**Published in:** **First International Conference on Industrial and Technology Innovations (ICITI)**

**Date of Conference:** 3-4 Dec 2025 **DOI:** 10.25212/lfu.qzj.11.1.30

**Publisher:** Qalaai Zanist **Scientific** Journal **Conference Location:** Iraq, Erbil

**E-ISSN:** 2518-6566 **Date Added to Qalaai Zanist Scientific Journal:** 30-1-2026

# Review of Medical Diagnostic Imaging Using Machine Learning: Research and Challenges

**Tara Arif Hussein**
Department of Artificial Intelligence and Robotics Engineering, Technical College of Computer and Informatics Engineering, Erbil Polytechnic University,
Erbil 44001, Iraq
Email: tara.hussein@epu.edu.iq

Information Technology Department, Computer Science Institute, Sulaimani Polytechnic University, Sulaimani, Iraq
Email: tara.arif.hussain@spu.edu.iq

**Chiman Haidar Salh**
Department of Artificial Intelligence and Robotics Engineering, Technical College of Computer and Informatics Engineering, Erbil Polytechnic University,
Erbil 44001, Iraq
Email: chiman.salh@epu.edu.iq

**Media Ali Ibrahim**
Department of Information System Engineering, Technical College of Computer and Informatics Engineering, Erbil Polytechnic University, Erbil 44001, Iraq
Email: media.ibrahim@epu.edu.iq

**Hazha Saeed Yahia**
Department of Artificial Intelligence and Robotics Engineering, Technical College of Computer and Informatics Engineering, Erbil Polytechnic University,
Erbil 44001, Iraq
Email: Hazha.yahia@epu.edu.iq

**Sozan Sulaiman Maghdid**
Department of Information Technology, Erbil Polytechnic University, Erbil, Kurdistan Region, Iraq
Email: Sozan.magdid@epu.edu.iq

**ARTICLE INFO**

***Keywords:*** *Medical Images, Machine Learning, Deep Learning, Image, Information Retrieval, Homomorphic Filtering.*

**ABSTRACT**

**Background:** Recent years have seen continuous progress in the medical industry to enable correct medical diagnosis. Machine learning is another key area which defines the capability of a system to learn from large-scale data entities within the field of medicine to diagnose illnesses.
**Purpose:** To this end, the review sought to assess the part that is played by machine learning in identifying certain diseases. This was in a bid to find commonalities and disparities of various supervised learning techniques that may be helpful in the diagnosis of illnesses.
**Materials and Methods:** Some of the machine learning techniques compared within the study included Supervised, Unsupervised, and Semi-supervised Machine Learning, Active Learning, Reinforcement Learning, Evolutionary Learning, as well as Deep Learning. The authors analyzed various approaches to machine learning used in healthcare to diagnose images, where preference was given to various medical specialties.
**Results:** After going through the various methods, the researcher suggested that deep learning should be implemented in Machine Learning processes since it has various functions in medical diagnosis. Moreover, the most compelling argument raised as to why one should adopt multiple approaches to learning indicated that learning improves the accuracy of medical diagnostic imaging.
**Conclusion:** Homomorphic Filtering (MHFIL) is applied to enhance the images contrast in medical diagnostic imaging hence is the recommendation. This method allows for the simultaneous overcoming of issues that low contrast machine learning poses in efficient diagnosis.

## 1. Introduction

Machine learning (ML) is the branch of artificial intelligence (AI) study that has been experiencing rapid growth in recent years. A lot of attention is being paid to the application of (ML) in the medical department (Dwivedi et al., 2021). Since the early days, medical datasets have been processed, employing machine-learning algorithms which have been conceived & developed based on the idea. ML is continuously playing a significant role in enabling the diagnosis of diseases. Explain diagnosis as the process of identifying which illness or condition an individual has based on examination. Diagnosis can be arrived at by checking on the patients' medical records, through the signs and symptoms portrayed, or by imaging (R. Pandey & Choudhary, 2023). Imaging has been identified as the most accurate way for accurately undertaking diagnosis. To help conduct efficient learning, machine learning plays a vital role because it presents information to medical practitioners to allow for making conclusions (Schrider & Kern, 2018). There are various techniques and methods used in clinical modalities to acquire physiological and functional medical imaging of the human body.

Diagnostic imaging is one of the new treatment benchmarks for diseases such as cancer, trauma, and etc. Modern imaging technologies focus on ease of use, which raises the question of how to increase throughput while maintaining a high level of specificity, such that information can be obtained quickly and efficiently (Tamimi et al., 2016). These ideas are effective inexpensive and suitable for multiple forms of treatments (Myszczynska et al., 2020). In particular, the development of digital imaging opened up a new generation of performance and speed because it offered new forms of data access and transmission and produced new amounts of data.

ML occurs with continuous improvement in technology, which results in an improvement in machines and their capabilities. The machines improve to increase efficiency and accuracy of diagnosis. Additionally, they enable to reduce the time taken to diagnose a condition. The medical sector thus highly benefits in the medical diagnosis. To enable increased accuracy in diagnosis, allowing for early treatment (Geras et al., 2019).

Machine learning refers to the capability of a system to obtain and incorporate knowledge by large-scale corporations using large datasets. This review aims to enhance the systems by enabling them to gain new knowledge autonomously rather than relying on the new knowledge to directly program the system.

Consequently, the information acquired through machine learning empowers the system to refine and expand its functions effectively.
The following paper takes a review of medical diagnostic imaging through the assessment of ML. The review was significant in understanding the views of different researchers regarding the significance of machine learning in undertaking diagnosis. Also, the conclusions about the arguments are presented. Additionally, the paper provides recommendations to help improve machine learning for improved medical diagnostic imaging.
Based on the regularities of the framework described in the review paper, it is suggested to advance the subjects of implementation. The subsequent sections of this work are systematically organized.

## 2. Methods of Measurements

This study's materials and data were collected from secondary sources. Books, online resources, journals, and peer-reviewed publications were among the sources used. The review gathered information from a number of sources to investigate the aspects of medical diagnosis imaging utilizing machine learning, as well as the issues found along the way. There was a discussion of many researchers' arguments on using machine learning to improve medical diagnostic imaging. The data collection process takes a month. The time was sufficient to allow for adequate information collection. The time allowed for the comparison of the similarities and differences between the sources. Also, it allowed for the making of conclusions as well as the identification of possible loops in the papers. Furthermore, it facilitated the identification of the challenges faced in machine learning regarding medical diagnostic imaging.
The information collection process started on the 1st of September after consideration of the important information needed to arrive at the ultimate conclusion. Approximately one and a half months was taken to acquire information from the diverse secondary sources from which the researcher compared the information. The research was a qualitative type and it used the Grounded Theory method. The grounded theory explains the reason(s) why a course of action progressed the way it did as elaborated (Tamimi et al., 2016). The objective was to describe how machine learning has evolved to facilitate medical diagnostic imaging and how this has taken place over time. It also evaluated diverse and multiple numbers of subjects, which is a characteristic of

the grounded theory method. In the case of this review, there was the use of different articles, journals, and books; were analyzed to provide sufficient information to make conclusions regarding machine learning use in medical diagnostic imaging.

The review was a retrospective type in which information from past analyses was collected and compared. The collected information enabled the making of conclusions and identification of challenges. These factors enabled the researcher to outline recommendations for improving ML, which can enhance the process of medical diagnosis imaging, especially in responding to the challenges involved.

## 3. Medical Image Modalities

Another area that is fast emerging as a standard in medical therapy for diseases like cancer and many others is medical imaging. Differences in using complex analytical means and methods of image analysis for accelerating the process of tumor identification and diagnosis can make cancer diagnosis more accurate (Abas, 2022)(Latif et al., 2019). Every technology could give detailed information about which part of the body is being assessed or attended to (Yassin et al., 2018). The principal function of a medical imaging review is to ascertain the positioning, measurements, and properties inherent in the organ by using ML (Murtaza et al., 2020). This is done to gain as much usable information from large volumes of information as possible. Therefore, several researchers focused on developing new types of medical images and on evaluating how such images could categorize the vast majority of diseases. Over the past few years, the field of medicine has experienced rapid growth and is even enriched by means of artificial intelligence and machine learning, specifically in the recognition of images (Leithner et al., 2019). Using other imaging techniques is quite well-established and productive in diagnosing breast cancer. This diagnostic technique includes; a CT scan, mammography, PET scan, MRI scan, duplex ultrasound scan, and radiographic imaging (Quintanilla-Domínguez et al., 2018).

## 4. Machine Learning and Issues Involved in Medical Diagnosis

The procedure of functioning assessment of digital imaging in medical diagnosis processing is complicated and contains numerous diverse properties as explained. Also, elaborates that digital imaging requires complex knowledge to understand the disease or pathogen, which presents the significant role of ML in identifying a disease-medical diagnosis (Syeda-Mahmood, 2018) (De Filippis et al., 2019). The processing techniques of digital imaging for medical diagnosis are embedded in different computer systems. The validation of image processing techniques is significant because it allows for the implementation of certain procedures. These procedures act as stimuli towards the performance of these systems. Hence, it avails decisions and actions depending on the techniques in medical imaging, which helps in disease diagnosis by medics (Langlotz et al., 2019).

So, elaborate that imaging provides numerous fundamental and advanced damage evaluation and visualization tools for improved disease identification. Thus, all researchers accepted the fact that machine learning and imaging are complex and necessary in the medical diagnosis process (De Filippis et al., 2019). It also, adds that ML plays a significant role in achieving (AI) and that the best way to portray human intelligence is through AI also outlined that artificial intelligence and machine learning are important in enabling medical diagnosis because of the imaging element (Bera et al., 2019). The authors further add the element of deep learning (DL), which they explain that combined with machine learning, the two enable AI. The authors argue that AI is the primary domain while ML and DL function under the primary domain in enabling medical diagnosis (R. Pandey & Choudhary, 2023) as presented in Figure 1 below :

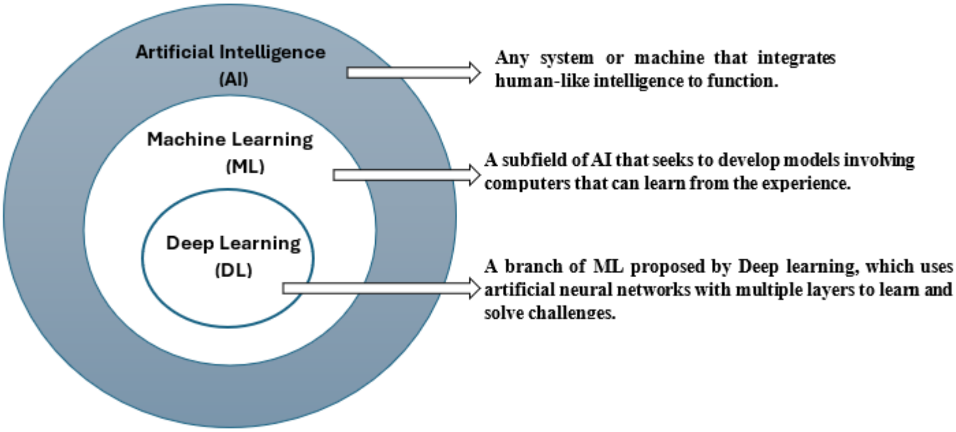


Figure (1): Artificial Intelligence, Machine Learning, and Deep Learning Domain

## 5. Steps Undertaken on Medical Images Before Medical Diagnosis

The purpose of this kind of analysis is to review the steps of medical imaging before coming up with a conclusion that tells the result of the operation, including a medical diagnosis (Langlotz et al., 2019). It starts with the feeding of the medical imaging into the machine along with the deep learning algorithms as parameters where deep learning is of immense importance. Subsequently, the particular image is subdivided into various parts to enhance the probability of zooming to the point of interest, which requires significant medical knowledge as well as proper practical experience (De Filippis et al., 2019) . The third phase is the isolation of features from these segments with the help of conventional information reclamation strategies. Lastly, it maintains all those necessary characteristics of an object while excluding any unnecessary characteristics.

This argument supports the notion that the use of machine learning demands a considerable level of specialty. Therefore, we evaluate the following ways used in the diagnosis of disease by using ML (Latif et al., 2019). This evaluation will seek to confirm whether indeed the claim that ML is impossible to implement without adequate experience among other factors as presented in Figure 2, the steps used in ML.

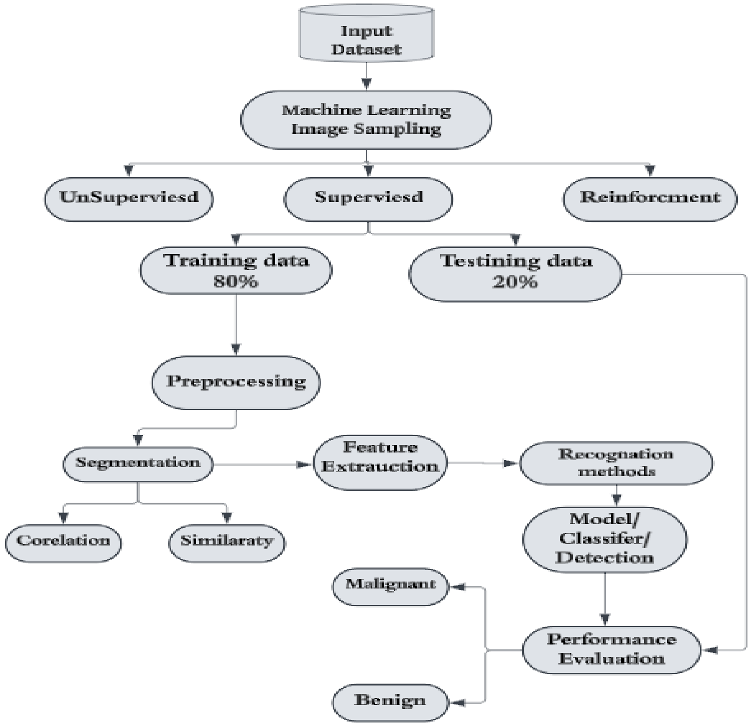


Figure (2): Techniques of machine learning to classify medical image diagnosis

## 6. Types of Machine Learning Techniques

For the efficient process of medical diagnostic imaging, there are different types of ML techniques that are considered important as shown in Figure 3.

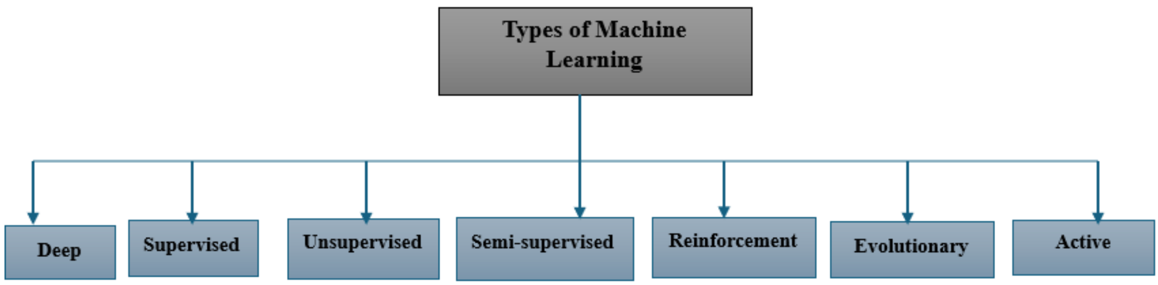

Figure (3): Machine learning approaches

### 6.1 Supervised Machine Learning

In this form of ML, there are specific goals and instances set for a training process. The type of training provides accurate feedback on given possible inputs. Supervised learning applies classification and regression as its subdivisions (Hirsch et al., 2022).

Classification: Classification entails the distribution of inputs into different classes, whereby the trained system produces actions that give classes to the hidden inputs through a process called multi-labeling. An example of classification is spam purification in emails.

Regression: Regression entails a supervised method whereby there are continuous results instead of having discrete results. The root means squared error (RMSE) is used for the evaluation of regression and they differ from the classification that considers the accuracy of outcomes. That supervised ML requires time to learn about it and how to use it, thus delaying the medical diagnosis process (Schrider & Kern, 2018). Also, there are possibilities of overfitting. Overfitting refers to the obtaining of results that perfectly fit training data.

### 6.2 Unsupervised Machine Learning

In this type of Machine Learning, the machine is not trained but instead, it decides by itself, based on some dataset. There is no labelling provided to the system that can enable forecasting. It is an efficient ML method that will enable future learning of the available data (R. Pandey & Choudhary, 2023). Through the use of unsupervised learning, it is possible to retrieve the concealed pattern with the aid of feature learning from specific data. Clustering is an illustration of an unsupervised learning method used to classify the inputs (Yap et al., 2018). The unsupervised learning method is argued to require minimal expert skills in undertaking since a majority of the work is done by the machine. Thus, it differs from the argument that it is impossible to undertake ML without having in-depth expertise. However minimal skills are vital in unsupervised machine learning, skills are significant in interpreting the results provided (Kim et al., 2020).

### 6.3 Semi-supervised Machine Learning

The system is supposed to have limited training data in Semi-supervised learning,such training is employed on trained data which can be used to target some absent results. This form of ML on disease diagnosis is assumed to be a partial training data. It is applied alongside some trained data that can target some absent outcomes. It is a type of algorithm that is applied to untagged data for training purposes. It entails training on both labelled and unlabeled data. The result is the portrayal of characteristics of the supervised as well as the unsupervised machine learning (Al-Azzam & Shatnawi, 2021).

### 6.4 Active Machine Learning

This type of ML entails obtaining training tags only for a limited set of manifestations. Active learning is commonly applied to increase the optimality of substances to obtain tags for the goals (S. K. Pandey & Janghel, 2019). This type of ML cannot be used in instances where there are extensive variances in the pre-determined ailment. Also outlines that because of the restriction of the method, it becomes almost impossible to apply in diagnosis because of the difficulties involved in pre-determining illnesses (Brooks, 2016). It is thus a hard task using the active learning method due to its limited knowledge. It could be an efficient strategy to use when a patient is diagnosed with a condition, and the person shows a similar condition. In such cases, active learning is the optimal learning method used to confirm that the patient suffers from the condition.

### 6.5 Reinforcement Machine Learning

In this type of ML, the trained data is given only as a reaction to the activities of the program. This occurs in a self-inspired case. According to, this method plays a significant role when reacting to a certain occurrence such as an outbreak of a new illness. The learning enables the identification of a disease as a reaction to the disease (Myszczynska et al., 2020). It elaborates that though it enables the diagnosis of a new illness, the method may be of minimal importance in medical diagnosis and early treatment of a disease because it is a reactive type. .

### 6.6 Evolutionary Machine Learning

In this type of ML for medical diagnosis, the main use is for understanding biological organisms. Elaborate that this role enables the prediction of the survival rate and casual of the offspring of a disease (Rundo et al., 2019). Hence, it does not only determine the cause of the disease, but it also identifies the length of time the disease micro-organisms will survive and identify the extent of potential survival. Beam also supports this argument and further says that for evolutionary learning, it is important to know about fitness (S. K. Pandey & Janghel, 2019).

### 6.7 Deep Machine Learning

This stage of the machine is on its high level. It primarily uses neural networks in learning and to facilitate the prediction of data (Dargan et al., 2020). Due to the associated complexities, such as neural networks and other factors, it is clear that this system of ML demands deep and broad knowledge and training. It is a type of ML consisting of a variety of different algorithms. These algorithms facilitate the planning of a composite to generalize system with the ability to overcome any challenge and give it prediction diagnosis (Tsochatzidis et al., 2017).Deep learning necessitates the utilization of the deep graph which comprises of various processing layers to assist in recognizing the existence of a disease. There are many linear and non-linear conversions within the layers as expounded. But as deep learning is capable of solving and predicting most of the diseases, it is not able to predict all the diseases as machines are not always 100 percent effective (Mahmood et al., 2022).

The neural network is applied in medical imaging to enable the acquisition of information regarding the details of the disease. The authors elaborate that it is through the neural networkers that scientists were able to discover cancer (Kong et al., 2015). The neural network is utilized to criticize the instances of situations in which a cell is normal with ultimate confidence in which each individual network has only two results- it will be either a normal cell or cancer. The capability to deliver the results demonstrated that the neural network can be capable of attaining a high degree of precision and a low degree of false-negative analysis. Of particular interest of all deep learning methods are the convolutional neural networks (CNNs).Using the methods of local connectivity exploiting shared weights efficiently, CNN, e.g., the one used in the Image Net competition has rapidly become a state-of-the-art image processing technique. Deep convolutional networks are some of the deep learning techniques that are actively applied to analyze medical images. The application areas provided in this category are abnormality detection, segmentation, disease classification, retrieval, and computer-aided diagnosis. This study provides a broad literature review of the latest state-of-the-art in medical image analysis with deep convolutional networks (Zhang et al., 2023). The problems and prospects of these methods are also pointed out.

## 7. Steps in Machine Learning and Deep Learning

Presented the different steps involved in ML and deep learning algorithms in medical diagnostic imaging as shown in Fig.4 below (R. Pandey & Choudhary, 2023). Similar to the aforementioned classification, regression, segmentation, and detection problem types, both ML and DL operate in a similar workflow process. Although, as was mentioned earlier, there are many similarities they also include the DL workflows using deep neural networks and automatic feature extraction. Feature extraction and selection are traditional activities in ML, and most of them are performed manually. Besides, DL can extract features automatically by using DNNs as shown in Figure 5.

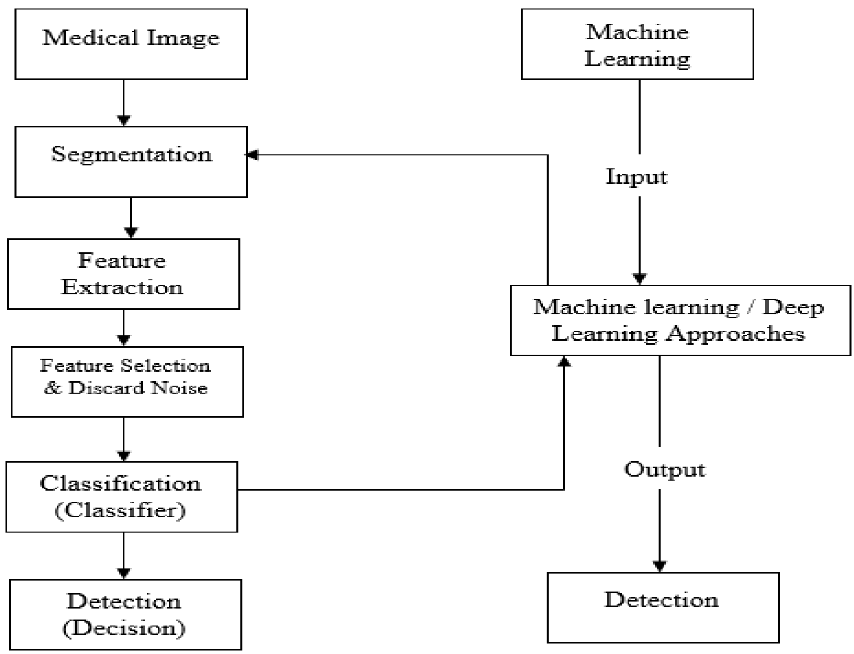


Figure (4): Machine and Deep Learning algorithms workflow in medical diagnosis imaging -Sourced from Latif et al. (2019)

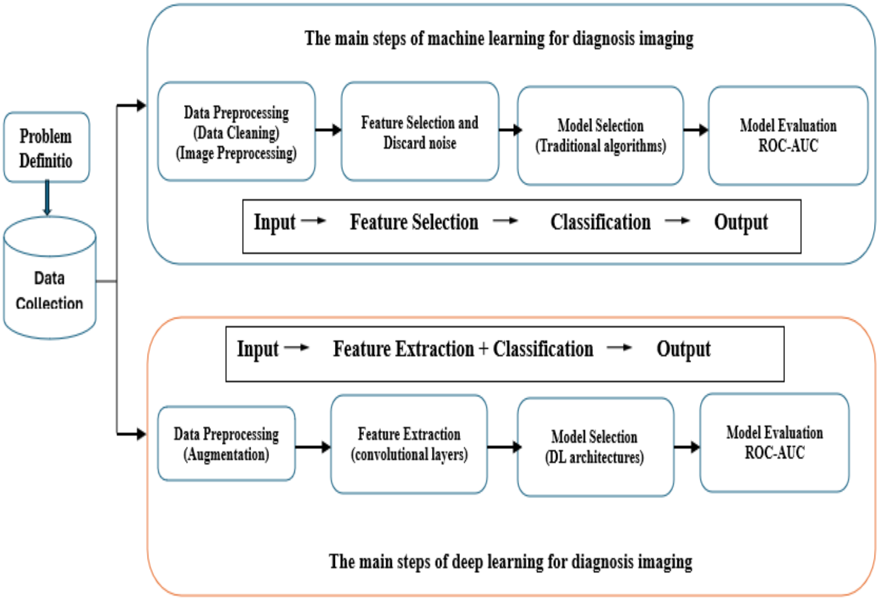


Figure (5): Medical diagnostic imaging using deep learning and machine learning

## 8. Machine Learning in Medical Imaging

Though many researchers argue that ML enables the medical diagnosis of multiple diseases, argue that ML algorithms are very efficient in specific illness determination (Khourdifi & Bahaj, 2019). ML is an efficient tool in identifying and comparing different types of entities like lesions. ML is used because it is difficult and complicated to be effective and well-shown by a simple mathematical resolution. A challenge that occurs in the use of ML in medical diagnostic imaging is when the image has low contrast. In such scenarios, it will be hard to investigate its properties (Yue et al., 2022).

To pixel analysis by outlining that it is more precise compared to others due to its lack of calculations and segmentations. The authors explain that the calculations are not needed in ML processes that make application of pixels. The preciseness is argued to occur because there may be errors in inaccurate segmentation and feature calculation (Byra et al., 2019). Another researcher, explains that in pixel analysis, there is a consumption of long training periods due to the high dimensionality of data. High dimensionality outlines the presence of a large number of pixels within an image (Tamimi et al., 2016). The author thus recommends Histogram Equalization as the most efficient strategy to use to enable improve contrast in the use of pixels. The need for contrast improvement occurs pixels provide low contrast medical images for analysis. Recommend the use of Modified Histogram-Based Contrast Enhancement using Homomorphic Filtering (MHFIL) as the best technique in Histogram Equalization (Rajinikanth et al., 2017). Table 1 presents a comparison of studies employing machine learning methods for diagnostic detection or classification.

Table (1): Comparison of Diagnostic Techniques for Cancer

| Ref. | Imaging Modality | Medical Disease | Dataset | Algorithms Used | Performance Metrics | Limitations |
|---|---|---|---|---|---|---|
| (Yunita & Kamayani, 2023) | MRI | Brain Cancer | BRATS | CNNs and SVMs | accuracy 98.40% precision 97% recall 96.75% and an F1-Score of 96.75%. | The dependency on pre-trained models and transfer learning, which is not necessarily the case to mirror the particular peculiarities of brain tumor MRI images. |
| (Mir et al., 2024) | 3D PET-CT imaging | Liver Cancer | Clinical datasets | HFCNN | accuracy of approximately 93.5% | The need for further investigation to confirm the validity and generalizability of proposed HFCNN model the need for large-scale datasets |
| (Sivasangari et al., 2022) | MRI | brain tumors | datasets from Kaggle | CNN models, with ResNet50 | accuracy of 90% | the need for a large amount of data to train the model, and the requirement for specialized hardware to train the model. |
| (Enuga et al., 2025) | X-ray | Bone cancer | Private dataset | CNNs, ResNet50, ResNet101, EfficientNet-B7 | ResNet101 94.46 % ,ResNet50 by 4.26 %, EfficientNet-B7 by 32.46 %, and | dataset diversity and scalability to other imaging modalities, such as MRIs and histopathological slides. |

| | | | | | | |
|---|---|---|---|---|---|---|
| | | | | | the custom CNN by 7.39 %. | |
| (Wankhade & S., 2023) | CT images | lung cancer | DICOM dataset | CNN | accurate | To make the prognosis accurate, the practitioners are using various imaging techniques like X-rays, |
| (Chaudhari & Patel, 2021) | X-ray diagnostic, MRI, CT SCAN. | Tongue cancer | Private dataset | ANN, SVM | 91.54% accuracy in SVM And 94.99% in ANN | |
| (Birendra Kumar Saraswat et al., 2024) | MRI | Tumour Detection | Kaggle | CNNs | recall of 95%, an accuracy of 95.44%, and an F1-score of 95.36%. | more generalizable technique is still needed |
| (Pachghare & Gawande, 2024) | CT images | Throat Cancer | Private dataset | CNNs and RNNs | High accuracy | develop more effective methods and need for more data to train and validate the models. |

## 9. Recommendation

Based on the above analysis, there has been continuous growth of machine learning skills, and the growth is expected to continue. Although machine learning and deep learning methods give good results in classifying images of cancer, increasing data sizes and architectural structure affect the classification performance results of these methods. On the other hand, deep learning methods, which is a sub-branch of machine learning, are neural network-based learning machines which have more layers than conventional neural network. In contemporary times, ML methods are extremely vigorous in practical environments. There is a possibility that ML may take advantage of the learning process concerning medical imaging. The results will be the re-alignment of medical imaging, which will occur at a faster pace shortly. Application of ML imaging enables better caring of patients through among other functions, proper diagnosis of diseases. The available challenges surrounding ML are many and at the same time, they are serious challenges. Each of the ML processes has weaknesses that make each of them incapable in one way or the other. There is a need to learn the best techniques to use in ensuring the efficient functioning of ML. The effectiveness of machines will allow for the proper diagnosis of illnesses. Though the presently available ML have enabled medical diagnosis imaging, there is still a need for better and improved techniques in handling the diseases. Some researchers have identified deep learning as an efficient strategy. Different researchers identify with different techniques that seem to be efficient. However, these could be relative to their areas of specialization. Thus, there is a need to identify a machine learning strategy to handle all the needs of the different medical fields as shown in Table 2.

Table (2): The following table presents the general comparison of approaches based on the analyzed articles

| Author(s) | Complexity | Accuracy of machine learning in medical diagnosis | Improvement |
|---|---|---|---|
| (R. Pandey & Choudhary, 2023) | Machine learning is very complex and requires intensive skills | | There is constant improvement |
| (De Filippis et al., 2019) | Digital medical diagnosis imaging requires intense skills | | There is room for improvement |
| (Langlotz et al., 2019) | Machine learning and imaging are complex | | Improvement is constant |
| (Latif et al., 2019) | Machine learning and imaging is a complex process for medical diagnosis | | ML has been improved and there is continuous improvement |
| (Aluka et al., 2023) | Unsupervised machine learning requires minimal skills | | |
| (Caron et al., 2018) | Unsupervised ML require minimal skills and expertise | Unsupervised machine leaning is accurate and efficient | |

| | | | |
|---|---|---|---|
| (S. K. Pandey & Janghel, 2019) | Require increased skills and expertise | Active ML has limited usability hence minimal accuracy | Can be imp-roved |
| (Dargan et al., 2020) | Require advanced skills level | High accuracy levels | Deep Machine Learning is an improvement in itself |
| (Rajinikanth et al., 2017) | Required extensive skills and professionalism | Accurate | ML in medical diagnosis can be improved using Homomorphic Filtering (MHFIL) as the best technique in Histogram Equalization |
| (Schrider & Kern, 2018) | Complex and requires deep skills to efficiently determine the diseases | Requires high levels of accuracy | There is a possibility of improving diagnosis by application of machine learning. |
| (Sarker et al., 2021) | Complex in knowledge acquisition and incorporation | Provides high accuracy levels | Can be continuously be improved with changing technology. |
| (Bera et al., 2019) | Simple and uses the imaging element for medical diagnosis | High accuracy because of the imaging component | Can be improved through among others deep learning. |
| (Park et al., 2024) | Require minimal skills in reading, hence not complex: Require complex skills in interpreting the data | | There is room for improvement. |
| (Brooks, 2016) | Complex to application in medical diagnosis. | Low accuracy levels due to the restriction of the method. | There is room for improvement |

| | | | |
|---|---|---|---|
| (Rundo et al., 2019) | Relatively high complexity | High accuracy and has extensive features | Requires improvement and there is room for improvement. |
| (Myszczynska et al., 2020) | It is complex to use in disease diagnosis | Low accuracy in medical diagnosis | Can be improved in diagnosis of a new disease |
| (Kong et al., 2015) | Complex in use | High accuracy levels. | It is an improved form that can detect cancer, but is subject to further improvements |
| (Prasadl et al., 2024) | Relatively low complexity. | Accurate in medical diagnosis of certain diseases | Has room for improvement for diagnosis of other diseases. |
| (Fatima et al., 2020) | Complex in use | High accuracy levels because it uses pixels instead of calculations. | Already improved to enable use of pixels |
| (Tamimi et al., 2016) | Complex to use | Limited accuracy because of long training time | Requires improvement to save on time |

## 10. General Limitations

The following are the challenges that are associated with the limitation of medical diagnosis imaging using machine learning. Nevertheless, cancer is still one of the major causes of death globally; therefore, it is indispensable to develop highly efficient diagnostic technologies. The choice and evaluation of models for the classification of malignant and benign tumors is especially challenging, and it can take considerable time and money.

Operations like image enhancement and image modification use filters which are on the other hand basic but have issues regarding data integrity. Furthermore, the emerging of new structures for architectural image analysis requires transformation of images into various formats, and this escalates the models complexity and may lead to variations in accuracy.

Another dimension that normalization, which is the important preprocessing method whereby feature values are divided by their maximum values, introduces to the process. These limitations put together reveal that the use of machine learning for diagnosis of cancer using medical images is not a walk in the park**.**

## Conclusion

Deep learning involvement is a form of machine learning, which enables systems to know and understand the world in terms of a pecking order of ideas. It is a structured system and it can have great role to play in medical diagnosis. It is possible to classify objects and images with deep learning. In addition, it allows detection of the organ and localization depend on the classification of an image or object. Deep learning is also useful when it comes to segmentation and allowing the processing of organ substructures of medical images with particular reference to the quantitative assessment of clinical characteristics. Some example the assessment of brain, heart and lung. Registration will also be possible with deep learning that entails the act of mapping different set of data to a single coordinate system. Thus, deep learning inclusion will come in very useful. It is already used in some machine learning techniques. Another suggestion that will facilitate effective learning in the medical diagnostic imaging field is the incorporation of over a single method of learning. Every machine learning method also has its pros, and it possesses personal defect. Thus, if integration is undertaken, it will enable an improved method of medical diagnosis. Different researchers in the healthcare industry seem to have alternative preferences, hence a need for a moderated ML approach. Using Modified Histogram-Based Contrast Enhancement using Homomorphic Filtering" (MHFIL) for improvement of the contrast in undertaking medical diagnostic imaging. Machine Learning should provide the opportunity for the application of MHFIL because it improves image contrast allowing for improved identification of diseases. Consequently, it will enable accurate disease diagnosis because there is accurate viewership of the disease pathogen. MHFIL will hence improve among other elements the treatment of diseases since treatment will begin at an early phase.

## References


Abas, S. M. (2022). *Diseases Diagnosis Using Machine Learning of Medical Images*. *December*.

Al-Azzam, N., & Shatnawi, I. (2021). Comparing supervised and semi-supervised Machine Learning Models on Diagnosing Breast Cancer. *Annals of Medicine and Surgery*, *62*(November 2020), 53–64. https://doi.org/10.1016/j.amsu.2020.12.043

Aluka, M., Dixit, R., & Kumar, P. (2023). Enhancing and Detecting the Lung Cancer using Deep Learning. *International Journal on Recent and Innovation Trends in Computing and Communication*, *11*(December 2022), 127–134. https://doi.org/10.17762/ijritcc.v11i3s.6173

Bera, K., Schalper, K. A., Rimm, D. L., Velcheti, V., & Madabhushi, A. (2019). Artificial intelligence in digital pathology — new tools for diagnosis and precision oncology. *Nature Reviews Clinical Oncology*, *16*(11), 703–715. https://doi.org/10.1038/s41571-019-0252-y

Birendra Kumar Saraswat, Shashikant Katiyar, & Ashish Kumar Sharma. (2024). Neuro Image Processor For Tumour Detection (NIPTI) using Machine Learning. *Journal of Advances in Science and Technology*, *21*(1), 53–57. https://doi.org/10.29070/62qdeh70

Brooks, B. A. (2016). *Bridging Early Diagnosis and Intervention : Enhancing Recommendations and Facilitating Access to Early Intervention*.

Byra, M., Galperin, M., Ojeda-Fournier, H., Olson, L., O'Boyle, M., Comstock, C., & Andre, M. (2019). Breast mass classification in sonography with transfer learning using a deep convolutional neural network and color conversion. *Medical Physics*, *46*(2), 746–755. https://doi.org/10.1002/mp.13361

Caron, M., Bojanowski, P., Joulin, A., & Douze, M. (2018). Deep clustering for unsupervised learning of visual features. *Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *11218 LNCS*, 139–156. https://doi.org/10.1007/978-3-030-01264-9_9

Chaudhari, V. B., & Patel, N. M. (2021). *Tongue Pre-Cancer Stages Classification Using Machine Learning*. *6*(9), 138–141.

Dargan, S., Kumar, M., Ayyagari, M. R., & Kumar, G. (2020). A Survey of Deep Learning and Its Applications: A New Paradigm to Machine Learning. *Archives of Computational Methods in Engineering*, *27*(4), 1071–1092. https://doi.org/10.1007/s11831-019-09344-w

De Filippis, R., Carbone, E. A., Gaetano, R., Bruni, A., Pugliese, V., Segura-Garcia, C., &

De Fazio, P. (2019). Machine learning techniques in a structural and functional MRI diagnostic approach in schizophrenia: A systematic review. *Neuropsychiatric Disease and Treatment*, *15*, 1605–1627. https://doi.org/10.2147/NDT.S202418

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(July), 0–1. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Enuga, P. S. R., Singh, S., & Santhi, V. (2025). Detection of Bone Cancer using Machine Learning: A Multi-Model Approach. *3rd International Conference on Electronics and Renewable Systems, ICEARS 2025 - Proceedings*, *Icears*, 1138–1144. https://doi.org/10.1109/ICEARS64219.2025.10941267

Fatima, N., Liu, L., Hong, S., & Ahmed, H. (2020). Prediction of Breast Cancer, Comparative Review of Machine Learning Techniques, and Their Analysis. *IEEE Access*, *8*, 150360–150376. https://doi.org/10.1109/ACCESS.2020.3016715

Geras, K. J., Mann, R. M., & Moy, L. (2019). Artificial intelligence for mammography and digital breast tomosynthesis: Current concepts and future perspectives. *Radiology*, *293*(2), 246–259. https://doi.org/10.1148/radiol.2019182627

Hirsch, L., Huang, Y., Luo, S., Saccarelli, C. R., Gullo, R. Lo, Naranjo, I. D., Bitencourt, A. G. V., Onishi, N., Ko, E. S., Leithner, D., Avendano, D., Eskreis-Winkler, S., Hughes, M., Martinez, D. F., Pinker, K., Juluru, K., El-Rowmeim, A. E., Elnajjar, P., Morris, E. A., … Sutton, E. J. (2022). Radiologist-level Performance by Using Deep Learning for Segmentation of Breast Cancers on MRI Scans. *Radiology: Artificial Intelligence*, *4*(1). https://doi.org/10.1148/ryai.200231

Khourdifi, Y., & Bahaj, M. (2019). Feature Selection with Fast Correlation-Based Filter for Breast Cancer Prediction and Classification Using Machine Learning Algorithms. *International Symposium on Advanced Electrical and Communication Technologies, ISAECT 2018 - Proceedings*, *1*, 1–6. https://doi.org/10.1109/ISAECT.2018.8618688

Kim, M. S., Park, H. Y., Kho, B. G., Park, C. K., Oh, I. J., Kim, Y. C., Kim, S., Yun, J. S., Song, S. Y., Na, K. J., Jeong, J. U., Yoon, M. S., Ahn, S. J., Yoo, S. W., Kang, S. R., Kwon, S. Y., Bom, H. S., Jang, W. Y., Kim, I. Y., … Choi, Y. D. (2020). Artificial intelligence and lung cancer treatment decision: Agreement with recommendation of multidisciplinary tumor board. *Translational Lung Cancer Research*, *9*(3), 507–514. https://doi.org/10.21037/tlcr.2020.04.11

Kong, K., Kendall, C., Stone, N., & Notingher, I. (2015). Raman spectroscopy for medical diagnostics - From in-vitro biofluid assays to in-vivo cancer detection. *Advanced Drug Delivery Reviews*, *89*, 121–134. https://doi.org/10.1016/j.addr.2015.03.009

Langlotz, C. P., Allen, B., Erickson, B. J., Kalpathy-Cramer, J., Bigelow, K., Cook, T. S., Flanders, A. E., Lungren, M. P., Mendelson, D. S., Rudie, J. D., Wang, G., & Kandarpa, K. (2019). A roadmap for foundational research on artificial intelligence in medical imaging: From the 2018 NIH/RSNA/ACR/The Academy workshop. *Radiology*, *291*(3), 781–791. https://doi.org/10.1148/radiol.2019190613

Latif, J., Xiao, C., Imran, A., & Tu, S. (2019). Medical imaging using machine learning and deep learning algorithms: A review. *2019 2nd International Conference on Computing, Mathematics and Engineering Technologies, ICoMET 2019*, 1–5. https://doi.org/10.1109/ICOMET.2019.8673502

Leithner, D., Moy, L., Morris, E. A., Marino, M. A., Helbich, T. H., & Pinker, K. (2019). Abbreviated MRI of the Breast: Does It Provide Value? *Journal of Magnetic Resonance Imaging*, *49*(7), e85–e100. https://doi.org/10.1002/jmri.26291

Mahmood, T., Li, J., Pei, Y., Akhtar, F., Ur Rehman, M., & Wasti, S. H. (2022). Breast lesions classifications of mammographic images using a deep convolutional neural network-based approach. *PLoS ONE*, *17*(1 January), 1–25. https://doi.org/10.1371/journal.pone.0263126

Mir, F. I., Raj, G., Lata, K., & Verma, A. S. (2024). Deep Data Analysis for Liver Cancer Prediction Using Machine Learning Approaches. *Proceedings - IEEE 2024 1st International Conference on Advances in Computing, Communication and Networking, ICAC2N 2024*, 864–870. https://doi.org/10.1109/ICAC2N63387.2024.10895272

Murtaza, G., Shuib, L., Abdul Wahab, A. W., Mujtaba, G., Mujtaba, G., Nweke, H. F., Al-garadi, M. A., Zulfiqar, F., Raza, G., & Azmi, N. A. (2020). Deep learning-based breast cancer classification through medical imaging modalities: state of the art and research challenges. *Artificial Intelligence Review*, *53*(3), 1655–1720. https://doi.org/10.1007/s10462-019-09716-5

Myszczynska, M. A., Ojamies, P. N., Lacoste, A. M. B., Neil, D., Saffari, A., Mead, R., Hautbergue, G. M., Holbrook, J. D., & Ferraiuolo, L. (2020). Applications of machine learning to diagnosis and treatment of neurodegenerative diseases. *Nature Reviews Neurology*, *16*(8), 440–456. https://doi.org/10.1038/s41582-020-0377-8

Pachghare, P. P., & Gawande, U. H. (2024). Throat Cancer Detection: A Comprehensive Review of Multimodal Analysis and Machine Learning Techniques. *2024 2nd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry, IDICAIEI 2024*, 2–7. https://doi.org/10.1109/IDICAIEI61867.2024.10842887

Pandey, R., & Choudhary, M. (2023). Cardiovascular Imaging using Machine Learning: A Review. *International Journal of Recent Technology and Engineering (IJRTE)*, *11*(6), 39–49. https://doi.org/10.35940/ijrte.f7480.0311623

Pandey, S. K., & Janghel, R. R. (2019). Recent Deep Learning Techniques, Challenges and Its Applications for Medical Healthcare System: A Review. *Neural Processing Letters*, *50*(2), 1907–1935. https://doi.org/10.1007/s11063-018-09976-2

Park, T. Y., Kwon, L. M., Hyeon, J., & Cho, B. (2024). *Deep Learning Prediction of Axillary Lymph Node Metastasis in Breast Cancer Patients Using Clinical Implication-Applied Preprocessed CT Images*. 2278–2288.

Prasadl, D. R. S., Ram, K. N. V. J. C., Manohar, M., Yasaswi, M., & Kavya, K. (2024). CNN-Based Deep Learning Approach for Early Diagnosis of Chronic Kidney Stones from MRI Images. *International Journal of Research Publication and Reviews*, *5*(4), 800–806. https://doi.org/10.55248/gengpi.5.0424.0917

Quintanilla-Domínguez, J., Ruiz-Pinales, J., Barrón-Adame, J. M., & Guzmán-Cabrera, R. (2018). Microcalcifications detection using image processing. *Computacion y Sistemas*, *22*(1), 291–300. https://doi.org/10.13053/CyS-22-1-2560

Rajinikanth, V., Satapathy, S. C., Fernandes, S. L., & Nachiappan, S. (2017). Entropy based segmentation of tumor from brain MR images – a study with teaching learning based optimization. *Pattern Recognition Letters*, *94*, 87–95. https://doi.org/10.1016/j.patrec.2017.05.028

Rundo, L., Tangherloni, A., Nobile, M. S., Militello, C., Besozzi, D., Mauri, G., & Cazzaniga, P. (2019). MedGA: A novel evolutionary method for image enhancement in medical imaging systems. *Expert Systems with Applications*, *119*, 387–399. https://doi.org/10.1016/j.eswa.2018.11.013

Sarker, M. M. K., Makhlouf, Y., Craig, S. G., Humphries, M. P., Loughrey, M., James, J. A., Salto-tellez, M., O'Reilly, P., & Maxwell, P. (2021). A means of assessing deep learning-based detection of ICOS protein expression in colon cancer. *Cancers*, *13*(15), 1–21. https://doi.org/10.3390/cancers13153825

Schrider, D. R., & Kern, A. D. (2018). Supervised Machine Learning for Population Genetics: A New Paradigm. *Trends in Genetics*, *34*(4), 301–312. https://doi.org/10.1016/j.tig.2017.12.005

Sivasangari, A., Sivakumar, Helen, S., Deepa, S., Vignesh, & Suja. (2022). Detection of Abnormalities in Brain using Machine Learning in Medical Image Analysis. *International Conference on Sustainable Computing and Data Communication Systems, ICSCDS 2022 - Proceedings*, 102–107. https://doi.org/10.1109/ICSCDS53736.2022.9761029

Syeda-Mahmood, T. (2018). Role of Big Data and Machine Learning in Diagnostic Decision Support in Radiology. *Journal of the American College of Radiology*, *15*(3), 569–576. https://doi.org/10.1016/j.jacr.2018.01.028

Tamimi, R. M., Spiegelman, D., Smith-Warner, S. A., Wang, M., Pazaris, M., Willett, W. C., Eliassen, A. H., & Hunter, D. J. (2016). Population attributable risk of modifiable and nonmodifiable breast cancer risk factors in postmenopausal breast cancer. *American Journal of Epidemiology*, *184*(12), 884–893. https://doi.org/10.1093/aje/kww145

Tsochatzidis, L., Zagoris, K., Arikidis, N., Karahaliou, A., Costaridou, L., & Pratikakis, I. (2017). Computer-aided diagnosis of mammographic masses based on a supervised content-based image retrieval approach. *Pattern Recognition*, *71*, 106–117. https://doi.org/10.1016/j.patcog.2017.05.023

Wankhade, S., & S., V. (2023). A novel hybrid deep learning method for early detection of lung cancer using neural networks. *Healthcare Analytics*, *3*(April), 100195. https://doi.org/10.1016/j.health.2023.100195

Yap, M. H., Pons, G., Martí, J., Ganau, S., Sentís, M., Zwiggelaar, R., Davison, A. K., & Martí, R. (2018). Automated Breast Ultrasound Lesions Detection Using Convolutional Neural Networks. *IEEE Journal of Biomedical and Health Informatics*, *22*(4), 1218–1226. https://doi.org/10.1109/JBHI.2017.2731873

Yassin, N. I. R., Omran, S., El Houby, E. M. F., & Allam, H. (2018). Machine learning techniques for breast cancer computer aided diagnosis using different image modalities: A systematic review. *Computer Methods and Programs in Biomedicine*, *156*, 25–45. https://doi.org/10.1016/j.cmpb.2017.12.012

Yue, W., Zhang, H., Zhou, J., Li, G., Tang, Z., Sun, Z., Cai, J., Tian, N., Gao, S., Dong, J., Liu, Y., Bai, X., & Sheng, F. (2022). Deep learning-based automatic segmentation for size and volumetric measurement of breast cancer on magnetic resonance imaging. *Frontiers in Oncology*, *12*(August), 1–14. https://doi.org/10.3389/fonc.2022.984626

Yunita, R., & Kamayani, M. (2023). Indonesian Journal of Computer Science. *Indonesian Journal of Computer Science*, *12*(2), 284–301. http://ijcs.stmikindonesia.ac.id/ijcs/index.php/ijcs/article/view/3135

Zhang, Y., Liu, Y. L., Nie, K., Zhou, J., Chen, Z., Chen, J. H., Wang, X., Kim, B., Parajuli, R., Mehta, R. S., Wang, M., & Su, M. Y. (2023). Deep Learning-based Automatic Diagnosis of Breast Cancer on MRI Using Mask R-CNN for Detection Followed by ResNet50 for Classification. *Academic Radiology*, *30*(2019326177), S161–S171. https://doi.org/10.1016/j.acra.2022.12.038