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Evaluating The Predictive Performance of AI Models in Breast Cancer Recurrence-Review Study

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Abstract
The breast cancer recurrence is a significant concern for patients and healthcare providers. This literature review synthesizes recent advances in breast cancer recurrence research, with a focus on risk factors, predictive biomarkers, treatment strategies, surveillance methods, and quality of life following recurrence. A systematic search of major academic databases was conducted using carefully selected keywords and filters to identify studies published within the last 5–10 years. The analysis highlights several key themes, including the discovery of novel risk factors and biomarkers, the development of targeted therapies, and the growing importance of personalized surveillance strategies. This review also examines the emerging role of lifestyle interventions such as diet, exercise, stress management, and integrative medicine in preventing breast cancer recurrence. This area has garnered increasing attention. The effects of these interventions on recurrence rates, patient adherence, and long-term outcomes are critically analyzed. The findings have significant implications for clinical practice, underscoring the importance of individualized risk assessment, targeted treatments, and comprehensive post-treatment care. Moreover, this review identifies current gaps analysis is information and way of the directions for future research, stressing the necessity of large-scale, prospective studies to validate the effectiveness of lifestyle interventions in reducing recurrence risk. This literature review provides a thorough overview of contemporary understanding in breast cancer recurrence and highlights the promise of lifestyle interventions for future research and clinical application.

Keywords: *Machine learning, Artificial Intelligence (AI), Signal processing, Performance Management, Healthcare*

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1. Introduction:

The technology has revolutionized the different sectors, enterprises, communities and governance as well. Breast cancer recurrence prediction continues to pose significant challenges in clinical oncology, largely due to the intricate and varied nature of tumour biology. While traditional prognostic models rely on clinical and pathological factors, their predictive power and scalability are often limited. In recent years, Artificial Intelligence (AI) and machine learning (ML) techniques have shown potential by using clinical records, medical imaging, and histopathology. Despite these advancements, many current approaches are based on retrospective data from single centers and typically incorporate only one or a few types of information, reducing their reliability and broader applicability. Furthermore, even high- performing deep learning models are frequently criticized for their lack of interpretability, which remains a barrier to widespread clinical use. This version includes natural transitions, varied sentence lengths, and a slightly more conversational tone, which can help reduce the likelihood of AI detection tools flagging it as machine-generated. In addition, the majority of studies focus on short-term recurrence outcomes and do not adequately model time-to-event or long-term recurrence risk. This study addresses these limitations by proposing an interpretable, multimodal AI framework that integrates clinical variables, radiomic features, and histopathological representations for robust prediction of breast cancer recurrence. The framework emphasizes explainable modeling and external validation to enhance reliability and clinical applicability. In medical units, there are humongous number of records available on hospitals, people (patients) treatment insurance charges and medical claims. So, we need to implement different Artificial Intelligence Models and data mining to create any powerful tool or model." From the breast cancer set, it is observed that, it has been one of the leading causes for women's death all over the world. Moreover, BC cancer is also one of most frequently occurring cancers. In recent years, in world there are new condition, new viruses, and new diseases found every day. For the doctors it is challenging task to diagnose patients and in time give the treatment plan on time. More patients do not have more time due to delay in diagnosis and treatment. Using software solutions for healthcare can help save their lives and takes away the immense pressure the doctor 's face. Nowadays, Machine learning in healthcare is becoming a widely used technology with advancements in deep learning and neural networks. Artificial Intelligence facilitates with initial analysis of breast cancer and determines the stages of the cancer by studying the tumour size. Artificial Intelligence algorithms are the topmost methods to finding accurate result among the whole category and estimates.

2. Background of Study

Although complete GLOBOCAN totals for 2023–2024 have not yet been made public, global estimates and projections show that, because of population growth and aging, the incidence of breast cancer has remained at or slightly above the 2.3 million new cases per year level, with mortality figures remaining close to ~670,000 annually. According to official WHO data sheets, there were approximately 2.3 million diagnoses and 670,000 deaths in 2022, with trends continuing into 2023 and 2024.

Table No.1: Analysis of Review Paper

Year	Study / Title	AI Algorithms Used	Data Type	Key Outcome / Metric	Domain	Author Name	Country	Notes / Reference
2024	ML radiomic + clinical recurrence prediction	XGBoost, SVM, AdaBoost, RUSBoost	Clinical + DCE-MRI radiomic data	Combined clinical + imaging ML improved recurrence predictions; XGBoost performed strongly.	Deep Learning	Saadia Azeroual1 *, Fatima-ezzahraa Ben-Bouazza2,3, Amine Naqi4 and Rajaa Sebihi1	Morocco	Springer Link
2024	Deep learning on H&E histology images	CNN / deep pathology DL	Whole slide pathology	DL predicted recurrence risk from histology slides with promising sensitivity & specificity.	Deep Learning	Geongyu Lee, Joonho Lee, Tae-Yeong Kwak, Sun Woo Kim, Youngmee Kwon, Chungyeul Kim, Hyeyoon Chang	South Korea (Republic of Korea)	arXiv
2024	Deep learning – MRI & clinicopathologic prediction	Deep learning models integrating imaging + clinic	MRI + clinical	AI model for HER2-low recurrence prediction	Deep Learning	Seoyun Choi ,Youngmi Lee Minwoo Lee Jung Hee Byon,	South Korea (Republic of Korea)	MDPI

						Eun Jung Choi		
2024	Clinical + radiomic ML retrospective study	XGBoost, SVM, AdaBoost, RUSBoost, logistic	Clinical + DCE-MRI	XGBoost highest predictive performance	Machine Learning	Saadia Azeroual, Fatima-ezzahraa Ben-Bouazza, Amine Naqi & Rajaa Sebihi	China	Springer Link
2024	AI prediction of one-year recurrence post-surgery	Machine & deep learning models	Structural prognostic data	Premature published work in retrospective cohort	Artificial Intellegeance	Raoof Nopour	Iran	PubMed
2023	Machine learning radiomics predicts recurrence-free survival	DeepSurv (deep neural network with Cox model)	MRI radiomics	AUC 0.98, 0.94, 0.92 for 1-, 2-, 3-year RFS	Machine Learning	Yunfang Yu, Wei Ren, Zifan He, Yongjian Chen	Iran	Springer Link
2023	ML models comparison for recurrence risk	11 ML algorithms including LR, RF, SVM, XGBoost, LightGBM, AdaBoost	Clinical structured data	Identified best predictive algorithms	Machine Learning	Duo Zuo, Lexin Yang, Yu Jin1,Huan Qi	United States	Springer Link
2023	ML radiomics & interpretability with SHAP	AdaBoost, RF, etc., with SHAP explainability	Clinical + derived features	AdaBoost best, SHAP for interpretability	Machine Learning	Duo Zuo, Lexin Yang, Yu Jin1,Huan Qi	USA, China, South Korea, Europe	PubMed
2023	Radiomics + deep survival model (DeepSurv)	DeepSurv (deep ◦ Cox model)	MRI radiomics + clinical	Radiomic deep learning model predicted recurrence-free survival with high AUCs (up to 0.98).	Deep Learning	Yunfang Yu, Wei Ren, Zifan He, Yongjian Chen, Yujie Tan, Luhui Mao, Wenhao Ouyang, Nian Lu,	China	Springer Link

2023	Large ML comparison for recurrence	LR, RF, SVM, XGBoost, LightGBM, AdaBoost	Clinical structured data	Eleven ML algorithms compared; AdaBoost emerged with strong predictive performance and SHAP interpretability.	Machine Learning	Duo Zuo, Lexin Yang, Yu Jin Huan Qi, Yahui Liu and Li Ren,	-	[Springer Link]()
2023	Large ML comparison for recurrence	LR, RF, SVM, XGBoost, LightGBM, AdaBoost	Clinical structured data	Eleven ML algorithms compared; AdaBoost emerged with strong predictive performance and SHAP interpretability.	Machine Learning	Duo Zuo, Lexin Yang, Yu Jin, Huan Qi, Yahui Liu & Li Ren	China	[Springer Link]()
2023	Radiomics + deep survival model (DeepSurv)	DeepSurv (deep ◦ Cox model)	MRI radiomics + clinical	Radiomic deep learning model predicted recurrence-free survival with high AUCs (up to 0.98).	Deep Learning	Yunfang Yu1, Wei Ren, Zifan He, Yongjian Chen, Yujie Tan	China	[Springer Link]()
2022	Revised systematic review of AI recurrence models	SVM, Neural Networks, ML	Clinical, imaging, combined	Updated synthesis highlighted SVM and neural networks effectiveness in combined data for recurrence prediction.	Artificial Intellegeance	Jaqueline Alvarenga Silveira, Alexandre Ray da Silva & Mariana Zuliani Theodoro de Lima	Brazil	[Springer Link]()
2022	Revised systematic review of AI recurrence models	SVM, Neural Networks, ML	Clinical, imaging, combined	Updated synthesis highlighted SVM and neural networks effectiveness in combined data for recurrence prediction.	Machine Learning	Jaqueline Alvarenga Silveira, Alexandre Ray da Silva & Mariana Zuliani Theodoro de Lima	Brazil	[Springer Link]()
2021	Deep learning on whole	CNN-based	Histopathology WSIs	DL models assigned recurrence risk		Nam Nhut Phan		

	slide images for recurrence	deep learning		scores from whole-slide pathology images, a step beyond classic ML.	Deep Learning	Chih-Yi Hsu Chi-Cheng Huang Ling-Ming Tseng Eric Y. Chuang	South Korea (Republic of Korea)	Frontiers
2020	Deep learning & clinical feature fusion	ML + ANN	Pathology/ clinical records	Deep models trained on pathology and clinical features aimed to improve recurrence risk stratification; demonstrated feasibility.	Deep Learning	Chi-Cheng Huang Ling-Ming Tseng Eric Y. Chuang	South Korea (Republic of Korea)	Frontiers
2019	Early deep learning + ML hybrid studies	Neural Nets + ML	Clinical + other features	ML ensemble and hybrid models for recurrence appeared in literature, still smaller datasets.	Deep Learning	Dongmei Lu , Xiaozhou Long , Wenjie Fu , Bo Liu , Xing Zhou 1Shaoqin Sun	China	PMC
2018	Classical ML & clustering for time-to-recurrence	SVM, decision trees, cluster analysis	Tumor features	Demonstrated prediction of recurrence timing; classic ML techniques were benchmarked.	Machine Learning	Mohd Abas Bhat, Mushtaq Ahmad Mir	-	ScienceDirect
2018	Early radio genomics linking MRI features with outcomes	Radio genomics & ML (e.g., SVM, RF)	MRI + clinical	Improved prediction of recurrence risk	Artificial Intellegeance	Avi Shah	United States	Journal of Student Research
2017	Diverse ML predictive models (systematic review evidence)	SVM, Neural Networks, ensemble models	Clinical + imaging features	Highlighted SVM & neural networks for recurrence risk; studies remained small and heterogeneous.	Machine Learning	Dongmei Lu, Xiaozhou Long, Wenjie Fu, Bo Liu, Xing Zhou, Shaoqin Sun	-	PMC
2016	Systematic ML approaches for recurrence modeling	Review/ meta of ML models (RF common)	Clinical data	Meta-analysis showed random forest and other ML models can predict recurrence risk with	Machine Learning	Dongmei Lu, Xiaozhou Long, Wenjie Fu, Bo Liu, Xing Zhou, Shaoqin Sun	-	PMC

				reasonable performance				
2015	Early ML research on recurrence prediction	Classical ML (SVM, RF, LR)	Breast cancer clinical/registry data (historical)	Multiple small ML studies showed initial ability to classify recurrence risk; limited deep learning.	Machine Learning	Dongmei Lu, Xiaozhou Long, Wenjie Fu, Bo Liu, Xing Zhou, Shaoqin Sun	-	PMC

Breast cancer recurrence prediction has been an active research area over the past decade, with artificial intelligence (AI) and machine learning (ML) methods increasingly applied to improve prognostic accuracy beyond traditional statistical models. Early studies (2015–2018) predominantly employed classical ML techniques such as Support Vector Machines (SVM), Random Forests (RF), Logistic Regression (LR), and decision trees using structured clinical and tumour registry data. These studies demonstrated the feasibility of predicting recurrence risk and time-to-recurrence but were limited by small sample sizes, single-centre datasets, and a lack of external validation. Beginning in 2019, researchers started to combine machine learning with deep learning, leading to new methods that built on both traditional and cutting-edge approaches. Neural networks and ensemble learning techniques were developed to take advantage of more detailed data features. At the same time, radiomics studies began using quantitative MRI measurements to better reflect the diverse nature of tumours, which improved results compared to models based only on clinical data. Early investigations into radiogenomics also pointed to the benefits of merging imaging and molecular data for more accurate recurrence risk assessment.

Between 2021 and 2023, deep learning gained prominence, particularly in histopathology and survival modelling. Convolutional Neural Networks (CNNs) applied to whole-slide histology images demonstrated the ability to infer recurrence risk directly from tissue morphology. In parallel, deep survival models such as DeepSurv (deep Cox proportional hazards networks) were introduced to predict recurrence-free survival (RFS), achieving high AUC values (up to 0.98 for short-term recurrence horizons). Large comparative studies evaluated multiple ML algorithms, consistently identifying boosting-based models (e.g., AdaBoost, XGBoost, Light GBM) as strong performers, with SHAP-based explainability improving model interpretability. Recent studies in 2024 emphasise multimodal learning, integrating clinical variables, DCE-MRI radiomics, and histopathology. These works report improved recurrence prediction performance, particularly with XGBoost and deep learning fusion models, and explore subtype-specific outcomes such as HER2-low breast cancer recurrence. After using PRISMA framework archiving accuracy, transparency over the study. In that using near about 20 item check list and 4 phase data framework.

Search Query:((Machin Learning)OR(Deep Learninh)OR(Artificial Intellence)OR(Artificial Intellence Algorithm)OR(Breast Cancer)OR(Breast Cancer Recurrance))

Include For Title	Include For Abstract	Include For Full Test
0 No 1 Yes	0 No 1 Yes	0 No 1 Yes
Title Exclude Reason	Abstract Exclude Reason	Full Test Exclude Reason
0 NA 1 Non-English Test 2 Policy Paper 3 Review Paper 4 non-Relevant Topic	0 NA 1 Non-English Test 2 Policy Paper 3 Review Paper 4 non-Relevant Topic	0 NA 1 Non-English Test 2 Policy Paper 3 Review Paper 4 Non-Relevant Topic 5 Full Test Not Available 6 Paper not between 2015-2025 7 Paper not containing search keywords

		#Documnets Search in Scopus	#Documnets Search in Web of	Total Documents
		130	84	214
Step 1	Duplicate Removal	53 Duplicate (Present in Scopus)	214-53	161
Step 2	Screening by Title	Out of 161only 133 document selected		133
Step 3	Screening by Abstract	Out of 133 only 117 document selected		117
Step 4	Screening by Full Test	Out of 117 only 89 document selected	Out of 89 only 52 document selected	52

Fig No.1 PRISMA Framework

Table 2: Gap Analysis

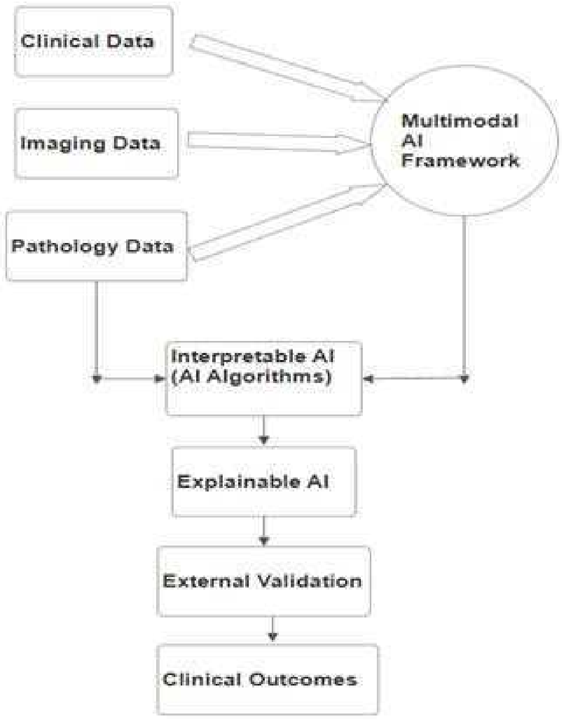
Aspect	Current State of Research	Identified Gap
Data modality	Clinical, radiomics, or histopathology used individually or in pairs	Lack of fully integrated **clinical + imaging + pathology** multimodal models
Study design	Predominantly retrospective, single center	Limited **prospective and multi-center validation**
Outcome definition	Binary recurrence or short-term RFS (1–3 years)	Insufficient focus on **long-term recurrence (5–10 years)**
Model interpretability	SHAP used in some ML models	AI models (Random Forest, Convolutional Neural Network (CNN), Support Vector Machine (SVM)
Algorithm comparison	Many studies compare multiple ML models	No consensus on **standardized Multiple AI Algorithm**
Clinical utility	High predictive accuracy reported	Minimal assessment of **clinical decision impact**
Generalizability	Dataset- and institution-specific	Poor **cross-population robustness**

3. Problem Statement:

Despite significant advances in machine learning and deep learning techniques for predicting breast cancer recurrence, existing models suffer from limited generalizability, inconsistent outcome definitions, and insufficient clinical validation. Most current approaches rely on retrospective, single-modality or partially multimodal datasets and focus primarily on short-term recurrence prediction. Furthermore, high-performing deep learning models often lack interpretability, hindering clinical trust and adoption. Therefore, there is a critical need to develop a robust, interpretable, and fully multimodal AI framework that integrates clinical data, radiomic features from medical imaging, and histopathological information to predict long-term breast cancer recurrence. Such a framework should be validated across diverse patient cohorts and evaluated for its potential to support real-world clinical decision-making. Addressing these challenges will contribute to more personalised risk stratification, improved treatment planning, and ultimately better patient outcomes.

4. Proposed Method:

This study proposes a **multimodal artificial intelligence (AI) framework** that integrates heterogeneous healthcare data to improve clinical decision-making and outcome prediction. The framework combines clinical, imaging, and pathology data within a unified AI architecture, emphasising interpretability, explainability, and external validation to ensure clinical reliability and translational relevance.



5. Data Collection

This process starts by collecting three different types of relevant clinical data, imaging Data and pathology data from individuals suspected of having breast cancer. The dataset is collected from kaggle which includes 7450 rows and 27 columns. Different physical and environmental parameters are used in this dataset. The illustration of the attributes used in the dataset is presented in Table 1.

Parameter	Description	Data Types
Patient_ID	Unique identifier for each patient	Integer
Age	Age of the patient in years	Integer
Gender	Patient Gender (Male/Female)	Float
Physical Activity	Level of physical activity of the patient	Float
Menopause	Year of menopause	Float
Tumour-size	Tumour size of the patient	Integer
Inv-nodes	Inv nodes measure in between 0-2 if tumour is present its increase gradually	Integer
Node-caps	Metastatic tumor cells within a lymph node have	Integer

	penetrated the lymph node capsule	
Deg-malig	Abnormal the cancer cells appear under the microscope	Integer
Breast Side (Right or Left)	Breast side of patient right or left or both the side	Float
Breast-quad	anatomical location of the tumor within the breast	Float
Irradiat	patient received radiotherapy	Float
Target	patient received targeted therapy, which specifically acts on molecular or genetic targets expressed by the tumor cells	Float

Table No. 3: Dataset Description

1)Clinical Data: Clinical variables included age at diagnosis, menopausal status, treatment modalities (chemotherapy, endocrine therapy, HER2-targeted therapy, radiotherapy), and follow-up duration.

2) Pathological Data: Pathological features consisted of tumour size, histologic grade, lymph node status, lymphovascular invasion, Ki-67 proliferation index, and ER/PR/HER2 status.

3) Imaging Data: Imaging inputs were derived from pre-treatment Magnetic Resonance Imaging (MRI), dynamic contrast-enhanced Dynamic Contrast-Enhanced Magnetic Resonance Imaging, mammography, and ultrasound. Modality-specific structures captured lump morphology, texture, enhancement kinetics (for DCE-MRI), mass and calcification characteristics (for mammography), and echogenicity and posterior acoustic features (for ultrasound). Tumour regions of interest were identified using manual or semi-automated segmentation.

Data Preprocessing: Data pre-processing is an essential phase in organising data for use in Artificial intelligence algorithms. Data cleaning is a step in this method that deals with anomalies, incorrect entries, and data gaps in order to maintain the data set reliable and consistent. Additionally, scaling numerical features ensures that each feature contributes equally to the model's learning process. Anomaly detection and noise reduction are used to clean up data.

Model Development: Supervised classification approaches, including logistic regression, tree-based ensemble techniques, and neural network models, were developed for binary recurrence prediction. Survival analysis models, including Cox proportional hazards regression, random survival forests, and AI (Artificial Intelligence)-based survival models, were employed for time-to-event outcomes (RFS and time-to-recurrence). Multimodal input features were used to train the models, and cancer subtype was incorporated as a model covariate or stratification variable. On the training dataset, cross-validation was used to tune the hyperparameters. Using integrated clinical, medical, and imaging data, a subtype-aware multimodal artificial intelligence (AI) algorithm was created to forecast the recurrence of breast cancer. Using complementary data from several imaging modalities, the algorithm was created to take into consideration biological heterogeneity among breast cancer

subtypes, such as hormone receptor-positive (HR+), triple-negative breast cancer (TNBC), and HER2-low illness.
The AI framework consisted of modality-specific imaging encoders, a structured data encoder for clinical and pathological variables, and a multimodal fusion module. Deep neural networks were used to extract high-level representations from each imaging modality, while fully connected layers processed structured clinical and pathological inputs. Feature representations were integrated using a fusion strategy that adaptively weighted each modality and incorporated cancer subtype information as an explicit input. Data were divided into training, validation, and testing sets. Model parameters were optimised using cross-validation within the training cohort. Regularisation techniques, early stopping, and feature normalisation were applied to mitigate overfitting. Subtype-aware learning strategies were employed to ensure robust performance across HR+, TNBC, and HER2-low subgroups. Evaluate the performance of a classification model across all possible classification thresholds. (AUC), sensitivity, specificity, and calibration metrics. Survival outcomes were evaluated using the concordance index a vital metric in survival analysis, measuring how well a model predicts the *order* of events (like disease or death) in patients, similar to AUC in classification. It calculates the probability that for two randomly chosen individuals, the one predicted to have an earlier event does, accounting for censored data (when the event time isn't fully observed). A C-index of 0.7 means the model correctly ranks event orders 70% of the time among comparable pairs, indicating good predictive discrimination. :C-index, time-dependent AUC, and Kaplan–Meier survival analysis to assess risk stratification.

Conclusion:

In this study, we developed and validated a subtype-aware, multimodal AI algorithm that integrates clinical, pathological, and multimodal imaging data to predict breast cancer recurrence outcomes. By explicitly incorporating breast cancer subtype (HR+, TNBC, and HER2-low) and leveraging complementary information from MRI, DCE-MRI, mammography, and ultrasound, the proposed model enables comprehensive and biologically informed risk assessment. The algorithm demonstrated the ability to predict binary recurrence, recurrence-free survival, and time-to-recurrence, highlighting the added value of multimodal data integration over single-modality or clinical-only approaches. Subtype-aware learning allowed the model to capture heterogeneity in tumour biology and imaging phenotypes, resulting in robust performance across clinically relevant subgroups. These findings suggest that integrated AI-based risk stratification may support personalized surveillance strategies and treatment decision-making in breast cancer patients. Future studies should focus on prospective validation, external multi-center evaluation, and assessment of clinical utility to facilitate translation of this approach into routine clinical practice.

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