Data-Driven Breast Cancer Detection: A Review of Machine Learning, Deep Learning, and Multimodal AI Approaches

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ABSTRACT

Breast cancer is a critical and life threatening disease among female individuals in the globe and the early diagnosis of this disease is quite important in enhancing the survival rates and treatment outcomes. The paper will provide a description of machine learning and deep learning algorithms of breast cancer diagnosis based on clinical data and medical images practices. These methods are Support Vector Machines (SVM), Decision Trees, Random Forest, Gradient Boosting, deep learning models, such as Convolutional Neural Networks (CNNs) and hybrid models among others. It has been argued that the ensemble and hybrid model can be used in not only high diagnostic accuracy of up to 98 but in part feature selection, dimensionality reduction, and data preprocessing on the model accuracy. Recent developments of contrastive learning, lightweight neural networks and explainable artificial intelligence (XAI) are addressed in order to make it more efficient and interpretable. Although these positive results are achieved, the issues that still exist are: the diversity of the datasets, the absence of the multi-center validation, and the complexity of the calculations. The results indicate that machine learning-based systems can be used as viable and scalable decision support systems in detecting breast cancer in its early stages.

Keywords: Breast cancer detection; Machine learning; Deep learning; Convolutional neural networks; Ensemble learning; Explainable artificial intelligence (XAI)

1. INTRODUCTION

1.1 Healthcare

Healthcare is crucial in promoting life quality and life expectancy of human beings by preventing, early diagnosis, successful management and frequent monitoring of patients. The modern healthcare systems are confronted with emerging demands with the fact that the population is increasing, the lifestyle is changing, and the cases of chronic and life threatening conditions are increasing. The classical premise of the traditional medical care approaches is framed on the traditional clinical knowledge which can lead to a breakdown, incoherence, and inaccuracy of the diagnosis particularly when the volume of patient data is too huge.

With the ongoing advancement of digital technologies, the sphere of healthcare is going to be smart and data-driven. Opting to use automated diagnostic tools, clinical decision support systems, and predictive analytics is a common trend to aid healthcare workers. These technologies are aimed at enhancing the precision, reducing the number of work hours, and providing an opportunity to make a timely diagnosis that will consequently advance the outcomes of patients.

1.2 Breast Cancer

Among women all over the world, breast cancer is one of the most commonly diagnosed cancers and a major cause of cancer-related deaths. Global health organizations like the Centers for Disease Control and Prevention (CDC) have reported that a high percentage of cancer incidences occur each year due to breast cancer. This disease is caused by the abnormal and uncontrolled proliferation of cells within the breast tissue, which usually occurs in the milk-producing lobules or in the ducts through which the milk flows to the nipple.

Connective or fatty breast tissues are also susceptible to developing breast cancer. Unless detected at an early stage, cancerous cells can spread to the neighboring healthy tissues and move to lymph nodes located under the arms and, ultimately, cause metastasis in other body organs. Breast tumors take the form of benign or malignant. Benign tumors are localized, and non-cancerous, in contrast to malignant tumors, which are aggressive and spread throughout the body. It is important to correctly distinguish between these types of tumors because it directly determines the type of treatment and the prognosis of the patient.

1.3 Importance of Early Breast Cancer Detection

Early screening of breast cancer is very important because it leads to better survival rates and lower complexity of treatment. In the earlier stages of the disease, breast cancer can be cured through less invasive modalities, which lead to better recovery and quality of life for the affected patients. Yet, many women do not show symptoms in the early stages of the disease, and in the end, it is diagnosed when the disease has progressed. Traditional methods of diagnosing breast cancer, like mammography, ultrasound, and biopsy, are commonly used for breast cancer diagnosis. Although such techniques are very effective, they are sometimes time-consuming, costly, and very reliant on the expertise of pathologists and radiologists. Moreover, human error and subjective interpretation are also possible when manual analysis is undertaken. Thus, there is an increasing need to develop smart systems that would help healthcare professionals to diagnose breast cancer more accurately.

1.4 Machine Learning

Machine Learning (ML) is a subdivision of artificial intelligence that aims to enable computer programs to learn from data and enhance their performance without necessarily being coded to handle every possible scenario. In contrast to conventional software systems, which are based on established rules and predefined logic, machine learning models are based on data-driven methods to extract unnoticed patterns, correlations, and structures in datasets. Such acquired patterns enable ML systems to do complicated tasks like classification, prediction, and decision-making. This ability contributes to the fact that machine learning is especially useful in areas where the complexity of the problem, the volume of data, and uncertainty are such that traditional programming methods are inefficient or infeasible.

The widespread use of machine learning has been driven by the rapid growth of digital data and important innovations in the computing infrastructure. ML algorithms have also been efficient because of the availability of large datasets coupled with advanced processors and cloud computing architectures. Consequently, machine learning has been applied in various fields, such as healthcare, finance, image and speech recognition, cybersecurity, and smart automation. ML systems can be used in these areas to convert unstructured data into information, automate processes that require complex decision-making, assist in making correct and time-sensitive decisions, and decrease human labor and bias.

Machine learning as a whole can be described as the process of training a model, based on historical data, and then using that model to make predictions on data that was not present before. At the training stage, input features are analyzed and matched with output labels to learn the underlying relationships between the input and the output. The model takes advantage of minimizing prediction errors and maximizing accuracy by iterating with its internal parameters to obtain improved accuracy. The model can adapt and learn from experience. Once trained, it is able to make sound predictions of new data. This ability to keep learning over time makes machine learning systems highly beneficial in creating intelligent, scalable, and robust solutions in the real world.

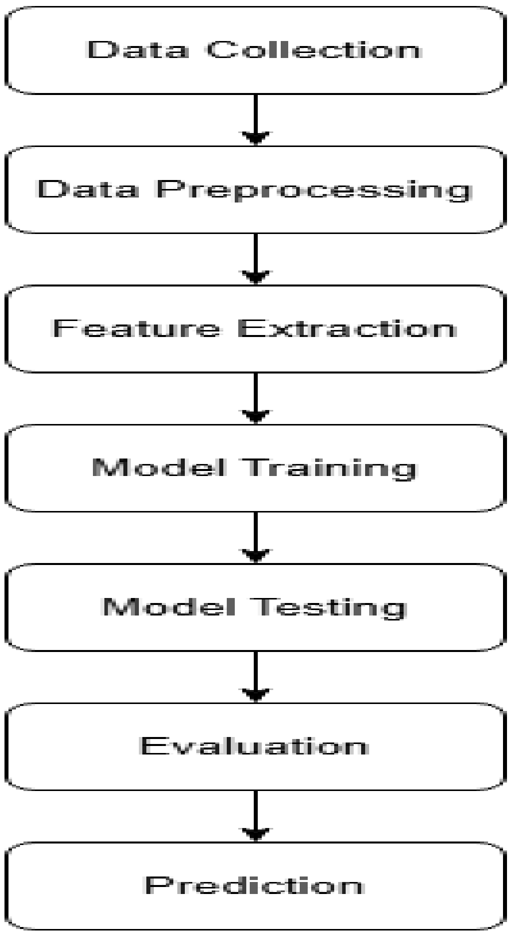

Figure 1. Breast Cancer Detection Using ML Architecture

1.5 Machine Learning In Healthcare

Machine Learning (ML) is a subdivision of artificial intelligence that allows systems to learn through past experiences, detect patterns and make predictions without being programmed. In the medical field, ML has become a strong medical diagnosis, disease prediction, treatment recommendation, and patient monitoring tool. ML algorithms are able to identify insights in large and complex datasets that can be used to aid clinical decision-making.

The implementation of ML in healthcare resulted in increased accuracy of diagnosis, a decrease in medical errors, as well as an increased efficiency of healthcare services. ML approaches are specifically useful in processing large volumes of medical data, such as medical images, electronic health records, and laboratory findings that cannot be analyzed with the help of conventional algorithms.

1.6 Why Machine Learning Is Used In Breast Cancer Detection

Machine learning can be employed in breast cancer detection because it has several benefits. ML-based systems are more diagnostic and consistent with less human subjectivity. They make possible early diagnosis through examination of minute patterns that might not be perceivable to the human eye. Moreover, ML models save time in diagnosis, help clinicians with decision-making, and enhance the efficiency of delivering healthcare services in general.

Furthermore, one can enhance ML-related diagnostic systems with a continuous learning bias, which enables them to be scalable and adaptable. Machine learning enhances the survival rates of patients and the rate of success at the treatment planning level with the assistance of early diagnosis and accurate classification of tumors.

The main contributions of the paper are:

1. **Comparative Analysis of ML and DL Models on a large scale** - The current paper will entail a massive and comparative analysis of the classical machine learning algorithms (SVM, Decision Trees, Random Forest, Gradient Boosting) and deep learning models (CNNs and hybrid networks) in breast cancer detection, their strengths, weaknesses, and diagnostic accuracy on different datasets.

2. **Data Analysis and Generalization Problems** - The most popular datasets (i.e., WDBC, BreaKHis, CBIS-DDSM, MIAS, Coimbra) are analyzed, and the following issues are found: bias in the datasets, insufficient diversity, and inability to extrapolate datasets to other clinical facilities, which affect the relevance of the findings to the real-life setting.

3. **Hybrid and Ensemble Learning Strategies** - The article acknowledges the usefulness of the hybrid and ensemble approaches by giving the models that combine clustering, optimization and classification methods and demonstrate higher predictive capability, stability and insensitivity to autonomous models.

4. **Research Gaps and Future-Oriented Directions** - The paper lists certain gaps in the available research i.e. a lack of balance in the class distribution, excessive complexity in the computational processes, inability to interpret them, and provides future directions i.e. transformer based architecture, explainable AI (XAI), multimodal data fusion and systems that can be deployed in clinical settings.

2. LITERATURE REVIEW

The authors seek to provide the solution to the emerging issue of early-stage disease diagnosis following the increased number of the global population, and the breast cancer, in this instance, is the second deadliest type of cancer that afflicts women. The significance of proper and early diagnosis in the minimization of mortality is emphasized in this study. In this respect, the authors introduce a novel hybrid machine learning model i.e. a combination of supervised learners i.e. Gradient Boosting (GB), Stochastic Gradient Descent (SGD), Quadratic Discriminant Analysis (QDA), Naive Bayes (NB) and Agglomerative Hierarchical Clustering (AHC). The similar instances are then clustered with the help of the clustering algorithm and then the instances are then classified to maximize the learning and prediction capacity of the classifier. Detailed performance metrics such as accuracy, precision, recall, F1-Score, sensitivity, specificity, and false positive and false negative rates were used to test the model. The hybrid AHC + GB was the most precise, and it got the highest score of 99.30 that is very high compared to the single methods of classification as the evidence in an experiment reveals. The article acknowledges the application of supervised and unsupervised learning techniques and combination of the two techniques as successful and it offers a reasonable ground in the formulation of competent and clinically feasible models in the prediction of breast cancer [1].

The authors in this paper underpin the significance of diagnosing breast cancer early in order to offer adequate treatment and better survivability rates in patients and how computer-aided diagnosis (CAD) systems can be used to improve the accuracy and efficiency of diagnosis. The paper identifies major constraints of available methods for histopathological image of classification of breast cancer, such as large model complexity, lack of global feature extraction, and higher computational cost that usually results in loss of information. To address these issues, the authors introduce an efficient Multi-Modal Feature Fusion Network of Histopathology (MFF-HistoNet), a combination of a Convolutional Neural Network (CNN) and a Quantum Tensor Network (QTN). The presented framework uses parameter compression to shrink the model size but allows more profound global feature representation. Also, data augmentation methods are used to sample the data and reduce the color difference. Discriminative local texture and cell shape features at multiple scales and orientations are obtained through the combination of Gray Level Co-occurrence Matrix (GLCM), Local Binary Pattern (LBP), and Gabor filtering. An experimental analysis of the BreaKHis dataset shows that MFF-HistoNet is effective in classifying eight types of breast cancer, and with better performance at the image and patient levels, it can classify with a high success rate of up to 98 percent and requires less computational cost. The interpretability and reliability of the proposed model can also be confirmed with the help of Grad-CAM [2].

The authors in this paper underscore that cancer is the second most significant cause of death in the world, while breast cancer is the major cause of cancer-related deaths in women. It has been indicated in the study that it is important to detect breast cancer at its early stages to enhance survival. Although numerous current methods are based on mammogram images, these techniques can cause false diagnoses and medical complications. To overcome these shortcomings, the authors develop a hybrid machine learning model with Support Vector Machine, Artificial Neural Network, K-Nearest Neighbor, and Decision Tree classifiers. The offered solution is affordable, less hazardous, and flexible to different types, including medical images and information about the blood tests, allowing the detection of breast cancer more consistently [3]. These authors consider the limitations of current AI systems on mammography screening in this paper because many of them rely on a heavy data augmentation process, as there is a shortage of labelled mammograms, and might not generalise to the clinical condition. They inject fresh life into it by introducing a new structure, Supervised Contrastive Pre-training followed by Supervised Fine-tuning (SCP+SF), where no data augmentation is needed in the pre-training stage, and feature representations are enhanced in the early stage before supervised training. The paper uses this model on two critical mammographic screening activities, namely, mammographic abnormality screening and mammographic malignancy screening, with large-scale clinical data. The experimental findings indicate that SCP+SF significantly optimises the performance in terms of Area Under the Curve (AUC), sensitivity, and specificity as compared to conventional supervised training and other state-of-the-art models reported previously. The authors demonstrate that SCP+SF acquires better discriminative embeddings with a Siamese contrastive learning unit and subsequent fine-tuning, resulting in better classification performance; hence, it is an effective alternative to regular supervised mammography models [4].

In the current paper, the authors work on maximizing the early detection of breast cancer with the use of the Breast Cancer Coimbra dataset, decreasing the number of features, and preserving high predictive rates. They observe that the earlier experiments that employed all nine characteristics of the dataset could not produce maximum accuracy and resulted in misclassifications. To solve this, the research adopts a wrapper model with metaheuristic algorithms, including Whale Optimization Algorithm (WOA), Bald Eagle Search Algorithm (BESA), and Sea Lion Optimization Algorithm (SLOA) to select features, with an Extreme Gradient Boosting (XGBoost) classifier. SHAP analysis revealed the importance of features and showed that Glucose was the most significant feature. The study performed well in terms of predictive performance, having reduced dataset features from 9 to 4, and in this case, it was essential to show that fewer features can be used to generate reliable predictions of breast cancer [5].

The authors present a deep learning-based model to detect breast cancer in its initial stages based on histopathological images in this study. The procedure involves transfer learning and the use of many classifiers- Support Vector Machine (SVM), Decision Tree (DT), and K-Nearest Neighbor (KNN) and tests the impact of Principal Component Analysis (PCA) in

extracting features. The methodology is expected to improve the efficiency of diagnostics, particularly in areas with fewer resources to access specialized healthcare, and demonstrates that the integration of deep learning with classical classifiers positively impacts the predictive performance based on all considered measures [6].

The authors of this paper explored the increased significance of early breast cancer detection through the case of publicly available datasets that are relied on to conduct diagnostic research using machine learning. The paper has also emphasized the role that the newer developments in medical imaging, access to data, and computational methods have played in the detection and diagnosis of breast cancer. The authors not only develop their algorithms, but they also analyze a wide range of well-known datasets, such as WDBC, BreaKeHis datasets, mammography, ultrasound, and thermography datasets, paying much attention to their peculiarities and uses. The review discussed how these datasets have been applied in feature-based machine learning models and image-based deep learning models and demonstrated that the datasets are applicable in various diagnostic scenarios. The paper has given important information on how dataset selection affects the performance of models and the research results by thoroughly examining the merits and demerits of both datasets. The results indicate that every dataset has a unique and complementary contribution towards the development of breast cancer detection and diagnosis, and thus aids researchers to make informed decisions during the development of effective computational models [7].

The authors presented Mammo-Light, a lightweight convolutional neural network in this paper that was created to identify breast cancer in mammography images at the onset of the condition. The method is proposed to use preprocessing to minimize noise and enhance the visibility of breast lesions in medical images. Besides, they rely on photometric data augmentation to enlarge the dataset and address class imbalance. The CBIS-DDSM dataset was used to train the model and subsequently tested with the MIAS dataset. The results of the experiments showed that the proposed method reached a 99.17 percent accuracy on CBIS-DDSM and 98.42 percent on MIAS, which are quite high diagnostic accuracies with reduced computational costs [8].

In this article, the authors propose a Lightweight Convolutional Neural Network (LWCNN) to detect automatic breast cancer in screening mammograms. In contrast to conventional ML methods that use hand-designed features, which are time-consuming to generate, the given deep learning model does end-to-end feature extraction and classification. The model can be trained on datasets that have full clinical annotations or with image-level cancer labels alone, which is why it applies to clinical settings in the real world. Experimental findings show that LWCNN has high accuracy and is robust to minimize false positives and false negatives during mammography screening [9].

Table 1. Summary of Breast Cancer Detection Research using Data, Algorithms and Accuracy.

Ref.	Dataset Used	Algorithms / Models Used	Limitation	Accuracy
[1]	Wisconsin Breast Cancer Diagnostic (569)	Agglomerative Hierarchical Clustering, Gradient Boosting, Stochastic Gradient Descent, Quadratic Discriminant Analysis, and Naive Bayes	The small dataset and the absence of clinical features incorporation can have an impact on practical implications.	Highest Accuracy: 99.30%
[2]	BreakHis (7909)	CNN and Quantum Tensor Network with GLCM, LBP, and Gabor filtering	Multimodal fusion architecture adds complexity and cost of computation to the models.	Image-level and patient-level accuracies exceeding 98%
[3]	WDBC(569)	SVM, ANN, KNN, Decision Tree (DT)	Structured datasets are predominantly used in the study, which potentially restricts the ability to work on various clinical data.	SVM: 99.8%
[4]	Large-scale clinical mammography dataset (FFDM) (134,488)	Supervised Contrastive Pre-Training (SCP), Supervised Fine-tuning (SF), CNN backbones (ResNet, ConvNeXt)	The model comparison has not been founded on large-scale or multi-institutional datasets.	SCP+SF framework achieved 92.7%

[5]	Coimbra dataset(116 subjects)	Metaheuristic algorithms (WOA, BESA, SLOA), XGBoost classifier, and SHAP analysis.	The algorithms of feature selection and optimization are essential for model performance.	97.43% F-score, 97.14% accuracy, 97.14% precision, and 100% recall
[6]	Large histopathologic al image dataset(2834)	Transfer learning with SVM, Decision Tree, Boosted Tree, and KNN	Needs big labeled data and can experience overfitting when trained on small data.	99.5% accuracy
[7]	WDBC (569)	SVM, KNN, DT, RF, NB	Compared to deeper networks, a lightweight design can decrease the ability of extracted features.	~98% accuracy
[8]	CBIS-DDSM (3100), MIAS (322)	Mammo-light (LightWeight Convolutional Neural Network)	The method is primarily aimed at mammography images and could fail to generalize to other medical images.	CBIS-DDSM: 99.17%, MIAS: 98.42%
[9]	Unnormalized Breast Cancer Histopathology Images(2480), BreaKHis (9109)	Lightweight Deep Convolutional Neural Network (LDCNN)	The assessment on small datasets can have an impact on the model's reliability and generalization.	Histopatholog y dataset- 99.2% accuracy and BreaKHis dataset- 98.6% accuracy

Table 1 is an overview of similar studies in breast cancer detection published recently and summarizes the dataset involved, machine learning and deep learning models implemented, year of publication, and performance measures. It emphasizes the tendencies in the choice of algorithms and shows the impacts of various datasets and model types on the diagnostic accuracy.

3. KEY FINDINGS AND OPEN RESEARCH CHALLENGES

- **Good Diagnostic Performance of the AI Models -** There are numerous studies that claimed quite high accuracy (above 98% on average) when hybrid machine learning and deep learning were used, which means that AI-based systems could be of great help in the early detection of breast cancer.
- **Efficacy of Hybrid and Ensemble Approaches -** A combination of different algorithms results in better prediction with combinations of clustering and supervised classifiers, or optimization and boosting models. But these complicated architectures can augment computational needs.
- **Significance of Quality Medical Datasets -** In the training and evaluation of models, the significance of such public datasets as CBIS-DDSM, MIAS, BreaKHis, and Coimbra can be crucial. One issue is that most of the models are only tested using small datasets, which could lower their applicability in real life.
- **Requirement of lean and fast models -** A number of works are aimed at creating a lightweight CNN implementation that is less costly in terms of computation but is as precise as possible. The difficulty lies in having the trade-off between model efficiency and high feature extraction ability.

- **Scanty Clinical validation and Generalizations -** Although these are promising experimental results, many of the models have not been tested on large and multi- hospital clinical data, and much more work is required to translate them into practice.

4. DISCUSSION

The analysis of the chosen research articles shows how machine learning and deep learning techniques become more and more important in improving the detection and diagnosis of breast cancer. Many papers proposed hybrid systems, which are a blend of clustering algorithms, optimization, and various classifiers to enhance the forecast. These techniques have high accuracy, which is usually more than 98 percent, demonstrating that a combination of techniques can give far superior diagnostic accuracy. In addition, feature selection and dimensionality reduction methods were also commonly utilized to pick the best features that were useful to the effectiveness of the model as well as to reduce the computational complexity.

The other urgent aspect is the popularity of deep learning models, particularly the convolutional neural networks (CNNs), as an instrument for analyzing mammography and histopathological pictures. The models can also discover intricate patterns in medical images automatically, without involving manual feature engineering. Several research papers also provided lightweight neural network models that reduced the computation requirements without compromising on the high classification accuracy. Such models can be mostly used in medical facilities where fast and efficient diagnosis is required.

The studies reviewed were based on publicly available datasets, including CBIS-DDSM, MIAS, BreaKHis, WDBC, and the Coimbra dataset, to train and test their models. Although these datasets have helped in making breakthroughs in breast cancer detection studies, most of the models have been tested on a few or a single dataset. Consequently, upcoming studies need to test such models on greater and more heterogeneous clinical samples so that they can guarantee enhanced generalization and practical application in medical diagnosis systems.

5. CONCLUSION

Breast cancer remains one of the most important health issues in women across the globe since early intervention is crucial to increase the survival rate and minimise the complexity of treatment. The analyzed studies indicate that machine learning and deep learning methods are now effective in enhancing the diagnosis of breast cancer. Medical datasets and mammography images have been analyzed using different methods, such as hybrid machine learning models, convolutional neural networks, feature selection methods, and lightweight deep learning architectures, among others. Most of these studies have obtained high predictiveness, which means that artificial intelligence can be of great help to medical practitioners in the early diagnosis of breast cancer.

Nevertheless, there are a number of limitations and challenges, even though these results are promising. Most research uses small or publicly available datasets that might not be a complete reflection of clinical diversity in the real world. Also, convoluted deep learning systems and hybrid models can consume high computational power, which can be constraining to the application in healthcare systems with the potential of limited infrastructure. There are also some approaches that pay more attention to the enhancement of the accuracy and less to the model interpretability, which is necessary to win the trust of healthcare specialists.

Subsequent research ought to then focus on developing more generalized and understandable frameworks by working with larger and more diversified clinical data, and the development of computationally efficient systems that are readily integrated into clinical decision-support environments. These will be addressed and will help in the creation of viable, scalable, and clinically viable breast cancer detection systems that can drive early diagnosis and maximize patient outcomes.

6. FUTURE SCOPE

Future research should prioritize the development of clinically robust breast cancer detection systems by addressing the limited generalizability of current models trained on small, single- source datasets . This necessitates the use of large-scale, multi-institutional cohorts and external validation protocols to ensure cross-domain reliability. From a modeling perspective, there is a need to transition from unimodal learning to multimodal frameworks that jointly learn from mammography, histopathology, and structured clinical variables using attention- based fusion mechanisms.

To overcome the trade-off between high accuracy and computational complexity observed in hybrid and deep learning models, future work should explore parameter-efficient architectures, including lightweight CNNs augmented with transformer-based modules (e.g., Vision Transformers or hierarchical attention networks) for capturing long-range dependencies. Rigorous evaluation strategies, such as nested cross-validation and statistically grounded performance comparison, should be adopted to mitigate overfitting and ensure reproducibility. Furthermore, advanced imbalance-aware learning techniques (e.g., focal loss, cost-sensitive optimization, and distribution-aware sampling) are required to improve minority-class detection. The integration of explainable AI methods, including gradient-based localization (Grad-CAM) and feature attribution (SHAP), should be embedded within the model pipeline to enhance interpretability and clinical trust. Finally, future systems should emphasize deployability through model compression, edge-compatible inference, and privacy-preserving learning paradigms to facilitate real-world clinical integration.

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