is a hybrid model of the fuzzy logic system and a neural network that works in coherence to provide the desired output. The fuzzy system uses Mamdani's laws. The neural network uses backpropagation for training.
- Using real-world depression cases to test the system.

Their algorithm on testing it on real-world depression cases gave an accuracy of 95.50%.

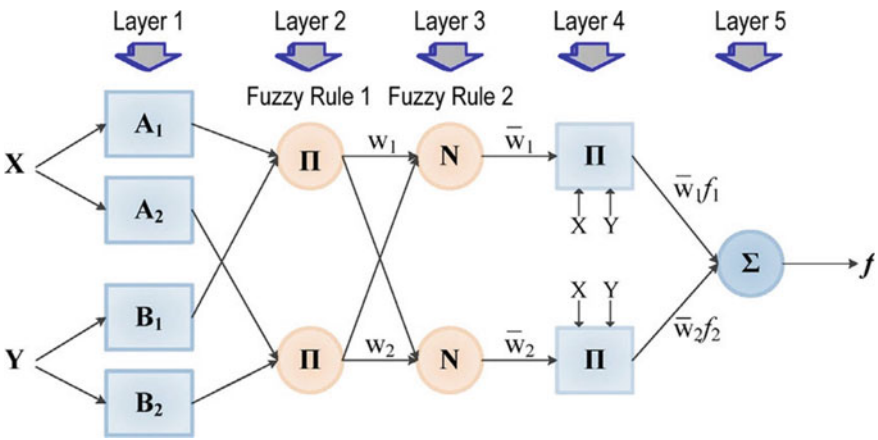

Fig. 3 Schematic diagram of a simple neuro-fuzzy system

6 Hybrid Techniques Used in Healthcare

Soft Computing (SC) is a collection of different techniques and methodologies which aim to harness the tolerance for uncertainty, partial truth, and imprecision to attain tractability, robustness, and low total cost [36]. It is different from hard computing in the sense that hard computing is deterministic and exact whereas soft computing is approximate and deals with problems intuitively and subjectively much like the human mind. Many algorithms in health care use hybrid techniques to solve problems computationally. Hybrid techniques are ubiquitous and every problem that uses soft computing probably has some pre-processing that is done using hard computing. Soft computing and hard computing are not opposite of each other rather they are complementary to each other and the fusion of these two computational disciplines provides humankind with the right tools to tackle the problems of the 21st century. There already exists a large number of systems in which soft computing is together used with hard computing [36].

6.1 Hybrid Solution for Skin Cancer Detection

Aswin et al. [37] proposed a hybrid technique for the detection of skin cancer given images of patches in the skin. The traditional method of diagnosis of cancer cells in the skin is the clinical biopsy, where suspicious parts of the skin are scraped off and sent to the lab for the detection of melanoma [37]. This procedure is time-consuming and expensive. A very cheap and fast method using a hybrid technique is proposed by Aswin et al. Their algorithms preprocess the dermoscopy images using hard computing techniques and the classification is done using soft computing techniques. The classifier they have used is the GA-ANN which is the fusion between genetic algorithm and Artificial Neural Network. In this type of neural network, the weights of the network are optimized to have the optimal value using genetic algorithms. This ensures that the classifier has a high accuracy.

A brief explanation of the steps of the above algorithm is given below.

- Image pre-processing: This is a hard-computing step and uses traditional image processing techniques. In this step, the dermoscopy image is filtered and blurred and smoothened.
- Segmentation: This is also a hard-computing step and the algorithm uses Otsu color threshold segmentation that separates the lesion from the background.
- Feature extraction: In this step features are extracted from the image using statistical techniques and we know that statistical techniques belong to the realm of hard computing.
- Classification using hybrid GA-ANN: The classification is done by using a hybrid fusion of the Genetic Algorithm and Artificial Neural network. In this algorithm, the weights of the neural networks are fine-tuned using genetic algorithms (Fig. 4).

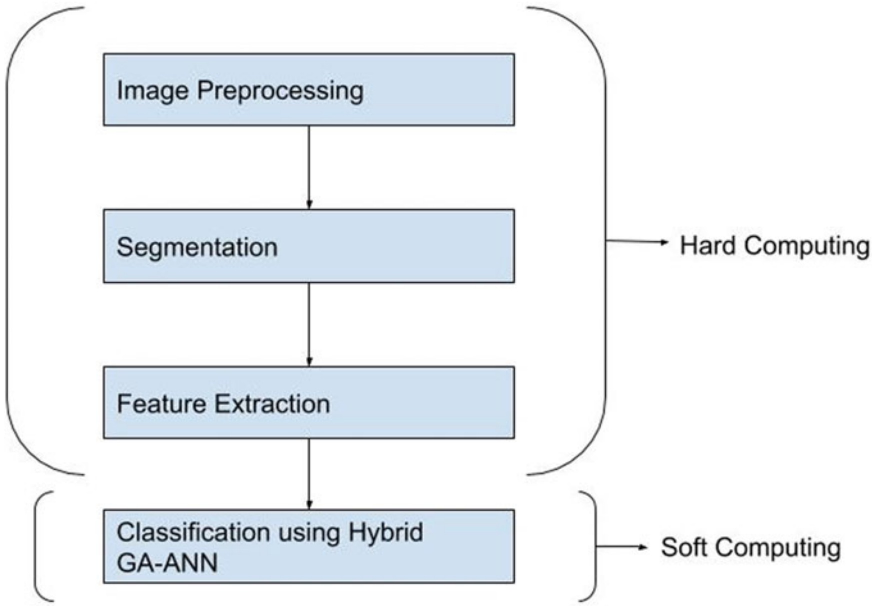

Fig. 4 A schema of a hybrid technique

7 Soft Computing in Clinical Applications

It is seen that soft computing methods are most widely used in clinical sciences. 48% of the soft computing methodologies were used in clinical domains [38]. Soft computing frameworks have been especially used in cardiology, neurology, anesthesia, and rehabilitation. A lot of these fields have applied neural fuzzy mechanisms for clinical assistance to the doctors [39]. The adaptive working of soft computing methodologies has been well utilized in clinical sciences such as controlling blood pressure, unconsciousness, analgesia, etc. A broad discussion of the specific fields and their use of soft computing methodologies have been discussed below.

7.1 Soft Computing in Cardiology

Soft computing is used a lot in Cardiology, particularly while working with ECG. In cardiology medical practitioners extensively use ECG. ECG data are used for diagnosis and monitoring of cardiac functions by enabling the doctors to identify people prone to any cardiovascular event or even death due to any cardiac abnormality. ECG or Electrocardiogram is a graph of the electrical activity of the human heart. In this graph, the y-axis represents the voltage of the electrical activity and the x-axis represents time. Nazmy et al. [40] proposed the classification of ECG signals using

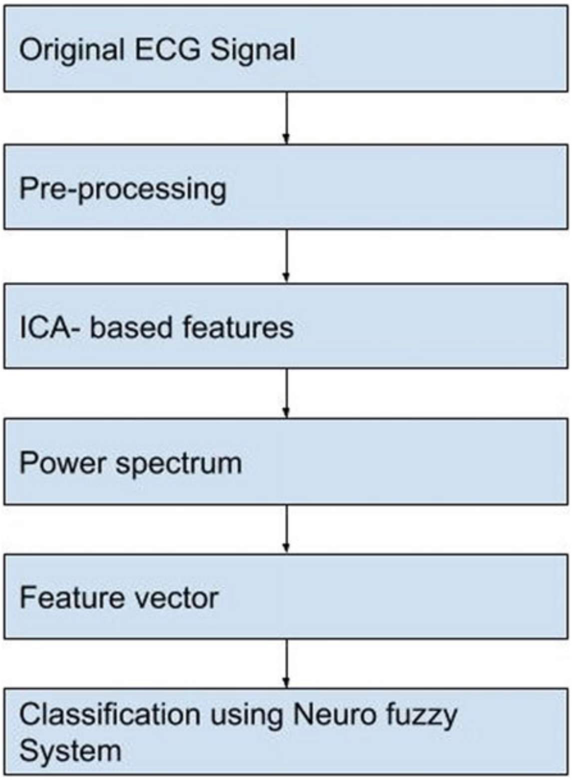

Fig. 5 Classification of ECG signals using adaptive neuro-fuzzy systems

adaptive neuro-fuzzy systems. Their model is shown in Fig. 5 gives an accuracy of more than 97%. Their algorithm consists of 5 steps and a brief description of each of the steps are as follows:

- Preprocessing: Firstly, the data is normalized all the features are standardized to the same level. Since ECG signals may be prone to noise there is the filtering of noise. The signal passes through a high pass filter, a low pass filter, and a Notch filter so that the filtering process is completed and the resulting signal is a noise-free signal.
- ICA based features and Power spectrum: ICA or independent component analysis along with the power spectrum is used for the extraction of useful features which will serve as the input feature vector
- ANFIS: Adaptive Neuro-fuzzy system is used as the classifier in this model. This classifier is used as the diagnostic tool that will help the medical practitioners to diagnose certain heart diseases using ECG signals. This ANFIS uses a hybrid approach of a fuzzy system and neural networks. This ANFIS system has a total of 128 fuzzy rules and one output. The Neural network part of the model uses backpropagation to train. The model can classify six types of ECG signals.

Heart rate signals are considered as a reliable indicator for any cardiac event. Keeping in this mind, Kannathal et al. [41] proposed an adaptive neuro-fuzzy inference system for the detection of heart abnormalities. The model was able to correctly classify cardiac anomalies in 10 different states with an accuracy of 85%. Similarly, Kashihara et al. [42] on an automated drug infusion system. They used a fuzzy-neural model to monitor mean arterial pressure (MAP) in hypotension. Using wavelet transform and fuzzy neural networks, Shyu et al. [43] proposed a method for ventricular premature contraction. Serhatlıoğlu [44] used neuro-fuzzy systems to investigate the consequences of diabetes mellitus on the carotid artery. Acampora et al. [45] recently proposed a combination of fuzzy logic system and fuzzy markup language to study on the ontologies to make the ECG-based knowledge more effective. This was an ECG-based decision-making approach for deducing cardiac health information through heart rate visibility. Using a fuzzy decision support system and genetic algorithms, Paul et al. [46] proposed a system for predicting the risk of heart disease in a currently well person and death risk for those who already had a cardiac abnormality. Similarly, Uyar et al. [47] also proposed a genetic algorithm based recurrent fuzzy neural network decision support system for diagnosing heart diseases.

7.2 Soft Computing in Neurology

Neurology involves the study of the central nervous system and its ontologies. Neurology deals with diagnosis, treatment, prognosis, and investigation of the diseases related to the central, peripheral, and autonomous nervous system [48]. Clinical neurology has immense amounts of imperfect or imprecise data. Hence, soft computing technologies can be applied in this field to aid clinicians for decision making and diagnosis with respect to several neurological disorders. Neurological studies are mostly concerned with electroencephalogram (EEG) analysis, sleep analysis and electromyogram (EMG) analysis. Zhang et al. [49] proposed a nonlinear adaptive fuzzy approximator that enables a non-linear separation of single-sweep evoked potentials. It was also efficient in forecasting non-stationary EEG time-series. Ogulata et al. [50] proposed a neural network method for classifying epilepsy using EEG signals. In epilepsy, the cortical excitability of a person gets completely ruptured. Hence, an accurate method for a correct diagnosis is needed for its treatment and further prognosis. Walczak et al. [51] were able to use artificial neural networks for classifying epilepsy. Their work was the first in this domain.

Schwaibold et al. [52], in their study, compared the classical signal processing approach, artificial neural network, and neuro-fuzzy systems for analysing sleep stages. Neural networks were found to be efficient in pattern recognition due to their robustness. On the other hand, the neuro-fuzzy system was able to grasp the contextual information very well. In their further studies, artificial intelligence in sleep analysis algorithm (ARTISANA) [53] was proposed that automated the entire process of sleep recognition. Khushaba et al. [54] proposed a cognitive fuzzy system for intelligent diagnosis of neurological disorders. It was efficient in assisting the physicians in making decisions with regard to a neuropsychological event in a person. Similarly, Das et al. [55] studied the application of fuzzy systems in hypertension. Hypertension engenders stroke, heart attack, and chronic kidney diseases. Das et al. have done a comparative study on a fuzzy expert system, fuzzy system, and artificial neural network for hypertension diagnosis. Similarly, Sharma et al. [56] proposed a rule-based expert system for neurological disorders, mainly, Alzheimer's, Parkinson's, Migraine, and Meningitis. This proposed system can be used as computer-based assistance for clinical doctors in decision-making processes. Detection of any neurological disorder is extremely essential for a healthy life, as any neurological event can be an early sign of a disorder. Hence, the proposed system is also motivated to provide a home diagnosis system that enables people in identifying a neurological disorder.

7.3 Soft Computing in Medicine and Rehabilitation

Soft computing methodologies can be applied to areas such as critical medicine, physical medicine, and rehabilitation. These areas are mostly associated with therapy, assisting in recuperating a person from a terminal illness, assisting them in living with their difficulties, or getting them habitual with their tasks after a strong medical disorder, such as shock or trauma. This also includes organ transplants and temporary replacement of organ functions by any technical device, such as a pacemaker. In this section, soft computing applications in areas such as intensive care, EEG monitoring, pulmonology, anaesthesia, blood pressure, and respiration regulation, and rehabilitation.

Kwok et al. [57] developed an adaptive neuro-fuzzy inference system (ANFIS) and a multilayer perceptron (MLP) model for ventilator control. Both of these models were able to efficiently model the clinician's decisions. The motivation behind the work was that artificial ventilation of the lungs is of supreme importance to provide oxygen and remove carbon-dioxide from patients whose lungs don't function well. The adaptive fuzzy-neural model was more interpretable than the MLP model. Similarly, Paetz et al. [58] developed a knowledge-based neural network for detecting and helpfully enabling septic shock avoidance for patients in the critical care unit. Belal et al. [59] developed a classifier for categorized pulses into valid and artefacts by implementing a fuzzy inference system. This method was able to monitor pulse oximetry for regulating respiration for neonates and pediatric patients and avoiding false results from probe movement.

Soft computing technologies can also be applied to physical medicine. Physical medicine involves body functional improvement after any injury, congenital disorder, or terminal illness. It is mostly concerned with optimizing the functions of the body and giving a palliative treatment rather than completely removing a disorder or disease. For this purpose, expert training, physical medicines, and physiological modalities are used to ameliorate the cases. Teodorescu et al. [60] developed neuro-fuzzy methods for controlling and diagnosing tremors in a tremor rehabilitation study.

The neuro-fuzzy predictor was a robust and versatile system for coping up with variations of tremor in different individuals. In another study, Deng et al. [61] studied fuzzy-neural models in applying it to a real-time monitoring system for an athlete's daily physical exercise according to the planned schedule. This method successfully improved the efficiency of physical training workload using a computer-aided system. Similarly, in anaesthesia, soft computing can be applied to anaesthesia for controlling and monitoring analgesia, unconsciousness, and blood pressure. Zheng et al. [62] developed a fuzzy logic model for controlling the depth of anaesthesia. This model was successfully able to assess the consciousness level of a patient in a surgery.

7.4 Soft Computing in Other Clinical Areas

Apart from the discussed clinical domains. Soft computing technologies have been extensively applied to other clinical areas such as endocrinology, dermatology, pediatrics, and oncology. In dermatology, the study of skin and skin-related problems, Ubeyli et al. [63] have done notable work in ameliorating the problems related with the detection of erythemato-squamous diseases. They proposed an ANFIS model for differentiating the six shapes of the disease that share the same clinical features. They developed a six ANFIS classifier model for this purpose. Soft computing techniques have been efficiently applied to endocrinology, the specialty associated with internal medicine and hormonal secretions with their interrelationship to physiology and pathology. Endocrinology is also closely related with metabolic functions of the body. The data in this field is hugely incomplete due to very less knowledge, hence soft computing plays a vital role in modeling metabolic systems. Bellazi et al. [64] developed a hybrid neuro-fuzzy method for dynamically modeling metabolic processes. The application also broadly works on intracellular thiamine kinetics.

Similarly, Chen et al. [65] developed a neuro-fuzzy technology for predicting the parathyroid hormone level. In hemodialysis patients, the monitoring of plasma parathyroid hormone is crucially important as their abnormal levels cause renal bone disease. Chen et al. proposed a coactive neuro-fuzzy inference system (CANFIS) for plasma PTH concentration by including clinical parameters. Tung et al. developed a neural fuzzy decision support framework for identifying cancer subtype. Gene expression data was used in their study. Their study was also efficient in detecting pediatric acute lymphoblastic leukemia. In a similar study, Sun et al. [66] used neuro-fuzzy methodologies in oncological applications. The Neuro-fuzzy model was considered a more reliable and accurate method for classifying prostate and breast tumors.

Gastroenterology, dealing with the digestive system and its disorders, is another field of clinical medicine where soft computing methodologies are widely used. Grossi et al. [67] found out in their study that artificial neural networks are well suited for diagnosing gastrointestinal ailments such as chronic pancreatitis, dyspeptic syndrome, or corrosive ulcers. Guler et al. [68] presented a neural network and genetic algorithm method for lung sound classification. For optimizing the parameters of the neural network model, a genetic algorithm was used. Spectral analysis was performed for the chosen breath cycles by a genetic algorithm that was later applied to the neural network. Heckerling et al. [69] proposed a neural network and genetic algorithm for pneumonia predictor variable selection. For the patients with respiratory complaints, the authors used genetic algorithms for searching optimal hidden-layer architectures and eventually diagnosing the problem.

Wu et al. [70] proposed a neural network and genetic algorithm hybrid model for examining patients that had ankle arthrodesis. The model classified the patients with solid arthrodesis with an accuracy of 98.8%. The model showed good performance in analyzing gait patterns in ankle arthrodesis.

8 Conclusion

Soft computing, hence, can bring a very unprecedented shift in the healthcare industry due to its ability to solve complex problems just like a human does. As it emulates the human way of decision making and logical reasoning, it is a perfect tool for solving the drawbacks of the traditional medical decision support systems that are based on traditional AI techniques and statistical or mathematical models. Soft computing is immune to imprecise, uncertain, and incomplete data to manage, manipulate, and mine the data. Healthcare data, being a high variability data and also with a lot of randomness, soft computing works perfectly well. Due to its high adaptability and information processing mechanisms, soft computing is especially useful in handling real-life ambiguous problems. Soft computing methods work better when they are combined rather than just a single method. The hybrid techniques, such as artificial neural network and fuzzy logic, or artificial neural network and genetic algorithms work wonders in manipulating data, extracting features, and providing a meaningful decision about the data. Medical data and records are sensitive in nature. They contain very subtle information that may be important in terms of diagnosis and treatment of a disease. Soft computing techniques help detect these nuances in medical data and assist the clinicians in their decision making. Soft computing techniques can be broadly classified as artificial neural networks, genetic algorithms, and fuzzy logic. All these models are inspired by the way humans have been evolving, developing, and surviving. Genetic algorithms, specifically, imitates the way humans evolve and survive in adverse conditions. The underlying principles lie in the survival of the fittest and natural selection. They work on three genetic operators, selection, crossover, and mutation. Fuzzy logic is mostly used in control tasks. Fuzzy logic involves human language to solve a problem, also known as fuzzy reasoning. It operates on IF-THEN statement schemes. Similarly, artificial neural networks, the imitation of the human neurons, are information carriers. They are interconnected with other neurons, and they collectively work together to pass information signals and come to a decision. Activation functions are the stimuli to these artificial neurons. A combined framework of these soft computing technologies can hence help in decision making just like humans do. This makes possible the use and development of intelligent systems, rule-based expert systems, and computer-aided diagnostics more reliable, robust, and cost and time-efficient. Soft computing techniques are approximations-based models, hence there is no any definite rule in which a system works or a process is modelled. Hence, it might be difficult to understand and choose the right method for solving a problem. Therefore, it is extremely crucial to select the best features of these algorithms, combine them and reach an accurate decision from imperfect, vague, and incomplete data.

References

1. Thapa, S., Adhiikari, S., Ghimire, G., Aditya, A.: Feature selection based twin-support vector machine for the diagnosis of Parkinson's disease. In: 2020 IEEE 8th R10 Humanitarian Technology Conference (R10-HTC). IEEE (2020)
2. Vial, A., Stirling, D., Field, M., Ros, M., Ritz, C., Carolan, M., Holloway, L., Miller, A.A.: The role of deep learning and radiomic feature extraction in cancer-specific predictive modelling: a review. Transl. Cancer Res. **7**(3), 803–816 (2018)
3. Thapa, S., Singh, P., Jain, D.K., Bharill, N., Gupta, A., Prasad, M.: Data-driven approach based on feature selection technique for early diagnosis of Alzheimer's disease. In: 2020 International Joint Conference on Neural Networks (IJCNN), pp. 1–8. IEEE (2020)
4. Thapa, S., Adhikari, S., Naseem, U., Singh, P., Bharathy, G., Prasad, M.: Detecting Alzheimer's disease by exploiting linguistic information from Nepali transcript. In: 2020 International Conference on Neural Information Processing (ICONIP), pp. 176–184. Springer (2020)
5. Davenport, T.H., Glaser, J.: Just-in-time delivery comes to knowledge management. Harv. Bus. Rev. **80**(7), 107–111 (2002)
6. Bush, J.: How AI is taking the scut work out of health care. Harv. Bus. Rev. 5 (2018)
7. Islam, M.M., Rahaman, A., Islam, M.R.: Development of smart healthcare monitoring system in IoT environment. SN Comput. Sci. **1**(3) (2020)
8. Banerjee, S., Roy, S.: Design of a photo plethysmography based pulse rate detector. Int. J. Rec. Trends Eng. Res. **2**, 302–306 (2016)
9. Gregoski, M.J., Mueller, M., Vertegel, A., Shaporev, A., Jackson, B.B., Frenzel, R.M., Sprehn, S.M., Treiber, F.A.: Development and validation of a smartphone heart rate acquisition application for health promotion and wellness telehealth applications. Int. J. Telemed. Appl. (2012)
10. Prasad, M., Lin, C.-T., Li, D.-L., Hong, C.-T., Ding, W.-P., Chang, J.-Y.: Soft-boosted self-constructing neural fuzzy inference network. IEEE Trans. Syst. Man. Cybern.: Syst. **47**(3), 584–588 (2015)
11. Gupta, D., Borah, P., Prasad, M.: A fuzzy based Lagrangian twin parametric-margin support vector machine (FLTPMSVM). In: 2017 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 1–7. IEEE (2017)
12. Borah, P., Gupta, D., Prasad, M.: Improved 2-norm based fuzzy least squares twin support vector machine. In: 2018 IEEE Symposium Series on Computational Intelligence (SSCI), pp. 412–419. IEEE (2018)
13. Futschik, M.E., Reeve, A., Kasabov, N.: Evolving connectionist systems for knowledge discovery from gene expression data of cancer tissue. Artif. Intell. Med. **28**(2), 165–189 (2003)
14. Catto, J.W., Linkens, D.A., Abbod, M.F., Chen, M., Burton, J.L., Feeley, K.M., Hamdy, F.C.: Artificial intelligence in predicting bladder cancer outcome: a comparison of neuro-fuzzy modeling and artificial neural networks. Clin. Cancer Res. **9**(11), 4172–4177 (2003)
15. Villmann, T., Hammer, B., Schleif, F., Geweniger, T., Herrmann, W.: Fuzzy classification by fuzzy labeled neural gas. Neural Netw. **19**(6–7), 772–779 (2006)

16. Ho, S.-Y., Hsieh, C.-H., Chen, H.-M., Huang, H.-L.: Interpretable gene expression classifier with an accurate and compact fuzzy rule base for microarray data analysis. Biosystems **85**(3), 165–176 (2006)
17. Agatonovic-Kustrin, S., Ling, L., Tham, S., Alany, R.: Molecular descriptors that influence the amount of drugs transfer into human breast milk. J. Pharm. Biomed. Anal. **29**(1–2), 103–119 (2002)
18. Ma, Y., Dai, R., Li, L., Wu, C.: The state and development of cell image segmentation technology. J. Biomed. Eng. **19**(3), 487–492 (2002)
19. Shen, S., Sandham, W., Granat, M., Sterr, A.: MRI fuzzy segmentation of brain tissue using neighborhood attraction with neural-network optimization. IEEE Trans. Inf Technol. Biomed. **9**(3), 459–467 (2005)
20. Meyer-Baese, A., Wismueller, A., Lange, O.: Comparison of two exploratory data analysis methods for fMRI: unsupervised clustering versus independent component analysis. IEEE Trans. Inf Technol. Biomed. **8**(3), 387–398 (2004)
21. Wismüller, A., Meyer-Bäse, A., Lange, O., Auer, D., Reiser, M.F., Sumners, D.: Model-free functional MRI analysis based on unsupervised clustering. J. Biomed. Inform. **37**(1), 10–18 (2004)
22. Lee, C.-C., Chung, P.-C., Tsai, H.-M.: Identifying multiple abdominal organs from CT image series using a multimodule contextual neural network and spatial fuzzy rules. IEEE Trans. Inf Technol. Biomed. **7**(3), 208–217 (2003)
23. Wang, S., Fu, D., Xu, M., Hu, D.: Advanced fuzzy cellular neural network: Application to CT liver images. Artif. Intell. Med. **39**(1), 65–77 (2007)
24. Raja, K.B., Madheswaran, M., Thyagarajah, K.: A hybrid fuzzy-neural system for computer-aided diagnosis of ultrasound kidney images using prominent features. J. Med. Syst. **32**(1), 65–83 (2008)
25. Benamrane, N., Aribi, A., Kraoula, L.: Fuzzy neural networks and genetic algorithms for medical images interpretation. In: Geometric Modeling and Imaging–New Trends (GMAI'06), pp. 259–264. IEEE (2006)
26. Pena-Reyes, C.A., Sipper, M.: A fuzzy-genetic approach to breast cancer diagnosis. Artif. Intell. Med. **17**(2), 131–155 (1999)
27. Verma, B., Zakos, J.: A computer-aided diagnosis system for digital mammograms based on fuzzy-neural and feature extraction techniques. IEEE Trans. Inf Technol. Biomed. **5**(1), 46–54 (2001)
28. Biswas, S.K., Baruah, B., Purkayastha, B., Chakraborty, M.: An ANN based classification algorithm for swine flu diagnosis. Int. J. Knowl. Based Comput. Syst. **3**(1), 31–42 (2015)
29. Abdalla, H.E.M., Esmail, M.: Brain tumor detection by using artificial neural network. In: 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), pp. 1–6. IEEE (2018)
30. Ghali, F.: Skin cancer diagnosis by using fuzzy logic and GLCM. J. Phys.: Conf. Ser. (IOP Publishing) **1**, 012020 (2019)
31. Ibrahim, D.: An overview of soft computing. Procedia Comput. Sci. **102**, 34–38 (2016)
32. Alalayah, K.M., Almasani, S.A., Qaid, W.A., Ahmed, I.A.: Breast cancer diagnosis based on genetic algorithms and neural networks. Int. J. Comput. Appl. **975**, 8887
33. Medjahed, H., Dorizzi, B., Istrate, D., Baldinger, J.L., Boudy, J., Bougueroua, L., Dhouib, M.A.: A Fuzzy Logic Approach for Remote Healthcare Monitoring by Learning and Recognizing Human Activities of Daily Living. INTECH Open Access Publisher (2012)
34. Zahras, D., Rustam, Z.: Cervical cancer risk classification based on deep convolutional neural network. In: 2018 International Conference on Applied Information Technology and Innovation (ICAITI), pp. 149–153. IEEE (2018)
35. Chattopadhyay, S.: A neuro-fuzzy approach for the diagnosis of depression. Appl. Comput. Inform. **13**(1), 10–18 (2017)
36. Ovaska, S.J., VanLandingham, H.F., Kamiya, A.: Fusion of soft computing and hard computing in industrial applications: an overview. IEEE Trans. Syst. Man Cybern. Part C (Appl. Rev.) **32**(2), 72–79 (2002)

37. Aswin, R., Jaleel, J.A., Salim, S.: Hybrid genetic algorithm—artificial neural network classifier for skin cancer detection. In: 2014 International Conference on Control, Instrumentation, Communication and Computational Technologies (ICCICCT), pp. 1304–1309. IEEE (2014)
38. Yardimci, A.: Soft computing in medicine. Appl. Soft Comput. **9**(3), 1029–1043 (2009)
39. Kiani, M., Andreu-Perez, J., Hagras, H., Papageorgiou, E.I., Prasad, M., Lin, C.-T.: Effective brain connectivity for fNIRS with fuzzy cognitive maps in neuroergonomics. IEEE Trans. Cognit. Dev. Syst. (2019)
40. Nazmy, T., El-Messiry, H., Al-Bokhity, B.: Adaptive neuro-fuzzy inference system for classification of ECG signals. In: 2010 The 7th International Conference on Informatics and Systems (INFOS), pp. 1–6. IEEE (2010)
41. Acharya, R., Kumar, A., Bhat, P., Lim, C., Kannathal, N., Krishnan, S.: Classification of cardiac abnormalities using heart rate signals. Med. Biol. Eng. Comput. **42**(3), 288–293 (2004)
42. Kashihara, K.: Automated drug infusion system based on deep convolutional neural networks. In: 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pp. 1653–1657. IEEE (2018)
43. Shyu, L.-Y., Wu, Y.-H., Hu, W.: Using wavelet transform and fuzzy neural network for VPC detection from the Holter ECG. IEEE Trans. Biomed. Eng. **51**(7), 1269–1273 (2004)
44. Serhatlioglu, S., Hardalaç, F., Kiriş, A., Özdemir, H., Yilmaz, T., Güler, İ.: A neurofuzzy classification system for the effects of diabetes mellitus on ophthalmic artery. J. Med. Syst. **28**(2), 167–176 (2004)
45. Acampora, G., Loia, V.: Using FML and fuzzy technology in adaptive ambient intelligence environments. Int. J. Comput. Intell. Res. **1**(1), 171–182 (2005)
46. Paul, A.K., Shill, P.C., Rabin, M.R.I., Akhand, M.: Genetic algorithm based fuzzy decision support system for the diagnosis of heart disease. In: 2016 5th International Conference on Informatics, Electronics and Vision (ICIEV), pp. 145–150. IEEE (2016)
47. Uyar, K., İlhan, A.: Diagnosis of heart disease using genetic algorithm based trained recurrent fuzzy neural networks. Procedia Comput. Sci. **120**, 588–593 (2017)
48. Ding, W., Lin, C.-T., Prasad, M., Cao, Z., Wang, J.: A layered-coevolution-based attribute-boosted reduction using adaptive quantum-behavior PSO and its consistent segmentation for neonates brain tissue. IEEE Trans. Fuzzy Syst. **26**(3), 1177–1191 (2017)
49. Zhang, J.-H., Böhme, J.F., Zeng, Y.-J.: A nonlinear adaptive fuzzy approximator technique with its application to prediction of non-stationary EEG dynamics and estimation of single-sweep evoked potentials. Technol. Health Care **13**(1), 1–21 (2005)
50. Oğulata, S.N., Şahin, C., Erol, R.: Neural network-based computer-aided diagnosis in classification of primary generalized epilepsy by EEG signals. J. Med. Syst. **33**(2), 107–112 (2009)
51. Walczak, S., Nowack, W.J.: An artificial neural network approach to diagnosing epilepsy using lateralized bursts of theta EEGs. J. Med. Syst. **25**(1), 9–20 (2001)
52. Schwaibold, M., Schochlin, J., Bolz, A.: Automated sleep stage detection with a classical and a neural learning algorithm–methodological aspects. Biomed. Tech. (Berl) **47**(suppl 1), 318–320 (2002)
53. Schwaibold, M., Schöller, B., Penzel, T., Bolz, A.: Artificial intelligence in sleep analysis (ARTISANA)–modelling visual processes in sleep classification. Biomed. Tech. Biomed. Eng. **46**(5), 129–132 (2001)
54. Khushaba, R.N., Wise, C., Kodagoda, S., Louviere, J., Kahn, B.E., Townsend, C.: Consumer neuroscience: assessing the brain response to marketing stimuli using electroencephalogram (EEG) and eye tracking. Expert Syst. Appl. **40**(9), 3803–3812 (2013)
55. Das, S., Ghosh, P.K., Kar, S.: Hypertension diagnosis: a comparative study using fuzzy expert system and neuro fuzzy system. In: 2013 IEEE International Conference on Fuzzy Systems (FUZZ-IEEE), pp. 1–7. IEEE (2013)
56. Sharma, A.K., Gupta, S.: Neurological disorder diagnosis system. Int. J. Appl. Sci. Eng. Technol. (IJRASET) **2**(5), 296–301 (2014)

57. Kwok, H., Linkens, D.A., Mahfouf, M., Mills, G.H.: Rule-base derivation for intensive care ventilator control using ANFIS. Artif. Intell. Med. **29**(3), 185–201 (2003)
58. Paetz, J.: Knowledge-based approach to septic shock patient data using a neural network with trapezoidal activation functions. Artif. Intell. Med. **28**(2), 207–230 (2003)
59. Bayes, T.: LII. An essay towards solving a problem in the doctrine of chances. By the late Rev. Mr. Bayes, FRS communicated by Mr. Price, in a letter to John Canton, AMFR S. Philos. Trans. R. Soc. Lond. (53):370–418 (1763)
60. Teodorescu, H.-N.L., Chelaru, M., Kandel, A., Tofan, I., Irimia, M.: Fuzzy methods in tremor assessment, prediction, and rehabilitation. Artif. Intell. Med. **21**(1–3), 107–130 (2001)
61. Deng, W., Sun, X., Fan, X.: Fuzzy control of the physical training intensity based on neural-network. J. Biomed. Eng. **20**(4), 700–703 (2003)
62. Zhang, X.-S., Huang, J.W., Roy, R.J.: Depth of anesthesia control with fuzzy logic. In: Fuzzy Logic in Medicine, pp. 83–112. Springer (2002)
63. Übeylı, E.D., Güler, I.: Automatic detection of erythemato-squamous diseases using adaptive neuro-fuzzy inference systems. Comput. Biol. Med. **35**(5), 421–433 (2005)
64. Bellazzi, R., Guglielmann, R., Ironi, L., Patrini, C.: A hybrid input-output approach to model metabolic systems: an application to intracellular thiamine kinetics. J. Biomed. Inform. **34**(4), 221–248 (2001)
65. Chen, C.-A., Li, Y.-C., Lin, Y.-F., Yu, F.-C., Huang, W.-H., Chiu, J.-S.: Neuro-fuzzy technology as a predictor of parathyroid hormone level in hemodialysis patients. Tohoku J. Exp. Med. **211**(1), 81–87 (2007)
66. Sun, X., Qian, W., Song, D.: Ipsilateral-mammogram computer-aided detection of breast cancer. Comput. Med. Imaging Graph. **28**(3), 151–158 (2004)
67. Grossi, E., Mancini, A., Buscema, M.: International experience on the use of artificial neural networks in gastroenterology. Dig. Liver Dis. **39**(3), 278–285 (2007)
68. Güler, İ., Polat, H., Ergün, U.: Combining neural network and genetic algorithm for prediction of lung sounds. J. Med. Syst. **29**(3), 217–231 (2005)
69. Heckerling, P.S., Gerber, B.S., Tape, T.G., Wigton, R.S.: Use of genetic algorithms for neural networks to predict community-acquired pneumonia. Artif. Intell. Med. **30**(1), 71–84 (2004)
70. Wu, W.-L., Su, F.-C., Cheng, Y.-M., Chou, Y.-L.: Potential of the genetic algorithm neural network in the assessment of gait patterns in ankle arthrodesis. Ann. Biomed. Eng. **29**(1), 83–91 (2001)

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