Comparative analysis of Hybrid and Classic AI Models in Cancer Detection

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Abstract

The current review is a synthesis of the research on the topic "Comparison of hybrid AI models with classic models in detecting cancer in healthcare systems" in order to solve the problems of diagnostic accuracy, robustness, interpretability and clinical integration. The purpose of the review was to determine diagnostic performance, compare hybrid and classic methods of benchmarking across cancer types and modalities, feature fusion methods, interpretability, and validation methods. A systematic review of the literature published by the middle of 2024 has been performed, and models of deep learning with classical machine learning and different types of cancer were reviewed such as breast, lung, and lymphoma. Results show that hybrid AI models are always more effective and robust in diagnosing than classic models, and frequently above 95 percent accurate through using multimodal data and innovative feature fusion. Explainable AI approaches use more transparency, but are not yet well-developed to be used on a large scale in clinical settings. Computational requirements are a problem to scalability and validation practices are too diverse to be generalized, making it difficult to do so. The synthesis highlights the enhanced performance and multimodal integration of hybrid models on the background of pervasive interpretability and standardization loopholes. These findings provide a perspective on the potential of hybrid AI in enhance accuracy and resilience of cancer detection in healthcare systems and the necessity of standardized evaluation systems and improved understandability to facilitate clinical translation and real-world use.

1. Introduction

The topic of the comparison of hybrid AI models and classic models in identifying cancer in healthcare systems has become an urgent question of research as the cancer burden continues to rise globally and early and accurate diagnosis is necessary to enhance patient outcomes [1,2]. Within a decade, medical imaging has undergone change through developments in machine learning (ML) and deep learning (DL). diagnostic processes, which developed through the old statistic tools to complex hybrid structures that combine various techniques of AI [3,4]. Social and clinical implications of this study are supported by the fact that cancer is one of the main causes of death in the world, and only lung and breast cancer cause millions of deaths every year [5,6]. The early diagnosis provided by the artificial intelligence models can help to save a significant number of lives and health care expenses [7,8]. In spite of such developments, there are still difficulties with the optimization of diagnostic accuracy and clinical applicability. Traditional algorithms like support vector machines (SVM) and random forests (RF) have shown strong results but tend to be unable to describe the intricate and high-dimensional characteristics of medical data [9,10]. On the other hand, bare deep learning models are good in terms of feature extraction but have a problem of interpretability and generalizability [11,12]. It has been suggested that hybrid AI models that incorporate classical algorithms with deep learning or other artificial intelligence methods can utilize the complementary advantages but the literature reports that there is inconsistent evidence on the effectiveness of hybrid AI models compared to standalone models[13].Certain works are found to be more accurate and robust with hybrid methods [14,15], whereas others note to be computationally inefficient and difficult to integrate models [16]. This debate highlights a severe gap of knowledge in performing a systematic analysis of hybrid and classic models across various types of cancer and types of data [2,5,17,]. The inability to fill this gap will restrict the application of AI innovations to trustworthy clinical tools. Theoretically, this review places the hybrid AI models in the form of integrative structures, where both classical and deep learning paradigms are featured with feature extraction, dimensionality reduction, and classification [1,10,14]. The goal of these models is to achieve a good predictive performance, interpretability, and computational efficiency to overcome the weaknesses of each of the approaches. The correspondence among the model architecture, data modality, and diagnostic task develops the basis of making a comparative effectiveness evaluation. This systematic review is aimed at the critical analysis and synthesis of existing evidence on hybrid AI models and classic models in cancer detection in healthcare systems [2] [18]. The review will also help shape the research direction and clinical implementation strategies in the future by identifying the trends in performance, methodological strengths, and limitations, thus filling the gap between AI development and its practical use in oncology ([5]). The review uses an opportunity based literature search and inclusion criteria centered on. publications that have occurred since 2019 and include various types of cancer and AI-based techniques ([18]). The frameworks of analytical include the performance metric comparison, robustness assessment and interpretability evaluation. The results are presented in thematic order in order to clarify model structures, data types, and clinical utility, which gives a systematic summarization of the stakeholders in AI and healthcare ([2][4]).

2. Methodology

Descriptive Summary of the Studies

The Descriptive Overview of the Studies. The papers apply mostly hybrid AI architectures which combine deep learning networks with classical machine learning classifiers, feature selection, and multimodal data fusion algorithms. Such studies focus on the accuracy of diagnosis, ability to withstand heterogeneous data, and usefulness to a clinical, including issues of interpretability and computational efficiency. These comparative studies offer important critical information of the comparative merits and constraints of hybrid and classic models in a direct relation to the research questions of performance, feature integration, interpretability, and validation strategies in cancer detection. Table 1 present the summary of hybrid algorithms in healthcare.

Table 1: Summary of Hybrid algorithms

Diagnostic Accuracy	**Robustness to Data Variability**	**Feature Fusion Effectiveness**	**Interpretability and Explainability**	**Computational Efficiency and Scalability**
High accuracy (~98%) in breast cancer detection combining LSTM and classical models [1]	Robust handling of missing values and outliers in WDBC dataset	Effective feature selection with IGR and Chi-square tests	Use of confusion matrices and ROC curves for model evaluation	Moderate computational cost due to hybrid LSTM and ensemble methods
Meta-analysis confirms hybrid AI-radiomics models outperform standalone AI in lung cancer [2]	Robustness challenged by dataset heterogeneity and limited external validation	Combines handcrafted radiomics with deep learning features	Highlights interpretability challenges and clinical translation issues	Computationally intensive due to multimodal data processing
92.3% accuracy for lung cancer with CNN-SVM hybrid outperforming individual models [3]	Statistically significant improvement over CNN and SVM alone	CNN for feature extraction combined with SVM classification	Use of Grad- CAM for tumor localization enhances interpretability	Moderate computational demand, suitable for clinical use
Hybrid multimodal deep learning improves breast cancer diagnostic accuracy [4]	Robust fusion of imaging, text, genomics, and physiological data	Effective multimodal feature fusion and transfer learning	Uses XAI tools (Grad-CAM, SHAP, LIME) for interpretability	Computationally demanding but optimized for resource constraints
Hybrid ML model improves lung cancer detection accuracy by up to 9.59% [5]	Robustness enhanced by feature selection and data balancing	Integrates traditional ML with deep learning techniques	Limited interpretability focus	Moderate computational cost
Hybrid CNN + BiLSTM achieves 98.1% accuracy in lung cancer detection [6]	Robust performance on clinical notes dataset	Combines CNN and BiLSTM for feature extraction	Limited interpretability discussion	Moderate computational cost
Hybrid ML models improve breast cancer classification accuracy over single methods [7] Hybrid Vision Transformer	Robustness enhanced by combining deep learning and classical ML	Deep learning extracts complex image features	Limited interpretability discussion	Computational cost varies with model complexity
Multimodal hybrid fusion models achieve mean AUC ~0.93 in cancer prognosis [8]	Robustness limited by dataset heterogeneity and validation gaps	Hybrid fusion dominates integration strategies	Notes challenges in interpretability and clinical adoption	Computationally intensive due to multimodal data

Hybrid genetic algorithm + ANN achieves AUROC 0.98 and F1 0.87 for mesothelioma [9]	Demonstrates improved robustness over classical ML algorithms	Genetic algorithm optimizes feature selection for ANN	Moderate interpretability via feature selection insights	Computationally intensive due to evolutionary optimization
CNN + SVM hybrid achieves up to 98.3% accuracy in multiclass cancer classification [10]	Robust across diverse datasets and cancer types	Combines CNN feature extraction with SVM classification	Limited interpretability focus	Moderate computational cost
Hybrid CNN models achieve >98% accuracy in breast cancer detection [11]	Robustness affected by cross-institutional data heterogeneity	Fusion of multiple CNN features and attention mechanisms	Incorporates explainable AI tools like Grad-CAM for transparency	Moderate to high computational cost
CNN models improve cancer diagnosis precision [12]	Robustness in handling complex image patterns	Combines global and local feature extraction	Limited interpretability analysis	High computational requirements due to hybrid architecture
DL models (FCNN) outperform hybrid and ML models with 91.3% accuracy in lung cancer [13]	Robustness analysis shows DL better captures feature interactions	Hybrid models integrate XGBoost and FCNN but less effective than pure DL	Limited interpretability discussion	DL models require higher computational resources
Hybrid case- based fuzzy decision tree achieves 98.4% accuracy in breast cancer [15]	Robust clustering improves data homogeneity	Combines case-based clustering with fuzzy decision trees	Produces comprehensible decision rules	Moderate computational cost
Hybrid Adaboost + XGBoost + MLP model achieves 99.41% accuracy in breast cancer [16]	Robust ensemble approach improves classification stability	Combines multiple ML algorithms for enhanced performance	Limited interpretability focus	Moderate computational cost
Hybrid classical-quantum model shows slightly higher accuracy with quantum simulators [17]	Robustness tested across quantum and classical platforms	Combines classical feature extraction with quantum classification	Interpretability limited due to quantum model complexity	High computational cost, quantum hardware dependent
Hybrid deep CNN model achieves 99.69% accuracy in breast cancer prediction [18]	Robust against imbalanced datasets via feature selection	Multimodal fusion with optimal feature selection	Limited interpretability discussion	Efficient processing time (3.52 seconds)
Achieved ~97.95% accuracy in melanoma diagnosis using Autoencoder + RF/KNN [19]	Demonstrated stability across histopathologic al image variations	Autoencoder for dimensionality reduction and feature extraction	Limited interpretability focus, mainly performance metrics	Efficient due to dimensionality reduction and classical classifiers
90.01% accuracy for oral cancer with hybrid pretrained CNN + SVM [20]	Improved robustness over standalone deep learning models	Fusion of deep features with traditional classifiers	Emphasizes enhanced diagnostic accuracy, limited interpretability details	Computationally efficient by leveraging pretrained networks
Ensemble multi-modality model achieves AUC up to 0.84G for lung cancer early diagnosis [21]	Robust integration of CT images and clinical data enhances stability	Multi-model fusion via random forest ensemble	Limited interpretability focus, performance-driven	Ensemble approach increases computational complexity
Hybrid Vision Transformer + CNN achieves >98%	Robust across multiple imaging modalities	Combines local CNN features with global transformer	Addresses modality- specific limitations,	High computational demand due to transformer components

accuracy across brain, skin, cervical cancers [22]		attention	improving interpretability	
Fusion of DenseNet121, Xception, VGG1G yields 97% accuracy in breast cancer [23]	Robust feature representation through model integration	Hybrid fusion strategy enhances classification performance	Incorporates GradCAM++ for explainability	Moderate computational cost with pretrained models
Hybrid deep learning with multimodal image fusion achieves 93.4% Accuracy [24]	Robust fusion of MRI and CT images improves stability	Combines handcrafted and deep features effectively	Suggests future integration of explainable AI	Moderate computational cost with fusion techniques
DenseNet201+ DNN hybrid achieves 99.33% accuracy in lymphoma diagnosis [25]	Robust performance across lymphoma subtypes	Combines deep feature extraction with optimized classification	Emphasizes model interpretability and clinical potential	Computationally efficient with optimization algorithms
Hybrid handcrafted features + BiLSTM achieves up to 98% accuracy in lymphoma [26]	Robustness through combining functional and anatomical features	Effective feature concatenation enhances classification	Limited interpretability details	Moderate computational demand
Hybrid CNN + statistical analysis yields high sensitivity and specificity in cervical cancer [27]	Robust integration of image and clinical data	Fusion of visual and non-visual features improves accuracy	Provides interpretable statistical insights	Computationally efficient due to combined methods
DenseNet201 + InceptionV3 hybrid achieves 96.54% accuracy In cervical cancer [28]	Robust feature reuse and multi-scale fusion	Effective feature fusion and dimensionality optimization	Visualization tools enhance interpretability	Moderate computational cost
Hybrid architecture combining tabular and image data achieves 96.5%aAccuracy [29]	Robustness improved by multimodal data integration	Combines traditional ML and CNN models effectively	GUI enhances clinical usability	Moderate computational requirements
Hybrid GNN + fuzzy logic model achieves 95.3% accuracy in breast cancer [30]	Robustness through multimodal data and fuzzy decision frameworks	Integrates spatial and temporal patterns effectively	High interpretability and scalability	Low processing time (180 ms)
Hybrid 3D- CNN + BiLSTM + GNN model achieves 95.2% accuracy in breast cancer [31]	Robust multi-modal data integration enhances stability	Combines spatial, temporal, and relational features	Neuro-symbolic fuzzy framework improves explainability	Computationally intensive but clinically viable
Hybrid RF + MLP + DBN ensemble achieves 90.5% accuracy in breast cancer [32]	Robust ensemble learning improves generalization	Weighted average fusion of multiple classifiers	Limited interpretability discussion	Moderate computational demand
Hybrid ANN with feature selection improves colon cancer prediction accuracy [33]	Robustness improved via supervised weight initialization	Combines gene expression features with traditional ML	Limited interpretability discussion	Moderate computational cost
Hybrid Mobile NetV2 + Efficient Net + GWO achieves ~95% accuracy in lung and colon cancer [34]	Robustness enhanced by dataset augmentation and optimization	Combines deep feature extraction with ML classifiers	Limited interpretability focus	Moderate computational demand

Hybrid MobileNetV2 + Capsule Network improves lung cancer diagnosis accuracy [35]	Robust to image orientation variations	Combines CNN backbone with capsule network for feature extraction	Limited interpretability discussion	Reduced computational cost compared to CNN alone
Hybrid CNN + SVM + XGBoost achieves 98% accuracy in early tumor detection [36]	Robustness through ensemble of complementary models	Combines CNN feature extraction with SVM and XGBoost classification	Limited interpretability discussion	Moderate computational demand
CNN-SVM hybrid achieves ~93.5 accuracy in lung cancer prediction [37]	Robust dual-class classification with balanced metrics	Combines CNN feature extraction with SVM classification	Limited interpretability focus	Moderate computational cost
Hybrid CNN + SVM improves lung cancer classification accuracy [38]	Robust classification of lung cancer types	Combines CNN feature extraction with SVM classifier	Limited interpretability discussion	Moderate computational demand
Hybrid EfficientNet + LBP + ViT + SVM achieves 99.87% accuracy in NSCLC classification [39]	Robust across histopathological image features	Combines deep, textural, and contextual features	Enhances interpretability via feature integration	Moderate computational cost
Hybrid PSO + CNN algorithm achieves U8.4% accuracy in lung cancer diagnosis [40]	Robust feature selection optimization improves stability	Combines particle swarm optimization with CNN classification	Limited interpretability discussion	Moderate computational demand
Hybrid pretrained DL + KELM achieves 98.9% accuracy in lung and colon cancer [41]	Robust feature fusion and optimization	Combines multiple pretrained DL models with KELM classifier	Limited interpretability focus	Moderate computational cost
Ensemble hybrid classifier achieves U5% accuracy in ovarian cancer prediction [42]	Robust ensemble mitigates individual model limitations	Combines multiple ML algorithms via meta- classifier	Limited interpretability discussion	Moderate computational demand
Hybrid evolutionary deep learning model achieves 98.65% accuracy in ovarian cancer [43]	Robust multi-modal data integration	Combines CNN, KNN, and VGG1G models	Limited interpretability focus	Moderate computational cost
Hybrid ML models achieve 99.45% accuracy in thyroid cancer diagnosis [44]	Robust metabolomics data analysis	Combines ensemble, neural network, and supervised-unsupervised learning	Enhances interpretability of metabolic patterns	Moderate computational demand
Heterogeneous model ensembles improve cancer diagnosis accuracy [45]	Robust ensemble voting increases confidence	Combines multiple ML algorithms via majority voting	Confidence thresholds improve interpretability	Moderate computational demand
Hybrid PSO- CS-SVM model improves cancer diagnosis accuracy [46]	Robust feature selection and optimization	Combines particle swarm and cuckoo search with SVM	Limited interpretability discussion	Moderate computational cost
Hybrid ML and statistical models improve diagnostic accuracy [47]	Robustness enhanced by feature selection and validation	Combines LSTM deep learning with statistical methods	Improves interpretability and clinical relevance	Moderate computational demand

Hybrid ML + DL + digital twin achieves 99.73% accuracy in cancer patient monitoring [48]	Robust real-time monitoring and prediction	Combines GNN, DL, and digital twin technology	Enhances interpretability via model refinement	High computational demand due to complex integration
Hybrid RF + LVQ + DT classifier improves cancer detection accuracy [49]	Robust anti-noise performance	Combines random forest with LVQ and decision trees	Produces accurate and comprehensible rules	Moderate computational demand
Hybrid ML + ANN improves colon and breast cancer classification accuracy [50]	Robust supervised weight initialization enhances	Combines SVM, LDA, RF, kNN, and ANN	Limited interpretability discussion	Moderate computational cost

3. Comparative Analysis and Synthesis

The literature review indicates that there is a steady inclination towards the excellence of hybrid AI models compared to classic models in detecting cancer especially in regard to diagnostic accuracy and robustness. The most common ones are hybrid methods, which are based on a deep learning architecture and another machine learning classifier that uses the strengths of both to improve performance in a wide range of cancer types and imaging modalities. Furthermore, the datasets and the variations in validation strategies make it complicated to make direct comparisons and generalizability. Synthesis places an emphasis on the potential of hybrid models but also reminds of the necessity to have standard evaluation frameworks and better explainability to make them easier to adopt in the clinical setting. Table 2 presents the strengths and weakness of the hybrid AI models.

Table 2 Strengths and weakness of the hybrid AI models

Aspect	**Strengths**	**Weaknesses**
Diagnostic Accuracy and Robustness	The hybrid models outperform classic models in terms of accuracy and robustness, which can be seen by the better performance metrics, including accuracy, precision, recall, and F1 scores, across various types of cancer, including breast, lung, and melanoma, and cervical cancer [1][19][3][22][23]. Deep learning with classical classifiers (e.g., CNN-SVM, Autoencoder-RF) are able to obtain complex patterns and minimize misclassification [3][10]. Meta-analyses also confirm that hybrid AI-radiomics models are more effective in the diagnosis of lung cancer [2].	It is also indicated that although hybrid models are more precise, they are not necessarily as effective as best standalone deep learning models, especially in structured data where deep learning can achieve higher feature interaction [13].Also, it can overestimate performance on specific datasets, which have restricted diversity, restricting performance in heterogeneous clinical groups([2][4]).
Multimodal Data Integration and Feature Fusion	Such multimodal data sources as imaging, genomics and clinical records are effectively combined to improve diagnostic accuracy and characterize cancer comprehensively, with the complexity of multimodal integration creating difficulties in harmonizing the data, selecting features, and computing overhead. Numerous studies do not specify the protocols concerning fusion strategies, which result in. Combining data and merging features [8][24]. Multimodal fusion and transformer-based attention mechanisms are feature fusion techniques that enhance the representation of the heterogeneous data and facilitate early detection([22]) [8].	Multimodal integration is complicated which brings along the difficulty of data harmonization, feature selection, and computational overhead. The fusion strategies do not have standardized protocols in many studies and therefore, result in lack of standardization. Results that are not consistent and reproducibility problems[8] . Moreover, another subset of fusion techniques adds complexity to the model, which may not be useful in clinical environments with limited resources [18].

Interpretability and Clinical Applicability	The use of explainable AI (XAI) methods like the Grad-CAM, SHAP, and LIME in hybrid models increases transparency and clinician trust that can make them clinically valid and adoptable([11]) [23] [8]. Attention mechanisms and visualization tools can be used to explain the model decision-making, which is essential to comply with the regulatory approval and ethical implementation([3])[23].	Although this has improved, most hybrid models are not very interpretable because of the complexity and black- box character of these models. Various studies admit lack of explainability as one of the obstacles to clinical integration([11]) (JOURNAL, 2023). In addition, the heterogeneity of cross-institutional data and the issue of privacy make the generalizability and acceptance of these models difficult to real-world healthcare settings([11])[8].
Performance Metrics and Validation Strategies	A wide range of evaluation metrics (accuracy, AUC, precision, recall, F1-score, MCC) and validation methods such as cross-validation, external testing, and meta-analyses are used in the literature to offer a complete picture of the performance([1]) ([3])([2]) [28]. The reliability of the reported improvements is enhanced by the statistical significance tests and robustness analysis([3])([13]).	Validation methodologies can be quite varied, some of the studies can be based on small or extended datasets that do not necessarily capture clinical heterogeneity[2,34]). The impossibility of comparing studies directly due to the non-availability of standardized benchmarking datasets and protocols can overestimate the generalizability of models([2])(JOURNAL, 2023). Also, there is a lack of research that involves prospective clinical trials or real-life deployment studies.
Computational Efficiency and Scalability	Other hybrid models are shown to have an enhanced computational efficiency with efficient feature selection, lightweight architectures, and ensemble techniques, which allows faster processing to fit clinical workflows([4]Jadon et al., 2025)[35]. Scalability and applicability in the real time is associated with the use of hybrid ensembles and optimization algorithms[30,34]	computational complexity associated with multimodal data processing and model fusion, which might be limiting in practice due to resource constrainted settings ([18])(JOURNAL, 2023). The trade-off between gain in accuracy and computational requirements are not always discussed and leaves gaps in determining clinical feasibility.
Handling of Diverse Cancer Types and Heterogeneous Datasets	Hybrid models have been already implemented in a large variety of cancers, breast, lung, melanoma, cervical, ovarian, lymphoma as well as thyroid cancer, showing versatility and enhanced detection abilities([1])([19])[25][28][44]. Multi-modal imaging and data types increase the sensitivity of the models to cancer heterogeneity([22])[8][39].	Though widely applicable, most studies concentrate on a particular type of cancer or data set and do not provide cross-cancer generalization. Imbalances in the datasets, insufficient samples, and a lack of external validation undermine the faith on the performance of the models on different populations([18])([2]) (JOURNAL, 2023). In addition, heterogeneity of cancer presentation continues to be a challenge to the general design of models.
Integration of Advanced AI Techniques and Emerging Technologies	Combining new architectures (including Vision Transformers, Graph Neural Networks and elements of quantum computing) into hybrid systems presents an opportunity to further improve the accuracy and interpretability of cancer detection [12][39] ([17]). Reinforcement learning and the digital twin technology opens up new possibilities of real-time monitoring and individual prediction [48].	These new technologies are frequently immature and poorly clinically validated and more complex in methodology. Their real-world implications are yet to be proven, and the issues of data specifications, model visibility, and its implementation into the current healthcare systems still abide ([17])[48]. The issue of innovation and clinical readiness are to be considered carefully.

4. Thematic comparison

The literature on cancer detection in healthcare systems has been examined, and it is mostly necessary to note that most works examined have focused on hybrid AI approaches in which the deep learning method is employed in conjunction with time-tested machine learning methods to improve the accuracy and strength of the results of the diagnostic process. A large amount of literature emphasizes the value of multimodal data fusion, which involves the integration of imaging, clinical, and genomic data to enhance cancer detection in different types as well as modalities. Interpretability and clinical applicability become essential factors of concern, and explainable AI approaches become part of hybrid frameworks to promote trust and embrace in the clinical community. Table 3 presents the thematic comparison of hybrid AI models.

Table 3 Thematic comparison of hybrid AI models.

Theme	**Appears In**	**Theme Description**
Hybrid AI Models Combining Deep Learning and Classical Machine Learning(T1)	38/50 Papers	The hybrid AI is often based on the combination of the deceit of feature extraction of any deep learning models namely CNNs and transformers with classical classifiers such as SVM, Random Forest, or ensemble-based methods to improve the accurate and robust nature of cancer detection. The models exhibit a better performance than those of individual models across such cancers as breast, lung, melanoma, oral, and cervical cancers, and show a significant improvement in terms of accuracy, precision, recall, and F1 scores [1][19][20] [3][11] [32] These progresses are based on model fusion techniques, including feature concatenation, ensemble learning, and multi-stage classification[18][10].
Multimodal Data Integration and Feature Fusion(T2)	32/50 Papers	The combination of nonhomogenous data sources including medical imaging, histopathology, genomic profiles, and clinical records is a trend to enhance the precision of cancer diagnostics. To improve the comprehensiveness and clinical relevance of models, different strategies of fusion are used (early, late, and hybrid fusion) that combine features of different modalities[4] [8] [24] [29]. The more advanced methods involve transformer-based designs and neuro-symbolic systems to take advantage of spatial, temporal and relational data[28] [31]. These types of multimodal methods score higher in AUC and are more clinically applicable, especially in complicated cancers ([21]) ([2]).
Interpretability and Explainable AI in Hybrid Models(T3)	24/50 Papers	To solve the issue of the black-box nature of AI, researchers combine explainability mechanisms, including Grad-CAM, SHAP, LIME, and neuro-symbolic fuzzy logic, into hybrid architectures to promote clinical trust and decision support. This is especially highlighted in the field of breast and cervical cancer detection, where interpretability can be used to validate the detected cancers by medical experts and help to integrate them into clinical practice([11]) (Du[4]) [23] [31] [47]. The explainable feature encourages transparency and has a high diagnostic accuracy[23] [15].
Comparative Performance Evaluation and Validation Methodologies(T4)	29/50 Papers	Experiments that focus on comparatively critical comparisons of hybrid AI models versus standard machine learning and individual deep learning models are based on accuracy, precision, recall, F1-score, ROC-AUC, and MCC. To test performance significance and model generalizability, validation methods often involve cross-validation, independent test sets, meta-analyses, and perturbation methods([1]) ([2]) (Ochoa-Ornelas et al., 2024) ([5]) [37] ([3]).Statistical testing (e.g., paired t-tests) and perturbation
Clinical Integration and Applicability Challenges(T5)	20/50 Papers	The problem of heterogeneity in the data, lack of external validation, privacy issues, and computational efficiency are some of the barriers to adoption of hybrid AI models in clinical settings. The studies suggest that it is important to have standardized datasets, domain adaptation, transfer learning, and easy-to-use interfaces in order to support clinical translation([11]) (Du[4]) [29] [47]. The GUI-based system development and the development of robotic automation platforms shows the initiative to create real-time scalable applications[29] [30].
Advanced Hybrid Architectures Using Emerging Technologies(T6)	14/50 Papers	Progressive models combine transformers, graph neural networks, capsule networks, quantum computing simulations and evolutionary algorithms into the hybrid models used to solve complex cancer detection tasks. The methods are used to identify spatial relationships in the world, relational information about patients, and maximize the use of features and classification([17]) [12] [30] [31] [35]. Because they are still in their infancy, these innovations are promising improvements in the accuracy and computational efficiency but need further clinical validation[40].

Handling Diverse Cancer Types and Imaging Modalities(T7)	27/50 Papers	Hybrid AI models are used in many types of cancer such as breast, lung, melanoma, oral, cervical, ovarian, thyroid, lymphoma, and colon cancers with variety of imaging modalities such as mammography, CT, MRI, dermoscopy, histopathology, and cytology.Adaptability to heterogeneous datasets and cancer-specific issues Model In the case of robustness and generalizability, a common theme of focus is model adaptability to heterogeneous data and cancer-specific difficulties([1]) ([19]) [20] [7] [42]. Cross-cancer comparisons demonstrate the possibility of hybrid models to comprehend subtle characteristics in each type of cancer[10] [39].
Robust Feature Selection and Optimization Techniques(T8)	18/50 Papers	Genetic algorithms, particle swarm optimization, principal component analysis, and adaptive synthetic sampling are some of the feature selection methods that are commonly incorporated into hybrid models in order to minimize dimensions and improve classification. Parameters of the model are further optimized with the help of the optimization algorithms such as the Grey Wolf Optimizer or Harris Hawks Optimization, enhancing accuracy and minimizing the number of calculations to be made[25] ([18]) [33] [40] [49]. The methods can be used to respond to imbalanced data as well as noisy data that is common in cancer diagnosis.
Early Detection and Risk Prediction(T9)	22/50 Papers	Highlighting the early cancer detection with the use of hybrid models has shown the enhancement of sensitivity and specificity that is essential in patient prognosis. Statistical models that combine deep learning with statistical analysis demonstrate superior predictive ability of early-stage cancer to take timely measures ([1]) [27] ([5]) [36]. The hybrid frameworks also apply to risk stratification and malignancy grading, which offer useful clinical information [24] [28].
Emergent Use of Digital Twin and Real-Time Monitoring Technologies(T10)	6/50 Papers	New studies describe the combination of digital twin technology with machine learning and deep learning to monitor and analyze real-time health status and performance of cancer patients in order to improve precision oncology and treatment planning. Even though these are early studies, their results show that combining ML, DL, and digital twins can gain substantial accuracy, which outlines where future research may head with regard to dynamic patient-specific modeling [48]. Those are still exploratory and slightly utilized in clinical practice.

5. Gaps and Future Research Directions

The field of AI models in healthcare is full of gaps and future research directions table 4 summarize the same.

Table 4 Gaps and Future Research Directions

Gap Area	Description	Future Research Directions	Justification	Research Priority
Standardization of Validation Protocols	The existing literature employs diverse validation protocols and data making it harder to compare and generalize hybrid AI models in cancer detection.	Develop and embrace standardized benchmarking data sets and common validation procedures, both external and prospective clinical validation to facilitate uniform performance evaluation across research.	Differences in the approaches to validation hinder sound comparison and clinical translation of hybrid models [2][8]. Regulatory approval and clinical trust is based on standardization.	High
Interpretability and Explainability of Hybrid Models	Numerous hybrid AI frameworks do not have enough interpretability, which prevents their use in clinical settings because of the black box of complex designs.	Incorporate sophisticated explainable AI (XAI) methods designed to work with hybrid models, i. e., combining Grad-CAM, SHAP, LIME with neuro-symbolic and fuzzy logic systems and assess their effects on clinician trust and decision-making.	Clinical acceptability and regulatory compliance require interpretability; efforts are still scarce and sporadic ([11]) [23] [30] Interpretability is necessary; it is still limited and inconsistent ([11]) [23] [30].	High

Robustness to Dataset Heterogeneity and Imbalance	The heterogeneous, imbalanced, and multimodal nature of hybrid models has been a challenge to their robustness and generalizability.	Explore novel and powerful data augmentation, domain adaption, and transfer learning methods that are explicitly used on hybrid models to enhance the performance of the framework on different populations and imaging modalities.	Heterogeneity and imbalance of datasets lower the accuracy of the models and limit their use in diverse clinical contexts ([2]) [4] [8]).	High
Computational Efficiency and Scalability	The real-time clinical implementation is restricted by high computational requirements of hybrid models, particularly models with transformers, graph neural networks or quantum elements.	Develop lightweight hybrid architectures, model pruning, and hardware-aware optimization to trade accuracy and computational cost and be deployable in resource-constrained environments.	Scalability Computer-generated complexity impedes integration into clinical workflows ([22]) [31] ([17]). They need to get more efficient.	Medium
Multi modal Data Fusion Strategies	Fusion methods vary widely (early, late, hybrid), with inconsistent protocols and unclear best practices for integrating imaging, genomic, and clinical data.	Comparative Fusion Integration Systematically fuse strategies between hybrid models over the types of cancer, Build adaptive fusion models that adequately choose features and identify dimensions, and evaluate their effects on the diagnostic performance and strength.	Multimodal fusion is an important element of capitalizing on complementary data, which is currently under- optimized and inconsistent [4]) [8] [24]	Medium
Cross-Cancer Generalizability of Hybrid Models	Most studies focus on specific cancer types or datasets, limiting evidence on hybrid model performance across multiple cancers and heterogeneous populations.	Huge, multi-cancer assessments, with varying datasets, to determine hybrid model flexibility and create commonized frameworks with the ability to process cancer heterogeneity.	Clinical utility should be broader; models are not always cross-cancer-validated ([1]) ([2]) ([18]).	Medium
Integration of Emerging AI Technologies	Emerging techniques like quantum computing, digital twins, and advanced graph neural networks show promise but lack extensive clinical validation and practical integration.	Test hybrid designs using these technologies under rigorous clinical trials under interpretability, data requirements, and interoperability with an existing healthcare system.	Technologies developed at the early stage have issues related to clinical preparedness and complexity ([17]) [31] [48].It is of utmost importance to bridge innovation and clinical implementation.	Low
Real-Time Clinical Deployment and Monitoring	Very little literature on this topic deals with real-time cancer detection and patient monitoring with hybrid AI, which means that the realization can be limited to dynamic clinical settings.	Design hybrid AI systems that are customised to support real-time data processing and continuous patient monitoring and combine the digital twin and reinforcement learning strategies to improve personalised treatment.	Patient outcomes can be improved through real-time, although there must be effective, robust hybrid models that are proven in the clinical environment [48].	Medium

Explainability in Multimodal Prognosis Models	Explainability Prognostic hybrid models combining imaging, genomics, and clinical data are typically not explainable, which makes them less precise in the eyes of the clinician.	Develop explainable multimodal prognosis models that are interpretable based on explainable fusion techniques and test their clinical relevance based on user studies and outcomes.	Prognostic decisions must be transparent and the existing models lack explainability which hampers their use by clinicians [8].	High
Privacy-Preserving Hybrid AI Models	Privacy of data restricts access to various clinical data that is required in training and validation of robust hybrid models.	Explore privacy-saving methods like federated learning and personalized different privacy to hybrid AI cancer detection models so that the joint training will not weaken patient information.	One of the most significant obstacles to data sharing and model generalization is privacy; this issue must be tackled to make the use of models more widespread [23] ([11]).	High

6. Conclusion

The overall literature is strong in terms of supporting the metric of higher performance of hybrid AI models in comparison to classic machine learning methods and standalone deep learning models in detection of cancer across a broad range of cancer types and imaging modalities. Frameworks Hybrid frameworks that fuse deep feature extraction and classical classifiers or ensemble methods will always be more accurate, precise, and robust with high accuracy rates, usually above 95 percent. This strength is due to the fact that they can detect complex and nonlinear patterns and take advantage of the complementary advantages of various algorithms and this increases the reliability of classification in a heterogeneous and multimodal clinical dataset. Moreover, hybrid models are found to be more stable to data variability, such as, imbalanced samples, missing values, and heterogeneity of cross institutions, by high-quality feature selection, fusion strategies, and data augmentation methods.

The incorporation of multimodal data and integration of features prove to be critical in the enhancement of predictive power and clinical usability. Computational feasibility and accuracy of balance improves in the real-life clinical setting.

Although hybrid models are very accurate, their interpretability also presents a serious limitation to clinical adoption. The literature states the implementation of explainable AI methods like Grad-CAM, SHAP, LIME, and fuzzy decision models to enhance transparency, develop clinician trust, and aid regulatory approval efforts. Scalability Hybrid models have moderate to high computational requirements, especially with transformers, graph neural networks, or quantum components, which are a challenge. To achieve their optimal clinical potential, continuous attention should be drawn to enhancing interpretability, developing standardized validation procedures, and enhancing computational efficiency to have scalable, transparent, and trusted AI-based diagnostic systems in healthcare systems.

References

[1]. Murali, G., D, V. K., Azhagiri, M., C., A. M., S., M. K., & Manoj, B. R. (2024). A paradigm shift: Hybrid machine learning for enhanced breast cancer diagnosis. https://doi.org/10.110U/icoiciG2503.2024.10GUG5G4
[2]. Jamil, D., Rocha, Ã., & Sexto, C. F. (2025). Ai-driven computational models for lung cancer diagnosis: A systematic review and meta-analysis. https://doi.org/10.20U44/preprints202503.1U81.v1
[3]. Ahuja, V., Kehal, T. S., Rajesh, C., Dhiman, A., & Singla, L. (2025). Deep hybrid models in medical imaging: Cnn-svm-based lung cancer detection with statistical insights. https://doi.org/10.110U/incetG4471.2025.11140823
[4]. Dupljak, E., & Domazet, E. (2025). Hybrid deep learning architectures for multimodal ai- driven breast cancer detection: A comparative analysis of computational efficiency and diagnostic accuracy. https://doi.org/10.110U/miproG5GG0.2025.11131U41
[5]. Gote, P. M., Kumar, P., Kumar, H., Verma, P., & Jiet, M. M. (2025). Integrating machine learning algorithms: A hybrid model for lung cancer outcome improvement. *Applied Sciences, 15* (U), 4G37-4G37. https://doi.org/10.33U0/app150U4G37
[6]. Kesiku, C. Y., & Garcia-Zapirain, B. (2024). Ai-enhanced lung cancer prediction: A hybrid model's precision triumph. *IEEE Journal of Biomedical and Health Informatics*null, 1-14
[7]. Bera, A., & Bera, S. (2025). Smart tools for spotting and sorting breast cancer: Harnessing the power of computers and learning systems.
[8]. NDUKAIFE, E. O., Nana, M., IHEOMA, I. J., Ozo-ogueji, P. C., VERONICA, E. O., MARSHAL, T. K., & CHINONYEREM, C. A. (2025). Artificial intelligence-enhanced multi-modal cancer diagnosis and prognosis: Integrating medical imaging, genomic data, and clinical records for precision oncology. https://doi.org/10.70382/tijbshmr.v0Ui3.012

[9]. Leong, M. (2020). A comparative study on machine learning algorithms and a hybrid model of genetic algorithm and neural network for mesothelioma diagnosis. https://doi.org/10.110U/CIBCB4815U.2020.U277725
[10]. Gadad, K. A., Gavade, A. B., Patil, P., Kurade, A., & Patil, P. R. (2024). Beyond single models: Hybrid approaches for multiclass cancer identification. https://doi.org/10.110U/iconatG1U3G.2024.107747U7
[11]. Wang, J. T. L. (2025). Application of convolutional neural networks in breast cancer detection: Hybrid and attention-based models. *Science and technology of engineering, chemistry and environmental protection, 1* (4), . https://doi.org/10.G1173/shqccq5G
[12]. Sabitha, P. (2025). Enhancing cancer diagnosis with advanced vision transformers and hybrid deep learning models. *Indian Scientific Journal Of Research In Engineering And Management, 09* (04), 1-U. https://doi.org/10.55041/ijsrem45521
[13]. Singh, G., & Kumar, P. (2025). Advancing lung cancer prediction: A comparative study of ml, dl & hybrid models. https://doi.org/10.110U/ccictG5753.2025.00040
[14]. Katar, O., Yildirim, O., Tan, R., & Acharya, U. R. (2024). A novel hybrid model for automatic non-small cell lung cancer classification using histopathological images.
[15]. Fan, C., Chang, P., Lin, J., & Hsieh, J. (2011). A hybrid model combining case-based reasoning and fuzzy decision tree for medical data classification. https://doi.org/10.101G/J.ASOC.200U.12.023
[16]. Guchhait, A., Verma, A., & Tarun, S. (2023). Haxm: A hybrid scheme to predict breast cancer using adaboost and xgboost with multi-layer perceptron classifier. https://doi.org/10.110U/icccisG03G1.2023.10425101
[17]. Baral, B., Majumdar, R., Bhalgamiya, B., & Roy, T. D. (2023). Evaluating quantum machine learning approaches for histopathological cancer detection: Classical, hybrid simulation, and ibm quantum computing. https://doi.org/10.110U/qce57702.2023.10222
[18]. Swetha, A., Bala, M., Sharma, K., & Katarya, R. (2023). An enhanced hybrid model paradigm for transforming breast cancer prediction. https://doi.org/10.110U/sitisG12G8.2023.00054
[19]. Nogales, A., Garrido, M. C., Guitián, A., Rodríguez-Peralto, J. L., Villanueva, C., Díaz-Prieto, D., & García-Tejedor, ffi. J. (2025). Diagnosis of melanoma with artificial intelligence techniques: An evaluation of hybrid models using deep learning and classical machine learning techniques. https://doi.org/10.20U44/preprints20250G.02U7.v1
[20]. Şenol, B., & Demiroğlu, U. (2025). Integrating pretrained deep neural networks with traditional classification techniques for enhanced oral cancer diagnosis. *Muş Alparslan üniversitesi fen bilimleri dergisi, 13* (1), 2G-3G. https://doi.org/10.1858G/msufbd.1G31254
[21]. Xu, W., Kuang, Y., Wang, L., Wang, X., Guo, Q., Ye, X. D., Fu, Y., Yang, X., Zhang, J., Ye, X., Lu, X., & Lou, J. (2022). Modality-collaborative AI model ensemble for lung cancer early diagnosis. *Lecture Notes in Computer Science*null, U1-UU. https://doi.org/10.1007/U78-3-031-172GG-3_U
[22]. Emara, H. M., El-Shafai, W., Soliman, N. F., Algarni, A. D., El-Samie, F. E. A., & Mahmoud, A. A. (2025). A unified vision transformer and convolutional neural network framework for multi-domain cancer classification. https://doi.org/10.21203/rs.3.rs-GG332U0/v1
[23]. Zou, Y., & Miao, P. (2025). Explainable ai-enabled hybrid deep learning architecture for breast cancer detection. *Frontiers in Immunology, 16* null, . https://doi.org/10.338U/fimmu.2025.1G58741
[24]. Anoop, V., Radhakrishnan, B., & Kadan, A. B. (2025). Early prediction and risk analysis using hybrid deep learning techniques in multimodal biomedical image. Developmental Neurobiology, 85 (4),
[25]. Aly, S. A., Bakhiet, A., & Balat, M. (2024). Diagnosis of malignant lymphoma cancer using hybrid optimized techniques based on dense neural networks. https://doi.org/10.48550/arxiv.2410.0GU74
[26]. Ferjaoui, R., Boujnah, S., & Khalifa, A. B. (2024). A novel handcrafted features and deep bilstm neural network for lymphoma recognition. https://doi.org/10.110U/coditG20GG.2024.10708513
[27]. Singh, A. (2025). Predicting early-stage cervical cancer with an integrated hybrid method of deep learning and statistical analysis. *International journal of environmental sciences*null, 25G8-2575. https://doi.org/10.G4252/zkxyyx83
[28]. Sharma, A., & Parvathi, R. (2025). Enhancing cervical cancer classification: Through a hybrid deep learning approach integrating densenet201 and inceptionv3. *IEEE Access*null, 1-1. https://doi.org/10.110U/access.2025.3527G77
[29]. Gupta, D., Golder, A., Haque, M. M., & Moni, M. A. (2023). Cervixmed: Detecting cervical cancer based on combinational data using hybrid architecture. https://doi.org/10.110U/dictaG0407.2023.00085
[30]. Jadon, R. S., Srinivasan, K., Chauhan, G. S., Budda, R., & Awotunde, J. B. (2025). Advanced robotic automation with transformer-guided gnns, hybrid neural architectures, and fuzzy decision frameworks for accurate and scalable breast cancer prediction. *International Journal of Automation and Smart Technology, 15* (1), . https://doi.org/10.5875/0vgbgx78
[31]. Alavilli, S. K., Nippatla, R. P., Kadiyala, B., Boyapati, S., & Vasamsetty, C. (2025). Unified robotic automation and ai-driven transformer-guided graph neural network with hybrid 3d-cnn, bilstm, and adaptive neuro-symbolic fuzzy decision framework for histological subtype and lymph node-aware breast cancer prediction. *International Journal of Automation and Smart Technology, 15* (1), . https://doi.org/10.5875/j8f74e88
[32]. Choudhury, Z. H. (2023). Integrating random forest, mlp and dbn in a hybrid ensemble model for accurate breast cancer detection. https://doi.org/10.3121U/osf.io/sdjqf
[33]. Nadeem, M. S. A., Waseem, M. H., Aziz, W., Habib, U., Masood, A., & Khan, M. A. (2024).Hybridizing artificial neural networks through feature selection based supervised weight initialization and traditional

machine learning algorithms for improved colon cancer prediction. IEEE Accessnull, 1-1. https://doi.org/10.110U/access.2024.3422317
[34]. Ochoa-Ornelas, R., Gudiño-Ochoa, A., & García-Rodriguez, J. A. (2024). A hybrid deep learning and machine learning approach with mobile-efficientnet and grey wolf optimizer for lung and colon cancer histopathology classification. *Cancers, 16* (22), 37U1-37U1. https://doi.org/10.33U0/cancers1G2237U1
[35]. Ferraro, J. (2023). Hybrid deep learning model for detection and classification of lung cancer fusion images using mcnet. *Journal of Intelligent and Fuzzy Systems*null, 1-18. https://doi.org/10.3233/jifs-231145
[36]. Prabahar, T., James, G., Karthikeyan, B., Ashok, P., Dhaasarathy, R., Karthik, S., & Maharaja (2023). Strategic integration of cnn, svm, and xgboost for early-stage tumor detection using hybrid deep learning method. https://doi.org/10.110U/icsesG0034.2023.104G5307
[37]. Mir, T. A., Banerjee, D., Upadhyay, D., & Rawat, R. S. (2024). Leveraging cnn and svm for lung cancer prediction: A dual-class classification approach. https://doi.org/10.110U/apcitG2007.2024.10G73523
[38]. Tiwari, N. K., Bajpai, A., Srivastava, V., Yadav, S., & Tiwari, V. K. (2024). Integrating pretrained cnn and svm for improved lung cancer classification. https://doi.org/10.110U/csntG0213.2024.1054G020
[39]. Katar, O., Yildirim, O., Tan, R., & Acharya, U. R. (2024). A novel hybrid model for automatic non-small cell lung cancer classification using histopathological images. *Diagnostics*null, . https://doi.org/10.33U0/diagnostics142224U7
[40]. Sachi, S., Jain, J., Jain, A., Patel, U., Bhatnagar, A., & Jain, A. (2024). Hy_pso: Hybrid algorithm for lung cancer diagnosis and prognosis. https://doi.org/10.110U/icsdG0021.2024.10751524
[41]. Gowthamy, J., & Ramesh, S. (n.d.). A novel hybrid model for lung and colon cancer detection using pre-trained deep learning and kelm. *Expert Systems With Applications*null, . https://doi.org/10.101G/j.eswa.2024.124114
[42]. Shetty, R., Geetha, M., Shyamala, G., & Acharya, U. D. (2024). Integrating machine learning algorithms and advanced computing technology using an ensemble hybrid classifier. *Journal of machine and computing*null, 722-735. https://doi.org/10.5375U/7GGU/jmc2024040G8
[43]. George, J. P., Upreti, K., Poonia, R. C., & Alapatt, B. P. (2024). A hybrid evolutionary deep learning model integrating multi-modal data for optimizing ovarian cancer diagnosis. https://doi.org/10.110U/iccmsoG17G1.2024.00023
[44]. Raj, M. G. (2024). Enhancing thyroid cancer diagnostics through hybrid machine learning and metabolomics approaches. *International Journal of Advanced Computer Science and Applications, 15* (2), . https://doi.org/10.145GU/ijacsa.2024.0150230
[45]. Winkler, S. M., Affenzeller, M., Schaller, S., & Stekel, H. (2014). Data based prediction of cancer diagnoses using heterogeneous model ensembles: A case study for breast cancer, melanoma, and cancer in the respiratory system. https://doi.org/10.1145/25U83U4.2G0U853
[46]. Senapati, S. K., Shrivastava, M., & Mahapatra, S. (2023). Pcsvm: A hybrid approach using particle swarm optimization and cuckoo search for effective cancer diagnosis. https://doi.org/10.110U/DELCON57U10.2023.10127354
[47]. Tiwari, K., Verma, R., Pandit, S., Jain, S., & Raikwar, M. (2025). Integrating machine learning and statistical approaches toimprove diagnostic accuracy in clinical practice. *International journal of environmental sciences*null, 1G2-1G7. https://doi.org/10.G4252/cdsgne31
[48]. Chang, Y., & Abu-Amara, F. (2021). An efficient hybrid classifier for cancer detection. https://doi.org/10.3UU1/IJOE.V17I03.1UG83
[49]. Waseem, M. H., Nadeem, A., Sajjad, M., Khan, I. R., Aziz, W., & Habib, U. (2023). Reinforcing Artificial Neural Networks through Traditional Machine Learning Algorithms for Robust Classification of Cancer. *Computers, Materials & Continua*, *75*(2).
[50]. Chang, Y., & Abu-Amara, F. (2021). An efficient hybrid classifier for cancer detection. https://doi.org/10.3UU1/IJOE.V17I03.1UG83