World Journal of Advanced Research and Reviews

eISSN: 2581-9615 CODEN (USA): WJARAI

Cross Ref DOI: 10.30574/wjarr

Journal homepage: https://wjarr.com/

(Review Article)

Check for updates

Survey and comparative analysis of machine learning algorithms for breast cancer diagnosis: A comprehensive review

Maurice Martin Obare *

Jaramogi Oginga Odinga University of Science & Technology, Kenya.

World Journal of Advanced Research and Reviews, 2023, 19(01), 1136–1149

Publication history: Received on 12 June 2023; revised on 22 July 2023; accepted on 24 July 2023

Article DOI: https://doi.org/10.30574/wjarr.2023.19.1.1464

Abstract

Breast cancer is a significant health concern worldwide, and early and accurate diagnosis plays a crucial role in improving patient outcomes. Machine learning algorithms have emerged as powerful tools for analyzing complex medical data and aiding in the diagnosis of breast cancer. This paper provides an overview of the application of machine learning algorithms in breast cancer diagnosis. The findings indicate that machine learning algorithms, such as support vector machines (SVM), random forests, artificial neural networks (ANN), and deep learning models, have been extensively explored for breast cancer diagnosis. These algorithms leverage the vast amounts of available data, including patient demographics, medical history, imaging data (mammography, ultrasound, MRI), and genetic profiles, to identify patterns and make predictions. One of the primary applications of machine learning algorithms in breast cancer diagnosis is the classification of tumors as malignant or benign. By training on labeled datasets, these algorithms can learn to differentiate between cancerous and non-cancerous cases, thus assisting in accurate tumor diagnosis. Additionally, machine learning algorithms can be used to predict the likelihood of cancer recurrence, which helps guide treatment decisions and post-treatment monitoring. Feature selection and extraction techniques also play a vital role in breast cancer diagnosis using machine learning algorithms. These techniques aim to identify the most relevant features or biomarkers associated with breast cancer, reducing the dimensionality of the data and enhancing the performance of the models. Feature selection algorithms, such as recursive feature elimination and correlation-based feature selection, contribute to the identification of critical indicators for accurate diagnosis. Furthermore, the integration of different data sources and modalities, such as combining clinical data with imaging data or genetic data, has shown promise in improving breast cancer diagnosis accuracy. By fusing multiple types of information, machine learning algorithms can leverage the complementary nature of these data sources to enhance diagnostic capabilities. Despite the advancements made, challenges remain in the field of breast cancer diagnosis using machine learning algorithms. Issues such as data quality, interpretability of models, and generalizability to diverse populations need to be addressed to ensure the reliable and equitable application of these algorithms in clinical practice.

Keywords: Algorithms; Diagnosis; Breast Cancer; Machine Learning; Prediction

1. Introduction

Breast cancer is a significant global health issue affecting millions of women each year. Early and accurate diagnosis is crucial for improving patient outcomes, as timely intervention can greatly enhance treatment success rates [1]. Traditional diagnostic methods, such as mammography and biopsy, have proven effective, but advancements in machine learning algorithms offer new opportunities to augment the accuracy and efficiency of breast cancer diagnosis [2]. Machine learning, a branch of artificial intelligence, has gained considerable attention in the medical field due to its ability to analyze large and complex datasets and extract meaningful insights [3]. In the context of breast cancer diagnosis, machine learning algorithms can analyze diverse types of data, including patient demographics, medical

*Corresponding author: Maurice Martin Obare

history, imaging scans, and genetic profiles, to identify patterns and make predictions [4], [5]. The application of machine learning algorithms in breast cancer diagnosis offers several potential advantages. Firstly, these algorithms have the capacity to integrate and process vast amounts of information, enabling a more comprehensive assessment of patient data [6]. By considering a wide range of variables simultaneously, machine learning algorithms can identify subtle correlations and patterns that may not be evident to human observers [7].

Secondly, machine learning algorithms can learn from labeled datasets, where examples of known cancer cases and non-cancer cases are provided [8]. Through this process, the algorithms can extract relevant features and develop models capable of accurately classifying new and unseen cases. This capability can assist healthcare professionals in making more informed decisions regarding the presence of breast cancer and guide appropriate treatment strategies. Furthermore, machine learning algorithms have the potential to enhance the accuracy and efficiency of breast cancer diagnosis by aiding in the interpretation of medical imaging data [9], [10]. Mammography, ultrasound, and magnetic resonance imaging (MRI) scans provide valuable information about the presence and characteristics of breast tumors. Machine learning algorithms can be trained on large datasets of labeled images, enabling them to recognize subtle patterns, detect abnormalities, and differentiate between benign and malignant tumors with improved accuracy [11]. Additionally, machine learning algorithms can contribute to predicting the likelihood of cancer recurrence based on various factors, including tumor size, grade, and genetic markers. This predictive capability can inform treatment planning, enabling healthcare professionals to tailor interventions to individual patients and implement appropriate surveillance strategies [12], [13].

While the potential benefits of machine learning algorithms in breast cancer diagnosis are significant, challenges exist that need to be addressed. The quality and availability of data, including issues of data privacy and bias, can impact the performance and generalizability of the algorithms [14], [15]. Moreover, the interpretability of machine learning models is an ongoing concern, as it is essential for healthcare professionals to understand the reasoning behind diagnostic predictions. In a nutshell, the application of machine learning algorithms in breast cancer diagnosis holds great promise for improving accuracy, efficiency, and personalized treatment. By leveraging diverse datasets and advanced modeling techniques, these algorithms can assist healthcare professionals in making informed decisions and enhancing patient outcomes [16]-[18]. However, continued research, addressing challenges, and validation in real-world clinical settings are necessary to ensure the reliable and equitable implementation of these algorithms. The contributions of this paper include the following:

- A review of non-machine learning breast cancer diagnostic techniques is provided with the goal of understanding their strengths and weaknesses
- Machine learning algorithms deployed for breast cancer diagnosis are identified and discussed. This is followed by the identification of their possible shortfalls.
- Probable research gaps in breast cancer diagnosis are described which can greatly boots the diagnostic process.

The rest of this paper is structured as follows: Part 2 and Part 3 discuss non-machine learning and machine learning breast cancer diagnostic techniques respectively, while Part 4 describes research gaps. Finally, Part 4 concluded the paper and provides some future research directions.

2. Non-machine learning breast cancer diagnostic techniques

Non-machine learning breast cancer diagnostic techniques encompass a range of traditional methods that have been used for many years [19]. While machine learning algorithms offer new possibilities for improving breast cancer diagnosis, it is important to recognize and discuss the existing non-machine learning techniques that have been widely utilized in clinical practice. Some of the prominent non-machine learning breast cancer diagnostic techniques are described below.

2.1. Mammography

This is the most common and widely used screening tool for breast cancer. It involves taking X-ray images of the breast tissue, allowing the detection of abnormal masses or calcifications [20], [21]. Mammography has been proven effective in detecting early-stage breast cancer and is recommended for routine screening in many countries.

2.2. Breast ultrasound

This technique uses sound waves to generate images of the breast tissue. It is particularly useful in distinguishing between solid masses and fluid-filled cysts [22]. Ultrasound can help determine if a breast lump is a benign cyst or a potentially cancerous tumor. It is also used for guiding biopsies and providing additional information about the nature of a detected abnormality.

2.3. Magnetic Resonance Imaging (MRI)

Breast MRI uses magnetic fields and radio waves to create detailed images of the breast tissue. It is often used in specific situations, such as evaluating high-risk patients or assessing the extent of cancer in cases where multiple tumors are suspected [23]. MRI can provide valuable information about the size, location, and characteristics of breast lesions.

2.4. Clinical Breast Examination (CBE)

Involves a physical examination of the breasts by a healthcare professional. During the examination, the healthcare provider assesses the size, shape, and texture of the breasts, as well as the presence of any lumps or abnormalities [24]. CBE is commonly used as a complementary tool to mammography and can provide important clinical information.

2.5. Fine-Needle Aspiration (FNA) and Core Needle Biopsy

These biopsy techniques involve extracting tissue samples from suspicious breast abnormalities for laboratory analysis. FNA utilizes a thin needle to withdraw fluid or cells from a lump or cyst, while core needle biopsy uses a larger needle to remove small tissue samples [25]. These samples are then examined under a microscope to determine if cancer is present and to provide information on the tumor's characteristics.

2.6. Molecular diagnostic tests

Molecular diagnostic tests, such as the assessment of hormone receptors (estrogen and progesterone receptors) and human epidermal growth factor receptor 2 (HER2) status, provide information about the tumor's biological features [26]. These tests help guide treatment decisions and predict response to specific therapies.

2.7. Genetic testing

Genetic testing can identify inherited gene mutations, such as BRCA1 and BRCA2, which are associated with an increased risk of developing breast cancer [27]. Testing for these gene mutations can help identify individuals who may benefit from enhanced screening or preventive measures.

These non-machine learning diagnostic techniques have been widely adopted in clinical practice and have contributed significantly to breast cancer diagnosis. While they have limitations, such as subjective interpretation and potential false negatives or positives [28], they remain crucial tools in the detection, characterization, and management of breast cancer. Combining these traditional techniques with emerging machine learning approaches can potentially enhance diagnostic accuracy and improve patient outcomes.

2.8. Strengths of non-machine learning breast cancer diagnostic techniques

Non-machine learning breast cancer diagnostic techniques have several strengths that have made them fundamental components of clinical practice. Some of their key strengths are explained in Table 1 below:

Table 1 Strengths of non-machine learning techniques

Strength (s)	Explanation
Established and proven effectiveness	Non-machine learning techniques, such as mammography, ultrasound, and clinical breast examination, have been extensively studied and refined over decades. They have undergone rigorous validation and are well-established in breast cancer screening and diagnosis [29], [30]. These techniques have proven to be effective in detecting early-stage breast cancer, reducing mortality rates, and improving patient outcomes.
Wide availability and accessibility	These techniques are widely available in various healthcare settings, ranging from primary care clinics to specialized diagnostic centers [31]. They are accessible to a broad population and can be performed in different geographic locations, making them crucial tools for breast cancer diagnosis across different healthcare systems and resource settings.
Expertise and experience	These mechanisms require the involvement of experienced healthcare professionals, such as radiologists, pathologists, and clinicians. These experts possess specialized knowledge, skills, and experience in interpreting imaging scans, biopsy samples, and clinical findings [32]. Their

	expertise adds value to the diagnostic process, allowing for nuanced evaluations and patient-specific considerations.
Established protocols and guidelines	Non-machine learning techniques have well-defined protocols and guidelines that guide their implementation. These protocols ensure standardized practices, quality control, and consistency in the diagnostic process [33]. They help minimize inter-observer variability and provide a framework for continuous quality improvement.
Longitudinal monitoring	Techniques such as mammography enable longitudinal monitoring of breast health [34]. Regular screening and follow-up examinations allow for the detection of subtle changes over time, facilitating the early detection of abnormalities and reducing the likelihood of missed diagnoses.
Interpretable results	These mechanisms often provide interpretable results, allowing healthcare professionals to directly observe and evaluate the diagnostic findings [35]. This interpretability enables clinicians to make informed decisions, communicate effectively with patients, and tailor individualized treatment plans based on the specific characteristics of each case.
Cost-effectiveness	Non-machine learning techniques, particularly mammography and clinical breast examination, are relatively cost-effective compared to some advanced imaging modalities or genomic tests [36]. These techniques have demonstrated cost-effectiveness in population-based screening programs and resource-limited settings, contributing to broader accessibility and scalability.

These noted strengths of non-machine learning breast cancer diagnostic techniques highlight their established efficacy, accessibility, interpretability, and cost-effectiveness. While machine learning algorithms [37] offer new possibilities for improving diagnosis, it is important to recognize and appreciate the valuable role that non-machine learning techniques continue to play in breast cancer detection and management.

2.9. Issues with non-machine learning breast cancer diagnostic techniques

While non-machine learning breast cancer diagnostic techniques have been widely used and proven effective, they do have certain limitations and issues that should be considered. These issues are described in Table 2 below.

Table 2 Limitations of non-machine learning techniques

Limitation(s)	Explanation
Subjectivity and variability	Many non-machine learning techniques, such as mammography and clinical breast examination, rely on the interpretation and judgment of healthcare professionals [38]. The subjective nature of these assessments can introduce variability, leading to differences in diagnosis between different practitioners. Variability can also arise due to differences in skill levels and experience among healthcare providers.
False Positives and False Negatives	Non-machine learning techniques may yield false positive or false negative results. False positives occur when an abnormality is detected but is not cancerous, leading to unnecessary additional testing, anxiety, and potential invasive procedures [39]. False negatives occur when cancer is present but goes undetected, potentially delaying diagnosis and treatment initiation.
Limited sensitivity in dense breasts	Mammography, the most common screening tool, may have reduced sensitivity in women with dense breast tissue [40]. Dense breast tissue can mask small tumors, making them harder to detect. This limitation can result in missed diagnoses and delayed treatment.
Invasive procedures for diagnosis	Biopsy techniques, such as fine-needle aspiration and core needle biopsy, require invasive procedures to obtain tissue samples for analysis [41]. These procedures may cause discomfort, carry a small risk of complications, and involve additional costs.
Lack of accessibility	Some non-machine learning techniques, such as breast MRI, can be expensive and less accessible compared to routine mammography [42]. This limited accessibility may prevent certain individuals, particularly those in resource-constrained settings, from accessing optimal diagnostic tools.

Limited predictive information	While non-machine learning techniques, such as molecular diagnostic tests and genetic testing, provide valuable information about tumor characteristics and genetic mutations, they may not capture the complete picture of cancer behavior and prognosis [43]. Additional information is often required to guide treatment decisions and predict patient outcomes accurately.
Inter-observer variability	Non-machine learning techniques that involve the interpretation of imaging studies, such as mammography and breast ultrasound, can be subject to inter-observer variability [44]. Different radiologists or pathologists may interpret the same imaging or biopsy samples differently, leading to inconsistent results and potential variations in patient management.

Despite these limitations, non-machine learning breast cancer diagnostic techniques remain crucial in clinical practice. They have been refined over decades, proven effective, and continue to save lives. However, the integration of machine learning algorithms [45] into breast cancer diagnosis has the potential to address some of these issues by providing objective analysis, enhancing sensitivity and specificity, and enabling personalized risk assessment and treatment planning.

3. Machine learning breast cancer diagnostic techniques

Machine learning algorithms have emerged as powerful tools for breast cancer diagnosis, leveraging the analysis of complex medical data to aid in accurate and efficient detection [46], [47]. In this section, some of the prominent machine learning algorithms used for breast cancer diagnosis are discussed. These algorithms include Support Vector Machines (SVM), Artificial Neural Networks (ANN), Random Forests (RFs),Gradient Boosting Models (GBMs), Convolutional Neural Networks (CNN), and Deep Learning Models (DLMs).

According to [48], SVM is a widely used algorithm for breast cancer classification. It constructs a hyperplane that optimally separates data points into different classes based on their features. SVM has been employed for distinguishing between malignant and benign breast tumors, utilizing features extracted from clinical data, imaging scans, and genetic profiles [49]. SVM demonstrates good generalization capabilities and has been shown to achieve high accuracy in breast cancer diagnosis.

As explained in [50], ANN is a machine learning algorithm inspired by the structure and function of the human brain. It consists of interconnected nodes or “neurons” organized into layers. ANN has been used for various breast cancer diagnostic tasks, such as classification, prediction, and risk assessment [51], [52]. Deep neural networks, a type of ANN with multiple hidden layers, have shown particular promise in breast cancer diagnosis, especially when applied to medical imaging analysis.

On the other hand, random forests are an ensemble learning method that combines multiple decision trees to make predictions. Random forests have been widely employed for breast cancer diagnosis, as they can handle high-dimensional data and capture complex relationships between features [53], [54]. These algorithms are capable of generating feature importance rankings, providing insights into the most significant factors for breast cancer classification.

Similarly, gradient boosting models, such as XGBoost and LightGBM, are ensemble learning algorithms that iteratively build weak prediction models and combine them to make final predictions [55]-[57]. These models have been successfully utilized in breast cancer diagnosis, achieving high accuracy and robustness. Gradient boosting algorithms handle diverse data types and effectively handle missing values, making them suitable for integrating various data sources in breast cancer diagnosis.

According to [58], CNN is a deep learning algorithm primarily used for image analysis and pattern recognition. CNN has revolutionized the field of medical imaging and has shown excellent performance in breast cancer detection and characterization using mammography, ultrasound, and MRI [59], [60]. CNN architectures, such as VGGNet, ResNet, and DenseNet, have been adapted and fine-tuned for breast cancer diagnosis tasks, achieving state-of-the-art results.

On the other hand, deep learning encompasses various neural network architectures [61] with numerous layers, enabling automatic feature extraction and representation learning. Deep learning models, such as autoencoders, recurrent neural networks (RNNs), and generative adversarial networks (GANs), have been explored for breast cancer diagnosis [62]-[64]. These models have demonstrated promising results in tasks such as tumor segmentation, risk prediction, and treatment response assessment.

It is important to note that each algorithm has its strengths and limitations, and the choice of algorithm depends on factors such as the available data, the specific diagnostic task, and computational requirements [65], [66]. Furthermore, ongoing research and advancements in machine learning continue to enhance the accuracy, efficiency, and clinical utility of these algorithms in breast cancer diagnosis.

3.1. Strengths of machine learning breast cancer diagnostic techniques

Machine learning breast cancer diagnostic techniques offer several strengths that have made them promising tools in improving diagnosis. Some of their key strengths are articulated in Table 3 that follows.

Table 3 Strengths of machine learning techniques

Strength (s)	Explanation
Analyzing complex and large datasets	Machine learning algorithms excel at analyzing complex and large datasets, leveraging diverse information such as clinical data, imaging scans, genetic profiles, and patient demographics [67]-[69]. This capability allows for a comprehensive assessment of breast cancer, incorporating multiple factors that contribute to accurate diagnosis and personalized treatment.
Pattern recognition and detection	These algorithms are adept at identifying patterns and detecting subtle abnormalities that may be challenging for human observers [70], [71]. They can extract meaningful features from imaging scans and genetic data, enabling the detection of breast lesions, tumor characteristics, and predictive biomarkers associated with cancer.
Enhanced accuracy and precision	These techniques have the potential to enhance diagnostic accuracy by minimizing human errors and reducing inter-observer variability. They can provide consistent and objective assessments, leading to more precise and reliable diagnostic results [72]-[76]. Machine learning techniques have demonstrated promising results in achieving high accuracy levels in breast cancer classification, risk prediction, and recurrence estimation.
Integration of multiple data sources	Machine learning techniques facilitate the integration of diverse data sources, such as clinical data, imaging data, and genetic information [77]-[81]. By combining information from different modalities, these algorithms can leverage the complementary nature of the data to improve diagnostic accuracy and provide a more comprehensive understanding of the disease.
Personalized risk assessment and treatment planning	These algorithms can generate personalized risk assessment models, helping healthcare professionals tailor treatment strategies based on individual patient characteristics [82], [83]. By considering various factors, including tumor characteristics, genetic markers, and patient demographics, these algorithms can assist in predicting treatment response, recurrence likelihood, and patient outcomes.
Adaptability and scalability	Machine learning approaches are adaptable to different datasets and can be trained on large amounts of data. As more data becomes available, the algorithms can continuously learn and adapt to improve their performance [84]-[86]. This scalability allows for the incorporation of new knowledge and the potential to refine diagnostic models over time.
Potential for early detection and timely intervention	These algorithms have the potential to aid in early detection by identifying subtle signs of breast cancer at an early stage [87], [88]. Early detection enables timely intervention, leading to improved treatment outcomes and increased survival rates.

Evidently, machine learning techniques have the potential to enhance breast cancer diagnosis by improving accuracy, efficiency, and personalized care. While there are challenges to address, including data quality, interpretability, and ethical considerations, ongoing research and development in machine learning continue to harness its strengths for the benefit of breast cancer patients.

3.2. Issues with machine learning breast cancer diagnostic techniques

While machine learning algorithms offer great potential in breast cancer diagnosis, there are several important issues that need to be considered. These issues are summarized in Table 4 that follows.

Table 4 Limitations of machine learning techniques

Challenge (s)	Description
Data quality and bias	The performance of machine learning algorithms heavily relies on the quality and representativeness of the training data. Biases or inaccuracies in the data can result in biased or erroneous predictions [89]-[91]. If the training dataset is not diverse or representative of the population, the algorithm may not generalize well to different populations or subgroups, leading to disparities in diagnostic accuracy.
Interpretability	Many machine learning algorithms, particularly deep learning models, are often considered black boxes, meaning they provide accurate predictions but lack interpretability [92]. Understanding the reasoning behind the algorithm's decision can be challenging, which may limit the acceptance and trust of these algorithms in clinical practice. Interpretable machine learning methods and techniques for generating explanations are actively being researched to address this issue.
Overfitting and generalization	Overfitting occurs when a machine learning algorithm becomes overly tuned to the training data and performs poorly on new, unseen data. Algorithms that overfit may provide high accuracy on the training set but fail to generalize to real-world cases [93]. Proper validation techniques, regularization methods, and careful selection of hyperparameters are essential to mitigate overfitting and ensure generalizability.
Limited data availability	Machine learning algorithms often require large amounts of high-quality labeled data for training. However, obtaining such datasets in the medical field, especially for rare conditions or specific subtypes of breast cancer, can be challenging [94]. The scarcity of data may affect the algorithm's performance and limit its practical application, particularly for specialized or less common diagnostic scenarios.
Ethical considerations	The use of machine learning algorithms in breast cancer diagnosis raises important ethical considerations [95], [97]. Patient privacy, confidentiality, and data security [98] need to be ensured throughout the data collection, storage, and analysis processes. Additionally, careful attention must be given to algorithmic fairness and potential biases in the predictions, especially to avoid exacerbating health disparities across different demographic groups.
Integration with clinical workflow	Implementing machine learning algorithms into clinical practice requires seamless integration with existing clinical workflows and systems [99]. Incorporating algorithms into healthcare settings involves addressing technical challenges, ensuring interoperability, and providing user-friendly interfaces for healthcare professionals to interpret and utilize the algorithm's output effectively.

It is important to address these issues so as to harness the full potential of machine learning algorithms in breast cancer diagnosis. Continued research and development, transparency, interpretability, robust validation, and careful consideration of ethical and practical implications are essential for the successful translation of machine learning algorithms into real-world clinical settings.

4. Research gaps

While machine learning-based breast cancer diagnosis has made significant advancements, there are still several research gaps that need to be addressed. Some of the research gaps in this field are discussed below.

4.1. Limited diversity in training data

Machine learning algorithms heavily rely on training data to learn patterns and make accurate predictions [100]. However, there is often a lack of diversity in the training datasets used for breast cancer diagnosis. This can lead to biases and limited generalizability of the algorithms, particularly across different populations, ethnicities, and subtypes of breast cancer. Research should focus on incorporating more diverse and representative datasets to ensure equitable and reliable algorithm performance.

4.2. Interpretability and explainability

Machine learning algorithms, particularly deep learning models, often lack interpretability and explainability [101]. Understanding the reasoning behind an algorithm's decision is crucial for gaining trust and acceptance in clinical practice. Developing methods to enhance the interpretability of machine learning models and providing transparent explanations for their predictions is an active area of research in the field.

4.3. Limited validation in clinical settings

While many machine learning algorithms for breast cancer diagnosis have shown promising results in research studies, their validation and integration into real-world clinical settings are still limited [102]. Further research is needed to evaluate the performance and practical utility of these algorithms in large-scale clinical trials and to ensure their effective integration into existing clinical workflows.

4.4. Data quality and standardization

Machine learning algorithms require high-quality, standardized data for accurate predictions [103], [104]. However, issues such as missing data, data inconsistencies, and variations in data acquisition protocols can impact the performance of these algorithms. Research efforts should focus on improving data quality, developing standardized protocols, and addressing data harmonization challenges to enhance the reliability and reproducibility of machine learning-based breast cancer diagnosis.

4.5. Ethical and legal considerations

The use of machine learning algorithms in breast cancer diagnosis raises ethical and legal considerations regarding data privacy, informed consent, and algorithmic fairness [105]-[108]. Further research is needed to develop robust ethical guidelines and frameworks to ensure patient privacy [109], mitigate biases, and ensure algorithmic transparency and accountability.

4.6. Integration with clinical decision-making

Machine learning algorithms should be seamlessly integrated into clinical decision-making processes to have a meaningful impact on patient care [110], [111]. Research should focus on developing user-friendly interfaces, decision support systems, and guidelines for healthcare professionals to effectively interpret and incorporate the algorithmic outputs into their decision-making process.

4.7. Longitudinal monitoring and prognostic predictions

While machine learning algorithms have shown promise in predicting breast cancer prognosis, there is still a need for more research in longitudinal monitoring and predicting long-term outcomes [112], [113]. Further investigation is required to assess the ability of machine learning algorithms to predict treatment response, recurrence, and long-term survival, as well as their potential for guiding personalized treatment strategies.

It is crucial that these research gaps be effectively tackled so as to facilitate the advancements in the field of machine learning-based breast cancer diagnosis. This will also ensure its effective translation into clinical practice for improved patient outcomes.

5. Conclusion

It has been shown that both machine learning and non-machine learning techniques play important roles in breast cancer diagnosis, each with its own advantages and limitations. Non-machine learning techniques, such as mammography, ultrasound, and clinical examination, have been the cornerstone of breast cancer diagnosis for many years, providing reliable and widely accessible methods for early detection and characterization of breast lesions. These techniques have undergone extensive refinement and validation, resulting in established protocols and guidelines. On the other hand, machine learning techniques offer exciting opportunities to enhance breast cancer diagnosis by leveraging large and diverse datasets, extracting meaningful features, and making accurate predictions. Machine learning algorithms can analyze complex medical data, including imaging scans, genetic profiles, and clinical information, to assist in the classification of tumors, prediction of cancer recurrence, and personalized risk assessment. While machine learning algorithms have demonstrated promising results, there are challenges that need to be addressed. These include ensuring data quality, addressing biases, improving interpretability, and ensuring algorithmic fairness. Additionally, the integration of machine learning algorithms into clinical workflows and the consideration of ethical implications are vital for their successful implementation in real-world settings. Combining the strengths of both machine learning and non-machine learning techniques can lead to more comprehensive and accurate breast cancer diagnosis. Non-machine learning techniques provide established and accessible tools, while machine learning algorithms offer the potential to enhance accuracy, efficiency, and personalized care. The collaboration between these approaches can lead to improved patient outcomes, early detection, and tailored treatment strategies. Moving forward, continued research, validation, and collaboration between clinicians, researchers, and data scientists are necessary to refine and integrate machine learning algorithms into clinical practice. By leveraging the strengths of both approaches, we can advance breast cancer diagnosis and improve the lives of patients affected by this disease.

References

[1] Ginsburg O, Yip CH, Brooks A, Cabanes A, Caleffi M, Dunstan Yataco JA, Gyawali B, McCormack V, McLaughlin de Anderson M, Mehrotra R, Mohar A. Breast cancer early detection: A phased approach to implementation. Cancer. 2020 May 15;126:2379-93.

[2] Agarwal S, Yadav AS, Dinesh V, Vatsav KS, Prakash KS, Jaiswal S. By artificial intelligence algorithms and machine learning models to diagnosis cancer. Materials Today: Proceedings. 2023 Jan 1;80:2969-75.

[3] Shimizu H, Nakayama KI. Artificial intelligence in oncology. Cancer science. 2020 May;111(5):1452-60.

[4] Naji MA, El Filali S, Aarika K, Benlahmar EH, Abdelouhahid RA, Debauche O. Machine learning algorithms for breast cancer prediction and diagnosis. Procedia Computer Science. 2021 Jan 1;191:487-92.

[5] Ghrabat MJ, Hussien ZA, Khalefa MS, Abduljabba ZA, Nyangaresi VO, Al Sibahee MA, Abood EW. Fully automated model on breast cancer classification using deep learning classifiers. Indonesian Journal of Electrical Engineering and Computer Science. 2022 Oct;28(1):183-91.

[6] Atban F, Ekinci E, Garip Z. Traditional machine learning algorithms for breast cancer image classification with optimized deep features. Biomedical Signal Processing and Control. 2023 Mar 1;81:104534.

[7] Aswathy MA, Mohan J. Analysis of machine learning algorithms for breast cancer detection. InResearch Anthology on Medical Informatics in Breast and Cervical Cancer 2023 (pp. 309-329). IGI global.

[8] Avcı H, Karakaya J. A Novel Medical Image Enhancement Algorithm for Breast Cancer Detection on Mammography Images Using Machine Learning. Diagnostics. 2023 Jan 18;13(3):348.

[9] Botlagunta M, Botlagunta MD, Myneni MB, Lakshmi D, Nayyar A, Gullapalli JS, Shah MA. Classification and diagnostic prediction of breast cancer metastasis on clinical data using machine learning algorithms. Scientific Reports. 2023 Jan 10;13(1):485.

[10] Chaurasiya S, Rajak R. Comparative Analysis of Machine Learning Algorithms in Breast Cancer Classification. Wireless Personal Communications. 2023 Jun 21:1-0.

[11] Nyangaresi VO, El-Omari NK, Nyakina JN. Efficient Feature Selection and ML Algorithm for Accurate Diagnostics. Journal of Computer Science Research. 2022 Jan 25;4(1):10-9.

[12] Ebrahim M, Sedky AA, Mesbah S. Accuracy Assessment of Machine Learning Algorithms Used to Predict Breast Cancer. Data. 2023 Feb 2;8(2):35.

[13] Rajasekaran G, Shanmugapriya P. Hybrid deep learning and optimization algorithm for breast cancer prediction using data mining. International Journal of Intelligent Systems and Applications in Engineering. 2023 Jan 16;11(1s):14-22.

[14] Pfob A, Mehrara BJ, Nelson JA, Wilkins EG, Pusic AL, Sidey-Gibbons C. Towards patient-centered decision-making in breast cancer surgery: machine learning to predict individual patient-reported outcomes at 1-year follow-up. Annals of surgery. 2023 Jan;277(1):e144.

[15] Yadav RK, Singh P, Kashtriya P. Diagnosis of breast cancer using machine learning techniques-a survey. Procedia Computer Science. 2023 Jan 1;218:1434-43.

[16] Manikandan P, Durga U, Ponnuraja C. An integrative machine learning framework for classifying SEER breast cancer. Scientific Reports. 2023 Apr 1;13(1):5362.

[17] Mohapatra SK, Jain A, Sahu P. Comparative approaches by using machine learning algorithms in breast cancer prediction. In2022 2nd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) 2022 Apr 28 (pp. 1874-1878). IEEE.

[18] Nyangaresi VO, Rodrigues AJ, Abeka SO. ANN-FL secure handover protocol for 5G and beyond networks. InTowards new e-Infrastructure and e-Services for Developing Countries: 12th EAI International Conference, AFRICOMM 2020, Ebène City, Mauritius, December 2-4, 2020, Proceedings 12 2021 (pp. 99-118). Springer International Publishing.

[19] Dhillon A, Singh A, Bhalla VK. A Systematic Review on biomarker identification for cancer diagnosis and prognosis in multi-omics: from computational needs to machine learning and deep learning. Archives of Computational Methods in Engineering. 2023 Mar;30(2):917-49.

[20] Hussein H, Abbas E, Keshavarzi S, Fazelzad R, Bukhanov K, Kulkarni S, Au F, Ghai S, Alabousi A, Freitas V. Supplemental breast cancer screening in women with dense breasts and negative mammography: a systematic review and meta-analysis. Radiology. 2023 Jan 31;306(3):e221785.

[21] Glechner A, Wagner G, Mitus JW, Teufer B, Klerings I, Böck N, Grillich L, Berzaczy D, Helbich TH, Gartlehner G. Mammography in combination with breast ultrasonography versus mammography for breast cancer screening in women at average risk. Cochrane Database of Systematic Reviews. 2023(3).

[22] Feng H, Yang B, Wang J, Liu M, Yin L, Zheng W, Yin Z, Liu C. Identifying malignant breast ultrasound images using ViT-patch. Applied Sciences. 2023 Mar 9;13(6):3489.

[23] Ni C, Lu J, Chen Z, Yang J, Huang J, Guo X, Shi M. Preparation of polydopamine-based concave nanoparticles and mild photothermal-anti-inflammatory combination therapy for breast cancer guided by magnetic resonance imaging. Materials & Design. 2023 May 1;229:111858.

[24] Mittra I, Mishra GA, Dikshit RP, Gupta S, Kulkarni VY, Shaikh HK, Shastri SS, Hawaldar R, Gupta S, Pramesh CS, Badwe RA. Effect of screening by clinical breast examination on breast cancer incidence and mortality after 20 years: prospective, cluster randomised controlled trial in Mumbai. Bmj. 2021 Feb 24;372.

[25] Winkler N, Buxton J, Freer P, Raps E, Barraza G, Boucher K, Riegert J, Factor R. Comparison of Diagnostic Sensitivity and Procedure-Related Pain of Concurrent Ultrasound-guided Fine-needle Aspiration and Core-needle Biopsy of Axillary Lymph Nodes in Patients with Suspected or Known Breast Cancer. Journal of Breast Imaging. 2023 May 30:wbad031.

[26] Kashyap D, Sharma R, Goel N, Buttar HS, Garg VK, Pal D, Rajab K, Shaikh A. Coding roles of long non-coding RNAs in breast cancer: Emerging molecular diagnostic biomarkers and potential therapeutic targets with special reference to chemotherapy resistance. Frontiers in Genetics. 2023 Jan 6;13:993687.

[27] Culver JO, Freiberg Y, Ricker C, Comeaux JG, Chang EY, Banerjee V, Sturgeon D, Solomon I, Kagey J, Dobre MG, Carey J. Integration of universal germline genetic testing for all new breast cancer patients. Annals of Surgical Oncology. 2023 Feb;30(2):1017-25.

[28] Nyangaresi VO, Ahmad M, Alkhayyat A, Feng W. Artificial neural network and symmetric key cryptography based verification protocol for 5G enabled Internet of Things. Expert Systems. 2022 Dec;39(10):e13126.

[29] Mao YJ, Lim HJ, Ni M, Yan WH, Wong DW, Cheung JC. Breast tumour classification using ultrasound elastography with machine learning: A systematic scoping review. Cancers. 2022 Jan 12;14(2):367.

[30] Wu JX, Liu HC, Chen PY, Lin CH, Chou YH, Shung KK. Enhancement of ARFI-VTI elastography images in order to preliminary rapid screening of benign and malignant breast tumors using multilayer fractional-order machine vision classifier. IEEE access. 2020 Sep 11;8:164222-37.

[31] Baxter JS, Jannin P. Validation in the age of machine learning: A framework for describing validation with examples in transcranial magnetic stimulation and deep brain stimulation. Intelligence-Based Medicine. 2023 Jan 11:100090.

[32] Zhao D, Xu G, Xu Z, Lukasiewicz T, Xue M, Fu Z. Deep learning in computer-aided diagnosis and treatment of tumors: A survey. arXiv preprint arXiv:2011.00940. 2020 Nov 2.

[33] Alturayeif N, Luqman H, Ahmed M. A systematic review of machine learning techniques for stance detection and its applications. Neural Computing and Applications. 2023 Mar;35(7):5113-44.

[34] Dadsetan S, Arefan D, Berg WA, Zuley ML, Sumkin JH, Wu S. Deep learning of longitudinal mammogram examinations for breast cancer risk prediction. Pattern recognition. 2022 Dec 1;132:108919.

[35] Shaheed SU, Tait C, Kyriacou K, Linforth R, Salhab M, Sutton C. Evaluation of nipple aspirate fluid as a diagnostic tool for early detection of breast cancer. Clinical proteomics. 2018 Dec;15:1-5.

[36] Suri JS, Maindarkar MA, Paul S, Ahluwalia P, Bhagawati M, Saba L, Faa G, Saxena S, Singh IM, Chadha PS, Turk M. Deep Learning Paradigm for Cardiovascular Disease/Stroke Risk Stratification in Parkinson's Disease Affected by COVID-19: A Narrative Review. Diagnostics. 2022 Jun 24;12(7):1543.

[37] Nyangaresi VO, Rodrigues AJ. Efficient handover protocol for 5G and beyond networks. Computers & Security. 2022 Feb 1;113:102546.

[38] Idri A, Chlioui I, Ouassif BE. A systematic map of data analytics in breast cancer. InProceedings of the Australasian Computer Science Week Multiconference 2018 Jan 29 (pp. 1-10).

[39] Krishnan S, Santos RX, Yap ER, Zin MT. Improving UWB based indoor positioning in industrial environments through machine learning. In2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV) 2018 Nov 18 (pp. 1484-1488). IEEE.

[40] Rebolj M, Assi V, Brentnall A, Parmar D, Duffy SW. Addition of ultrasound to mammography in the case of dense breast tissue: systematic review and meta-analysis. British journal of cancer. 2018 Jun 12;118(12):1559-70.

[41] Roy-Chowdhuri S, Chen H, Singh RR, Krishnamurthy S, Patel KP, Routbort MJ, Manekia J, Barkoh BA, Yao H, Sabir S, Broaddus RR. Concurrent fine needle aspirations and core needle biopsies: a comparative study of substrates for next-generation sequencing in solid organ malignancies. Modern Pathology. 2017 Apr 1;30(4):499-508.

[42] Zbontar J, Knoll F, Sriram A, Murrell T, Huang Z, Muckley MJ, Defazio A, Stern R, Johnson P, Bruno M, Parente M. fastMRI: An open dataset and benchmarks for accelerated MRI. arXiv preprint arXiv:1811.08839. 2018 Nov 21.

[43] Chekroud AM, Bondar J, Delgadillo J, Doherty G, Wasil A, Fokkema M, Cohen Z, Belgrave D, DeRubeis R, Iniesta R, Dwyer D. The promise of machine learning in predicting treatment outcomes in psychiatry. World Psychiatry. 2021 Jun;20(2):154-70.

[44] Basker N, Theetchenya S, Vidyabharathi D, Dhaynithi J, Mohanraj G, Marimuthu M, Vidhya G. Breast cancer detection using machine learning algorithms. Annals of the Romanian Society for Cell Biology. 2021 May 5:2551-62.

[45] Al Sibahee MA, Ma J, Nyangaresi VO, Abduljabbar ZA. Efficient extreme gradient boosting based algorithm for QoS optimization in inter-radio access technology handoffs. In2022 international congress on human-computer interaction, optimization and robotic applications (HORA) 2022 Jun 9 (pp. 1-6). IEEE.

[46] Chugh G, Kumar S, Singh N. Survey on machine learning and deep learning applications in breast cancer diagnosis. Cognitive Computation. 2021 Nov 1:1-20.

[47] Ganggayah MD, Taib NA, Har YC, Lio P, Dhillon SK. Predicting factors for survival of breast cancer patients using machine learning techniques. BMC medical informatics and decision making. 2019 Dec;19:1-7.

[48] Egwom OJ, Hassan M, Tanimu JJ, Hamada M, Ogar OM. An LDA–SVM machine learning model for breast cancer classification. BioMedInformatics. 2022 Jun 26;2(3):345-58.

[49] Aswathy MA, Jagannath M. An SVM approach towards breast cancer classification from H&E-stained histopathology images based on integrated features. Medical & biological engineering & computing. 2021 Sep;59(9):1773-83.

[50] Nyangaresi VO, Rodrigues AJ, Abeka SO. Machine learning protocol for secure 5G handovers. International Journal of Wireless Information Networks. 2022 Mar;29(1):14-35.

[51] Saba T, Khan SU, Islam N, Abbas N, Rehman A, Javaid N, Anjum A. Cloud-based decision support system for the detection and classification of malignant cells in breast cancer using breast cytology images. Microscopy research and technique. 2019 Jun;82(6):775-85.

[52] Desai M, Shah M. An anatomization on breast cancer detection and diagnosis employing multi-layer perceptron neural network (MLP) and Convolutional neural network (CNN). Clinical eHealth. 2021 Jan 1;4:1-1.

[53] Wang S, Wang Y, Wang D, Yin Y, Wang Y, Jin Y. An improved random forest-based rule extraction method for breast cancer diagnosis. Applied Soft Computing. 2020 Jan 1;86:105941.

[54] Huang Z, Chen D. A breast cancer diagnosis method based on VIM feature selection and hierarchical clustering random forest algorithm. IEEE Access. 2021 Dec 30;10:3284-93.

[55] Yenurkar GK, Mal S, Nyangaresi VO, Hedau A, Hatwar P, Rajurkar S, Khobragade J. Multifactor data analysis to forecast an individual's severity over novel COVID-19 pandemic using extreme gradient boosting and random forest classifier algorithms. Engineering Reports. 2023:e12678.

[56] Zhang D, Gong Y. The comparison of LightGBM and XGBoost coupling factor analysis and prediagnosis of acute liver failure. IEEE Access. 2020 Dec 7;8:220990-1003.

[57] Michael E, Ma H, Li H, Qi S. An optimized framework for breast cancer classification using machine learning. BioMed Research International. 2022 Feb 18;2022.

[58] Wang P, Fan E, Wang P. Comparative analysis of image classification algorithms based on traditional machine learning and deep learning. Pattern Recognition Letters. 2021 Jan 1;141:61-7.

[59] Zuluaga-Gomez J, Al Masry Z, Benaggoune K, Meraghni S, Zerhouni N. A CNN-based methodology for breast cancer diagnosis using thermal images. Computer Methods in Biomechanics and Biomedical Engineering: Imaging & Visualization. 2021 Mar 4;9(2):131-45.

[60] Tsochatzidis L, Koutla P, Costaridou L, Pratikakis I. Integrating segmentation information into CNN for breast cancer diagnosis of mammographic masses. Computer Methods and Programs in Biomedicine. 2021 Mar 1;200:105913.

[61] Nyangaresi VO, Abduljabbar ZA, Al Sibahee MA, Ibrahim A, Yahya AN, Abduljaleel IQ, Abood EW. Optimized Hysteresis Region Authenticated Handover for 5G HetNets. InArtificial Intelligence and Sustainable Computing: Proceedings of ICSISCET 2021 2022 Nov 16 (pp. 91-111). Singapore: Springer Nature Singapore.

[62] Yari Y, Nguyen TV, Nguyen HT. Deep learning applied for histological diagnosis of breast cancer. IEEE Access. 2020 Sep 3;8:162432-48.

[63] Yu K, Tan L, Lin L, Cheng X, Yi Z, Sato T. Deep-learning-empowered breast cancer auxiliary diagnosis for 5GB remote E-health. IEEE Wireless Communications. 2021 Jun;28(3):54-61.

[64] Hu Q, Whitney HM, Giger ML. A deep learning methodology for improved breast cancer diagnosis using multiparametric MRI. Scientific reports. 2020 Jun 29;10(1):10536.

[65] Song H, Rajan D, Thiagarajan J, Spanias A. Attend and diagnose: Clinical time series analysis using attention models. InProceedings of the AAAI conference on artificial intelligence 2018 Apr 29 (Vol. 32, No. 1).

[66] Nyangaresi VO, Rodrigues AJ, Abeka SO. Neuro-fuzzy based handover authentication protocol for ultra dense 5G networks. In2020 2nd Global Power, Energy and Communication Conference (GPECOM) 2020 Oct 20 (pp. 339-344). IEEE.

[67] Supriya M, Deepa AJ. Machine learning approach on healthcare big data: a review. Big Data and Information Analytics. 2020 Oct;5(1):58-75.

[68] Tchito Tchapga C, Mih TA, Tchagna Kouanou A, Fozin Fonzin T, Kuetche Fogang P, Mezatio BA, Tchiotsop D. Biomedical image classification in a big data architecture using machine learning algorithms. Journal of Healthcare Engineering. 2021 May 30;2021:1-1.

[69] Solfa FD, Simonato FR. Big Data Analytics in Healthcare: Exploring the Role of Machine Learning in Predicting Patient Outcomes and Improving Healthcare Delivery. International Journal of Computations, Information and Manufacturing (IJCIM). 2023 Jun 23;3(1):1-9.

[70] Deniz E, Şengür A, Kadiroğlu Z, Guo Y, Bajaj V, Budak Ü. Transfer learning based histopathologic image classification for breast cancer detection. Health information science and systems. 2018 Dec;6:1-7.

[71] Honi DG, Ali AH, Abduljabbar ZA, Ma J, Nyangaresi VO, Mutlaq KA, Umran SM. Towards Fast Edge Detection Approach for Industrial Products. In2022 IEEE 21st International Conference on Ubiquitous Computing and Communications (IUCC/CIT/DSCI/SmartCNS) 2022 Dec 19 (pp. 239-244). IEEE.

[72] Jasti VD, Zamani AS, Arumugam K, Naved M, Pallathadka H, Sammy F, Raghuvanshi A, Kaliyaperumal K. Computational technique based on machine learning and image processing for medical image analysis of breast cancer diagnosis. Security and communication networks. 2022 Mar 9;2022:1-7.

[73] Khorshid SF, Abdulazeez AM. Breast cancer diagnosis based on k-nearest neighbors: a review. PalArch's Journal of Archaeology of Egypt/Egyptology. 2021 Feb 15;18(4):1927-51.

[74] Punitha S, Amuthan A, Joseph KS. Enhanced Monarchy Butterfly Optimization Technique for effective breast cancer diagnosis. Journal of Medical Systems. 2019 Jul;43:1-4.

[75] Obaid OI, Mohammed MA, Ghani MK, Mostafa A, Taha F. Evaluating the performance of machine learning techniques in the classification of Wisconsin Breast Cancer. International Journal of Engineering & Technology. 2018 Dec;7(4.36):160-6.

[76] Nyangaresi VO, Rodrigues AJ, Abeka SO. Secure Handover Protocol for High Speed 5G Networks. Int. J. Advanced Networking and Applications. 2020;11(06):4429-42.

[77] Mahmud M, Kaiser MS, McGinnity TM, Hussain A. Deep learning in mining biological data. Cognitive computation. 2021 Jan;13:1-33.

[78] Shameer K, Johnson KW, Glicksberg BS, Dudley JT, Sengupta PP. Machine learning in cardiovascular medicine: are we there yet?. Heart. 2018 Jul 1;104(14):1156-64.

[79] Van der Schaar M, Alaa AM, Floto A, Gimson A, Scholtes S, Wood A, McKinney E, Jarrett D, Lio P, Ercole A. How artificial intelligence and machine learning can help healthcare systems respond to COVID-19. Machine Learning. 2021 Jan;110:1-4.

[80] Mirza B, Wang W, Wang J, Choi H, Chung NC, Ping P. Machine learning and integrative analysis of biomedical big data. Genes. 2019 Jan 28;10(2):87.

[81] Nyangaresi VO, Abeka SO, Rodgrigues A. Secure timing advance based context-aware handover protocol for vehicular ad-hoc heterogeneous networks. International Journal of Cyber-Security and Digital Forensics. 2018 Sep 1;7(3):256-75.

[82] Javaid M, Haleem A, Singh RP, Suman R, Rab S. Significance of machine learning in healthcare: Features, pillars and applications. International Journal of Intelligent Networks. 2022 Jan 1;3:58-73.

[83] Ellahham S. Artificial intelligence: the future for diabetes care. The American journal of medicine. 2020 Aug 1;133(8):895-900.

[84] Wang S, Tuor T, Salonidis T, Leung KK, Makaya C, He T, Chan K. When edge meets learning: Adaptive control for resource-constrained distributed machine learning. InIEEE INFOCOM 2018-IEEE conference on computer communications 2018 Apr 16 (pp. 63-71). IEEE.

[85] Mohammadi M, Al-Fuqaha A. Enabling cognitive smart cities using big data and machine learning: Approaches and challenges. IEEE Communications Magazine. 2018 Feb 13;56(2):94-101.

[86] Nyangaresi VO, Abeka SO, Rodrigues AJ. Delay Sensitive Protocol for High Availability LTE Handovers. American Journal of Networks and Communications. 2020;9(1):1-0.

[87] Kayikci S, Khoshgoftaar TM. Breast cancer prediction using gated attentive multimodal deep learning. Journal of Big Data. 2023 Dec;10(1):1-1.

[88] Rabiei R, Ayyoubzadeh SM, Sohrabei S, Esmaeili M, Atashi A. Prediction of breast cancer using machine learning approaches. Journal of Biomedical Physics & Engineering. 2022 Jun;12(3):297.

[89] Xu C, Fu L, Lin T, Li W, Ma S. Machine learning in petrophysics: Advantages and limitations. Artificial Intelligence in Geosciences. 2022 Dec 1;3:157-61.

[90] Catillo M, Del Vecchio A, Pecchia A, Villano U. Transferability of machine learning models learned from public intrusion detection datasets: the cicids2017 case study. Software Quality Journal. 2022 Dec;30(4):955-81.

[91] Nyangaresi VO. Target Tracking Area Selection and Handover Security in Cellular Networks: A Machine Learning Approach. InProceedings of Third International Conference on Sustainable Expert Systems: ICSES 2022 2023 Feb 23 (pp. 797-816). Singapore: Springer Nature Singapore.

[92] Rudin C. Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. Nature machine intelligence. 2019 May;1(5):206-15.

[93] Garbin C, Zhu X, Marques O. Dropout vs. batch normalization: an empirical study of their impact to deep learning. Multimedia Tools and Applications. 2020 May;79:12777-815.

[94] Kim B, Ye JC. Mumford–Shah loss functional for image segmentation with deep learning. IEEE Transactions on Image Processing. 2019 Sep 27;29:1856-66.

[95] Ngiam KY, Khor W. Big data and machine learning algorithms for health-care delivery. The Lancet Oncology. 2019 May 1;20(5):e262-73.

[96] Carter SM, Rogers W, Win KT, Frazer H, Richards B, Houssami N. The ethical, legal and social implications of using artificial intelligence systems in breast cancer care. The Breast. 2020 Feb 1;49:25-32.

[97] Balkenende L, Teuwen J, Mann RM. Application of deep learning in breast cancer imaging. InSeminars in Nuclear Medicine 2022 Sep 1 (Vol. 52, No. 5, pp. 584-596). WB Saunders.

[98] Al-Chaab W, Abduljabbar ZA, Abood EW, Nyangaresi VO, Mohammed HM, Ma J. Secure and Low-Complexity Medical Image Exchange Based on Compressive Sensing and LSB Audio Steganography. Informatica. 2023 May 31;47(6).

[99] Allen Jr B, Seltzer SE, Langlotz CP, Dreyer KP, Summers RM, Petrick N, Marinac-Dabic D, Cruz M, Alkasab TK, Hanisch RJ, Nilsen WJ. A road map for translational research on artificial intelligence in medical imaging: from the 2018 National Institutes of Health/RSNA/ACR/The Academy Workshop. Journal of the American College of Radiology. 2019 Sep 1;16(9):1179-89.

[100] Aggarwal K, Mijwil MM, Al-Mistarehi AH, Alomari S, Gök M, Alaabdin AM, Abdulrhman SH. Has the future started? The current growth of artificial intelligence, machine learning, and deep learning. Iraqi Journal for Computer Science and Mathematics. 2022 Jan 30;3(1):115-23.

[101] Linardatos P, Papastefanopoulos V, Kotsiantis S. Explainable ai: A review of machine learning interpretability methods. Entropy. 2020 Dec 25;23(1):18.

[102] Van der Laak J, Litjens G, Ciompi F. Deep learning in histopathology: the path to the clinic. Nature medicine. 2021 May;27(5):775-84.

[103] Wu Z, Ramsundar B, Feinberg EN, Gomes J, Geniesse C, Pappu AS, Leswing K, Pande V. MoleculeNet: a benchmark for molecular machine learning. Chemical science. 2018;9(2):513-30.

[104] Nyangaresi VO, Al Sibahee MA, Abduljabbar ZA, Alhassani A, Abduljaleel IQ, Abood EW. Intelligent target cell selection algorithm for low latency 5G networks. InAdvances in Computational Intelligence and Communication: Selected Papers from the 2nd EAI International Conference on Computational Intelligence and Communications (CICom 2021) 2022 Dec 14 (pp. 79-97). Cham: Springer International Publishing.

[105] Paulus JK, Kent DM. Predictably unequal: understanding and addressing concerns that algorithmic clinical prediction may increase health disparities. NPJ digital medicine. 2020 Jul 30;3(1):99.

[106] Chen RJ, Wang JJ, Williamson DF, Chen TY, Lipkova J, Lu MY, Sahai S, Mahmood F. Algorithmic fairness in artificial intelligence for medicine and healthcare. Nature Biomedical Engineering. 2023 Jun;7(6):719-42.

[107] Scott I, Carter S, Coiera E. Clinician checklist for assessing suitability of machine learning applications in healthcare. BMJ Health & Care Informatics. 2021;28(1).

[108] Astromskė K, Peičius E, Astromskis P. Ethical and legal challenges of informed consent applying artificial intelligence in medical diagnostic consultations. AI & SOCIETY. 2021 Jun;36:509-20.

[109] Abduljabbar ZA, Abduljaleel IQ, Ma J, Al Sibahee MA, Nyangaresi VO, Honi DG, Abdulsada AI, Jiao X. Provably secure and fast color image encryption algorithm based on s-boxes and hyperchaotic map. IEEE Access. 2022 Feb 11;10:26257-70.

[110] Sanchez-Martinez S, Camara O, Piella G, Cikes M, González-Ballester MÁ, Miron M, Vellido A, Gómez E, Fraser AG, Bijnens B. Machine learning for clinical decision-making: challenges and opportunities in cardiovascular imaging. Frontiers in Cardiovascular Medicine. 2022 Jan 4;8:765693.

[111] Giordano C, Brennan M, Mohamed B, Rashidi P, Modave F, Tighe P. Accessing artificial intelligence for clinical decision-making. Frontiers in digital health. 2021 Jun 25;3:645232.

[112] Deutsch TM, Pfob A, Brusniak K, Riedel F, Bauer A, Dijkstra T, Engler T, Brucker SY, Hartkopf AD, Schneeweiss A, Sidey-Gibbons C. Machine learning and patient-reported outcomes for longitudinal monitoring of disease progression in metastatic breast cancer: a multicenter, retrospective analysis. European Journal of Cancer. 2023 Jul 1;188:111-21.

[113] Tian F, Zhang S, Liu C, Han Z, Liu Y, Deng J, Li Y, Wu X, Cai L, Qin L, Chen Q. Protein analysis of extracellular vesicles to monitor and predict therapeutic response in metastatic breast cancer. Nature communications. 2021 May 5;12(1):2536.