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A REVIEW ON HYBRID AI TECHNIQUES FOR CANCER DETECTION

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Abstract

Since this is a main issue in healthcare, new approaches are required to increase the accuracy of cancer diagnosis and the results for patients. "This paper proposes a hybrid artificial intelligence framework combining several AI approaches like rule-based systems, deep learning, and machine learning to improve cancer detection across several modalities, including genetic data, radiological scans, and histopathological images. While addressing issues such imbalanced datasets, overfitting, and interpretability, the framework makes use of the capabilities of particular approaches, such ensemble methods for robustness, convolutional neural networks (CNNs), and support vector machines (SVMs). Current augmentation techniques preprocess the data to guarantee diversity and lower noise. They then cross-evaluate the model after optimizing it with hyperparameter changes. Area under the curve (AUC-ROC), recall, accuracy, precision, and F1-score all show rather notable increases when compared to stand-alone methods. Using explainability systems, case studies show the model may effectively detect early-stage malignancies, lower false positives and negatives, and offer insightful analysis. These results suggest that hybrid artificial intelligence systems could drastically enhance cancer detection, therefore enabling more customized treatments and better quality of living for patients. As researchers investigate how to combine wearable devices, real-time applications, and scalable frameworks to identify several kinds of cancer, more easily available and comprehensive healthcare solutions will be feasible.

Keywords: *Cancer Detection, Hybrid Artificial Intelligence, Machine Learning, Deep Learning, CNN, SVM, Healthcare AI, Interpretability, Personalized Medicine, Ensemble Methods.*

Introduction

Cancer is still one of the most critical worldwide health issues considering its diagnosis and treatment influencing patient survival rates and quality of life (Dhruv et al., 2021). Early identification considerably increases the possibility of successful treatment; nonetheless, limits including invasiveness, expensive expenses, and varying accuracy based on different cancer types usually cause popular diagnosis methods such biopsies and imaging to fail. Since artificial intelligence can evaluate massive amounts of complex data and uncover trends buried from human perspective, it is fast becoming a game-changing tool for solving these problems. Although all artificial intelligence methods have shortcomings, machine learning, deep learning, and other approaches show potential. Among issues are overfitting, bad interpretability, and largely depending on large, high-quality datasets. This demands AI solutions combining many methodologies to transcend their own limitations (Fati et al., 2022). Strong classification is provided by SVMs; CNNs excel in feature extraction from image data; and ensemble approaches improve lifespan and general system performance. comprising these methods into a full diagnostic framework helps one to analyze multimodal data comprising histopathological pictures and genetic sequences, so enhancing accuracy and dependability (Kumar et al., 2022). Furthermore, addressing significant issues including class imbalance, noise reduction, and the desire for explainable artificial intelligence, hybrid AI models ensure that systems are accurate, open, and consistent for application in healthcare situations. Emphasizing its capabilities to revolutionize diagnosis, improve patient outcomes, and open the route for more reasonably priced and individualized healthcare solutions, this work

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analyses the design, implementation, and assessment of a hybrid artificial intelligence system for cancer detection. This work aims to overcome current shortcomings in traditional and standalone artificial intelligence techniques, thus establishing a new benchmark in cancer diagnosis and so supporting innovations outside of the healthcare industry.

Role of AI in Medical Diagnostic

Artificial intelligence (AI) has revolutionized the field of medical diagnostics by letting quick, accurate, scalable analysis of difficult medical data. Artificial intelligence algorithms, learning from massive databases, occasionally identify trends and connections outside human ability. Deep learning (DL) and machine learning (ML) have been very useful in deciphering imaging data, identifying anomalies, and projecting disease development (Kumar et al., 2022). For processing histological and radiological images, for instance, convolutional neural networks (CNNs) shine and can help early cancer detection. These devices benefit doctors a lot since they reduce human error and significantly cut the diagnosing time. Moreover, offering a whole view of a patient's condition, artificial intelligence models can aggregate information from many modalities, including clinical notes, imaging scans, and genomic sequences. Customized treatment strategies developed dependent on individual patient profiles rely on this integration in personalized medicine. Apart from accuracy, artificial intelligence technologies provide scalability and consistency, so enabling the solution of the shortage of medical experts in many nations. Still challenges exist for algorithms interpretability, data protection, and artificial intelligence integration into existent healthcare systems. Through addressing these issues, artificial intelligence could help to eliminate gaps in diagnosis efficiency and accessibility, so opening the road for equitable and efficient healthcare solutions all around (Liberini et al., 2022). Hybrid artificial intelligence systems combine several methods to overcome individual constraints, so ensuring strong and consistent diagnosis results.

- **Cancer - Screening and Early Detection**

Early detection of cancer greatly increases the chances for successful treatment. The 2 components of early detection of cancer are early diagnosis (or downstaging) and screening. Early diagnosis focuses on detecting symptomatic patients as early as possible, while screening consists of testing healthy individuals to identify those having cancers before any symptoms appear.

- **Early Diagnosis**

Early diagnosis programmes aim at reducing the proportion of patients who are diagnosed at a late stage (Sengupta et al., 2022). They have 2 main components:

  - Increased awareness of first signs of cancer, among physicians, nurses and other health care providers as well as among the general public; and
  - Improved accessibility and affordability of diagnosis and treatment services, and improved referral from first to secondary and tertiary levels of care.

Early diagnosis is particularly relevant to cancers of the breast, cervix, mouth, larynx, colon and rectum, and skin.

- **Screening**

Screening refers to the use of simple tests across a healthy population to identify those individuals who have a disease, but do not yet have symptoms (Wang et al., 2022). Examples include breast cancer screening using mammography or clinical breast exam, and cervical cancer screening using pap smears, human papillomavirus test or visual inspection with acetic acid. Screening programmes should be undertaken only when their effectiveness has been demonstrated, when resources (personnel, equipment, etc.) are sufficient to cover nearly all of the target group, when facilities exist for confirming diagnoses and for treatment and follow-up of those with abnormal results, and when prevalence of the disease is high enough to justify the effort and costs of screening. Even when implemented properly, screening programmes are associated with undesirable effects which include:

  - Falsely positive screening tests that result in additional testing, invasive diagnostic procedures and patient anxiety;
  - Falsely negative screening tests that provide false reassurance and can result in delayed presentation/diagnosis when symptoms appear; and
  - Over diagnosis/treatment of preclinical cancers that could have never cause symptoms nor pose a serious health threat and which involve unnecessary treatment that injures the patient (Wang et al., 2022).

The importance of these harms varies according to the screening tests, population groups targeted for screening and quality of screening programmes. Weighing the harms against the benefits of screening has led WHO not to recommend mammography screening in women less than 50 years of age. Based on the existing evidence, mass population screening can be advocated only for cervical, breast and colorectal cancer.

Systematic prostate cancer screening of all men above a certain age using prostate-specific antigen (PSA) is not recommended by WHO. The high harm/benefit ratio has resulted in the abandonment of population-based PSA screening for prostate cancer in many countries of western Europe in the past years.

Review Literature

Authors	**Study**	**Objective**	**Hybrid AI Approach**	**Dataset /Scope**	**Performance Metrics**	**Key Findings**
Naglaa F. Noaman, Bassam M. Kanber, Ahmad Al Smadi, et al. (2024)	Lung Cancer Detection (IEEE Access)	Early detection of lung cancer using histological image analysis.	DenseNet201 + Color histogram + Multiple ML algorithms.	LC25000 dataset.	Accuracy: 99.68%.	DenseNet201 with hybrid features significantly enhances early lung cancer detection capabilities.
Sepideh Molaei, Stefano Cirillo, Giandomenico Solimando (2024)	Cancer via MicroRNAs (Big Data Cogn. Comput.)	Detection of cancer using microRNA pattern recognition.	Particle Swarm Optimization (PSO) + Artificial Neural Networks (ANN).	Diverse cancer datasets.	Improved precision in microRNA analysis.	PSO-ANN integration effectively identifies key miRNAs for cancer detection and diagnosis.
Molaei S., Cirillo S., Solimando G.(2024)	Cancer Detection Using miRNAs	Detection of cancer using hybrid feature recognition via microRNA analysis.	PSO + ANN	Various cancer datasets.	Precision: High; Accurate miRNA selection.	Hybrid PSO-ANN model optimizes miRNA selection and significantly improves diagnostic accuracy.
Multiple authors (Arch Breast Cancer) (2023)	Breast Cancer Detection	Diagnosis of breast cancer metastasis.	MLP + Genetic Algorithm (GA).	Wisconsin Breast Cancer dataset.	High accuracy, sensitivity, and specificity.	Hybrid MLP-GA algorithm outperformed standalone AI methods.
Unnamed Review (Systematic Review)(2023)	Systematic Review of AI in Breast Cancer	Review of ML and DL techniques in breast cancer detection using histopathological imaging.	Analysis of DL vs. classical ML methods.	Multiple public datasets reviewed.	Varies by approach.	DL models (e.g., CNNs) show high effectiveness in breast cancer classification and treatment planning.
Mohammed B. A., Senan E. M., Al-Mekhlafi Z. G., et al. (2022)	Cervical Cancer Detection (Applied Sciences)	Early detection of cervical cancer using liquid-based cytology (LBC).	VGG-16 + SVM; GoogLeNet + SVM; Fusion features with ANN.	Whole-slide images (WSIs).	Accuracy: 99.4%; Specificity: 100%; Sensitivity: 99.35%.	Hybrid feature extraction methods significantly improve diagnosis accuracy and reduce manual efforts.
Saima Rathore, Mutawarra Hussain, Asifullah Khan (2025)	Colon Cancer Detection (Comp. Biol. Med.)	Automated detection of colon cancer using hybrid features.	Geometric + Texture Features + SVM.	174 colon biopsy images.	Accuracy: 92.62%.	Hybrid feature sets with geometric and texture properties outperform conventional classification methods.
Warda M. Shaban(2023)	Insight into breast cancer detection: New hybrid feature selection method	Introduce a hybrid feature selection method combining PSO and bat algorithm for improved accuracy.	PSO + Bat algorithm (NHFSM) for feature selection.	Breast cancer mammography imaging dataset.	Accuracy: 97%, Precision: 76%, Recall: 75%.	NHFSM improved classification accuracy, precision, and recall compared to existing feature selection methods.
Mohammed Al-Jabbar et al.(2023)	Multi-method diagnosis of histopathological images for	Diagnose breast cancer using a hybrid CNN and SVM	CNN (AlexNet + GoogLeNet) + SVM, Fusion features (FCH,	Histopathological images of breast cancer (40×-	Accuracy: 100% (400× dataset).	Achieved perfect metrics for histopathological images at 400×

	early detection of BC	approach with handcrafted features.	LBP, GLCM).	400× magnification).		magnification using CNN-SVM fusion features.
Sameh Zarif et al. (2023)	Using hybrid pre-trained models for breast cancer detection	Utilize hybrid CNN and EfficientNetV2B3 for breast cancer classification.	CNN + EfficientNetV2B3 pre-trained model.	Breast histopathology images (Kaggle dataset).	Accuracy: 96.3%, Precision: 93.4%, Recall: 86.4%, AUC: 97.5%.	Outperformed contemporary models with high accuracy and robustness.
Duhita Sengupta et al. (2022)	A deep hybrid learning pipeline for ovarian cancer diagnosis	Develop a hybrid model combining classical ML and deep learning for ovarian cancer detection.	Dual pipeline: Classical ML + CNN-based feature extraction.	Ovarian cancer image dataset.	AUC: 1.00.	Achieved perfect differentiation between cancerous and non-cancerous samples.
Xiaomei Wang et al.(2022)	Intelligent hybrid deep learning model for breast cancer detection	Develop a CNN-GRU hybrid model for breast cancer detection.	CNN + GRU hybrid deep learning model.	PCam Kaggle dataset.	Accuracy: 86.21%.	Enhanced detection performance compared to standalone CNN or GRU models.
K. Padmanaban et al.(2023)	Hybrid data mining technique-based breast cancer prediction	Use hybrid data mining techniques for accurate breast cancer prediction.	ML models + Feature extraction techniques.	Breast cancer imaging dataset.	Improved Accuracy.	Hybrid data mining approaches effectively enhanced prediction accuracy.

Statistical Learning

Numerous benefits may result from incorporating AI with statistics. For example, ML algorithms are inherently flexible. To begin with, their produced models are more opaque and cumbersome to manipulate than those of classical statistics. On the flip side, they can handle a broad range of variables in different formats. Radiomics and other quantitative image analysis applications might benefit greatly from this. Medical images are more than pictures to be visually interpreted, states the guiding idea of radioomics, a subfield of image analysis that extracts vast amounts of data regarding the pathophysiology and development of sick. Through the use of radiomics, a vast array of features defining a lesion, organ, or tissue can be generated. The term radiomics eventually came to mean precision medicine, or the art of providing individualized care to patients by analyzing their imaging-based biomarkers. The development of personalized treatment and the acceleration of biological discoveries are dependent on the reliability and precision of imaging-derived biomarkers.

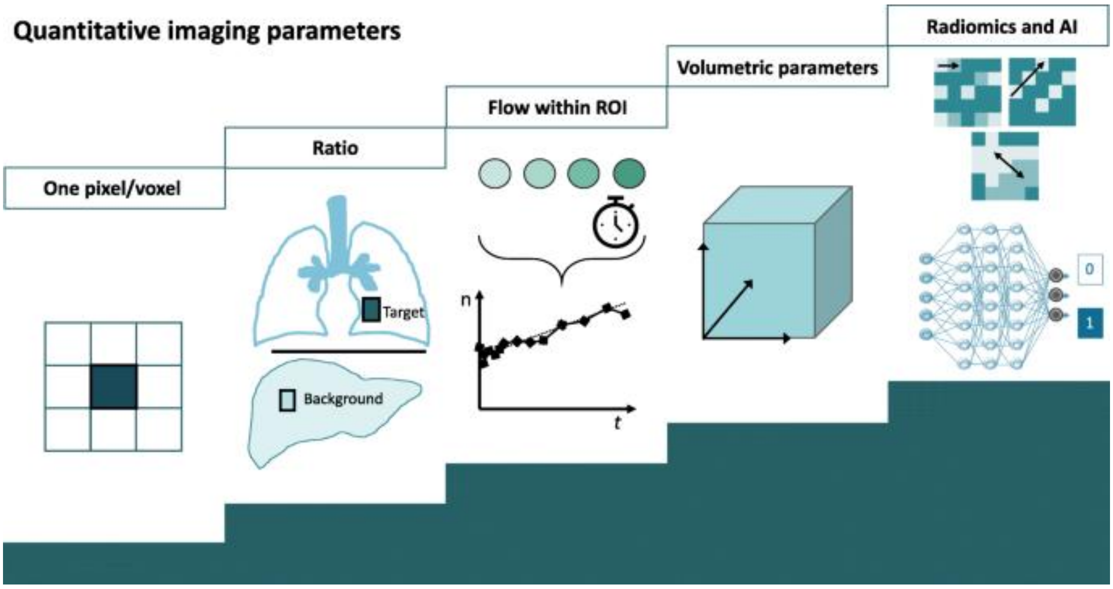
Still, there's a problem with how interpretable features are; this is mostly dependent on the calculation method (e.g., classical parameters, size-and form-based first-order features vs. higher-order features based on Laplacian or wavelet features). (Ibrahim et al., 2020). When making a diagnosis or prediction, radiomics is best utilized (or should be used) alongside other clinically important variables. So, radiomic analysis can be used to create models based on a wide variety of inputs. One machine learning approach that may work better with radiomic data than more conventional statistical approaches is unsupervised feature selection. Lambin et al. (2017) states that cancer detection and treatment decisions can be substantially improved by combining image-derived biomarkers with other data sets such as demographics, clinical information, gene expression profiles, and more. According to the National Cancer Institute's Quantitative Imaging Network (QIN) and other comparable projects within the NCI Cancer Imaging Program, radiomics has mostly been employed to study cancer up until now. The treatment of benign disorders is just one of many possible applications of radiomics.

Natural Language Processing (NLP)

Research article and clinical note creation, interpretation, and classification are the primary uses of natural language processing (NLP) in the medical field, as stated by (Davenport and Kalakota 2019). Natural language processing (NLP) enables a wide range of tasks, including text classification and translation, information retrieval, text production, and question answering. The last capability of NLP is that it enables the comprehension and decoding of spoken languages. (Davenport and Kalakota 2019) state that NLP systems can evaluate sentiment, mimic human interactions (including conversation), interpret unstructured medical data, and suggest reports. Siri and Alexa, two examples of smart voicedriven interfaces developed using natural language processing, are able to understand and answer questions posed vocally. Natural language processing (NLP)" has numerous potential uses in healthcare, including disease diagnosis and prediction using EMR data, patient inquiry through chat boxes, and similar applications (Table 2). Cardiovascular illness, depression, and schizophrenia are among of the areas where this skill is presently being investigated by researchers. Pons et al. (2016) noted that medical imaging could benefit from natural language processing (NLP) in several ways, such as clinical trial case selection, diagnostic screening and surveillance programs, and clinical report quality assessment. found that natural language processing (NLP) can help with scan interpretation and lexical prediction in hybrid PET/CT imaging. Natural language processing (NLP) offers process automation, which is one of its primary benefits. This paves the way for previously unimaginable jobs since it reduces or eliminates the need for human review and inspection of massive data sets (Pons et al. 2016). By quietly watching reports, ranking them, and alerting imagers or referring doctors of any possible problems, natural language processing (NLP) could potentially enhance clinical and diagnostic operations.

Clinical Applications of AI to Oncological Hybrid Imaging

There is a vast variety of architectures, goals, and applications of AI approaches, all of which depend on the end goal. "Detecting and segmenting lesions, differentiating between benign and malignant illnesses, staging patients as early or advanced, and providing a favorable or terrible prognosis are the primary goals of using AI-based technologies in hybrid imaging. Algorithms can utilize both structured raw data and data that has been manually retrieved, as stated by. Quantification of imaging biomarkers for use in nuclear medicine has become more complicated over time (Fig. 2). Quantitative information is frequently extracted from nuclear imaging data for analysis. found that by combining tracer kinetic modeling methods with appropriate image correction and reconstruction algorithms, traditional semiquantitative metrics like standard uptake value (SUV), metabolic tumor volume (MTV), and total lesion glycolysis (TLG) can be obtained. Coronary blood flow and glomerular filtration rate are two examples of absolute quantitative variables that can be calculated. But state-of-the-art hybrid image analysis is changing in vivo disease characterisation with its integration of machine learning and radiomics (Gillies et al., 2016).

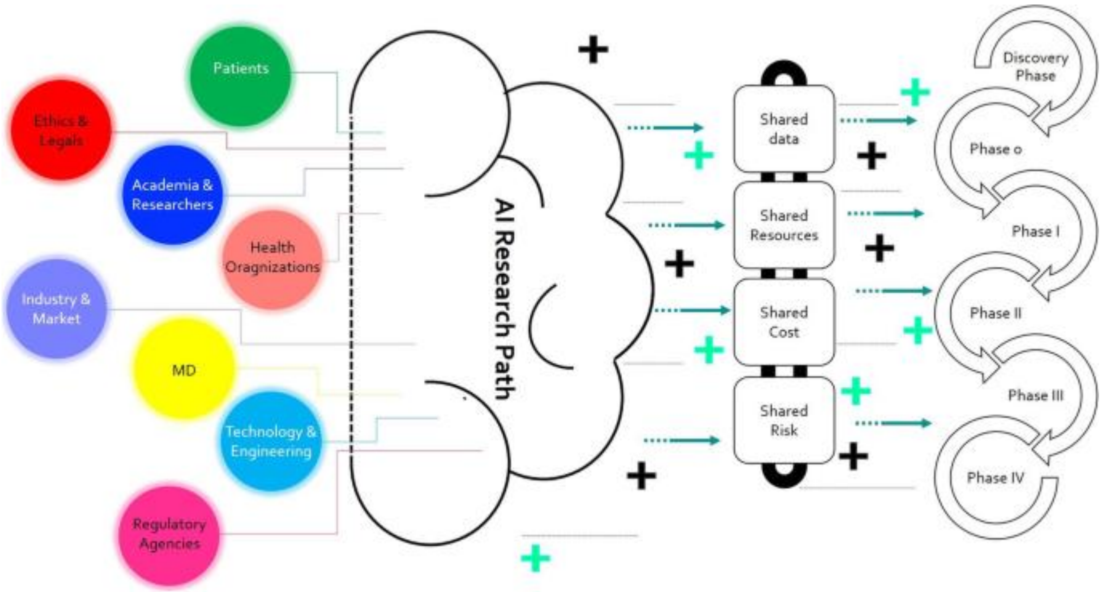


Source: Sollini, M.(2020)

Radiomic characteristics, which also define the connection between a picture's voxels or pixels, can tell us about the space and texture on grayscale patterns. As a means to enhance customized medicine, there is optimism that AI-based systems utilizing features specified by humans can assist with diagnosis and therapy recommendation. Research using radiomic PET and PET/CT has increased the prevalence of visual assessment and conventional semiquantitative criteria. The PET scan radiomic characteristics showed better test-retest stability and better predictive capacity than the inter-observer variability in future PET exams (Leijenaar et al. 2013). The Holomics concept is gaining traction as a means to increase the predictive power of models and open up new possibilities for hybrid imaging. (Holzinger et al. 2019) state that a thorough front end strategy is necessary for understanding complex diseases. This strategy should take into account the control and interaction of several actors at the molecular, cellular, and organismal levels, including microenvironments, host defenses, and pathogens. In the case of stage I primary non-small cell lung cancer, for instance, our approach increased recurrence risk prediction compared to genetic biomarkers. The majority of research and focus has been on lung cancer among all potential clinical scenarios. We will use this as a starting point to explore the potential medical effects of AI.

Standard and Quality

The results of artificial intelligence (AI) must be trustworthy, understandable, and comprehensible before they can be applied to real-world therapeutic decision-making. Each step of the model development process—from the image methodology used for developing the model to the training and testing methodologies used for image labeling, feature extraction, reference standard, and validation—must follow these guidelines. Moreover, strong evidence is necessary. Quality assurance in medical research is essential, regardless of the index test. Quality assessment is of the utmost importance for AI-based investigations to produce results that are interpretable, transparent, reproducible, and meaningful (Ninatti et al., 2020).



Multi-Dimensional Interactions among Stakeholders Involved in the AI Research Path

Source: Sollini, M.(2020)

An RQS, which stands for radiomics quality score, was devised to quantify the comprehensiveness and reliability of radiomics investigations. The RQS, which covers sixteen different domains, was inspired by the TRIPOD initiative, which stands for Transparent Reporting of a multi-variable prediction model for Individual Prognosis OR Diagnosis. The feasibility of a modified TRIPOD checklist for assessing AI-based models was established by Ninatti et al., who deleted or amended a few elements that were not relevant or applicable to AI-based studies. According to (Leijenaar et al. 2013), a fresh proposal for a TRIPOD declaration has been put up in this regard. The study's reproducibility, robustness, and reusability should be confirmed by data sharing, as per the FAIR principles—findability, accessibility, interoperability, and reusability". The abundance of publicly available repositories makes this feasible at the moment.

Conclusion

By combining the best features of several AI systems, hybrid AI approaches show great potential to revolutionize cancer diagnoses. The results showed that using a combination of convolutional neural networks (CNNs), support vector machines (SVMs), and ensemble learning improved cancer detection accuracy and efficiency. When it comes to interpretability, data imbalances, and multimodal data integration, hybrid models really shine. These solutions greatly enhance individualized healthcare by enhancing diagnostic accuracy and offering practical insights. To expand the benefits of hybrid AI systems to global healthcare challenges, future research should concentrate on improving scalability, investigating other types of cancer, and implementing the system in real-time.

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