Chapter

Computational Intelligence Approaches for Enhancing Biomedical Image Processing Applications Based on Breast Cancer

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Abstract

Recent advances in the cutting-edge technologies of biomedical sensing and image processing tools provide us with big data of biomedical and various types of images that can't be processed within a finite period by professional clinicians. Various techniques for processing biomedical images comprise mathematical algorithms that extract vital diagnostic features from biomedical information and biological data. Because of the complexity and big size of the data computation, intelligence techniques have been applied in processing, visualizing, diagnostic, and classification tasks. This study will explore the effectiveness of the variously artificial intelligence approaches on biomedical signal and image processing applications. The researchers and community entirely will benefit from this study as a guide to the state-of-the-art artificial intelligence techniques for biomedical signal and image processing applications.

Keywords: biomedical signal, medical image, image processing, computational intelligence, signal processing

1. Introduction

The human body naturally automates, controls, manages, and coordinates all the activities in it via various systems called biomedical signals. However, let's understand what is signal. It is a sequence of ordered numbers that depict trends and changes in quantity [1]. Any changes in biomedical signal features are an alarm of revamping in the part of the body. To reason the physiological systems more accurately, hence, the root of the biomedical signals. This led to the development of unprecedented methods that ease monitoring and diagnoses of health status [2]. While, image processing is an area both in computer science and applied mathematics that concentrate on digital images and their metamorphosis, to enhance their quality or extract knowledge from them in application domain such as medicine, real life, geography, photography, etc. [3]. In addition, image processing is a subset of signal processing with a focus on images and other derived data such as video.

Before the widespread of digital computers, all processing of biomedical signals and image processing were performed directly by professionals in that domain. For example, for analyzing and processing blood pressure, the experts depended on their experience, hearing, and visuals. The manual method of diagnostic process accuracy and reliability are limited by several factors, such as limited experts identifying and extracting certain characteristics from signals, the manual method was overcome by fatigue due to human nature, which led to error, and making decision process personal. However, the recent advancement of digital computers and the emergence of cutting-edge technology such as imaging technology and biomedical sensing machine feed us with big data of biomedical data that would be very difficult to handle by a medical expert within a fine range of time [1].

Biomedical signals are measured in many different ways, variation of voltage caused by eye movement is measured by electrooculogram (EOG), which is utilized to observe the direction users' eyes on with help of signal variation [4], and electrical activities of the brain are recorded with electroencephalogram (EEG), which help in diagnoses of the central nervous system [1] and detecting stress [5]. Electromyogram (ERG) is used determine whether muscles respond properly or not to the nervous system, which helps in detecting neural damage, disease, and disorder [6]; in addition, hand or finger gestures are detected using ERG. Electrocardiograms (ECGs) are utilized to record heart muscles' electrical activities to diagnose and analyze the cardiovascular system [7].

Biomedical signals and image processing consist of methods that applied mathematical algorithms to extract vital knowledge from biomedical and biological datasets for analytic and diagnostic reasons. However, because bulkiness and complexity of the dataset and the growth of artificial intelligence methods embolden researchers to utilize computational intelligence techniques to analyze and find a pattern to visualize, classified, and characterized disease behavior [6]. All over the globe currently are undertaking studies in AI healthcare research. The front liner of these countries includes the USA, United Kingdom, Israel, and many others [6].

This study centers on the progress of computational intelligence techniques based on biomedical image processing of breast cancer. One of the three causes of death among women is breast cancer; therefore, early detection and diagnosis can reduce the mortality rates. One of the sources of data relevant to the diagnosis and detection of breast cancer is medical images. Tumor detection and diagnoses utilizing medical image processing and computational intelligence approaches can help medical specialists in enhancing the accuracy of diagnoses and identification of breast cancer.

Several research articles related to this exist, like [8], which focus on biomedical signals techniques for the detection of Covid-19, [9], which centered on monitoring systems remotely for personal health during Covid-19 pandemic using biomedical signals, an overview of the diagnosis of Schizophrenia using a medical image by [10], recent advances, challenges, and way forward of medical image analysis utilizing machine learning techniques by [11], generative Adversarial Networks for Biomedical Image Analysis by [12, 13] biomedical applications using machine learning techniques. All these articles focus on medical image processing or biomedical signals. This article centered on breast cancer disease. However, this chapter contributes the following:

- Provide biomedical image processing techniques based on diagnoses and detection of breast cancer diseases.

- Highlight different types of models utilized for biomedical image processing solutions based on breast cancer.

- Provide recommendations on how to enhance breast cancer disease diagnoses based on computational intelligence techniques.

- Play vital roles in promoting the use, development, and enhancing the effectiveness of computational intelligence techniques, which can be utilized for monitoring various health issues in the medical domain by taking advantage of image processing datasets.

The structure of this chapter is organized as follows: section 2 presents the concept of biomedical signal and image processing. Role of computational intelligence techniques in biomedical signals and image processing applications is presented in section 3. Breast cancer Datasets and Techniques in Computational Intelligence Utilized in Biomedical image Processing are presented in Sections 4 and 5. While how to enhance computational intelligence techniques for biomedical image processing is presented in section 6, conclusion and future direction are presented in section 7.

2. Concept of biomedical signals and image processing

Sketching and extracting measures that are important for the decision of biomedical frameworks is the main job of biomedical signal and image processing. However, there is a need to understand what is signal. It is a sequence of ordered numbers that depicted trends and changes in quantity [1]. In another word, it is a space and time report of an event in a biological system such as a heart beating, body temperature, and muscle contraction [14]. Several activities occur in the biological body system in the form of electrical, chemical, and mechanical event, which produces signals that can be analyzed and measured. These signals can be one-dimensional or multidimensional. For instance, a report of the electrical activities of a heart muscle is a one-dimensional signal, while an image is a multidimensional signal, which records a two-dimensional sequence of data in both directions where the numbers are ordered in space. For instance, $g\ (x, y)$ is a set of coordinate values of an image that represent the signal.

Analyzing and processing of a signal can be conducted in a wide range of ways relaying open the targets of the signal analysis. Each of these processing strategies endeavors to highlight, emphasize, and extract certain properties of a signal. For example, to determine the number of hot days over a given year, one can only record the number of days when the temperature is signal rise above a threshold figure that determines hot weather. Thresholding is one instance of several varieties of proceeding methods and transformations that can exploit a signal to outline some of its properties. Other transformations are peculiar and assess the signal based on a time circle, while some center on another circle such as a frequency circle, etc., various biomedical signal and image processing concept have been utilized in the diagnosis and interpretation of many different sophisticated medical practices and applications.

3. Role of computational intelligence techniques in biomedical signals and image processing applications

Biomedical science is defined as a branch of science that works with body organs; this information is taken from the body organs that come in a form of text, image, video, and audio. Computational intelligence techniques are used in the medical domain as an adjunct in the diagnosis of disease based on signal (one-dimensional) processing and medical images (two-dimensional); these techniques are utilized in the diagnosis, prediction, and management of diseases. The data consist of images, videos, and physiological signals [15].

3.1 Biomedical signals with computational intelligence techniques

Biomedical signals deal with the collection of information that is in a formed signal of electrical change or image [16]. This information is collected either using an embedded node on a smartphone, smartwatch, or any wearable device that gathers physiological signals [17]. Biomedical signals are gathered from the human body at the organ, molecular, and cellular levels. These signals are based on the detection or diagnosis of a specific pathological or physiological state. Biomedical signals are processed in various ways, which include: some biosensors used to detect breast cancer through various biomarkers [18] taken from patients' pathological test, one of the biomedical signal processing success is the classification of accurate malignant tumor, which help patients in sustaining dispensable remediation, that is the reason why identifying breast carcinoma into malignant and benign has become a trend in the area of breast cancer diagnosis using machine learning [19]. Machine learning techniques are used in identifying patterns from these biomarkers. A study by [20] explored a way of monitoring biomedical signals using some biomarkers of patients with the KNN algorithm. [21] compared four (4) different algorithms, namely: Naïve Bayes, Multilayer Perception (MLP), Decision Tree, Random Forest, and Support Vector Machine for classifying breast cancer.

3.2 Image processing with computational intelligence techniques

Big data in healthcare has to do with significant datasets that are complex and big for health actors in the interpretation or processing of this dataset using an existing tool. This dataset is being generated from different sources and at an unprecedented rate like in the laboratory, patient signals uploaded from a sensor, clinical data, pharmaceutical data, and hospital operations [22]. The medical image provides information on the functions of organs and the visualization of tissues for helping practitioners in detecting disease and revolutionizing the area of medicine. The areas of medical images include dermatology, obstetrics, gynecology, cardiology, ophthalmology, surgical procedures, etc.; these areas are invasive and do not need any procedures such as biopsy, with the progress of biomedical image analysis on the dataset, it has so many benefits. Like the application of radiological service remotely (allows practitioners to monitor their patients for easy prescription). Furthermore, professional practitioners are few and are unable to diagnose millions of images generated. With the rise of biomedical image data, there are so many demands of AI for ML systems in learning complex images and making a decision [15]. Some of these areas that are well established in the health sector setting for the capturing of images are ultrasound, X-ray, computed tomography, molecular imaging, fluoroscopy, positron emission tomography-computed tomography, photoacoustic imaging, and magnetic resonance imaging [15]. Apart from disease detection, computational intelligence can also be used for image segmentation, thermal imaging, and multidimensional imaging [22].

According to [23], machine learning and deep learning techniques have played a major role in the detection, classification, and diagnosis of breast cancer disease. These techniques are a very powerful tool for modeling tasks in several clinical specialties, for instance, radiology and pathology, and have achieved the same

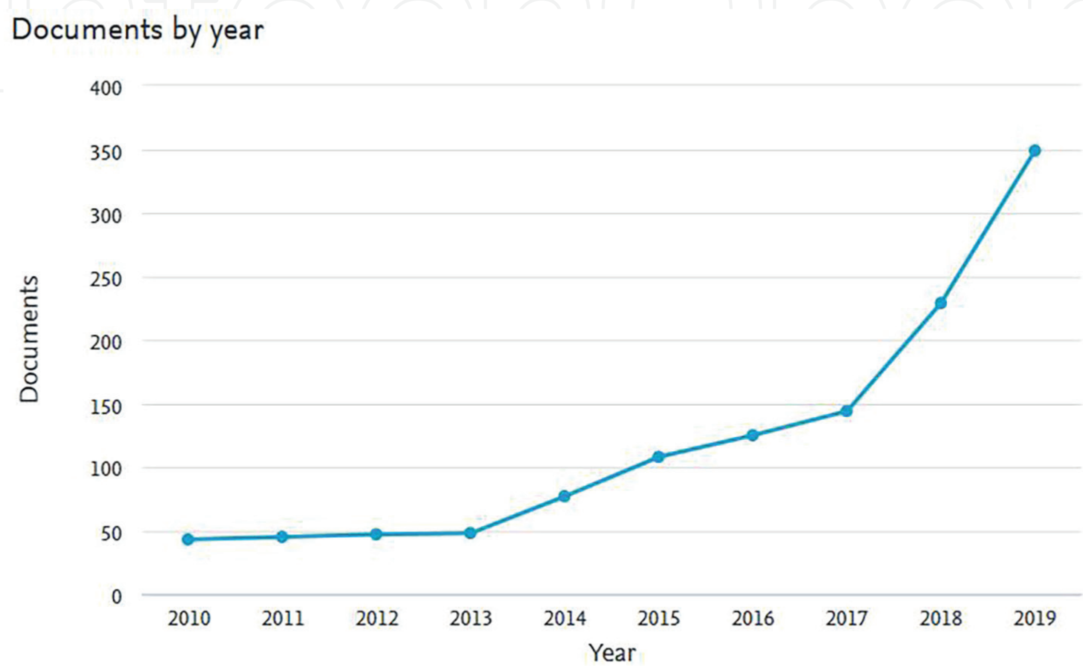

Figure 1.
Breast cancer detection and classification publications based on machine learning techniques [23].

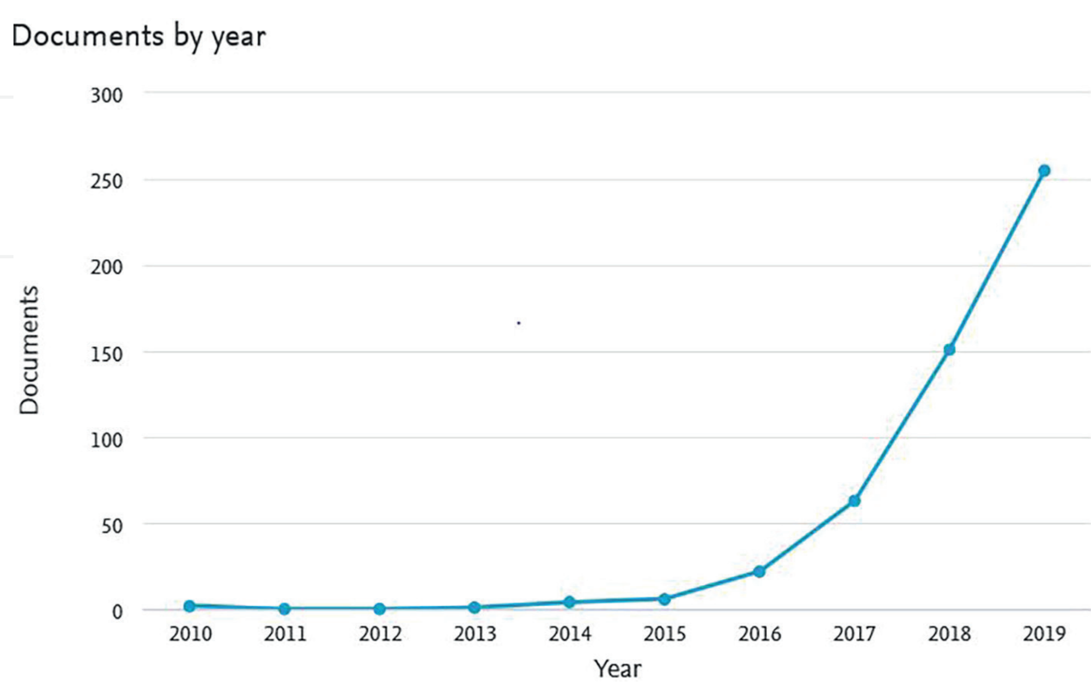

Figure 2.
Breast cancer detection and classification publications based on deep learning techniques [23].

performance in some cases comparable with human specialists [24]. Computational intelligence techniques have been applied to biomedical images to extract information on prognoses, molecular status, and treatment sensitivity that are difficult to identify by human experts [25, 26]. Several parts of human activities have been replaced by computational intelligence techniques [27]. **Figures 1** and **2** present statistics based on the Scopus database of publications for a decade, from 2010–2019 breast cancer disease classification and diagnoses for machine learning and deep learning techniques.

4. Publicly available datasets of breast cancer

Several datasets are available for biomedical image processing based on breast cancer. One of them is the Breast Cancer Wisconsin Dataset, which consists of features computed from a digitized image of a breast mass that describes the presence of cell nuclei in the image. This dataset can be downloaded from Kaggle [28–31]. Other available datasets include Image Retrieval in Medical Applications (IRMA), Breast cancer data repository (BCDR), a Digital Database for Screening Mammography (DDSM), INBreast, Mammographic Image Analysis Society (MIAS) /mini-MIAS, Wisconsin Breast Cancer Dataset (WBCD), Wisconsin Diagnosis Breast Cancer (WDBC), and Breast Cancer Histopathological Image (BreakHis). **Table 1** outlines various breast cancer datasets and their corresponding URL that can be easily downloaded at any time.

S/No.	Dataset name	URL
1	BCDR	https://bcdr.ceta-ciemat.es/information/about
2	MIAS	https://www.repository.cam.ac.uk/handle/1810/250394
3	DDSM	http://marathon.csee.usf.edu/Mammography/Database.html
4	mini-MIAS	http://peipa.essex.ac.uk/info/mias.html
5	INBreast	http://medicalresearch.inescporto.pt/breastresearch/index.php/Get_INBreast_Database
6	BreakHis	https://web.inf.ufpr.br/vri/databases/breastcancer-histopathological-databasebreakhis/
7	WBCD	https://archive.ics.uci.edu/ml/datasets/Breast+Cancer+Wisconsin+(Diagnostic)
8	IRMA	https://data.world/datasets/irma
9	WDBC	http://networkrepository.com/breast-cancer-wisconsin-wdbc.php

Table 1.
Publicly available breast cancer datasets and their corresponding URL [23].

5. Techniques in computational intelligence utilized in biomedical signal and image processing

5.1 Supervised, unsupervised, and reinforcement learning

Supervised learning: This type of model is utilized when the target/outcome of the interest is provided, and the dataset is labeled. An example of supervised learning is when the target value is either presence or absence of a disease such as hypertension or diabetes [32].

Unsupervised learning: This type of model in which the outcome/target value of a dataset is not specified, and the dataset is unlabeled. The algorithm of unsupervised machine learning must identify and relate patterns from the dataset, one of the types of unsupervised machine learning is the cluster, where data points are grouped [32].

Reinforcement learning: This is the type of machine learning that is a practical application of a machine that makes a decision based on some feedback, whatever decision is been made is directly based on received feedback [32].

5.2 ML techniques used for biomedical signal and image processing

In this section, machine learning algorithms used for biomedical signal and image processing are highlighted based on the latest trends.

5.2.1 Support vector machine

Support Vector Machine (SVM) is a supervised machine learning that can be used for regression or classification problems. SVM is a method used to find a specific type of linear model to maximize the margin of hyperplanes. The maximization of the hyperplane margin affects maximizing the separation between different classes [33]. SVM can be applied to various fields to solve problems, one of the areas is the medical sector where SVM has shown tremendous contribution, a study by [34] used the Hough transform to extract features of mammograms images and applied SVM in classifying these extracted images and their study shown that, SVM has efficiency in classifying abnormal classes of these images, [35] proposed a fuzzy multilayer SVM (FMSVM) model for evaluation of extracted features and its effects, an accuracy of 98% was achieved in their study. Furthermore, [36] used feature selection called Boruta to select features and applied these features to SVM and RF, and based on their results, SVM outperforms better than RF with 95% and 90% accuracy scores.

5.2.2 Naïve Bayes

Naïve Bayes (NB) is a type of supervised machine learning algorithms theorem that relies on naïve assumption, where input factors are independent [37], meaning, the occurrence of a particular element in a class is not identified with the occurrence of another element in the same class, in Naïve Bayes, recurrence table is made for each of the indicators against the class and computation of the probability of the relative multitude of indicators. The Naïve Bayes classifier result is the class with the most elevated likelihood among all the class probabilities [17]. An example area where NB can be used for biomedical signal and image processing is in detecting breast cancer, [38] applied SVM for prediction of Pathological Complete Response (PCR) before Neoadjuvant Chemotherapy, and their results.

5.2.3 Logistic regression

Logistic regression (LR) is a type of supervised machine learning, which is applied to classification problems. It estimates the result of an absolute variable dependent on the autonomous factors. Logistic regression predicts the probability of a certain instance occurring by fitting information to a strategic capacity [17]. Some researcher has tried to show the usefulness of LR in the area of detecting breast cancer [39] using this model has managed to classify breast cancer disease and compared it with the model on two features of maximum perimeter and maximum texture, which the second results show an improvement compared with the previous result. [40] proposed a new LR model for classifying breast images based on some microarray expression data. [41] had shown the use of LR for eliminating fewer important features.

5.2.4 Random forest

Random Forest (RF) is used in supervised learning, which is a form of multiple decision trees that are combined based on randomly selected subsets of training data points, then assign votes to the various decision trees so that the final class of test object is selected [37] RF is one of the most used algorithms in the area of the health sector for solving several diseases, RF is used for diagnosis and prognosis of breast cancer, a study by [42] had proposed the same model for the same task and feature selection. RF can be used for the medical diagnosis of breast cancer [43]. Alam et al. [25] had utilized the use of feature extraction with RF on different data namely: breast cancer, diabetes, liver, hepatitis, heart disease, and EEG.

5.2.5 Decision Tree

A Decision Tree (DT) can be applied to both regression and classification problems. It decides different levels via tree data structure, it is suitable for predicting problems since it is easy to interpret and its structure is stable [37]. A decision tree is a tree-based technique where paths start from the root that is described by a data point separating sequence until the target Boolean results are achieved [44]. Decision trees have shown success in both biomedical signal and image processing applications, a study by [45] proposed the use of DT and KNN algorithms in classifying breast cancer tumors after selecting the best features from the dataset using Principal Component Analysis (PCA) and the result shown tremendous performance by these algorithms with KNN having the best performance score. Assegie [46] had explored the use of DT on breast cancer, even though the dataset was highly imbalanced, an accuracy of 80.80% was achieved.

5.3 Deep learning techniques used in biomedical signal and image processing

5.3.1 Convolutional neural network

Convolutional Neural Network (CNN) is a type of feedforward neural network that can extract features from data using convolution structures, CNN is not like the traditional feature extraction techniques because it doesn't require manual feature extraction, and it is stirred by visual perception. It has four components, which are: convolution, which is used for feature extraction, the output; which is called the feature maps, padding; which is used when information is lost in the border when setting up kernel, stride; which is used for controlling the density of convolving, pooling; used for overcoming the issue of overfitting [47]. One of the advantages of CNN over conventional machine learning models is that it can handle a tremendous amount of data using multilayer architecture and also, it can handle imbalanced datasets and execute without bias on the majority instances of the dataset [48]. [49] had highlighted three key areas where CNN Mammographic Breast Cancer Diagnosis can be categorized, which are: to design or modify existing models for decreasing the number of training instances as well as time cost, to utilize the use of pre-trained

CNN for fine-tuning and transfer learning and the final one is, the use of CNN for feature extraction and the ability to differentiate between malignant lesions and benign. Many works have been explored with CNN for biomedical signal and image processing, most importantly the breast cancer disease, a study [50] has shown that CNN had outperformed slightly better than Multi-Layer Perception (MLP) in detecting and diagnosing breast cancer malignancies. Also, [51] proposed a Convolutional Neural Network Improvement for Breast Cancer Classification (CNNI-BCC), which can help experts in classifying medical images as normal, Benign, and Malignant patients with an accuracy of 90.50%.

5.3.2 Long short-term memory

Long Short-Term Memory (LSTM) Model is defined as a powerful Recurrent Neural Network (RNN) system to overcome vanished gradient and exploding problems that come up when learning long-term dependencies. [a review on the long and short term] It has proven to be reliable for long-term dependencies. LSTM has played a vital role in biomedical image processing, for example, LSTM for classifying breast cancer was proposed by [52] where feature extraction was performed with CNN and LSTM was used for the classification of Nuclear Atypia Grading Breast Cancer Histopathological images, which show the model outperforming the current studies from their work.

5.4 Challenges of computational intelligence techniques in image processing based on breast cancer disease

This section presents computational intelligence challenges based on breast cancer classification and detection. Despite the success recorded in this domain, there are still some limitations that need to be addressed in the detection and classification of breast cancer disease. However, image processing applications have been extensively utilized in various studies for the recognition of images [80], synthesis of the image [81], reconstruction of the image [82], segmentation of the image [83], etc., using a Generative adversarial network (GAN). However, deep learning models with the assistance of GANs have been able to generate synthetic images so that biomedical datasets size can be multiplied [84, 85]. Based on the literature review, many challenges have been identified as discussed as follows:

a. **Issues with Generative adversarial network (GAN):** GANs suffer several limitations such as mode collapse when a similar output image is produced by a generator when the input features taken are different. Instability, which occurs because of the issue of gradients vanishing, and non-convergence issue were due to the inability to reach Nash equilibrium by GANs.

b. **Methods of processing:** methods of processing data and acquiring accurate results required a large number of parameters. These result in uncertainty based on choosing the best technique that facilitates operation. Bias and interpretability errors are also limitations of computational intelligence techniques, which are not acceptable in the clinical domain [86].

c. **Insufficient dataset**: the initial challenge noticed based on publications reviewed was the lack of adequate training datasets has been the biggish challenge in training biomedical images, for instance, breast cancer images based on deep learning approaches. The data size and quality determine the performance of deep learning techniques because they required a large training dataset. Therefore, the insufficient dataset has become a major obstacle to the success of biomedical image processing, for example, breast cancer. This is due to the difficulty in creating medical image datasets. Because it requires annotating the data by a specialist, which they are very limited and requires a lot of time and effort.

d. **Models' performance:** most of the investigations examined utilized different datasets for their analysis. The major limitations of this argument are that models' performance across different investigations is difficult to compare.

e. Another drawback of some investigations is the refusal to apply transferred learning methods, but rather utilized data expansion, which causes overfitting.

f. **Unsupervised learning approach:** there is a need for the classification and detection of breast cancer based on an unsupervised learning approach. Most investigations utilized a supervised learning approach, which required labeled images for training. However, it's difficult to collect breast cancer images that have been labeled by a specialist in real life. There is a huge number of unlabeled breast cancer images available, which required a group of unsupervised learning techniques for training.

g. **Methods of data collection:** there is need to address issues of the method of data collection in several clinical situations to enable the system to gather more datasets slowly. Like utilizing a variety of scanners for image acquisition, a variety of lighting conditions, distinct views and sizes in different image modalities, and presentation of varied features of the enlargement and coloring factor.

6. How to enhance computational intelligence techniques for image processing of breast cancer disease

This section presents how computational intelligence techniques for biomedical image processing, for instance, breast cancer image can be enhanced. The points are outlined as follows:

- Global Public breast cancer images datasets: there is a need for global public breast cancer image datasets that contains a variety of image modalities, such as Mammogram images, Ultrasound images, MRI images, Histological images, Thermography, and Computed Tomography (CT) images, etc., that will be utilized for classification and detection of breast cancer based on a variety of modality and enclosed more information from a different perspective.

- The emergence of Explainable Artificial Intelligence (XAI) has become a trending topic of discussion recently; there is a need to incorporate XAI in computer-aided diagnosis systems based on breast cancer disease.

- To enhance computer-aided diagnosis systems performance of breast cancer, there is a need to incorporate 3D mammography in the development of the framework. This should be taken into consideration in the future production of computer-aided diagnosis systems.

- There is a need to develop a robust framework that will aid medical professionals in an early diagnosis of breast cancer disease.

- For Generative adversarial network (GAN), many published studies have shown how Generative Adversarial Networks (GANs) limitations have been addressed by researchers, due to their immensely use in the medical industry, more specifically in medical images, such as mode collapse addressed utilizing synthetic-image filtering mechanism [87], a combination of a Variational Auto-Encoder GAN with a Code Discriminator [88], generating an image from random vectors by learning the data distribution [89], supervised generative adversarial nets method [90], modify standard GAN architecture [91]. Instability in biomedical imagery has also been addressed by [87–89, 92–94]. The non-convergence issue has been addressed by utilizing generators and discriminators that are modified as in [95–97].

7. Conclusion and future direction

Computational intelligence techniques have recently contributed immensely to processing biomedical signals and image-processing tools that can't be processed within a finite period by professional clinicians. The human body naturally automates, controls, manages, and coordinates all the activities in it via various systems called biomedical signals. Any changes in biomedical signal features are an alarm of revamping in the part of the body. To reason the physiological systems more accurately, hence, the root of the biomedical signals. This led to the development of unprecedented methods that ease monitoring and diagnoses of health status. While image processing is a subset of signal processing with a focus on images and other derived data such as video.

Biomedical signals are measured in many different ways such as Electrooculogram (EOG), Electroencephalogram (EEG), Electromyogram (ERG), Electrocardiogram (ECG), etc. Biomedical signals and image processing consist of methods that applied computational intelligence techniques to extract vital knowledge from the biomedical and biological dataset for analytic and diagnostic reasons. This is only possible as shown how biomedical signals are conceptualized as one-dimensional signals and image processing as multidimensional signals as described in section 2. Computational intelligence techniques played major roles in collecting and processing biomedical images as described in section 3. With the rise of biomedical image data, there are demands for a computational intelligence framework in learning complex images and making a decision. There are several available open-source datasets for medical images, for example, breast cancer that can be accessed freely as outlined in section 4.

Several techniques have also been described in processing biomedical image applications, such as supervised, unsupervised, and reinforcement learning as well as machine and deep learning techniques as indicated in section 5. A summary of various models utilized in various studies on breast cancer has been highlighted in **Table 2**. In addition, several challenges of computational intelligence techniques on biomedical image processing applications based on breast cancer have been highlighted. Section 6 presented recommendations on how to enhance the process of breast cancer diagnoses.

Author(s)	Task	Models
[53]	Biomedical Image Processing	Fully Convolutional Network (FCN) and Bi-LSTM
[54]	Biomedical Image Processing	CNN and LSTM
[52]	Biomedical Image Processing	LSTM
[51]	Biomedical Image Processing	CNNI
[49]	Biomedical Image Processing	CNN
[50]	Biomedical Image Processing	MLP and CNN
[46]	Biomedical Signal Processing	DT and Adaptive Boosting
[45]	Biomedical Signal Processing	DT and KNN
[55]	Biomedical Signal Processing	RF and Extremely Randomized Trees or Extra Trees (ET)
[36]	Biomedical Signal Processing	RF and SVM
[37]	Biomedical Signal Processing	RF
[11]	Biomedical Signal Processing	RF
[40]	Biomedical Signal Processing	LR
[41]	Biomedical Signal Processing	LR
[39]	Biomedical Signal Processing	LR
[38]	Biomedical Signal	NB
[56]	Biomedical Signal Processing	SVM and ANN
[36]	Biomedical Signal Processing	RF and SVM
[57]	Biomedical Image Processing	Deep Neural Network (DNN) and Multiclass Support Vector Machine (MSVM)
[35]	Biomedical Image Processing	Fuzzy-Multi Layer SVM (FMSVM)
[58]	Biomedical Signal Processing	Gated Recurrent Unit SVM LR, MLP, Nearest Neighbor (NN) Search, Softmax Regression, and SVM
[59]	Biomedical Signal Processing	KNN
[37]	Biomedical Signal Processing	SVM, DT, NB, and KNN
[60]	Biomedical Signal Processing	SVM, ANN, NB
[61]	Biomedical Signal Processing	ANN, Standard Extreme Learning Machine (ELM), SVM, and KNN
[62]	Biomedical Image Processing	CNN, SVM, and RF
[63]	Biomedical Image Processing	KNN and SVM
[64]	Biomedical Image Processing	SVM
[65]	Biomedical Image Processing	CNN
[66]	Biomedical Image Processing	CNN
[67]	Biomedical Image Processing	Inception Recurrent Residual Convolutional Neural Network (IRRCNN)
[68]	Biomedical Image Processing	Hybrid Deep Neural Network
[69]	Biomedical Image Processing	CNN
[70]	Biomedical Image Processing	CNN

Author(s)	Task	Models
[71]	Biomedical Image Processing	CNN
[72]	Biomedical Image Processing	CNN and RNN
[65]	Biomedical Image Processing	CNN
[73]	Biomedical Image Processing	Ensemble Prediction Fusion (Gradient Boosting Machine, LR, and SVM)
[74]	Biomedical Image Processing	Deep Convolutional Neural Network (DCNN)
[75]	Biomedical Image Processing	CNN
[76]	Biomedical Image Processing	Fully Convolutional Autoencoder
[77]	Biomedical Image Processing	Deep Learning ResNet Approach
[78]	Biomedical Image Processing	CNN
[79]	Biomedical Image Processing	SVM

Table 2.
Models utilized in image processing based on breast cancer disease.

In future research, the investigator(s) should compare the accuracy, strengths, and limitations of the computational intelligence techniques for biomedical image processing applications based on breast cancer. Lack of access to medical services in most less developed countries can be mitigated, by implementing computational intelligence techniques and cloud computing, which can be utilized to diagnose and detect breast cancer disease remotely. The biomedical image data of a patient can be sent to the cloud based on an accurate computational intelligence model. The outcome of the model will be sent back to server of the hospital. The outcome of the diagnosis can be given to the patient after confirmation from the specialist clinician. The privacy of biomedical images is still an open issue that needs to be addressed. Privacy, scalability, and accuracy trade-off in biomedical image processing solutions need to be investigated in the future.

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Conflict of interest

The authors declare no conflict of interest.

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