



Exploring the Potential of Machine Learning and Deep Learning for Predictive Breast Cancer Analytics

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Abstract

Breast cancer remains a significant global health challenge affecting millions of people worldwide. Early detection is crucial for improving treatment outcomes and survival rates. With the rapid advancement of technology, artificial intelligence (AI) has emerged as a transformative tool in medical diagnostics, particularly in breast cancer detection. This review examines how state-of-the-art machine learning (ML) and deep learning (DL) methodologies have revolutionized breast cancer diagnostics. Techniques such as convolutional neural network (CNN), ensemble learning, transfer learning, explainable AI, and federated learning (FL) have been analyzed for their contributions to addressing multifaceted challenges in medical image analysis. Each approach was evaluated for its capacity to enhance detection accuracy, interpretability, and scalability in real-world applications. The integration of these methodologies offers a comprehensive solution by combining the strengths of individual techniques. For instance, CNN excels in feature extraction, ensemble learning enhances robustness,

and transfer learning influences the efficiency of pre-trained models. Concurrently, explainable AI improves transparency, and FL ensures data privacy while enabling collaborative research. Collectively, these innovations facilitate early diagnosis and pave the way for personalized treatment strategies, ultimately improving patient outcomes. By synthesizing recent findings, this study aims to provide insights into the current state of AI in breast cancer diagnostics, identify research gaps, and encourage future developments. Through the effective integration of AI technologies, healthcare systems can optimize resource allocation and deliver improved care to those affected by breast cancer.

Keywords: artificial intelligence, breast, cancer, machine learning, deep learning.

1 Introduction

Breast cancer continues to be the most frequently diagnosed cancer and a leading cause of cancer-related mortality among women worldwide. In 2020, the world health organization (WHO) estimated approximately 2.3 million new cases globally, resulting in around 685,000 deaths [1]. The incidence and mortality are projected to rise due to population aging, lifestyle factors, and increased screening uptake [2]. Early detection and accurate diagnosis are critical to improving prognosis and survival



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rates, yet conventional imaging modalities such as mammography, ultrasound, and magnetic resonance imaging (MRI) face challenges including limited sensitivity in dense breast tissue and inter-observer variability [3, 4].

Recent advances in AI, particularly in ML and DL, have demonstrated significant potential to enhance breast cancer detection and diagnosis. DL models, such as CNN, have shown superior performance in image classification tasks, surpassing traditional methods by extracting hierarchical features directly from raw data without manual engineering [5, 6]. For example, AI algorithms could outperform expert radiologists in breast cancer screening using mammography data from large population cohorts [7–9]. Building on these foundations, studies published through 2023 to 2025 have focused on improving model interpretability, generalizability, and privacy preservation to facilitate clinical integration [10–13].

Transformer-based architectures, originally developed for natural language processing, have recently been adapted for medical image analysis, offering improved context modeling and attention mechanisms that highlight diagnostically relevant regions [14–16]. FL approaches have emerged as a critical tool enabling multi-institutional collaborations without direct data sharing, thus overcoming patient privacy concerns and dataset heterogeneity [17–19]. Such frameworks have been shown to produce AI models with performance comparable to centralized training on pooled data.

Furthermore, multi-modal AI systems that integrate imaging with clinical records, genomic data, and pathology reports are advancing personalized risk stratification and treatment planning [20–22]. For instance, The demonstrated enhanced breast cancer risk prediction by combining mammography images with patient demographic and clinical data [23–25]. Large-scale prospective trials are now validating the efficacy and safety of AI-assisted screening workflows, highlighting reductions in false positives and improvements in diagnostic accuracy [10, 26, 27].

Despite these promising developments, challenges remain in standardizing datasets, addressing algorithmic biases, and ensuring explainability to gain clinician trust and regulatory approval. Rigorous clinical validation and ethical deployment frameworks are essential for transitioning AI tools from research to routine clinical practice [28, 29]. This review synthesizes the most recent and impactful studies published from 2023 through 2025, providing a

comprehensive overview of current AI methodologies, datasets, clinical applications, and future directions in breast cancer detection. Studies demonstrated the potential of ML and DL techniques to improve the accuracy of thyroid cancer diagnosis. According to the results, the research attained higher sensitivity levels (92.6%) and specificity (85.7%), suggesting that ML techniques can enhance diagnostic precision in thyroid cancer detection. This success also implies the potential for similar advancements in breast cancer detection by employing ML methods, which could contribute to earlier detection and improved patient outcomes [30]. ML and DL techniques can achieve high accuracy rates in breast cancer, often outperforming traditional detection methods [31].

The primary objective of this study was to conduct a comprehensive review of frameworks that have documented outcomes using mammograms, the most widely employed breast imaging modality that medical practitioners typically prescribe as an initial test for detecting breast cancer. Furthermore, mammography imaging techniques can focus on the availability of labelled datasets that enhance the effectiveness of these models [32]. Additionally, this study delves into the application of DL techniques for the early detection of breast cancer by examining the performance metrics and datasets commonly used in this context. Examine the impact of ML and DL on breast cancer diagnosis. In addition, we investigated how breast cancer can be classified as either malignant or benign using various breast cancer imaging modalities, exploring publicly and privately available image datasets and diverse pre-processing and feature extraction techniques. This study compares the conventional ML approach with various CNN architectures and explores how transfer-learning techniques can be applied in breast cancer diagnosis.

This study investigated and analyzed the diagnostic capabilities of DL algorithms for the early detection of breast and cervical cancers using a meta-analysis approach. Researchers have explored the impact of four subgroups versus clinicians: cancer type, validation type, imaging modalities, and DL algorithms. Of the 35 studies considered, we selected 20 for the meta-analysis, which revealed that DL algorithms demonstrated a pooled sensitivity of 88% (95% CI 85%–90%), specificity of 84% (79%–87%), and AUC of 92% (90%–94%), indicating a satisfactory level of diagnostic performance. Moreover, we found that DL algorithms performed consistently well across all subgroups.

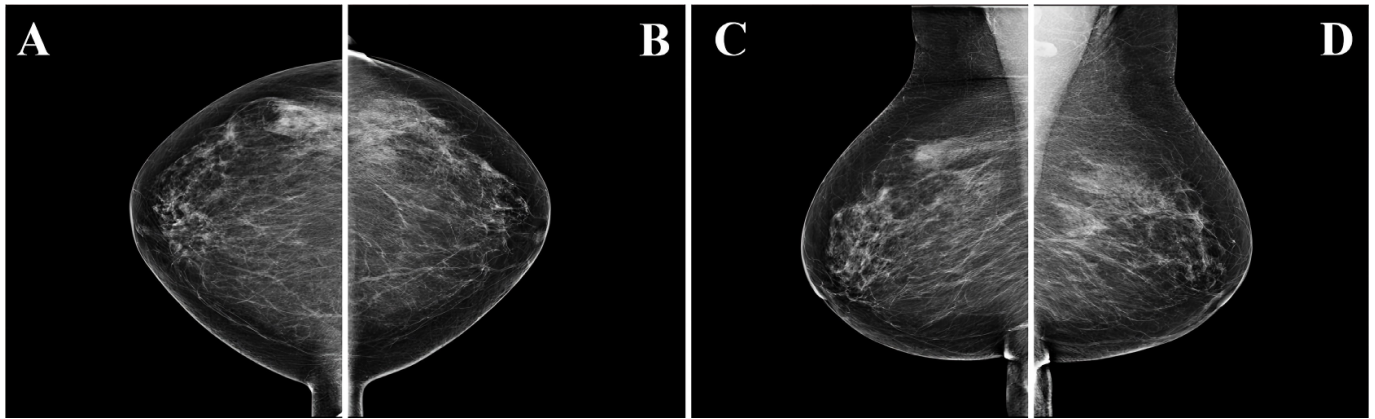


Figure 1. Different mammographic views are available as illustrations: (a) right craniocaudal view, (b) left view, (c) right mediolateral oblique view, and (d) left mediolateral oblique view.

2 Literature Review

Exploring the potential of combining multiple imaging modalities, such as mammography and MRI, to improve the accuracy of breast cancer detection. The study proposed a multimodal DL framework that combined mammography and MRI data to detect breast cancer and achieved an accuracy of 92.3% [33]. Another study developed a hybrid DL model that integrated mammography and ultrasound data and achieved an area under the curve (AUC) of 0.912 [34]. This study demonstrates the potential of combining multiple imaging modalities to improve the accuracy of breast cancer detection. Many studies have investigated the use of explainable AI to enhance the interpretability of ML and DL models used to detect breast cancer. AI techniques aim to offer an understanding of how ML and DL models reach their decisions, which can enhance the transparency and credibility of these models [35, 36]. AI has brought transformative capabilities to computing, allowing machines to undertake tasks once they rely on human expertise. Applications such as finger vein recognition [37], detection of diabetic retinopathy [38–43], RNA engineering [44–46], cancer diagnosis [47–50], and innovations in healthcare [51, 52] have demonstrated their significant impact. These advancements have been driven by progress in computational technologies, increased data availability, and refinement of complex algorithms. This review covers various techniques, their applications, and their effectiveness in improving breast cancer detection accuracy using medical images and patient records.

Mammography is the primary method for screening and detecting breast cancer using low-energy X-rays to identify unusual formations within breast tissue [53]. This technique requires acquiring two

separate images of each breast, creating two unique projections: craniocaudal (CC) and mediolateral oblique (MLO). Specifically, the CC mammogram image is obtained from above. In contrast, the MLO projection is captured from a side angle that reveals the pectoral muscle, as displayed in Figure 1. It is possible to quantify the percentage of non-dense tissue in comparison to dense tissue in mammograms, ultimately allowing for the classification of mammograms based on breast density. The breast imaging reporting and data system (BI-RADS) outlines the thickness stages as follows: Figure 2(a) almost entirely fatty, Figure 2(b) scattered areas of fibro-glandular density, Figure 2(c) heterogeneously dense and Figure 2(d) extremely dense providing a comprehensive overview of the various classifications Figure 2. Assessing images becomes increasingly challenging as the tissue density increases because the similarity in appearance between dense and irregular tissues can cause difficulties.

The American cancer society (ACS) has reported that mammography imaging process sensitivity decreases by approximately 30%, leading to an elevated risk of breast cancer [54, 55]. Mammography employs a low-dose X-ray method for diagnostic imaging, capturing detailed images of the breast tissue to aid in detecting potential abnormalities. The efficacy of mammography for detecting and diagnosing various breast conditions, including infections, has been widely recognized. In this case, we have three images, two of which are from the same breast and right breast. Figure 3(a) shows a healthy breast without visible signs of cancer or abnormalities. The breast tissue appeared homogeneous and uniform in density, with no visible lumps, calcifications, or distortions. This image serves as a reference point and helps to

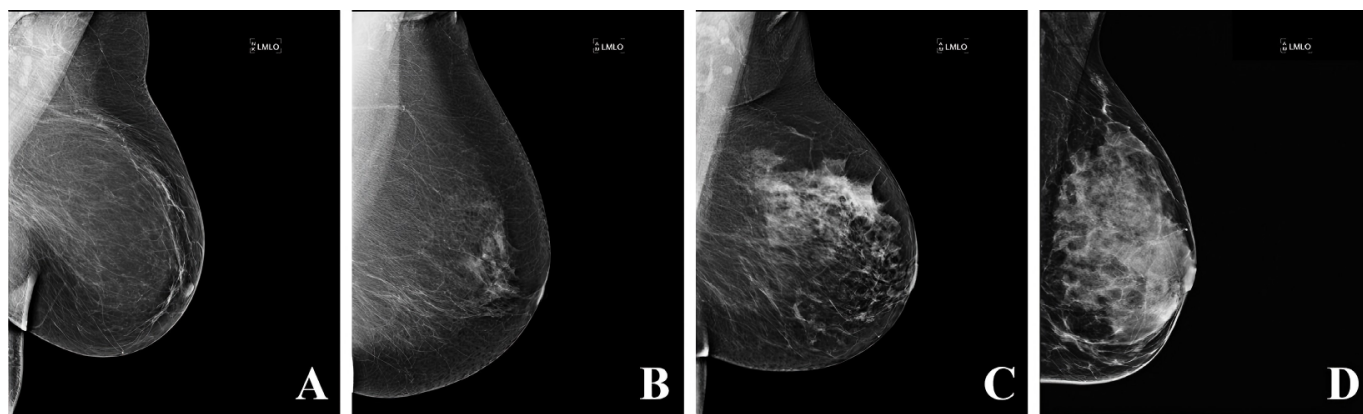


Figure 2. As outlined by the BI-RADS, there are four levels of mammographic density: (a) designation of almost entirely fatty, (b) scattered areas of fibro-glandular density, (c) heterogeneously dense, (d) extremely dense.

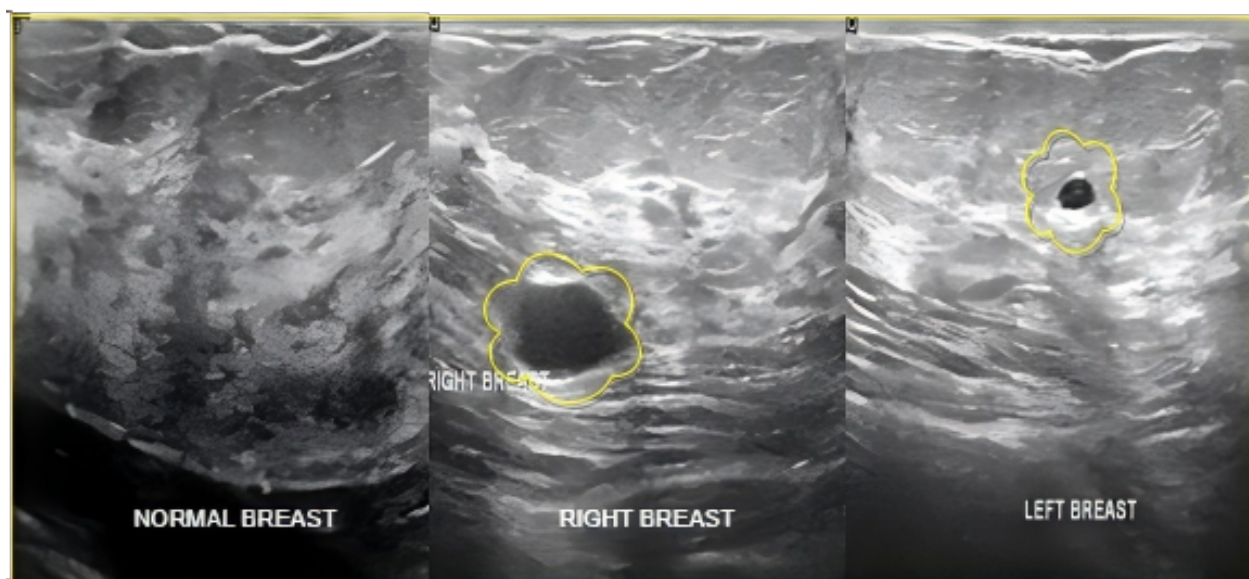


Figure 3. (a) Normal breast (b) right infected breast (c) left infected breast.

establish a baseline for comparison with subsequent mammography scans. Figure 3(b) shows the right breast, where the presence of cancer is apparent. The infected area appeared as a dark, dense region in the breast tissue that was distinguishable from the surrounding healthy tissue. This part is visible to the naked eye and can indicate an infection or other underlying breast conditions. Figure 3(c) provides a close-up view of the cancer of the left breast, allowing for a more detailed examination of the affected area. This image confirms the presence of cancer in the breast tissue, which can be further investigated and treated by a medical professional. Mammography images are essential for the diagnosis and further processing of breast cancer, as they provide a non-invasive and accurate method of detecting abnormalities in breast tissue.

By identifying these abnormalities early, medical

professionals can administer prompt and effective treatments. This can lead to critical improvement in the patient's personal satisfaction and overall prognosis.

Breast cancer is a pressing public health issue that demands immediate attention and effective early detection, which is crucial for successful treatment. The use of computer-based intelligent ML and DL has shown promising results in additional cancer-distinguishing proof precision. Numerous studies have been conducted from 2000 to 2024 and have contributed significantly to advancing breast cancer detection. Computer-aided digital diagnosis processes use neural networks to identify breast cancer tumors in mammograms [30] accurately. Using radiological characteristics, researchers have developed an ML strategy to group breast masses as either harmless or threatening [56]. Enhancing breast cancer detection accuracy using ML to combine

clinical and imaging data [57]. DL procedures have become progressively well-known in breast cancer growth discovery research, as evidenced by a study in which CNN was developed for automated breast cancer diagnosis using histopathological images [58]. A DL digital diagnosis system was proposed in 2017 to improve breast cancer detection by combining multiple types of medical images [59]. To further improve breast cancer subtype classification, researchers developed a hybrid DL method that combines CNN and recurrent neural network (RNN) [60].

Additional studies have significantly contributed to the progress in breast cancer detection by utilizing ML and DL models. Researchers have developed an ML model that combines mammographic features and clinical risk factors to predict breast cancer risk [61]. Several recent studies have demonstrated advancements in breast cancer detection using ML and DL. DL models have been developed to group breast cancer as harmless or dangerous with high precision [62]. Another study proposed a DL model for detecting breast cancer from clinical ultrasound images with high precision [63]. A DL model for breast cancer detection using mammography images was proposed in a recent study [64]. This model utilizes residual attention blocks to enhance the feature representation and accurately classify malignant and benign cases. Similarly, a DL model was developed for breast cancer identification and classification, consolidating a CNN and LSTM network [65]. This model outperformed several existing state-of-the-art methods and achieved a high accuracy in classifying breast cancer cases. Other clinical imaging modalities, such as ultrasound and MRI, have also been used for breast cancer detection. Table 1 provides a detailed summary of various imaging modalities, their underlying techniques, and the scope of their medical applications. Ultrasound utilizes high-frequency sound waves to generate images of internal organs and tissues, which is critical in diagnosing and monitoring conditions such as pregnancy, heart disease, and liver problems. Mammography, a specialized X-ray imaging technique, is widely used for detecting breast cancer and other breast-related abnormalities, making it a cornerstone in breast cancer screening. Magnetic resonance imaging (MRI) employs powerful magnets, radio waves, and computers to create detailed images of organs and tissues, particularly useful for diagnosing neurological disorders, musculoskeletal injuries, and cancers. Similarly, CT scans leverage X-ray imaging combined with computer technology to produce

cross-sectional images, aiding in diagnosing and monitoring injuries, infections, and cancers.

Thermography, a non-invasive technique that detects heat changes, is primarily used to identify variations in skin temperature that could indicate inflammation or breast cancer. General X-rays, utilizing electromagnetic radiation, remain versatile and are frequently applied in diagnosing bone fractures, lung diseases, and other internal abnormalities. Lastly, Tomography shares similarities with ultrasound, as it uses high-frequency sound waves for imaging internal organs and is commonly employed in monitoring heart conditions and pregnancies. Collectively, these modalities highlight the breadth of imaging technologies available in modern medicine, each uniquely suited to specific diagnostic and monitoring needs. This summary underscores their critical roles in improving diagnostic accuracy, enhancing patient care, and facilitating early disease detection across various medical conditions.

DL-based approach for automatic detection of breast tumours using contrast-enhanced MRI images. The study utilized a deep residual network with a dense block to extract features from images and achieved high accuracy in detecting breast tumours [78]. Researchers have proposed a novel approach for breast cancer diagnosis and treatment planning using a combination of DL and radiomics. The proposed model utilizes imaging and clinical data to predict the likelihood of tumour malignancy and estimate the optimal treatment plan. The model accurately predicted tumour malignancy and showed potential for personalized treatment planning.

Furthermore, several recent studies have focused on DL techniques for classifying breast cancer subtypes and proposed [79] a DL-based model for breast cancer subtype classification using gene expression data. The model utilizes a deep neural network with attention mechanisms to classify breast cancer subtypes accurately. Similarly, [67, 80] proposed a hybrid DL model for breast cancer subtype classification, combining a CNN and RNN to achieve high accuracy in classifying breast cancer subtypes, surpassing several existing state-of-the-art methods.

3 Methodology

This study conducted a comprehensive review of the literature on applying ML and DL techniques in breast cancer detection. To ensure thorough examination, a meticulous exploration of scientific

Table 1. Presents a summary of available imaging modalities and their scopes.

Sr.No	Modalities	Techniques	Scope	References
1	Ultrasound	High-frequency sound waves are used to produce images of internal organs and tissues.	Diagnosis and monitoring of various medical conditions, including pregnancy, heart disease, and liver problems.	[66]
2	Mammographic	X-ray imaging produces detailed images of the breast tissue.	Detection of breast cancer and other breast-related abnormalities.	[67, 68]
3	MRI	Powerful magnets, radio waves, and a computer produce detailed images of internal organs and tissues.	Diagnosis and monitoring of various medical conditions, including neurological disorders, musculoskeletal injuries, and cancers.	[69, 70]
4	CT SCAN	X-ray imaging uses a computer to produce detailed cross-sectional images of internal organs and tissues.	Diagnosis and monitoring of various medical conditions, including injuries, infections, and cancers.	[71, 72]
5	Thermography	A non-invasive imaging technique that uses heat detection to produce images of the body.	Detection of changes in skin temperature that may indicate various medical conditions, including breast cancer and inflammation.	[73, 74]
6	X-Ray	Electromagnetic radiation is used to produce images of internal organs and tissues.	Diagnosis and monitoring of various medical conditions, including bone fractures and lung diseases.	[75]
7	Tomography	High-frequency sound waves are used to produce images of internal organs and tissues.	Diagnosis and monitoring of various medical conditions, including pregnancy, heart disease, and liver problems.	[76, 77]

databases, including PubMed, IEEE Xplore, and Google Scholar, was conducted using keywords such as breast cancer, ML, and DL detection. In addition, manual searches of relevant conference proceedings and journals were performed to incorporate the latest research in this domain. The search results were screened based on relevance, quality, and pre-established inclusion criteria. These criteria ensured that only high-quality, pertinent articles were considered for review. Specifically, the selected articles that focused on breast cancer detection using ML or DL were published in peer-reviewed journals or reputable conferences and were written in English. Duplicate entries were removed, and the remaining articles were further assessed by reviewing their abstracts and titles to confirm their relevance to the study.

After identifying relevant articles, key data were

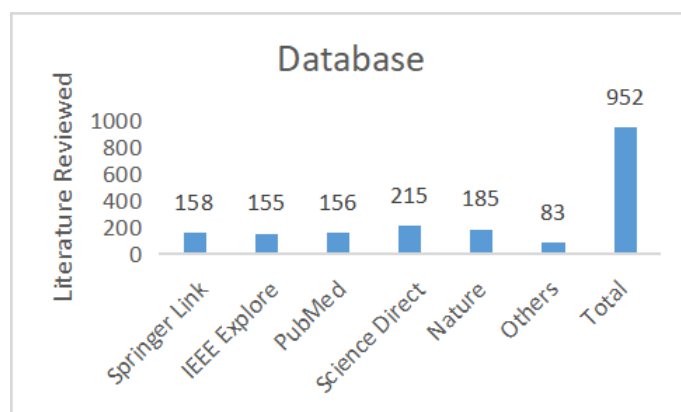


Figure 4. Distribution of reviewed literature across different databases, highlighting the total number of articles analyzed.

systematically extracted to facilitate a comprehensive analysis. These data encompassed study design,

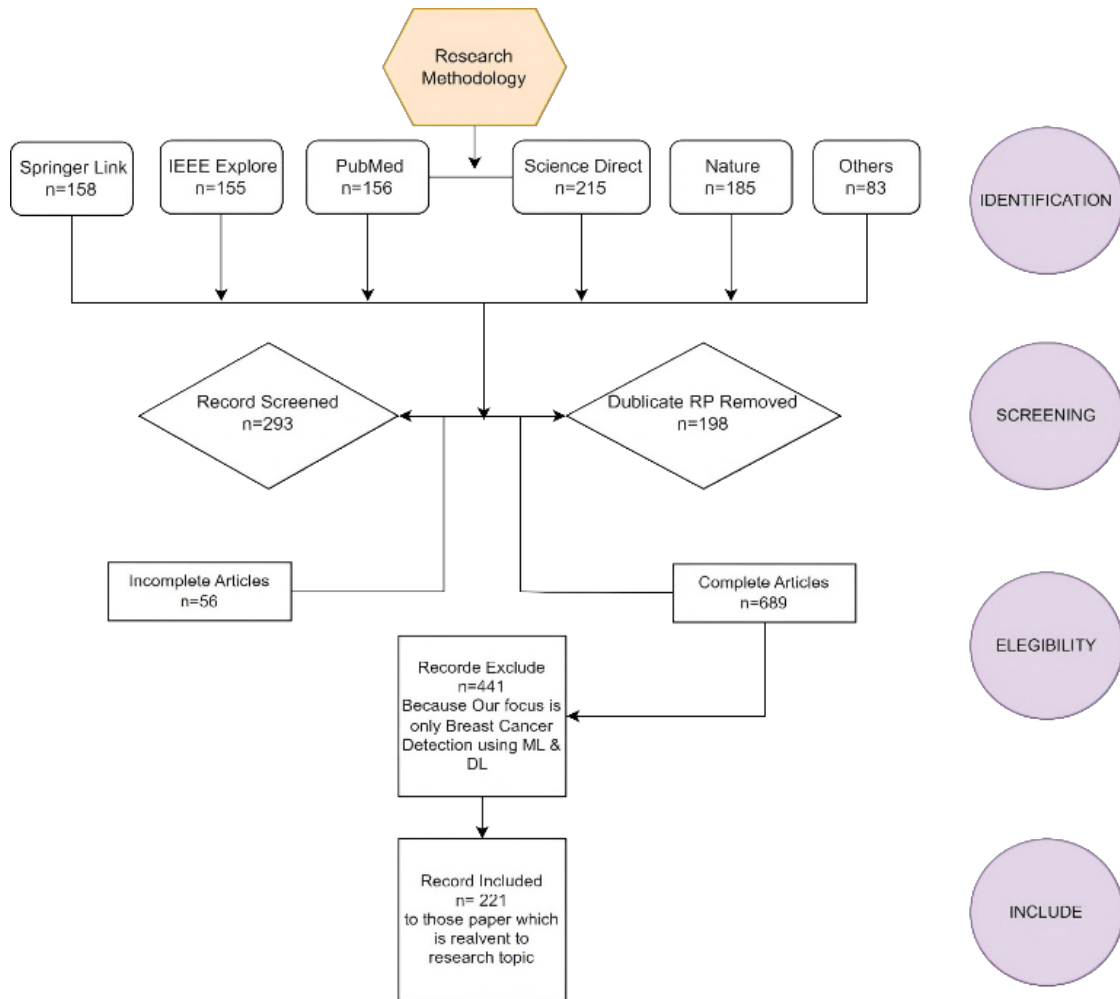


Figure 5. Prism flow chart of research methodology depicting the identification, screening, eligibility, and inclusion processes for selecting relevant articles in the review.

sample size, datasets used, ML or DL techniques employed, evaluation metrics, and reported results. Two reviewers conducted data extraction independently to ensure accuracy and consistency, and any discrepancies were resolved through mutual agreement.

The extracted information was then synthesized and analyzed to establish the current state of breast cancer detection using the ML and DL techniques. This analysis examined the methods used, their strengths and limitations, and the evaluation metrics applied to measure their efficacy. Two reviewers independently performed the synthesis, and differences in interpretation were resolved through consensus. Additionally, gaps in the existing literature were identified, and potential areas for further research were highlighted, providing valuable insights for future investigations.

A comprehensive review was subsequently conducted based on the data analysis findings. This review

outlines the current landscape of breast cancer detection using ML and DL techniques and discusses their potential applications, associated challenges, and prospective future directions. Although a significant number of papers were reviewed, the study maintained a focused approach by selecting and analyzing only papers that were most relevant to developing and enhancing ML and DL approaches in breast cancer detection. This careful selection ensured that the outcomes and conclusions of this research were highly applicable and valuable for advancing the field. Figure 4 illustrates the total number of papers reviewed during the study, while Figure 5 outlines the research methodology, emphasizing the breadth of resources explored. These include scientific databases, such as Springer, IEEE Xplore, PubMed, Science Direct, and Nature, ensuring a robust and exhaustive foundation for the review.

3.1 Types of Machine Learning

ML, a subset of AI, involves the creation of models and algorithms capable of learning from data and making predictions or decisions based on that data. The field of medicine has tremendous potential for machine-learning applications, including disease diagnosis, patient outcomes prediction, and new treatment development. Among these potential applications, breast cancer research has shown promise. As it is the most prevalent form of cancer in women worldwide, its early detection is essential for effective treatment. ML algorithms can improve the accuracy of breast cancer diagnoses and predict patient outcomes. Medical images such as mammograms can be analyzed using ML models trained to identify patterns indicative of breast cancer. For instance, in a 2019 study published in *Nature*, ML models accurately detected breast cancer in women up to five years before clinical detection [81]. In addition to its role in breast cancer diagnosis, ML is utilized to predict patient outcomes and assist in drug discovery and development for breast cancer treatment. ML can be divided into different subtypes, as shown in Figure 6.

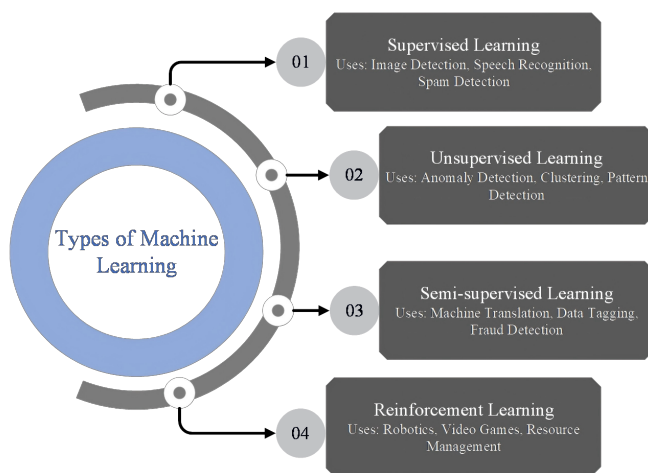


Figure 6. Types of machine learning techniques commonly used in different state-of-the-art techniques.

ML models can be used to analyze data from many patients with breast cancer to identify factors that could be indicative of patient survival or recurrence. This valuable information can help physicians devise personalized treatment plans for each patient. A study published in scientific reports in 2018 demonstrated the ability of an ML algorithm to forecast the likelihood of breast cancer reappearance based on gene expression in tumour tissues. Similarly, by examining large datasets of the molecular makeup of breast cancer cells, ML algorithms can identify potential drug targets and predict the efficacy of new treatments. An

example is a study that employed a machine-learning algorithm to classify promising medicine mixtures for the treatment of triple-negative breast cancer [82]. ML models have revolutionized various fields by enabling computers to learn from data and make predictions and decisions. These fields incorporate picture and discourse acknowledgement, regular language handling, recommender frameworks, and fraud detection. Owing to ML, computers can now perform tasks previously considered impossible, such as recognizing human speech and identifying fraudulent transactions. As technology continues to advance, the possibilities for its applications are seemingly endless. Figure 7 presents a diagram categorizing machine learning algorithms into four main types: supervised, unsupervised, semi-supervised, and reinforcement learning, with their respective subcategories and hierarchical structures.

Supervised Learning: In ML, supervised learning involves providing labelled data to a computer and allowing it to learn how to forecast new labels based on data patterns. This learning method is commonly used for classification problems, such as determining whether an image features a lion or a leopard. Additionally, supervised learning algorithms can be utilized for regression issues, such as predicting the cost of a building. Numerous studies have investigated the effectiveness of supervised learning models in different fields, with one example being a study that compared the performance of various models, such as logistic regression, support vector machines, and neural networks in image classification tasks [83]. The researchers discovered that in the given tasks, CNN exhibited better execution when compared to other models, setting the benchmark by achieving the best-in-class results on different datasets.

Unsupervised Learning: Unsupervised learning is an ML model that involves training a model on data without explicit labels, enabling it to identify and learn from hidden patterns or structures in the data. This technique is commonly used for clustering problems where the objective is to group items with similar characteristics based on their features. Clustering algorithms are typically used in unsupervised learning. For example, [84] examined the performance of various clustering models for image-segmentation tasks. The authors found that spectral clustering outperformed other clustering algorithms in these tasks, achieving higher accuracy and faster convergence.

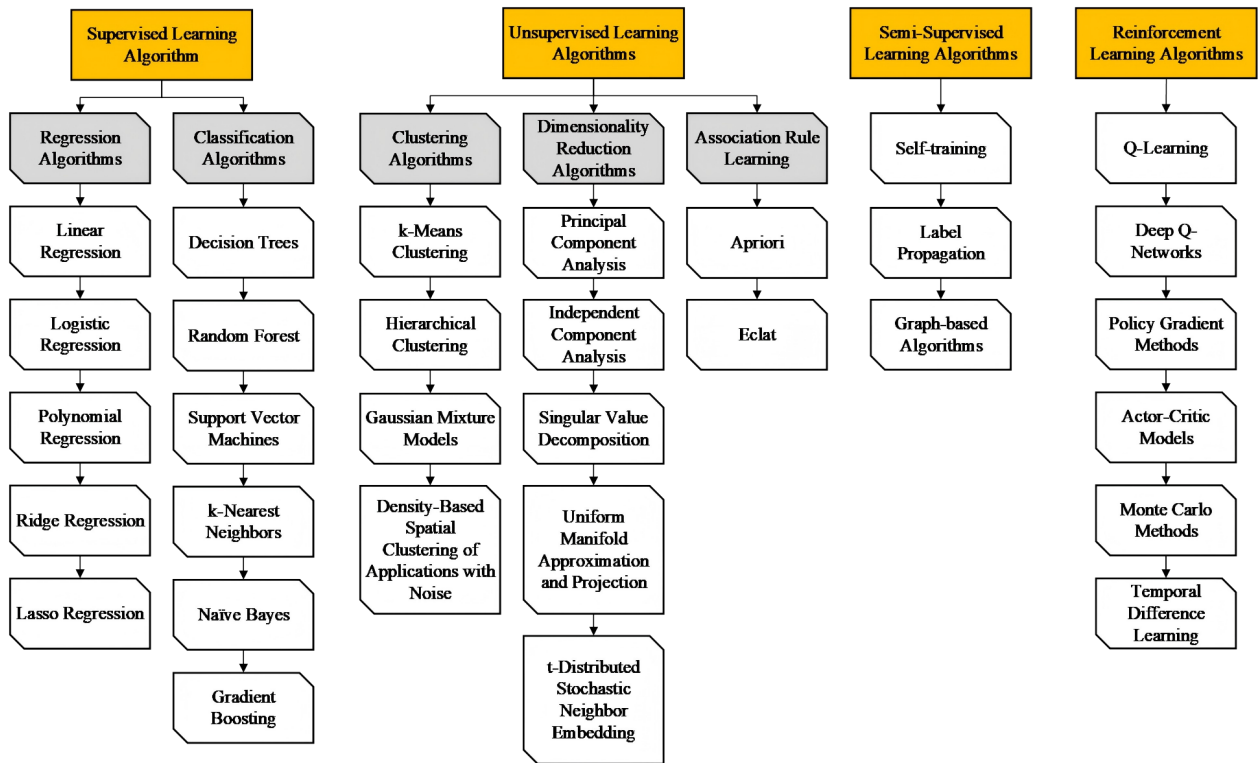


Figure 7. Hierarchical overview of machine learning algorithms categorized by learning paradigm: supervised, unsupervised, semi-supervised, and reinforcement learning.

Semi-Supervised Learning: This involves training a model on labelled and unlabeled data. This type of learning is often used when labelled data are scarce but unlabeled data are abundant. By leveraging both labelled and unlabeled datasets, the algorithm can improve the accuracy of predictions and examine the use of semi-supervised learning for sentiment analysis, which is simple in natural language processing [85]. The authors have reported the utilization of both labeled and unlabeled data through a semi-supervised learning approach as an effective strategy, as their research findings achieved higher accuracy than supervised learning alone.

Reinforcement Learning: In reinforcement learning, a model can be instructed to make decisions based on receiving either rewards or punishments to maximize the overall reward over time. This learning approach has practical applications in the gaming and robotics domains. One study [86] explored reinforcement learning, specifically in the game of Go, achieving human-level performance in this complex game.

The detection of breast cancer is a crucial aspect of medical diagnosis, and ML methods have proven to be valuable tools in this regard. The following table summarizes several supervised and unsupervised learning approaches for detecting

breast cancer. Logistic regression, decision trees, linear regression, and random forest are commonly employed supervised learning techniques for breast cancer classification. According to the results, logistic regression and decision trees accurately identified breast cancer by analyzing mammogram images [87]. Breast cancer detection is critical in medical diagnosis, and machine-learning techniques have demonstrated promising results in supporting this task. Various supervised and unsupervised learning methods have been employed in breast cancer detection.

Linear regression, logistic regression, decision trees, and random forests are commonly employed supervised learning techniques for classification tasks in breast cancer detection. In addition, logistic regression and decision trees have shown high accuracy in detecting breast cancer using mammogram images. Support vector machines (SVM) are another frequently used technique in classification tasks, as indicated by a study [88], which found SVM to be highly effective in detecting malignant breast tumours. K-nearest neighbours (KNN) is another supervised learning technique commonly used in breast cancer detection, achieving high accuracy in classifying breast tumours as benign or malignant. Finally, principal component analysis (PCA), a dimensionality reduction technique widely

used for feature extraction in breast cancer detection [89], was employed to decrease the number of features utilized for breast cancer classification, resulting in improved accuracy [90].

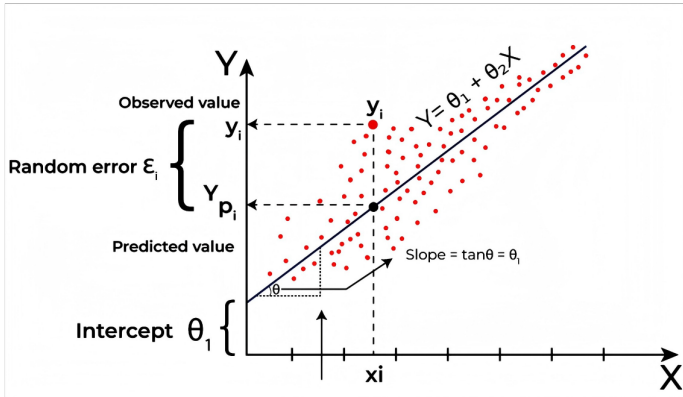


Figure 8. Linear regression visualization: showing the relationship between observed values, predicted values, and the regression line.

Linear Regression: Linear Regression is a foundational supervised learning model for regression tasks. This establishes a linear relationship between a dependent variable and one or more independent variables by fitting a straight line to the data. Known for its simplicity and interpretability, this model is widely applied to sales forecasting and trend analysis tasks. Its effectiveness and ease of implementation make it suitable for many predictive applications. Figure 8 illustrates a fundamental concept of linear regression in ML, where a linear model is fitted to a set of data points to predict outcomes.

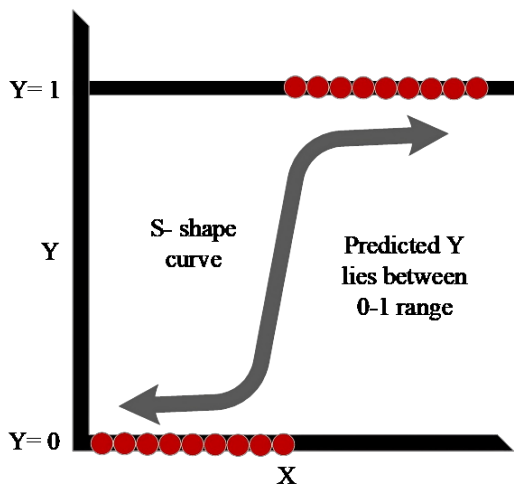


Figure 9. Logistic regression: an s-shaped curve showing probabilities between 0 and 1 for binary classification.

Logistic Regression: Logistic Regression is a popular supervised learning model for classification problems. It predicts the binary outcomes by applying a

logistic function to the input data. This model benefits applications like spam detection and medical diagnosis, where a probabilistic output is desirable. Its simplicity and robustness make it one of the most widely used classification models. Figure 9 shows a logistic regression model commonly used for binary classification tasks. In this graph, the x-axis represents the independent variable, whereas the y-axis represents the probability that the dependent variable takes one of two binary states (e.g., 0 or 1).

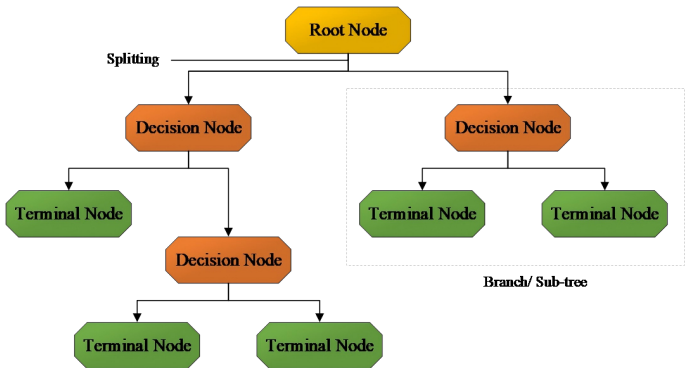


Figure 10. Decision tree: A hierarchical model with root, decision, and terminal nodes used for data-driven predictions.

Decision Trees: Decision trees are intuitive and versatile models for classification and regression. They split the data based on feature values, forming a tree-like structure that is easy to visualize and understand. Figure 10 illustrates a decision tree starting with a Root Node that splits the dataset based on a specific feature. Decision Nodes refine the data through intermediate splits, while Terminal Nodes (leaf nodes) provide final predictions or classifications. The branches represent paths based on conditions, making the hierarchical structure effective for segmenting data and facilitating decision-making.

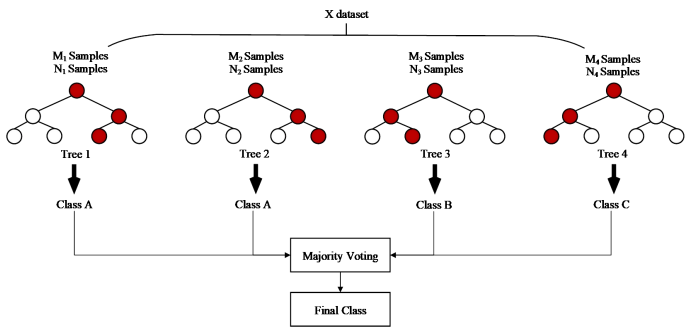


Figure 11. Random forest: An ensemble method combining multiple decision trees with majority voting for improved accuracy and robustness [91].

Random Forest: Random Forest builds on the simplicity of Decision Trees by combining multiple

trees to form an ensemble. This model improves accuracy and reduces overfitting, making it highly robust. It is widely used in applications like fraud detection and recommendation systems, where reliability and performance are critical. Its ability to handle missing and large datasets further enhances its popularity. Figure 11 depicts an ensemble learning method, specifically a random forest model, which combines multiple decision trees to improve the classification or regression accuracy. The dataset was split into subsets, and each subset was used to train an individual decision tree. These trees independently predict a class, and the final prediction is determined by a majority-voting mechanism, where the class with the highest votes becomes the final output. This approach reduces overfitting and enhances the model's robustness by aggregating the predictions of multiple models.

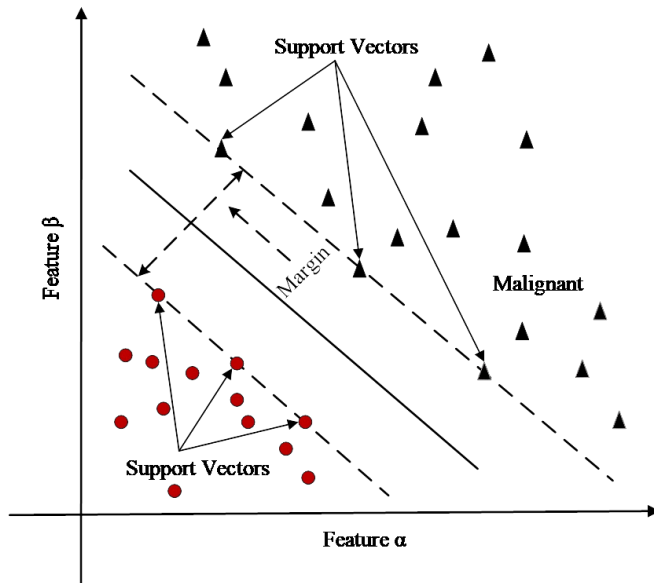


Figure 12. Support vector machine Optimal hyperplane with support vectors maximizing class separation [92].

Support Vector Machines: Support vector machines (SVM) are powerful supervised learning models designed to classify data by finding the optimal hyperplane that separates different classes. Owing to their high accuracy, SVMs are widely used in complex classification tasks such as bioinformatics and image recognition. They are particularly effective for datasets with clear class separation and have applications in numerous industries. Figure 12 shows an SVM separating the two classes with an optimal hyperplane. Support vectors define the margin and ensure maximum separation between the classes.

k-nearest Neighbors: The k-NN algorithm is a simple

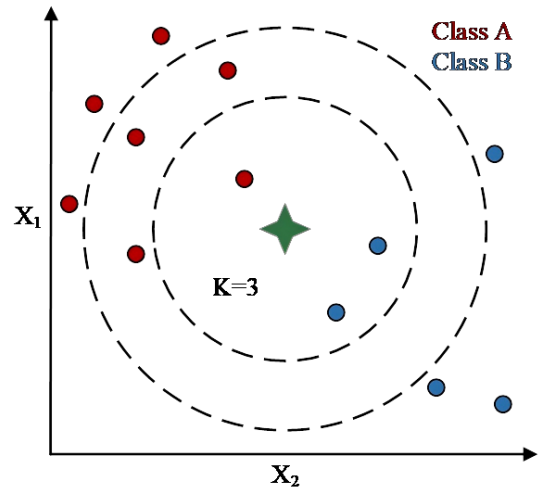


Figure 13. Classifying a point by a majority vote of its nearest neighbours.

yet effective supervised learning model. It classifies data points based on their similarity to nearby points, which makes it ideal for smaller datasets. Frequently applied in recommendation systems and anomaly detection, k-NN is valued for its ease of implementation and ability to adapt to diverse datasets. Figure 13 illustrates the KNN classification of a point based on its three nearest neighbours, assigning it to the majority class.

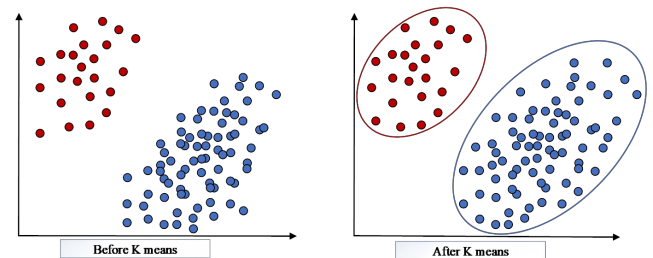


Figure 14. K-means clustering: grouping data points into distinct clusters based on similarity.

k-means clustering: k-means clustering is a widely used unsupervised learning algorithm for grouping data into clusters based on their feature similarity. This model is commonly employed in applications such as market segmentation and image compression. Its simplicity and effectiveness make it a staple for clustering tasks, particularly in exploratory data analyses. Figure 14 shows the K-means clustering algorithm. On the left side, the data points are ungrouped before clustering. On the right, the algorithm groups the points into distinct clusters (red and blue) based on similarity, with each cluster represented by its centroid.

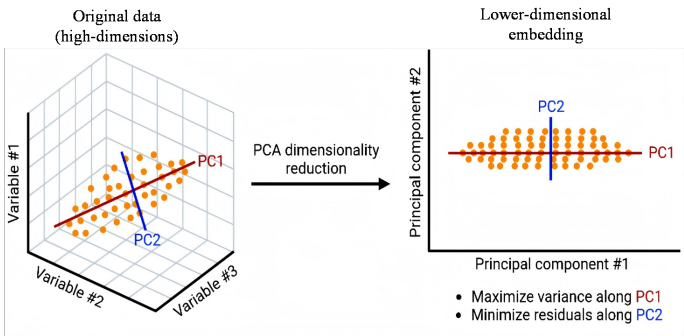


Figure 15. Principal component analysis: reducing dimensionality by projecting data onto principal components while preserving variance.

Principal Component Analysis: Principal component analysis (PCA) is a powerful dimensionality reduction technique that simplifies high-dimensional data by projecting it onto fewer dimensions while retaining essential information. This model is often used for feature extraction and data visualization, making it a critical pre-processing step for high-dimensional datasets. Its ability to improve computational efficiency while preserving the data structure has made it indispensable. Figure 15 illustrates PCA for dimensionality reduction. On the left, the data exists in a high-dimensional space (three variables). PCA projects these data onto a lower-dimensional space (right) by identifying the principal components (PC1 and PC2). PC1 captures the maximum variance, while PC2 minimizes the residual variance, simplifying data representation while retaining key patterns.

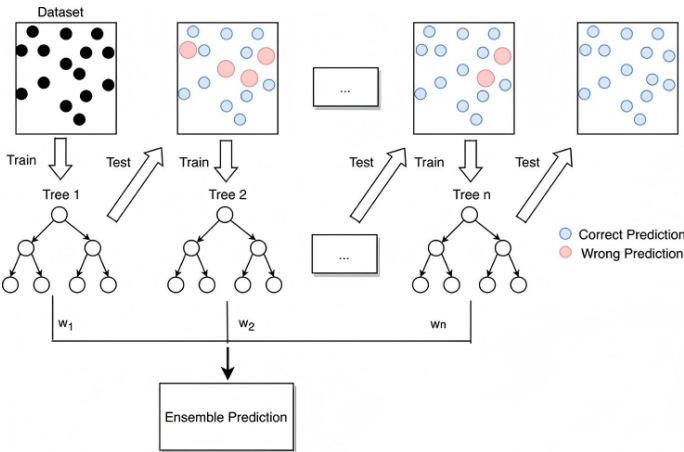


Figure 16. Gradient boosting process: sequential training of weak classifiers with weighted error correction for improved ensemble predictions [93].

Gradient Boosting Machines (e.g., XGBoost, LightGBM, and CatBoost): an ensemble learning model that sequentially builds upon weak learners to improve performance. Known for their exceptional

accuracy, these models have been widely applied in predictive analytics and structured data tasks. Popular implementations such as XGBoost, LightGBM, and CatBoost are frequently used in competitive ML because of their speed and scalability. The flow diagram in Figure 16 illustrates the gradient boosting machine’s (GBM) working mechanism. This method sequentially trained multiple weak classifiers (decision trees). Each tree focuses on correcting the errors of the previous tree by assigning higher weights to incorrectly predicted data points. This iterative process reduced the overall prediction error. The final prediction is made by taking a weighted average of the projections from all trees and combining their strengths for improved accuracy.

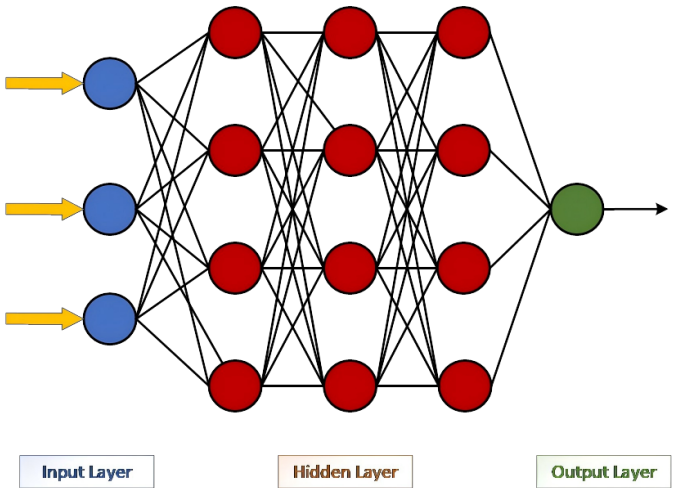


Figure 17. neural network: a fully connected model with input, hidden, and output layers for data processing and prediction.

Neural Network: The foundation of DL, mimicking the human brain through interconnected layers of neurons. Specialized architectures, such as convolutional neural networks (CNN) for image processing, recurrent neural networks (RNN) for sequential data, and transformers, such as BERT and GPT for natural language processing, have driven remarkable advancements in AI. These models are integral to facial recognition, text analysis, and language translation applications. Figure 17 shows a fully connected artificial neural network. It consists of three layers: the Input Layer, where data enters; multiple Hidden Layers, which process the data through interconnected neurons; and the Output Layer, which produces the final prediction or classification. Each connection between neurons represents a weight-adjusted during training to optimize the performance.

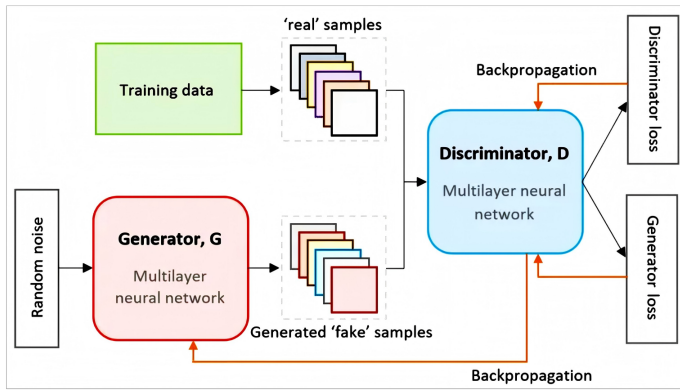


Figure 18. Generative adversarial network: a framework where the generator creates data, and the discriminator evaluates its authenticity through adversarial training.

Generative Adversarial Network: A revolutionary unsupervised learning model. Considering a generator and discriminator, the GAN competes to create realistic synthetic data. They have transformed fields such as image generation, video creation, and data augmentation. Generative adversarial networks (GAN) are particularly notable for their use in deep fake technologies and creative AI applications. Figure 18 illustrates the GAN architecture. It comprises two components, the Generator and the Discriminator, implemented as neural networks. The Generator creates fake samples from random noise, whereas the discriminator distinguishes between authentic and counterfeit samples (from training data). Through an adversarial process, both networks improve iteratively; the generator minimizes the discriminator's ability to differentiate, and the discriminator enhances its classification accuracy.

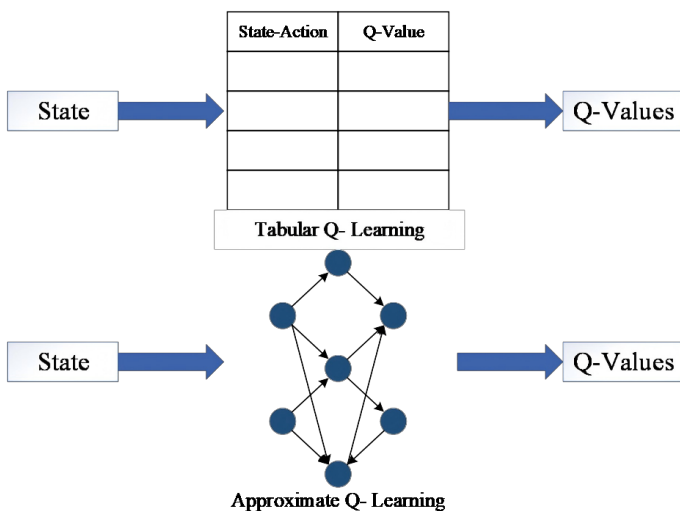


Figure 19. Q-learning mapping states the Q-values for decision-making in reinforcement learning.

Q-learning: Q-learning is a foundational

reinforcement learning algorithm that optimizes decision-making by maximizing cumulative rewards. It is widely applied in robotics, game-playing AI (e.g., AlphaGo), and other sequential decision-making tasks. Its ability to learn optimal policies through environmental interaction has made it a cornerstone of reinforcement learning research. The image compares Q-learning. Q-values are stored in a table in Q-learning to map state-action pairs to their respective values. A neural network estimates the Q-values in approximate Q-learning, making it scalable for large or continuous state spaces where tabular methods are infeasible is presented in Figure 19.

Table 2 provides a comprehensive overview of ML, detailing their methods, applications, and underlying techniques. Traditional ML models, such as linear and logistic regression, are widely used to predict numerical outcomes and binary classifications. Models like decision trees and random forests extend this functionality by leveraging tree-based architectures, with Random Forests offering ensemble learning for improved accuracy in classification and regression tasks. SVM excels in binary and multi-class classification, relying on hyperplanes to maximize the margin between data points. Similarly, Naive Bayes applies probabilistic modelling for text classification and spam filtering, while KNN classifies data based on its proximity to surrounding points. In unsupervised learning, PCA and K-means clustering are pivotal for dimensionality reduction and clustering, respectively. GMM provides robust alternatives for segmenting and analyzing datasets based on similarity or probabilistic distributions. For anomaly detection, methods like Isolation Forest, One-Class SVM, and LOF are valuable in identifying outliers across various applications. DL models bring significant advancements by automating feature extraction and handling unstructured data. Inspired by the human brain, ANN is widely used for classification and regression. Specialized DL models such as CNN and RNN excel in image and sequential data processing, respectively, with object detection and natural language processing applications. Advanced variants like LSTM networks retain information over long sequences, enhancing tasks like speech recognition. Generative models such as GAN are transformative in data augmentation and image synthesis, while Autoencoders support dimensionality reduction and anomaly detection. This table underscores the versatility of ML and DL models across supervised and unsupervised learning paradigms, highlighting their potential to address

diverse challenges in domains ranging from predictive analytics to anomaly detection and unstructured data processing. The choice of model depends on the data type, problem complexity, and application requirements.

3.2 Types of Deep Learning

In recent years, DL, a branch of ML, has gained widespread attention owing to its exceptional performance in diverse applications such as picture and discourse acknowledgement, normal language handling, drug discovery, and gaming. This approach uses the ANN method to identify the patterns and relations of the data intricately. ANN features multiple layers of interconnected nodes or neurons that can learn to extract high-level features from raw data, thereby enabling the network to make accurate predictions and decisions. DL has benefited from numerous research studies, leading to the development of new techniques and architectures. For example, CNN has emerged as the preferred architecture for clinical images and video analysis, delivering exceptional results in object recognition and segmentation [104, 142, 143]. In contrast, RNNs have been applied in sequence modelling and generation, displaying exceptional outcomes in speech recognition and language translation [144–146].

Another noteworthy architecture is the GAN network, which has gained considerable attention owing to its ability to perform generative modelling and unsupervised learning. GAN has been applied in domains such as image synthesis, video generation, and data augmentation [86, 147, 148]. In addition, deep reinforcement learning has been used for game playing and robotics and has shown promising results in complex environments [86, 149, 150]. The major strength of DL is its ability to learn hierarchical representations of data. Each layer in the network can progressively extract more intricate and abstract features than the previous layer, enabling DL models to achieve cutting-edge performance on diverse tasks, often surpassing human-level performance in some instances [61, 151, 152]. Despite the impressive achievements of DL, it has some challenges and limitations. An essential hurdle in the widespread adoption of DL is the requirement of extensive annotated training data. Acquiring such data can be arduous or expensive in specific domains, presenting a significant challenge for practitioners [153, 154].

Another challenge is the difficulty in interpreting and understanding the internal workings of DL models,

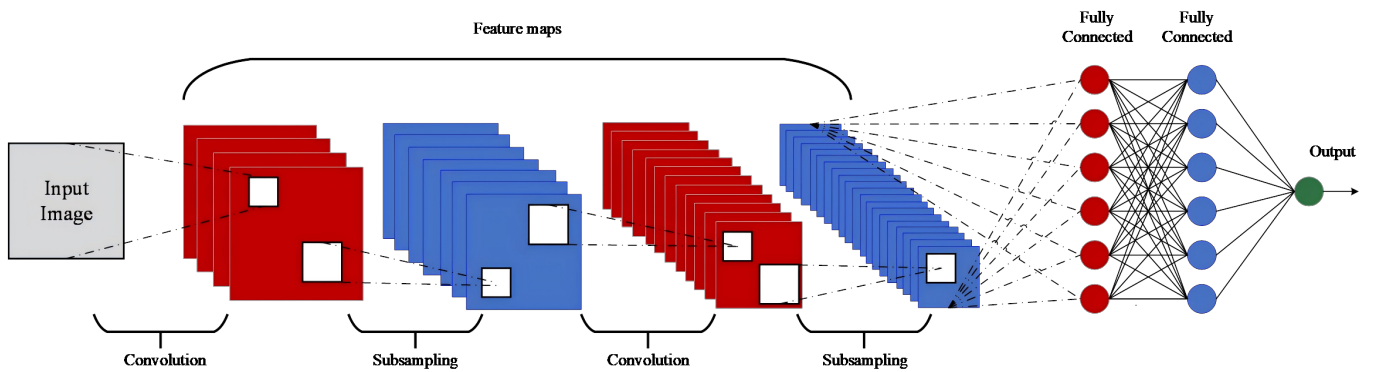
which can hinder their adoption in safety-critical applications [154–156]. Researchers are exploring new architectures and techniques to overcome these challenges and achieve further advancements. Attention mechanisms improve the efficiency and decipherability of DL models [157]. Transformers, which were initially introduced for natural language processing, are implemented in other areas, such as image recognition [158]. Graphical networks have been created to handle data organized as networks and graphs [159]. Moreover, new techniques for training DL models are emerging, such as transfer learning, which allows models to be prepared to perform a specific task and then applied to related tasks [151]. Meta-learning, which involves learning to learn, has also shown promise in improving the efficiency of DL [156]. Lifelong learning enables a model to learn continuously from new data and adapt to new tasks, which can potentially revolutionize how ML is approached [160]. DL applications are also expanding to new domains such as healthcare [160], autonomous vehicles [161], and environmental monitoring [162]. DL remains an integral part of the evolution of artificial learning owing to continual progress in this field.

Convolutional Neural Network: It is an artificial neural network (ANN) widely used for image recognition and object classification tasks. These networks are composed of several convolutional layers designed to identify features within data [163]. The structure of a CNN is intended to capitalize on the spatial correlations prevalent in image data. Figure 20 illustrates the architecture of the CNN. It processes the input images through a series of layers: convolution for feature extraction, pooling for dimensionality reduction, and fully connected layers for final classification. The hierarchical structure helps identify patterns, such as edges and textures, progressing to complex features.

Recurrent Neural Network: An RNN is designed to work with sequential data, including temporal sequences and natural language processing. These models can model the temporal dependencies between input data points using feedback connections in a network [164]. RNNs have been used in various fields, including speech recognition, language translation, and video analysis. Figure 21 shows a recurrent neural network. It includes an input layer for receiving data, multiple hidden layers for processing, and an output layer for predictions. The connections between nodes transmit weighted inputs, enabling the network to learn and make decisions.

Table 2. Overview of machine learning methods, models, and applications.

Machine Learning	Description	Method	Model	Applications	Ref#
Linear Regression	A linear technique builds a straight-line model to depict the link between a dependent variable and one or more independent variables.	Supervised Learning	Linear Model	Predicting numerical values based on a set of input features	[94, 95]
Logistic Regression	A model based on statistics that examines the association between a response flexible than one or different illustrative variable quantity and estimates the probability of an event occurring	Supervised Learning	Logistic Function	Binary classification, such as in medical diagnosis	[96, 97]
Decision Trees	A decision tree model depicting potential outcomes and consequences, widely employed across various fields, classify or predict outcomes.	Supervised Learning	Tree Model	Classification or regression tasks	[98, 99]
Random Forest	A technique in troupe discovering that utilizes numerous choice trees to foresee the class mode.	Supervised Learning	Ensemble of Tree Models	Classification or regression tasks	[100, 101]
Support Vector Machines (SVM)	An analytical approach to supervised learning that seeks out the hyperplane with the widest margin between two classes for both classification and regression analyses	Supervised Learning	Hyperplane Model	Binary or multi-class classification, regression, and outlier detection	[102, 103]
Naive Bayes	A classification algorithm utilizing Bayes' theorem, which assumes feature independence and calculates the probability of a given class given the observed features	Supervised Learning	Probabilistic Model	Text classification, spam filtering, and sentiment analysis	[104–106]
K-Nearest Neighbors (KNN)	An algorithmic approach in non-parametric methods is utilized for characterization and relapse examination. It dispenses an item to a class in light of most of its k-nearest neighbours.	Supervised Learning	Instance-based Model	Classification or regression tasks	[106–108]
Principal Component Analysis (PCA)	A method utilized to compress data and reduce dimensionality that identifies the linear combinations of variables that account for the most considerable variance in the data	Unsupervised Learning	Linear Transformation Model	Dimensionality reduction, data visualization	[108–110]
Artificial Neural Networks (ANN)	Computer models mimicking the human brain's structure and function can learn and generalise.	Supervised Learning	Multilayer Perceptron Model	Classification, regression, and many other tasks	[111, 112]
Convolutional Neural Networks (CNN)	A neural network model for analyzing images and videos., that learns local patterns through convolutional layers	Supervised Learning	Convolutional Model	Image classification, object detection, and many other tasks	[113–115]
Recurrent Neural Networks (RNN)	It processes sequential data by using feedback connections, allowing information to persist.	Supervised Learning	Recurrent Model	The same technology accomplishes NLP, speech recognition, and numerous other assignments.	[116, 117]
Long Short-Term Memory (LSTM)	The network uses storage cells and gating mechanisms to retain and forget information selectively.	Supervised Learning	LSTM Model	NLP, speech recognition, and many other tasks	[118, 119]
Autoencoders	Dimensionality reduction, which learns to reconstruct input data from a lower-dimensional representation	Unsupervised Learning	Encoder-Decoder Model	Data compression, anomaly detection, and different works	[120–122]
Generative Adversarial Networks	The network used for generative modelling, A generator, and a discriminator trained adversarially as part of the system	Supervised Learning	GAN Model	Image generation, data augmentation, and many other tasks	[123–125]
K-Means Clustering	clustering analysis, panels of statistics point to k clusters based on their proximity to the cluster centres	Unsupervised Learning	Clustering Model	Clustering, data segmentation	[126–128]
Hierarchical Clustering	Creates a hierarchy of nested clusters by iteratively Grouping or dividing clusters based on their similarity.	Unsupervised Learning	Clustering Model	Clustering, data segmentation	[129–131]
Gaussian Mixture Models (GMM)	A type of unsupervised learning used for clustering analysis that models' data points as a mixture of Gaussian distributions	Unsupervised Learning	Probabilistic Model	Clustering, anomaly detection, and many other tasks	[132, 133]
Isolation Forest	A type of unsupervised learning used for anomaly detection that isolates anomalies by recursively partitioning data points into subsets	Unsupervised Learning	Ensemble of Tree Models	Anomaly detection, outlier	[134–136]
One-Class SVM	An Anomaly finding finds a hyperplane that captures most data points and labels the rest as anomalies.	Unsupervised Learning	Hyperplane Model	Anomaly detection, outlier	[137–139]
Local Outlier Factor (LOF)	Compares data facts' local mass to neighbours to identify outliers.	Unsupervised Learning	Density-Based Model	Anomaly detection, outlier	[140, 141]

**Figure 20.** Convolutional neural network architecture: extracting features from images using convolution, pooling, and fully connected layers for classification.

Generative Adversarial Network: It can learn to create new data samples that resemble the data used for training[165]. This type of AI consists of two networks: a generator that produces novel information and a discriminator designed to differentiate between

legitimate and counterfeit samples. The generator is taught to generate data that confuse the discriminator, whereas the discriminator is trained accurately to determine the difference between the actual and bogus samples. Figure 22 depicts the working mechanism of

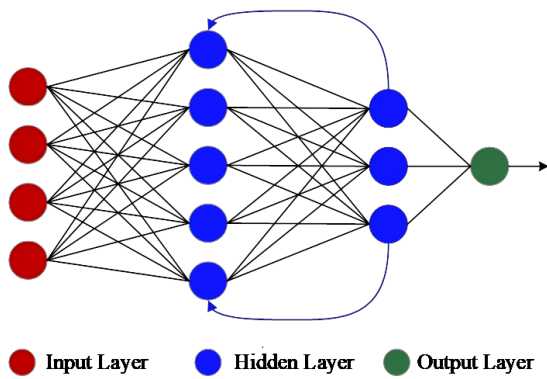


Figure 21. Recurrent neural network: processing data through input, hidden, and output layers for predictions.

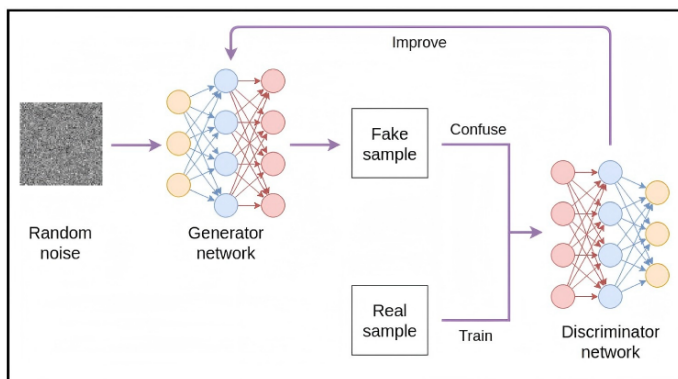


Figure 22. Generative adversarial network architecture: a generator creates fake data, and a discriminator evaluates it, improving both through adversarial training.

GAN. It consists of two neural networks: a generator, which creates fake samples from random noise, and a discriminator, which evaluates whether the input is real or fake. The Generator improves by attempting to confuse the Discriminator, while the Discriminator learns to better distinguish real from fake, thereby creating an adversarial learning process.

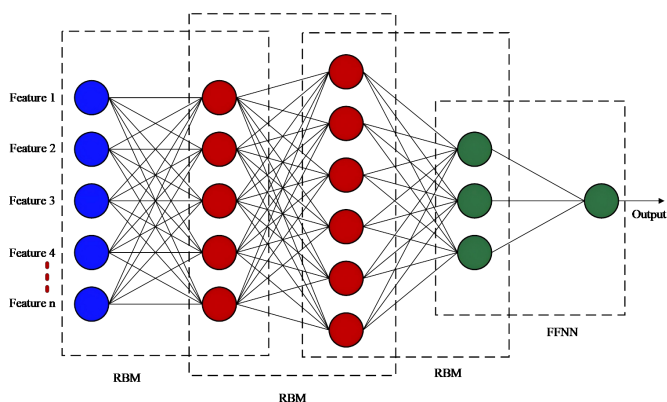


Figure 23. Deep belief network: a layered generative model using RBMs for feature learning and predictions.

Deep Belief Network: It is used for unsupervised learning tasks like feature recognition and data

compression. DBNs are composed of several layers of restricted Boltzmann machines (RBM) used to create a representation of the input data [166]. This technique can be augmented using supervised learning techniques to perform tasks such as classification and regression. Figure 23 shows a deep belief network (DBN), a generative neural network. It is composed of multiple layers of RBM for feature learning and pretraining. The input features were processed through hidden layers to extract high-level representations. Finally, the output layer provides the predictions. DBNs are trained layer-by-layer, making them efficient for unsupervised learning and fine-tuning supervised tasks.

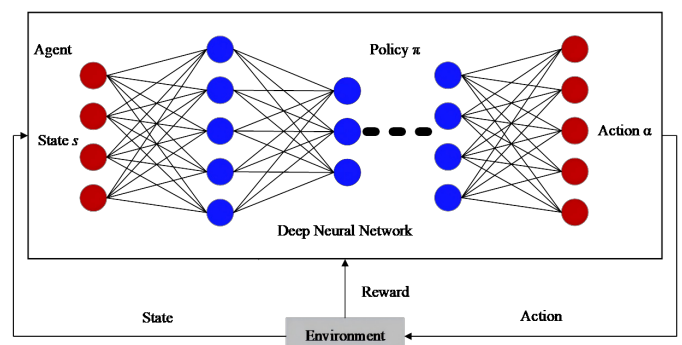


Figure 24. Deep reinforcement learning: an agent learns optimal actions through interaction with the environment, and feedback rewards.

Deep Reinforcement Learning: The combination of DL and RL is deep reinforcement learning, enabling agents to develop sophisticated behaviours in various environments [167]. This approach has been used to successfully train agents to play games such as Atari and Go and control robots and autonomous vehicles. Figure 24 shows the architecture of deep reinforcement learning. The agent, represented by a deep neural network, interacts with the environment by taking an input state and outputting an action based on the learned policy. The environment provides feedback as a reward that the agent uses to refine its policy and improve future decision-making.

Variational Autoencoders: This technique is used for generative modelling. These models were devised to uncover hidden images of the given data, which can be employed to create new samples reminiscent of the original training data [168]. Variational autoencoders use a probabilistic approach to model latent representations, allowing them to generate diverse and realistic samples. Figure 25 illustrates the architecture of the variational autoencoder (VAE). It consists of an encoder (left) that compresses the

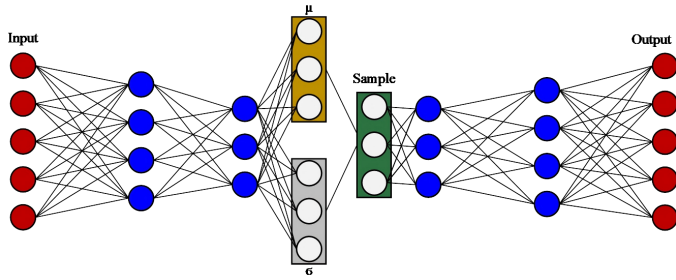


Figure 25. Variational autoencoder: a neural network for encoding inputs into a latent distribution and reconstructing them through sampling.

input into a latent space represented by mean (μ) and variance (σ). A sample was drawn from this distribution and passed to the decoder (right), which reconstructed the original input. This probabilistic approach allows VAE to generate new data by sampling from the latent space.

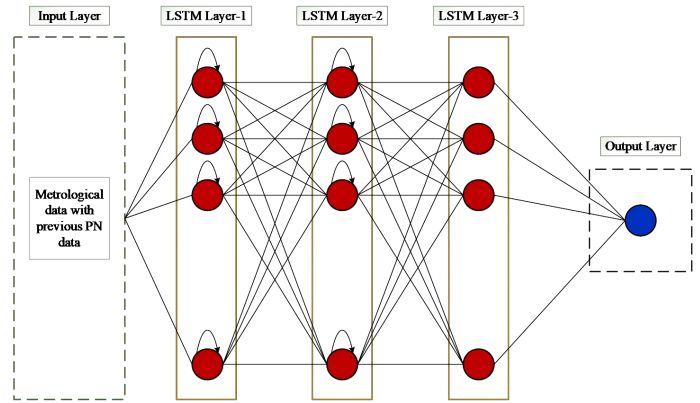


Figure 27. A deep recurrent network for capturing complex temporal dependencies in sequential data.

of gates to selectively update and read from memory, allowing it to capture long-term dependencies in sequential data [170]. LSTM is used in diverse applications such as speech detection, linguistic translation, and image captioning. Figure 27 illustrates a stacked LSTM, a recurrent neural network that handles sequential data and long-term dependencies. The architecture consisted of multiple LSTM layers stacked on each other, allowing the model to capture hierarchical temporal patterns. The input layer processes sequential data that flows through the LSTM layers, and the output layer generates predictions based on the learned patterns.

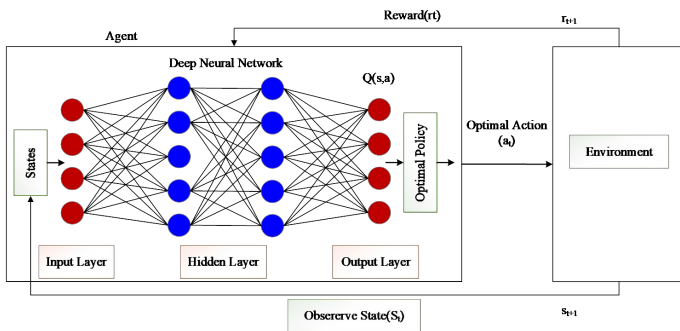


Figure 26. A neural network-based reinforcement learning model to approximate Q-values and optimize decision-making.

Deep Q-Network: The deep reinforcement learning algorithm uses neural networks to obtain the expected recompense of an action in a given state relative to the Q-function [169]. A deep Q-network (DQN) has been used to train agents to play Atari games and has been shown to achieve superhuman performance in some cases. Figure 26 shows the DQN architecture used in reinforcement learning. It combines a deep neural network to approximate the Q-value function, which maps the states and actions to their expected rewards. The agent observes the state from the environment, selects the optimal action based on the Q-values, and receives a reward from the environment, iteratively improving its policy through learning.

Extended Short-Term Memory Network: These networks are a unique type of recurrent neural network developed to combat the problem of endangered slopes in standard RNN. An extended short-term memory network (LSTM) uses a memory cell and a set

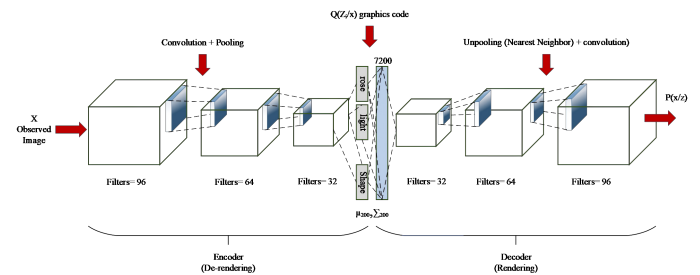


Figure 28. Deep convolutional inverse graphics network, a neural network for 3D shape reconstruction from 2D images [171].

Deep Convolutional Inverse Graphics Network: This type of neural network is used for 3D shape reconstruction from 2D images [171]. A deep convolutional inverse graphics network (DC-IGN) uses a generative model that learns to reconstruct the form of a 3-dimensional item that can be derived from a single 2-dimensional representation. Research has demonstrated that they can achieve the highest level of precision in various shape reconstruction tests. Figure 28 illustrates DC-IGN, a neural network designed to reconstruct 3D shapes from 2D images. The model uses a generative approach to infer the 3D

structures of objects based on their 2D representations. Through convolutional layers and latent feature extraction, DC-IGN achieves high precision in shape reconstruction tasks, making it valuable in computer vision and graphics applications.

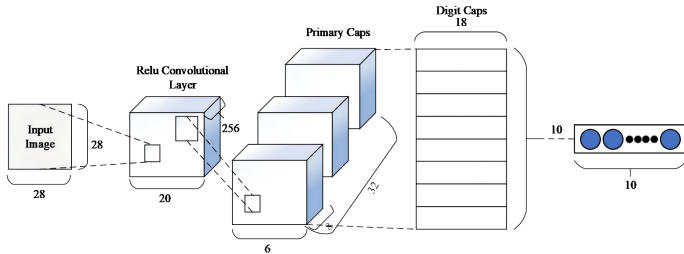


Figure 29. Capsule network: a deep learning model that captures spatial hierarchies for image classification and object recognition.

Capsule Network: Capsules are designed to overcome the limitations of traditional convolutional neural networks in capturing the hierarchical relationships between features [172]. Capsule networks (CapsNet) use groups of neurons called capsules to represent different parts of an object and use dynamic routing to enable the network to develop the ability to amalgamate these parts into a coherent representation of the object [173]. Capsule networks have demonstrated remarkable accomplishments in several image detection responsibilities, achieving more advanced outcomes than the present leading edge. Figure 29 shows a CapsNet architecture designed to capture spatial hierarchies in data more effectively than traditional convolutional networks. It starts with convolutional layers to extract basic features, followed by Primary Capsules that encode the spatial relationships. The digit capsule layer refines this information, and the final output represents the likelihood of each class. CapsNet is particularly effective for tasks requiring spatial awareness, such as image classification and object recognition.

Residual Network: Residual network (ResNet) uses skip connections to address the difficulty of vanishing gradients in deep neural networks. These skip connections simplify the system’s learning and reduce the number of gradients transmitted through the network [174]. ResNet can achieve the highest levels of accuracy in selecting image classification tasks. The diagram in Figure 30 illustrates the concept of the residual block used in ResNet. Residual blocks address the vanishing gradient problem in deep neural networks by introducing a shortcut connection (identity mapping) that allows the input (x) to bypass one or more weight layers. The output of

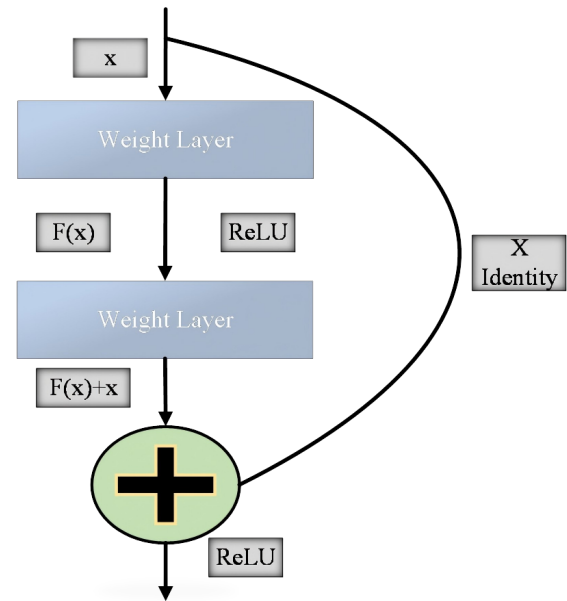


Figure 30. Residual block in resnet: combining identity mapping and weighted layers to enable efficient training of deep networks.

the weight layers, $F(x)$, is added to the bypassed input (x) before passing through a ReLU activation function. This approach simplifies the training of deep networks by enabling gradient flow through shortcut connections and ensures better performance in very deep architectures.

Table 3 overviews diverse DL techniques, their methodologies, and applications. FNN uses unidirectional data flow for tasks like image and text classification, while CNN extracts spatial features for image classification and object detection using architectures like AlexNet and ResNet. RNN handles sequential data, with variants like GRU and LSTM excelling in language and time-series tasks. GAN generates realistic data for applications such as image synthesis and style transfer, and autoencoders perform feature extraction and anomaly detection through efficient data representation. Deep reinforcement learning enables agents to learn optimal actions in robotics and gaming, while transfer learning adapts pre-trained models like MobileNet for new tasks with minimal data. Capsule networks improve object recognition by modelling hierarchical relationships, and FL supports privacy-preserving collaborative model training for personalized recommendations.

Table 3. A deep learning model summary is used in different studies with their applications.

Deep Learning	Description	Method	Model	Applications	Ref#
Feedforward Neural Networks (FNN)	information is passed in one way from the input end to the output end.	Supervised learning, classification	Multilayer Perceptron (MLP)	Image classification, speech recognition, text classification	[175, 176]
Convolutional Neural Networks (CNN)	process images by using convolutional layers that abstract features from given data	Supervised learning, image classification	AlexNet, VGG, ResNet	Image classification, object detection, facial recognition	[177–179]
Recurrent Neural Networks (RNN)	capable of handling sequential data by using recurrent connections between the neurons.	Supervised learning, sequence forecast	Gated Recurrent Unit, Long Term & short Memory	Employing Voice Identification, Interpretation, and Time-Projected Estimation	[180–182]
Generative Adversarial Networks	Utilized and that compete with each other to generate realistic-looking data.	Unsupervised learning, generative models	(DCGAN), (WGAN)	Image synthesis, text-to-image generation, style transfer	[183, 184]
Autoencoders	A type that learns to encode and decode input information by using an encoder and a decoder	Unsupervised learning, feature extraction	Denoising Autoencoder (DAE), Variational Autoencoder (VAE)	Image compression, anomaly detection, generative modelling	[185, 186]
Deep Reinforcement Learning	agent to acquire knowledge by engaging with its surroundings and being rewarded or penalized for its behaviour is a form of AI trained model to be used in a neural network to be adapted to a new task with limited amounts of labelled data.	Reinforcement learning	Deep Q-Network (DQN), Actor-Critic	Game playing, robotics, recommendation systems	[187, 188]
Transfer Learning	capsule units to model the hierarchical relationships between parts of an object.	Supervised learning, transfer learning	Inception, Mobile Net	Image classification, object detection, natural language processing	[189, 190]
Capsule Networks	A technique that enables multiple parties to collaborate on a machine learning task without sharing their data by training models locally and exchanging model updates.	Supervised learning, image classification	Capsule Network (CapsNet)	Image classification, object recognition	[191, 192]
Federated Learning		Distributed learning	Federated Averaging, Federated Distillation	Privacy-preserving machine learning, personalized recommendation	[193, 194]

4 Comparison of Machine Learning and Deep Learning

ML and DL are integral branches of AI, each offering distinct methodologies and applications. ML involves algorithms designed to learn patterns from data and make predictions or decisions, often requiring human intervention for feature selection and engineering. Models like linear regression, decision trees, and SVM are common in ML, excelling in tasks involving structured data or small-to-medium datasets. These models are computationally efficient and relatively easy to interpret, making them a practical choice

for fraud detection, customer segmentation, and predictive maintenance applications. In contrast, DL, a specialized subset of ML, relies on ANN modelled after the human brain. DL automatically extracts features from raw data through multiple hierarchical layers, eliminating the need for manual feature engineering. This capability makes DL particularly effective in handling unstructured data, such as images, audio, and text. Advanced architectures like CNN and RNN have revolutionized fields such as image recognition, natural language processing, and autonomous systems. However, DL requires significantly larger datasets and

higher computational power, often relying on GPU or TPU for training complex models.

A key distinction lies in their data dependency. While ML performs well with smaller datasets, its performance plateaus as data complexity increases. On the other hand, DL thrives in data-rich environments, with larger datasets enabling neural networks to learn intricate patterns and achieve superior accuracy. This difference is evident in applications such as autonomous driving, medical imaging, and recommendation systems, where DL consistently outperforms traditional ML methods. Another notable difference is computational demand. ML models are lightweight and efficient, suitable for environments with limited resources or the need for rapid deployment. In contrast, DL's resource-intensive nature, driven by complex architectures and iterative training processes, requires substantial computational infrastructure and longer training times. These demands make DL less accessible for resource-constrained scenarios but highly effective in high-stakes applications. Interpretability also sets them apart. ML models, like decision trees or linear regression, provide clear insights into how predictions are made, fostering transparency and trust. Conversely, DL models are often perceived as "black boxes," making it challenging to understand their decision-making processes. This lack of explainability can be a limitation in healthcare or finance, where transparency is critical. ML is ideal for more straightforward tasks, smaller datasets, and applications requiring interpretability and efficiency. With its ability to process unstructured data and solve complex problems, DL is indispensable for advanced AI applications, provided sufficient data and computational resources are available. Understanding these distinctions allows organizations to select the most appropriate approach for their unique challenges and objectives.

Table 4 comprehensively compares ML and DL, emphasizing their unique characteristics, requirements, and applications. ML, a subset of AI, relies on algorithms and statistical models to perform specific tasks, often using structured data and requiring manual feature engineering. In contrast, DL, a specialized subset of ML, employs multi-layered neural networks capable of automatically learning patterns and representations from raw data, making it particularly effective for complex and unstructured data such as images, audio, and text. ML models typically require smaller datasets, making them more

accessible for scenarios with limited data, while DL demands vast quantities of labelled data to train its complex architectures. This distinction extends to feature extraction, where ML depends on domain experts for manual feature engineering.

In contrast, DL automates this process, as seen in CNN, which extracts hierarchical features from images. ML models, such as decision trees and SVM, are more straightforward, involve fewer parameters, and have shorter training times than DL models like CNN and RNN, which are computationally intensive and require specialized hardware like GPU or TPU. This makes ML models more practical for quick deployment in resource-constrained environments. However, DL models excel in performance on unstructured data and have demonstrated exceptional capabilities in fields like medical imaging, natural language processing, and autonomous systems. Another key distinction lies in interpretability; ML models are generally more transparent and easier to understand, making them suitable for applications like finance and healthcare, where explainability is crucial. While more accurate and versatile, DL models often function as "black boxes," posing challenges in understanding their decision-making processes.

Overall, ML remains a strong choice for tasks involving structured data, smaller datasets, and the need for interpretability. At the same time, DL is the preferred option for handling large-scale, complex, and unstructured data. The decision between ML and DL depends on the problem domain, the availability of data, computational resources, and the desired balance between accuracy and explainability. This comparison highlights how ML and DL complement each other in advancing AI applications across diverse fields.

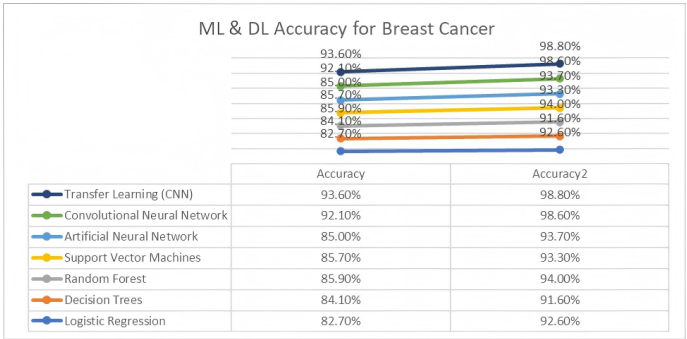


Figure 31. Graphical view of ML and DL accuracies for breast cancer detection.

The graph compares the accuracy of various ML and DL techniques for breast cancer detection, showing that transfer learning (93.6%–98.8%)

Table 4. The evaluation of artificial intelligence: a comparison of machine and deep learning.

Criteria	Machine Learning	Deep Learning	Ref#
Definition	The subset of computerized reasoning (simulated intelligence) that includes utilizing calculations and measurable models to play out a particular undertaking.	A subset of AI that includes utilizing counterfeit brain networks with numerous layers to play out a particular errand	[195–197]
Data Requirements	Requires smaller amounts of labelled information compared to DL.	It needs more significant quantities of labelled information compared to ML	[150, 198]
Feature Engineering	Requires extensive feature engineering to extract relevant features from raw data.	Automatically extracts relevant features from raw data using deep neural networks.	[195–197, 199–201]
Model Complexity	Models are more straightforward with fewer parameters compared to DL.	Models are more complex with more parameters compared to ML	[196, 202–204]
Training Time	Training time is relatively shorter compared to DL.	Training time is longer compared to ML	[196, 202–204]
Hardware Requirements	Can be trained using traditional CPU or GPU.	Requires specialized hardware such as GPU or TPUs to train effectively	[195–197, 202–204]
Performance on Structured Data	Performs well on structured data such as numerical data and tabular data.	Can deal with both organized and unstructured information like pictures, sound, and text	[195–197, 199, 200, 205]
Performance on Unstructured Data	Performs inadequately on unstructured information like pictures, sound, and text.	Performs very well on unstructured information like pictures, sound, and text	[195, 196, 199, 200, 205]
Interpretability	Models are more interpretable and easier to understand compared to DL.	Models are less interpretable and more challenging to comprehend compared to ML	[152, 203, 206, 207]
Popular Algorithms Methods	Decision trees, random forest, support vector machines.	Convolutional neural network, recurrent neural network, generative adversarial network	[195, 196, 200, 208, 209]

and convolutional neural networks (92.1%–98.6%) outperform traditional methods like Logistic Regression and Decision Trees shown in Figure 31. This highlights the superior predictive power of DL approaches over conventional ML models. Table 5 presents a comparative summary of the ML and DL techniques used in breast cancer detection, highlighting their accuracy ranges and definitions. Logistic regression demonstrated 82.7%–92.6% accuracy by modelling binary outcomes using statistical strategies. Decision trees achieve 84.1% to

91.6% accuracy by splitting data into subsets based on significant attributes, whereas Random Forests improves this range to 85.9% to 94.0% by aggregating multiple decision trees. SVM excels with accuracies between 85.7% and 98.43% and advanced hyperplanes for optimal class separation. ANN, which mimics biological neural systems, offers an accuracy range of 85.0% to 93.9%. The CNN, specializing in image feature extraction, enhanced the accuracy from 92.1% to 98.6%. Transfer Learning surpasses other techniques with the highest accuracy of 93.6%–98.8%

by advancing the pre-trained CNN and fine-tuning them on specific tasks with limited data. This table underscores the progressive improvements in the accuracy achieved by transitioning from traditional ML methods to advanced DL approaches.

5 Discussion

Integrating ML and DL in breast cancer diagnostics has marked a transformative shift in medical imaging and predictive healthcare. This review highlights the significant advancements in applying AI techniques to improve breast cancer detection accuracy, sensitivity, and specificity. These findings emphasize that CNN remains the cornerstone of DL models in image analysis, excelling in feature extraction and classification. Transfer learning and ensemble learning enhance the model performance by advancing pre-trained models and combining multiple classifiers. Transfer learning demonstrates remarkable efficiency, achieving high accuracy even with limited datasets, as evidenced by the accuracy range of 93.6% to 98.8%. Moreover, adopting explainable AI addresses one of the critical limitations of traditional AI models: interpretability. Including AI in models such as Bayesian CNN provides insights into decision-making processes, fostering trust among medical professionals and enhancing clinical usability. Multimodal frameworks integrating mammography, ultrasound, and MRI data offer promising avenues for improving diagnostic accuracy. This review underscores the potential of hybrid models that combine different imaging modalities and ML/DL techniques, achieving higher sensitivity and specificity. For instance, frameworks integrating CNN with RNN and radiomics have demonstrated a robust ability to identify malignancies across diverse datasets.

Despite this progress, several challenges remain to be overcome. DL models often require extensively annotated datasets to perform optimally, a significant barrier in medical imaging due to data scarcity and privacy concerns. FL has emerged as a viable solution that enables collaborative model training without compromising data privacy. However, its implementation across institutions poses both technical and operational challenges. Another limitation is the computational complexity and hardware dependency of the DL models. The need for high-performance computing resources such as GPUs or TPUs restricts their accessibility, particularly in low-resource settings. Furthermore, many DL models' "black-box" nature limits their adoption in

safety-critical environments, emphasizing the need for ongoing research on model interpretability.

Future research should focus on developing lightweight and interpretable AI models to bridge the gap between accuracy and practicality. Hybrid approaches that combine ML and DL, along with advanced techniques such as FL and attention mechanisms, hold promise for achieving scalable and privacy-preserving solutions. Additionally, efforts to standardize the datasets and evaluation metrics will be instrumental in ensuring the reproducibility and reliability of AI-driven diagnostic tools. The successful integration of AI into breast cancer diagnostics offers transformative potential for personalized medicine. By enabling early and accurate detection, AI-powered tools can optimize treatment strategies, improve patient outcomes, and reduce healthcare costs. However, interdisciplinary collaboration among AI researchers, clinicians, and policymakers is essential to realize this potential.

6 Conclusion

The integration of ML and DL techniques in breast cancer diagnosis has opened new avenues for early detection and improved patient outcomes. This study comprehensively reviews the landscape of ML and DL methodologies, their applications, and their impact on breast cancer diagnosis. The versatility of these technologies, spanning imaging and genomic and clinical data analysis, underscores their transformative potential in healthcare. Advanced algorithms, including CNN and hybrid models, have consistently demonstrated superior sensitivity and specificity to traditional diagnostic methods such as mammography.

Although the achievements in this field are promising, challenges persist in data accessibility, model interpretability, and scalability in real-world applications. Techniques, such as transfer and FL, show promise in addressing these barriers by enabling efficient learning from limited datasets while preserving data privacy. However, the success of these techniques depends on interdisciplinary collaboration and the development of robust, standardized datasets to ensure reproducibility and reliability.

Ethical considerations, particularly in ensuring transparency, fairness, and patient trust, remain paramount as ML and DL models are increasingly integrated into clinical workflows. Addressing potential biases and ensuring equitable deployment

Table 5. Discussion of machine learning and deep learning models accuracy in breast cancer detection.

Technique	Accuracy	Brief Definition	Reference
Logistic Regression	82.7% -92.6%	A measurable model that utilizes a strategic capability to demonstrate a paired ward variable.	[210, 211]
Decision Trees	84.1% - 91.6%	A tree-based model that recursively splits data into smaller subsets based on the most significant attribute in each split.	[212, 213]
Random Forest	85.9% - 94.0%	A decision tree-based model that builds multiple decision trees and combines their results to improve accuracy.	[214, 215]
Support Vector Machines	85.7% - 98.43%	A model that shows the best hyperplane to detach data into classes by extending the edge between the classes	[216, 217]
Artificial Neural Network	85.0% - 93.9%	A model that uses interconnected layers of nodes to simulate the function of a biological neural network.	[218, 219]
Convolutional Neural Network	92.1% - 98.6%	A profound learning model that utilizes convolutional layers automatically learns features from images.	[220, 221]
Transfer Learning	93.6% -98.8%	A technique that uses pre-trained convolutional neural networks and fine-tunes them on new tasks with limited data.	[221–223]

is critical for the widespread acceptance of these technologies.

The continued evolution of ML and DL has immense potential to revolutionize breast cancer detection and treatment. By fostering innovation and collaboration between researchers, clinicians, and policymakers, these technologies can play a pivotal role in reducing the global burden of breast cancer, enhancing patient care, and improving survival rates. As the field advances, the focus must remain on optimizing these systems for real-world applications while prioritizing ethical and transparent implementation.

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Conflicts of Interest

The authors declare no conflicts of interest.

Ethical Approval and Consent to Participate

Not applicable.

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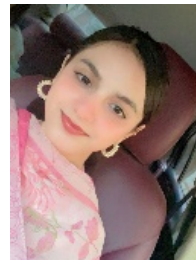
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