Deep Science Publishing
https://doi.org/10.70593/978-93-49910-80-5_5

Chapter 5: Utilizing artificial intelligence for biomedical signal and image processing applications

5.1. Introduction

The importance of biomedical signal and image processing (BSIP) applications is increasing heavily in the last decade from both societal and commercial points of view. The rampant increase of the size of the aging population worldwide, as well as the rapid advancement of computer technology, sensors, and communication networks are some of the key factors contributing to this increase. The BSIP applications include health-monitoring and disease-detection devices based on biomedical signals and images. The types of biomedical signals include electrocardiograms, electromyograms, electroencephalograms, as well as other electronic signals generated with electrical pulses from the human body. For the types of biomedical images, these include X-ray, MRI, Ultrasound, CT, and PET images, which are generated by the high-definition flexible scanners currently available in the market (Alrowaily & Lu, 2018; Gusev & Dustdar, 2018; Harvie, 2024).

The mainstream use of biomedical signal and image processing is mainly centered around clinical and upsized applications. For clinical purposes, the applications are used mainly by doctors or caregivers to provide services to patients in hospitals or at home. The BSIP applications provide and communicate information to the doctor or the caregivers about the disease-related condition of the patient and where the disease is situated in the body, and the type of damage, so that they may take necessary action. Within the upscaled applications, the devices are aimed at the general public, and are used by the general patients to monitor signals and images to help detect any potential disease-related condition, and may share this information with their doctors or caregivers, so that they can advise the patients about the type of action that should be taken (Yu et al., 2018; Jeong et al., 2022).

5.1.1. Background and Significance

The convergence of artificial intelligence (AI) with an affordable and ubiquitous computational infrastructure has catalyzed vast advancements in the field of computer vision research over the past decade. Although traditional landmark-based statistical methods for face recognition have been used for more than a decade, it is only recently that deep learning models are able to leverage very large public datasets to completely erase the limitations in performance of these methods. This success story in computer vision has resulted in vision-based AI systems being used for a plethora of applications in domains such as security and surveillance, banking, and smart cities. Finally, the vast potential of face recognition systems has made them a target for exploitation, with sophisticated malware being developed to compromise the security and privacy of vision-based AI systems. In the field of biomedical signal and image processing, activity and gesture recognition systems have leveraged the associated advancements in computer vision to enable applications for rehabilitation, therapy, human-robot interaction, and healthcare.

The integration of AI into biomedical signal and image processing applications such as PA detection, activity recognition via sensible displays, speech and emotion recognition via graphical displays, gesture tracking and recognition via smart devices, and therapeutic drug delivery via sensitive devices represents the next frontier in the development of future HCI systems that will be deployed in a myriad of domains serving numerous end-users or specific niche communities. Efficiently detecting and recognizing audio-visual activities and non-quiescent gestures in real time will help alleviate BA and PA and have their applications in unobtrusive therapy, rehabilitation treatment, and therapy robot applications. Essentially, the advances in computer vision presented in the previous sections have enabled these seamless HCI systems resulting in a high practicality factor. Such non-intrusive and sensitive device-enabled HCI systems are an important auxiliary to future Internet of Things ecosystems deployed in homes, hospitals, office spaces, and smart cities on a projected scale. These systems represent, in our opinion, the true synergy of AI with sensor data processing.

5.2. Overview of Biomedical Signal Processing

Biomedical signal processing is a sub-field of signal processing that deals with signals originating from or applied to the human body. Such signals may be biological indicators of disease as is the case with EEG and ECoG signals, physiology investigated with contactless methods such as IR thermal imaging or applied signals leading to the interaction with or modulation of physiological properties particularly for therapeutic purposes such as electrical stimulation or EMF targeted therapies. The processing of such signals is usually carried out with the goal of improving the quality of the signals

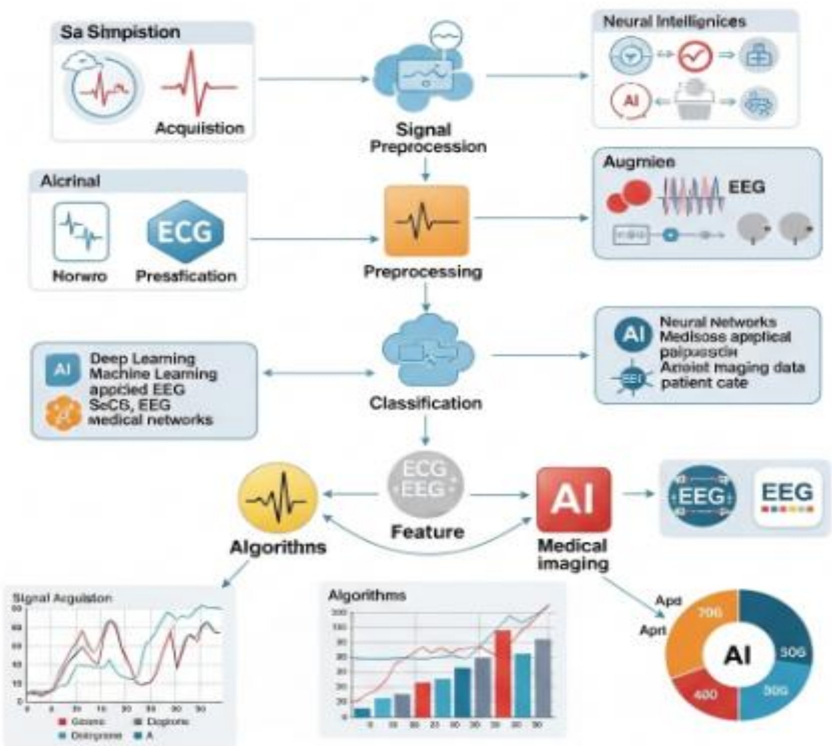

Fig 5.1 : Overview of Biomedical Signal Processing.

through noise reduction, increasing reliability for automatic detection of events, classification of specific states, monitoring, or analyzing changes over time due to a natural cause or for drug testing. Biomedical signal processing has made increasingly important contributions to accurate and efficient reliability research through careful design of noise reduction, denoising and deblurring, and classification procedures. This paper presents an overview of the state-of-the-art of electrophysiological biomedical signal processing followed by two novel examples EEG denoising and discrete classification. There are three broad categories of biomedical signal processing problems: (1) denoising and restoration of minimally processed, acquired signals (2) applications of design or feature analysis to processed signals for the detection and analysis of conduction known signal events (3) classification of specific held stationary or non-stationary states from acquired records for monitoring. To achieve the goals mentioned above, a wide variety of techniques have been proposed for various signals during the last few decades. The most well-known methods from the early years include spatial filtering, epoch averaging, time-frequency representations, and Fourier, Wavelet, and Empirical Eigenfunction decompositions. A variety of supervised and unsupervised nonlinear machine learning techniques, including local spatial covariance methods, have also been utilized. However, it has been one of the drawbacks that many of these techniques were not adequately tested particularly with respect to their detection and classification performances.

5.2.1. Types of Biomedical Signals

The health and physiological state of a subject can be quantitatively represented with biomedical signals, which vary over time or space. Biomedical signals can be broadly classified into electrical, mechanical, chemical, optical, thermal, and magnetic signals, based on the type of alteration recorded. Most projects utilizing AI for biomedical signal processing involve the use of electrical signals. Though EEG, ECG, EGG and EMG are common signals from the electrical category, more specific signals for a body part or function may also be used. The eye is known as the mirror of the brain and eyelid signals are recorded to study fatigue, while galvanic skin activity is indicative of emotional state, impedance cardiography is sensitive to cardiac cycle, and SCG is indicative of heart function. Bioelectric signals can be obtained from various body tissues like the brain, heart, muscles, skin, and viscera. While speech can be considered as a mechanical signal such as vibrations occurring after the production and articulation of speech sound, speech is also modeled on electrical basis obtained from underlying airflow and pressure in the vocal tract and resultant neural activity. Speech and non-speech vocal sounds, the vibration of skin around the vocal tract caused by articulation of voiced and voiceless phonemes, are involved in non-verbal communication.

However, there have been studies to classify phonemes utilizing neural activity. Several pure chemical signals serve to clinically identify and differentiate health conditions. Other biochemical signals such as glucose, cholesterol, triglyceride, sodium, phosphate, calcium, magnesium, and potassium levels can be manually assessed for biochemical tests of blood or serum. Oximetry utilizes photoplethysmography signals or blood absorption spectrum in infrared and red regions to determine oxygen saturation of arterial blood. Common examples of optical signals include MRI and fluorescent optical images. Infrared-based thermal signals can also be assessed to determine the health condition of a subject. Though magnetic signals are not frequently assessed, magnetoencephalography has been employed for neurological disorders.

5.2.2. Challenges in Signal Processing

In digital signal processing, processing biomedical signals is a challenging task and requires a predefined level of expertise. Most biomedical signals contain distortions, noise, overlapping patterns, and outliers, which complicate analysis. The frequency composition of the biomedical signal is typically low, and detecting low-frequency emissions presents a risk of data loss. In some applications, particularly in motor imagery brain-computer interfaces based on electroencephalograms, attracting an observer's attention to a detectable task using specified stimuli is difficult. The noise pollution of physiological signals by electromyograms, power lines, and the surrounding electromagnetic field may corrupt event-related data processing. Moreover, nonlinear, nonstationary, and complex multiscale characteristics of physiological signals make them difficult to model and process. Using a stationarity mathematical model to evaluate a nonstationary signal is also a challenging task. Most nonstationary signals, such as blood pressure waveforms, cerebral oxygenation index, and QRS complex, contain a high-frequency component and become more pronounced during the labor period.

Preprocessing signals is a standard block in the biomedical signal processing pipeline that solves detection issues, removes stimulated artifacts, noise, and distortions, filters out high-frequency components, and improves the susceptibility of event detection. The denoising performance is related to the denoising algorithm parameters and the signal-to-noise ratio. Maintaining content variability using a stringent threshold may adversely affect the denoising performance. The requirements of various processing tasks impose additional constraints on the design of biomedical signal denoising algorithms. An effective denoising algorithm is crucial for signal retention and analysis accuracy.

5.3. Overview of Biomedical Image Processing

Biomedical image processing is a technique that makes use of image processing techniques to process biomedical data obtained from various modalities such as CT, MRI, X-Ray, Ultrasound, PET, SPECT Imaging, Scintigraphy Imaging, Thermograph Imaging, Laser Scanning, Near Infrared Spectroscopy, Mass Spectrometry Imaging, Micro-CT, Optical Coherence Tomography Imaging, etc. The images acquired using these modalities contain various diseases such as tumor, fractures, cysts, multiple sclerosis, hematoma, joint disorders, stroke, Alzheimer's disease, epilepsy, cardiac disease, bleeding, precancerous states, brain white matter injury, infections, etc.

The challenge in biomedical image processing lies in the fact that the images are not ideal and can be corrupted with noise, blurring, and artifacts. The images are of very low contrast and even some areas of the image are absent. The content of the image can be touching with adjacent organs in the body and even mixed with other content and also have large similar intensity pixels. The volume of biomedical data is also huge and very difficult to manage and manipulate; the data are hard to interpret and visualize with the available resources. The above parameters lead to misinterpretation of the image data due to the use of conventional techniques available in the image processing community. Therefore, it is very important to explore AI techniques which can help and make the use of this data easier and more accurate. The discussion of various aspects is presented in the following sections whose benefits will enhance the process in a variety of manners.

5.3.1. Types of Biomedical Images

Image processing has gained popularity over the last few decades as a powerful tool for information analysis in multiple domains ranging from advanced scientific applications to daily-life applications. Image processing is applied specifically to the analysis of biomedical images, which include but are not limited to, images acquired from medical imaging modalities, images acquired in-hospital from video cameras, microscopic images, images acquired from non-imaging diagnostic tests, and other biomedical images. The advancement in imaging technologies has helped increase both the quality and quantity of biomedical images making the quantitative evaluation of these images vital for proper diagnosis, follow-up, and treatment of various critical diseases.

Biomedical images can be classified based on various criteria and aspects. For instance, living beings, modification, modality, dimensionality, dimensional resolution, image intensity, color resolution, groups, stages, and diagnostic probability are some of the criteria used to classify biomedical images. Each biomedical imaging modality offers distinctive advantages and disadvantages, which must be considered by the physician when performing the medical diagnosis.

5.3.2. Challenges in Image Processing

Biomedical images provide valuable information that, if correctly processed and analyzed, could support diagnosis decisions and aid healthcare professionals. There is a risk that image processing will fail in identifying clinically important features, particularly with the massive influx of image data from evolving imaging technologies and modalities complemented by features that are challenging to characterize incorporating complexities such as proximity to one another and likeness in size, shapes, and textures. Moreover, existing diagnostic protocols might be restricted and thereby not particularly effective due to images housing diverse artifacts, adopting substantial variations, only having little representation of diseased classes with benign samples predominating, or lacking important imaging features deemed useful for clinical analysis.

However, achieving effective processing and analysis of biomedical images is not a straightforward task. Besides the risk of lack of clinical interpretation when employing conventional automated approaches, a need to balance sensitivity and specificity might also arise from the prerequisites for ensuring welfare and safety to patients. Finally, network architectures for deep learning and their analytics must also be specifically tailored to address particular characteristics of biomedical images throughout the processing pipeline. Nowadays, frameworks show significantly improved results as long as the biomedical images are annotated and the dataset dimensions are larger.

Recognizing the above-mentioned challenges, the following sections outline the key areas underpinning frameworks alongside their contributions in addressing the challenges while analyzing biomedical images. This chapter therefore serves as a research guide to the field of biomedical image processing for researchers and professionals.

5.4. Artificial Intelligence Fundamentals

We begin this section by providing necessary background information on some important concepts and algorithms that are commonly used in AI, especially as applied to biomedical S/I processing. The topics discussed in this section represent only a small subset of AI-related concepts and algorithms; however, they provide a solid foundation for understanding the AI techniques used in the subsequent sections. First, we discuss the broad concepts of AI and some key application areas, as well as ML and DL, which are foundational to the AI algorithms used in the other chapters. Second, within ML, we discuss the concept of supervised versus unsupervised learning and the notion of classification and regression tasks, and highlight some traditional ML approaches, including hidden Markov models, Gaussian mixture models, and support vector machines with kernels. Next, we present the DL concept with an overview of artificial neural networks and briefly touch upon the convolutional neural network and recurrent neural network DL architectures, which are commonly used in biomedical S/I processing tasks. Finally, to motivate the use of both ML and DL APs presented, we discuss selected ML and DL applications within the biomedical S/I processing areas of detection, classification, and segmentation.

Presently, the focus in the field of AI is on ML, specifically neural network-based DL. While AI is indeed an interdisciplinary field, which combines concepts from many areas of computer science, it is deeply rooted in the field of mathematics, especially optimization, statistics, linear algebra, and computers. Subsequent to the birth of the field of AI in the 1950s, advances were made in the AI area of symbolic processing. However, advances in other fields of computer science and the predictive power of the subsequent data-hungry ML and DL AI approaches have, in recent years, led to the widespread use of ML and DL solutions across many application areas, including computer vision, natural language processing, robotics, and biomedical S/I processing.

5.4.1. Machine Learning Basics

The structure of AI is divided into wide levels; the higher, the more complex the system. At the lowest level is programming, where we directly write algorithms that are able to recognize or classify. However, programming usually cannot tackle complex problems:

instead, Machine Learning comes to serve as an intermediate level, focusing on "learning" the tasks directly from data, rather than from explicitly programmed algorithms. Finally, the highest level is called Deep Learning, where Artificial Neural Networks "learn" complex representations through multiple processing structures.

Machine Learning seeks to find strategies to emulate typical human behavior, which could solve tasks from different areas of knowledge, such as medicine, education, image processing, etc. The area has attempted to find "general purposes" solutions that could solve different kinds of problems, such as classification, object detection, segmentation, etc. Motivated by biological observations of how the human brain works, Artificial Neural Networks are inspired by the inner layers of dense cells that compose the cortex of the human brain. The observation of how humans recognize objects in photorealistic images led to Deep Convolutional Neural Networks.

Thus, a Neural Network learns a mathematical mapping function, through experience, from data of a given feature space to another target space. The main objective to perform this mapping task is to minimize an empirical risk, through iteratively adjusting the weights of the network. This space minimization is usually carried out using gradient descent, its variants, or other second-order methods. The loss function quantifies how well the model predicts the target values for a given set of data. During training, design choices made by data scientists determine the shape of the network and its hyperparameters. Through several iterations, the neural network is prompted to find weight values that minimize the loss function defined, thus learning the specific mapping function of the given task.

5.4.2. Deep Learning Overview

Deep learning, popularly known as hierarchical learning or deep neural learning, is part of the machine learning family of methods based on learning data representations as opposed to task-specific feature extraction. The term "deep" refers to the use of multiple layers in a neural network architecture. The depth of the architecture is the main source of performance boost in deep learning over traditional machine learning methods. Deep learning also relies on large datasets to train the additional parameters present in deep networks, and the advent of large amounts of online data for computer vision as well as the ability to use GPUs to accelerate the training of large neural networks made deep learning a key component of most state-of-the-art computer vision methods. The term "deep learning" has largely come to refer to a class of techniques based on deep neural networks, including convolutional networks for images and recurrent networks for sequences. There has also been much work on semi-supervised learning from weak labels and user-provided supervision, a direction that is especially relevant to biomedical applications where labels are often scarce and expensive to acquire.

A key aspect of deep learning for supervised tasks such as classification is the need to learn good features for the task. Learning to predict tasks such as object relationships enables the classification of novel objects and reidentification across multiple locations on one object or across objects undergoing a common change. Recurrent networks have recently yielded impressive results on sequence prediction tasks, compressing long inputs and generating sequences, as well as related tasks such as image captioning. While sequence labeling, that is asking labels for every input in a sequence, is perhaps the simplest extension to the image classification problem, many other tasks such recognizing entity translations or ordered lists of objects undergo a corresponding change.

5.4.3. Neural Networks in Biomedical Applications

Artificial neural networks provided the first class of algorithms to learn directly from the characteristics of the problem, and even in its simpler versions they were able to overcome some limitations of classical statistical techniques. For many years, there were a lack of training algorithms capable of adjusting the large number of parameters in realistic configurations. However, thanks to a better understanding of the optimization landscape and major advances in computing power, the introduction of backpropagation, and the availability of large datasets, neural networks soon became the preferred method for many problems in computer vision, speech recognition, machine translation, and other applications. In 2012, neural networks called deep learning led to unprecedented improvements in the quality of results for a key milestone for image classification accuracy, with the best submissions based on convolutional neural networks that were three times better than the best previous algorithms based on hand-engineered features. Since then, convolutional neural networks became the preferred choice for image processing. The research and success of deep learning for image classification tasks sparked interest from other research communities, including medical imaging. Neural networks are now the preferred method for many medical image analysis problems, including tumor detection, delineation, characterization, and diagnosis. Medical decision support systems based on neural networks have been successfully developed for a variety of imaging modalities, including computed tomography, magnetic resonance imaging, magnetic resonance spectroscopy, digital mammography, and positron emission tomography, among many others.

5.5. AI Techniques in Signal Processing

Signal processing techniques aiming to extract useful information from a signal traditionally rely on block processing. First, any noise must be rejected or compressed, followed by relevant signal features and patterns being identified. Only after these first micro-decisions can the classification or segmentation process act on the features chosen. Work towards the automation and improvement of these blocks of work traditionally done by the engineer involved research in the last couple of decades, and thus, several AI-based signal processing techniques are now available. Deep learning utilized techniques present state of the art results in most of the block tasks. However, being data hungry, they require a lot of annotated data. Structuring the block approach in a learning-like scheme that can be trained to deal with what previously required human intervention for decisions can in many occasions fill-in the gap.

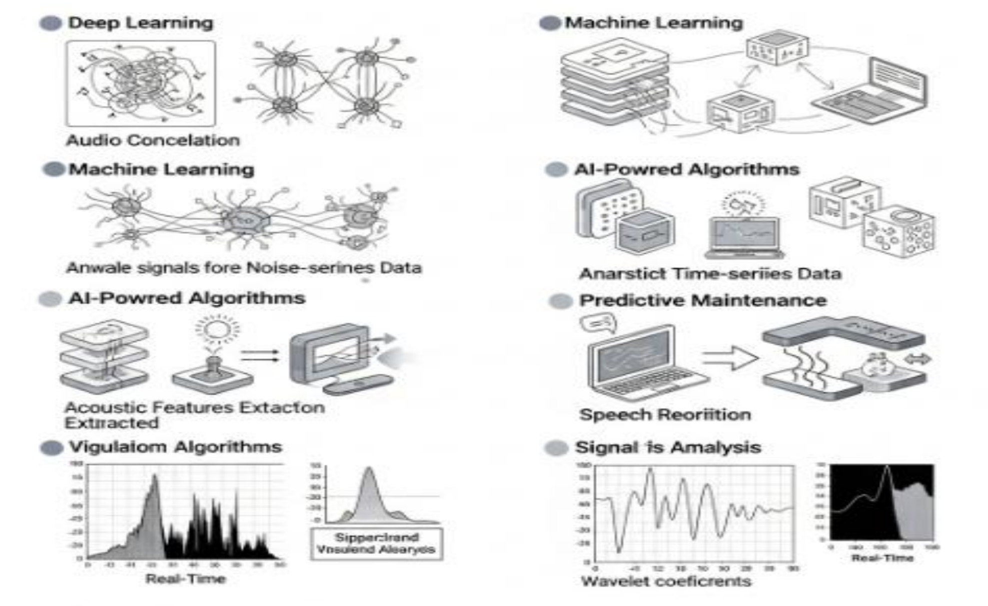

Fig 5.2: AI Techniques in Signal Processing.

We can arrange the use of AI techniques within two broad categories. A first category is concerned with methods, tools, and techniques that allow assisting feature extraction methods applied to signals, either traditional methods or the implementation of some form of transformation in a learning-like scheme. A second category of methods relates to the automation of block operational analysis and modifications, or higher macro-decision blocks as mentioned previously. We can devote the rest of this section on how AI techniques have affected both categories and the domains of apprenticeship signal processing algorithms researched in this direction. The terminology descriptive of any AI sub-field, such as computational intelligence, neuromorphic techniques, and more specifically, machine learning, shallow learning, and deep learning, arithmetic techniques, blocks operations, algorithms, and learning networks might overlap throughout the section.

5.5.1. Feature Extraction Methods

The field of signal processing is undergoing an evolution, primarily spurred by the incorporation of powerful computational tools and technologies, which are empowering scientists and researchers to make rapid advancements in various knowledge domains. Within the signal processing domain, the elemental themes of signal representation, detection, restoration, reconstruction, filtering, and feature extraction are gaining significantly from artificial intelligence approaches. Researchers and scientists are keen to integrate AI-powered algorithms for automating key functions in designing signal processing systems. These functions include automatic selection of network architecture, model hyper-parameter optimization, and determination of the best loss function, among others. Similarly, AI techniques can be effectively employed within signal processing paths, such as feature extraction or feature engineering in machine learning-based paradigm, where the extracted features can be passed to conventional classification or supervised models.

Whatever the approach, whenever AI techniques are utilized for the signal processing task, it is necessary that the core signal processing techniques be generalized with integrated enabling mechanisms that can allow these artificial neural networks-based AI techniques to learn the underlying signal structure. It is in this context, AI techniques involving representation learning, hierarchical learning, or supervised models for automatic task-specific learning have gained maximum attention and success in elaborate brain signal processing applications. Feature extraction is an essential and critical step in biomedical signal processing, especially in classification-based supervised learning approaches. Traditional feature design-based methods require expert knowledge for designing task-specific features for the desired application, depending on the specific type of biomedical signals, applications of interest, and classification methods employed. Moreover, these features are often shallow representations of perceptually-useful attributes and are affected by the generalization error for incomplete features due to the subjective nature of their design.

5.5.2. Classification Algorithms

The relationship between features and the target class, learned from the training data or feature space, is captured by a classification model at the heart of AI and machine learning. To build a relationship matrix and convert new unseen examples into predicted classes of interest, a classifier requires a lot of representative examples for each class, especially for effective generalization, as well as a final solution of neural network architecture and hyperparameters. Neural network-based approaches, such as convolutional neural networks for image classification and recurrent neural networks, have recently shown remarkable success in representation learning. With sufficient training data, these methods can produce classification accuracy that has reached and surpassed human performance on popular benchmark datasets in many areas. However, these approaches require a lot of manually labeled examples. In many learning applications, it is very expensive to obtain the labels and it's time-consuming to hire experts and some specialized tasks, such as image or speech recognition, labeled data can be difficult to obtain. In particular, while it is easy to collect data from many sources, it is often difficult to obtain the subset of that data that is relevant to the task at hand and even more difficult to obtain the labels for the examples in that subset.

Supervised classification learns the mapping from the available labeled training examples. As we may only have a small set of labeled data but possibly a spectrum of other data without labels, few-shot learning has emerged as a possible alternative when we have a few labeled data of interest and still want to classify new unseen samples for which no training data was collected. These methods use a variety of architecture and training strategies to achieve this goal. Semi-supervised learning aims to use some labeled data together with a significantly larger set of unlabeled data.

5.5.3. Anomaly Detection Techniques

Medical Signal Processing is the Field of Study Closely Related to Biomedical Signal Analysis. However, a very different study is proposed for the Various files that make up the Underlying Signals that make up these Techniques. In general, Methods based on Classification Algorithms Require the Patient to Have Reference Signals for Classification Purposes, while the Detection of Anomalies Allows the Healthcare Professional to Observe Only the Signals. Therefore, for Diagnostic Purposes, Anomaly Detection Techniques Assume Greater Importance. These Algorithms Allow the Medical Professional to Only Study the Detection of One or More Anomalies in Signals. So, After Application, the Signal Will Have to Be Analyzed, Just as in the Classification. However, It Will Be Seen that This Study Will Only Pose the Detection of Anomalies, with the Over Mend that Are Observed Like Detections in Classification Techniques That Will Be Described Later. Due to the Complexity and Diversity of Signals Generated by the Human Body, the Use of Different Methods for the Detection of Anomalies and the Classification of Signals Is Also Very Varied, Depending on the Type of Detected Anomalies. Some Studies Are Only Basic Studies that Explore Different Techniques to Observe Which Algorithms Are the Most Efficient in Diverse Situations, and Others Are Techniques Used for the Analysis of Different Patients. Different Artificial Intelligence Techniques Such as MLP, SOM, or SVM Have Been Used for the Detection of ECG Signal Anomalies, Where the Inputs of the Algorithms Have Been the Totals of the Segments of the Signals. Different Anomalies Have Been Detected, and Different Results Have Been Obtained Depending on the Technique and the Input. Attention Has

Also Been Paid to the Detection of QRS Waves or Low-Frequency Noise Correction, Where New Techniques Have Also Been Developed.

5.6. AI Techniques in Image Processing

Artificial intelligence (AI) approaches have become popular tools for solving image processing problems. AI techniques are used for image segmentation, classification, enhancement, restoration, description, and recognition tasks. The most important image processing techniques are image segmentation, image classification, and image enhancement. This section explains the AI techniques in these three areas.

Image segmentation is defined as the partitioning of an image into specific regions for simplifying its representation and analysis. Multilevel thresholding based on minimization variance criterion is a useful technique for the segmentation of image gray levels into specific regions based on their gray value characteristics. This technique finds multiple threshold values in order to divide an image into different segments allowing the removal and modifying of non-meaningful areas to ease the image analysis tasks. Various AI techniques including support vector machines, artificial neural networks, fuzzy rules, and genetic algorithms have been combined with this approach.

This technique is very useful and has led to spectral band problems. This approach integrates various type classification techniques to optimally find characteristic threshold values. However, the approach can be slow for large images due to the necessity of evaluating large computational loads, high-dimensional search spaces, and low convergence rates. Hybrid approaches have utilized efficient exploration operators to conduct speed-up computations, improving optimization quality while solving the search problem. These methods have been proposed based on fuzzy K-means, genetic algorithms and hybrid approaches, artificial neural networks, and other hybrid approaches.

5.6.1. Image Segmentation Approaches

Artificial Intelligence has been extensively used for image segmentation tasks, which cut objects from their backgrounds in images and shapes. Image segmentation techniques can primarily be classified into three major categories, including thresholding techniques, contour-based techniques, and region-growing techniques. Currently, there are many methods using Artificial Intelligence for image segmentation. Image segmentation is one of the most challenging problems in image processing, especially for color images due to inconsistency in colors in different regions of objects.

AI techniques for image segmentation may be divided into four groups. The first group is region-based segmentation, which consists of mostly Fuzzy and Neural Network thresholding or segmentation methods. The second group is pixel-based segmentation, which asymptotically approximates the optimal Bayes or maximum likelihood estimators for image segmentation. The third category is Geometric Active Contours, which are regularized partial differential equations solving some level set techniques. The last group is the recent convolution Neural Network. Convolution Neural Network (CNN)-based approaches come with an end-to-end structure, are supervised-trained, and have gained great attention since the ImageNet competition in 2012. The supervised nature of CNN needs a huge number of labeled training images, which is not always possible. Therefore, models based on CNNs trained on associated techniques are introduced to other data sets to utilize other data sets due to limited labeled training data. However, labeled training data are available for many medical problems nowadays. Even though deep learning methods are widely popular for classification tasks, they are also used in many segmentation applications.

5.6.2. Image Classification Methods

The fields of medicine and healthcare have made extensive use of image classification for centuries, with human experts routinely reviewing scholarly images and scans to identify anatomical irregularities or physical abnormalities indicating disease. Image classification stems from mathematical pattern recognition, deep in the computer science and artificial intelligence traditions, and often utilizes mathematical and statistical means, especially statistics and probabilities. More recent methods also capture the high-dimensional nature of medical images through deep learning—using vast neural networks to derive representations of imagery conditioned on the presence of different diagnostic labels and outcomes.

These derived representations can then be further analyzed using statistical or mathematical means to recognize objects or patterns. Deep learning has several clear advantages over traditional means of analysis, which had to be handcrafted by engineers with decades of subject matter knowledge and experience: such constraints are either no longer necessary or require far fewer expert hours from specialized personnel. Likewise, shared representations of input data are typically braiding large collections of public data for many classifications tasks; these representations can then be efficiently tuned on smaller corpora of ‘private’ labeled data for specific classification tasks or used as is, in a transfer learning paradigm, if no further labeling is possible.

However, labeling large amounts of image data within a supervised paradigm is the bottleneck for the vast majority of image classification applications both within and outside of the medical domain: the time and cost associated with manual and accurate labeling are two orders of magnitude larger than those for traditional machine-generated labels, and deep learning methods can often achieve accuracy levels on par with human experts in typical image classification tasks. For this reason, unsupervised methodologies, such as traditional clustering analysis and more recent deep learning enabled ones, continue to command at least equivalent mindshare among experts, if not higher.

5.6.3. Image Enhancement Techniques

There are many image enhancement techniques, including image denoising, contrast improvement, shadow or haze removal, deblurring, and super-resolution, that have been incorporated into deep learning pipelines. Image denoising or removal of additive noise is widely studied in computer vision for its vast applications in biomedical imaging. Some works apply a CNN model to the noisy images as a direct denoising method or incorporate a generative adversarial network to perform image de-noising. An image restoration work applied supervised deep learning to pre-trained models to denoise magnetic resonance images. A CNN network was proposed to recover clear phase contrast x-ray slice images from noisy and gradient-embedded original images without de-blurring operation. A multiple learning technique was proposed to reduce noise in wet-capturing infrared biomedical images using gray-scale and colored textured models.

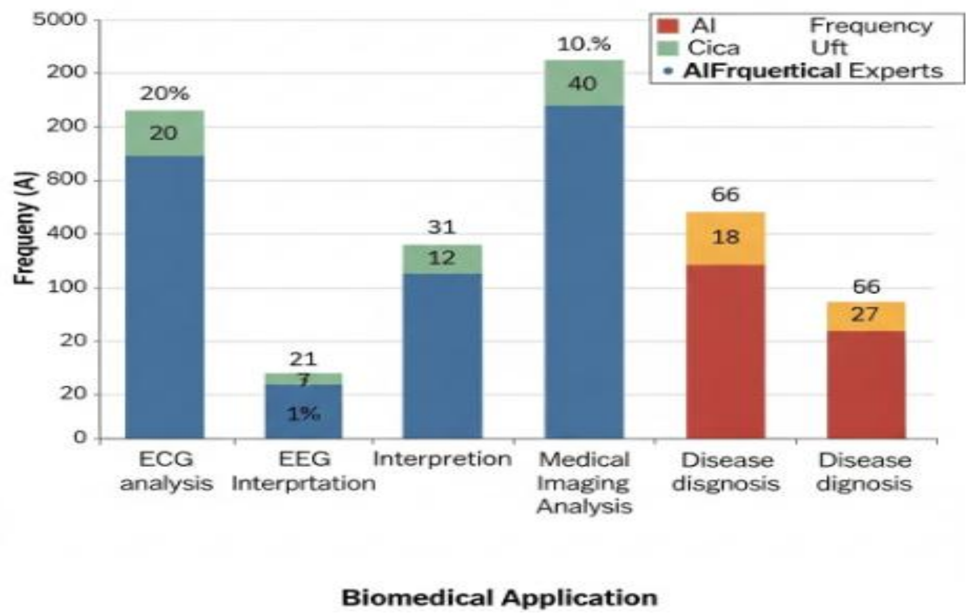

Fig : Utilizing Artificial Intelligence for Biomedical Signal and Image Processing Applications.

Many contrast enhancement techniques exist based on histogram specification or contrast-limited adaptive histogram equalization methods. Some methods claimed advantages of using deep learning or hybrid models to perform contrast enhancement to grayscale or colored natural images due to their simpler architectures. A conditional GAN model was also tested for low-light retinal images by conditioning GAN on circular patches. Shadow detection and removal pipeline provided an image-based solution built with the help of a deep learning network to remove shadows in low contrast bioluminescence images. An image shadow effect mitigation on global illumination applied deep learning and post-processing techniques to smooth shadow transition areas of the negative infrared images. Haze is known to disparate the colors of the image, degrade the visibility of faraway objects in images, and diminish the image quality by saturating it with light in all directions. Several algorithms are attempted to restore hazy images by calculating the atmospheric light and transmission map in a semi-supervised way.

5.7. Applications in Healthcare

The earliest successful application of artificial intelligence was pioneered in the mid-twentieth century in the field of clinical medicine. More specifically, the DENDRAL system was used to derive chemical structural formulas based on mass-spectra data, and then the MYCIN expert system was successfully implemented to aid medical students in the diagnosis and identification of infectious diseases. Subsequently, since the late twentieth century, several AI studies have been conducted in healthcare domains, such as computer-aided diagnostic devices, clinical decision support systems, automated medical laboratory systems, clinical patient data mining, medical robotics, and psychological support systems. Especially in the past decade, artificial intelligence has experienced a renaissance, primarily due to the development of advanced deep learning algorithms, and has been successfully applied in various healthcare solutions, such as diagnostic imaging, wearable health monitoring, and telemedicine solutions. We will review relevant research studies in the following sections.

The use of AI and machine learning in healthcare applications has been rapidly gaining interest in the past few years, with many contributions across diverse healthcare domains. These domains include diagnostic and prognostic predictions in multiple diseases such as diabetic retinopathy, Alzheimer’s disease, and liver disease. Other domains include resource management, patient risk management, predictive and historical research for patient demographics, patient satisfaction prediction, and hospital readmission, as well as other predictions associated with biomarkers, genomics, and proteomics. Indeed, applications of AI in healthcare continue to flourish and multiply, covering nearly every healthcare issue of modern clinical importance.

5.7.1. Diagnostic Imaging

During the last decade, artificial intelligence (AI) applied to diagnostic imaging has experienced progress on both an implementation and research level, mainly in the context of transfer learning. Considerable increases in processing performance by graphics processing units (GPUs) led to interrupted developments and improvements. The use of convolutional neural networks (CNNs) has become novel and has raised the majority of the interest. Research with doing it with little labeled data and without labeled data is ongoing.

The present chapter describes available AI methods and their application, particularly deep learning (DL) methods, in diagnostic imaging, starting with imaging of the brain with magnetic resonance imaging (MRI), followed by the remaining body and multimodal imaging. Neural networks go back to their formulation in 1943, having the merit of exhibiting behaviors asymptotically analogous to those of certain types of biological neurons. For the first time in 1986, parallel distributed processing, which used backpropagation, was proposed for a multilayer perceptron (MLP). It was only in 2012, however, that a MLP had features for designing CNNs, followed by a suitable architecture for CNNs designed in 2014. With CNNs having indeed a superior image classification performance compared with MLPs, CNNs had the merit of breaking the celebrity image classifier.

Research has included having virtually but not entirely eliminating the need for expert labels, generating prospects with segmentation, and using unsupervised learning for unusual radio-morphologies, among many examples. Considerable increases in transfer learning and processing performance have enabled image rectification; landmark-based sparse landmark-less, generative adversarial networks (GANs)-based, and part-based image registration; image inpainting and video inpainting; image and video restoration; image and video super-resolution; image and video compression; image quality enhancement; and model selection method. Some of these developments are still awaiting rigorous validation, but several of such methods have patients undergoing testing or even being clinically deployed. For the remainder of the chapter, the focus is mainly on the above methods using convolutional and GANs.

5.7.2. Wearable Health Monitoring

Digital health monitoring is commonly associated with smartwatches capable of recording user health data. However, a great variety of wearable devices have emerged since the 1990s, monitoring not only heart and respiratory rates, but also different aspects of user health. Wearable health monitoring is mainly based on sensors that continuously acquire user physiological data, typically placed on body parts, such as the wrist, finger, ear, temple, scalp or torso. Newer sensing modalities include approaches for biomolecular sensing and Tattoo Electronics for monitoring electromyography signals. Wearable technologies have demonstrated to be useful for detecting user health status, e.g., symptoms of heart disease, sleep apnea, or respiratory disease, as well as for monitoring user health, e.g., chronic obstructive pulmonary disease or neurological and cardiac diseases, mainly associated with aging.

Wearable health monitoring devices face the same limitations of traditional sensors, such as non-appropriate sensor signals, interference with other signals, lack of some key physiological parameters, or data loss associated with low sampling rates. Major advantages of wearable devices with respect to standard methods are continuous acquired data over a long time period, easy to wear, wireless, small, lightweight, and maybe also less expensive and non-invasive. These advantages lead to a high user compliance and may increase the real-time detection of deviation from normal ranges and status changes when the person is at home. User data are typically stored in a cloud where algorithms perform health signal processing, detect anomalies or patterns, infer user health status, train an alert model, and send alerts to physicians for enabling early diagnosis.

5.7.3. Telemedicine Solutions

Conventional medicine relies on centralized clinics or hospitals, where specialists diagnose patients and issue prescriptions based on physical examinations and tests. While this approach ensures accurate diagnoses, it is inefficient and inaccessible for large populations. Telemedicine leverages technology to remotely assist patients, relieving the pressure on specialist clinics and allowing real-time treatment anywhere in the world. However, for telemedicine solutions to become even more widespread in the future, they need to perform as well as in-person examinations. Intelligent or 'smart' telemedicine buildings are quickly becoming the answer due to their flexibility, real-time interaction with patients, and support for a large range of applications. These buildings are based on the integration of intelligent solutions, such as AI-driven medical devices, which feature mobile, wearable, and wired autonomous sensing and diagnostic units for various medical specialties, and AI-assisted actions to deliver confidence and precision to patients.'Smart' solutions provide real-time assistance and prescription validation to patients, and improve the doctors' ability to manage and take timely decisions. Vision-based AI algorithms can be deployed on the camera sensor built into mobile devices or wearable hardware. They provide assistance in real-time consultations, during tele-assistance sessions, remote examinations, or even during remote and continuous monitoring of patients. Infrared and visible-light cameras can capture important medical signs, including movement analysis; eye tracking, with and without the use of eye glasses; body imbalance determination; eye iris and pupil recognition; and facial expression recognition. Contacts between physicians and patients through sensors allow for better monitoring of diseases, real-time signals of clinical changes, possibilities to preventive therapy to apply new treatments and allow physicians to give prescriptions and solutions for medical conditions easier.

5.8. Conclusion

As research progresses, Artificial Intelligence (AI) is quickly entering the biomedical signal processing and imaging field as a method, simplifying the development of high-performance solutions for numerous issues. Now that it has demonstrated its efficacy, there is a genuine alarm that in a few years AI could substitute the nervous systems of biomedical engineers, reducing their function to simply a box containing input/output data. This is a lost opportunity, as the supervisory function of these engineers permits the signification and anthropomorphism of models that on their own are nothing more than a mathematical representation of a problem. There would be a clear risk of wasting vital knowledge wealth about the implementation of many subsystems decoupled from the model. This would ensure that some components continue to be used without an adequate scientific basis and a real understanding of how and why they work, which can be harmful. But in addition, these models may not generalize outside the available population or not have sufficient robustness to be used in personalized medicine, an area in which little or nothing has been developed.

The present state of the art in AI implementation in biomedical signal and image processing demonstrates this reversal of roles: Machines serve to help scientists and engineers, to make them much more efficient and capable of providing answers that machines alone could not offer. This presents numerous advantages in validation and interpretation and allows for the reduction of time and resources needed to complete complex image analysis and biomarker discovery. Consequently, in the very near future, computer vision and AI will both continue to grow almost omnipresent within the BSI domain. Large annotated data may create a distribution shift, where class distributions differ for the training data compared to the test or application data. However, it is essential to check whether the need for large numbered annotated training datasets is conditioned only by current technological limitations or whether it is intrinsic to the nature of the analyzed problems.

5.8.1. Future Trends

The rapid development and growing popularity of AI, especially deep learning, has inspired many research works in the broad area of biomedical signal and image processing. For biomedical applications, experts often know what kind of features are required for different tasks based on their hands-on experiences. In the last few years, we have witnessed a great success in hand-crafted feature engineering based statistical models, or "shallow" machine learnt classifiers. With the growing popularity of AI, it is easy to forget the existence of such research works by medical experts, as they are not as easily accessible as deep neural net codes.

Deep learning is a great tool but it is not the only tool. In this chapter, we have emphasized, analyzed, and showcased the collaborative aspects between AI and domain researchers for biomedical applications. Throughout the entire chapter, we have laid specific examples of how to integrate domain knowledge with AI technologies. As we move towards a future of AI applications, the right combination of machine learnt models and domain handcrafted models is likely to be the right way forward. With the excitement around AI, it is important for the domain experts to know and understand its capabilities as well as limitations. From folklore, we know that with intelligence comes arrogance. It is therefore important to bridge increased dependency on AI and waning spirit of exploration by domain experts. The future of biomedical signal and image processing is likely to be an expert + AI model rather than an AI only model nor a feature engineered only model. Hence, we foresee collaborative models would remain as the gold standard even with the growing applicability and scalability of AI.

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