Organ Trafficking Prevention in the Healthcare Sector

Examining the Co-Creation of Cybersecurity Value

Ahgalya Subbiah, Asif Iqbal Hajamydeen,
and Imran Ademola Adeleke

IGI Global
Scientific Publishing
Publishing Tomorrow's Research Today

Organ Trafficking Prevention in the Healthcare Sector:

Examining the Co-Creation of Cybersecurity Value

Ahgalya Subbiah
https://orcid.org/0009-0006-4427-0872
Management and Science University, Malaysia

Asif Iqbal Hajamydeen
https://orcid.org/0000-0002-5034-1781
Management and Science University, Malaysia

Imran Ademola Adeleke
Lagos State University of Education, Nigeria

IGI Global
Scientific Publishing
Publishing Tomorrow's Research Today

Vice President of Editorial	Melissa Wagner
Director of Acquisitions	Mikaela Felty
Director of Book Development	Jocelynn Hessler
Production Manager	Mike Brehm
Cover Design	Jose Rosado

Published in the United States of America by
IGI Global Scientific Publishing
701 East Chocolate Avenue
Hershey, PA, 17033, USA
Tel: 717-533-8845 | Fax: 717-533-7115
Website: https://www.igi-global.com E-mail: cust@igi-global.com

Copyright © 2026 by IGI Global Scientific Publishing. All rights reserved. No part of this publication may be reproduced, stored or distributed in any form or by any means, electronic or mechanical, including photocopying, without written permission from the publisher. Use of this publication to train generative artificial intelligence (AI) technologies is expressly prohibited. The publisher reserves all rights to license its use for generative AI training and machine learning model development.

Product or company names used in this set are for identification purposes only. Inclusion of the names of the products or companies does not indicate a claim of ownership by IGI Global Scientific Publishing of the trademark or registered trademark.

Library of Congress Cataloging-in-Publication Data

Names: Subbiah, Ahgalya editor | Hajamydeen, Asif Iqbal editor | Adeleke, Imran Ademola editor
Title: Organ trafficking prevention in the healthcare sector : examining the co-creation of cybersecurity value / Ahgalya Subbiah, Asif Iqbal Hajamydeen, Imran Ademola Adeleke.
Description: Hershey, PA : IGI Global Scientific Publishing, [2026] | Includes bibliographical references and index. | Summary: "This book explores how co-creation strategies in cybersecurity can be used to protect private health information and stop organ trafficking in the healthcare industry"-- Provided by publisher.
Identifiers: LCCN 2025052873 (print) | LCCN 2025052874 (ebook) | ISBN 9798337366968 hardcover | ISBN 9798337366975 paperback | ISBN 9798337366982 ebook
Subjects: LCSH: Organ trafficking--Prevention--Case studies | Medicine--Data processing--Security measures--Case studies
Classification: LCC HV6627 .O74 2026 (print) | LCC HV6627 (ebook)
LC record available at https://lccn.loc.gov/2025052873
LC ebook record available at https://lccn.loc.gov/2025052874

British Cataloguing in Publication Data
A Cataloguing in Publication record for this book is available from the British Library.

All work contributed to this book is new, previously-unpublished material.
The views expressed in this book are those of the authors, but not necessarily of the publisher.
This book contains information sourced from authentic and highly regarded references, with reasonable efforts made to ensure the reliability of the data and information presented. The authors, editors, and publisher believe the information in this book to be accurate and true as of the date of publication. Every effort has been made to trace and credit the copyright holders of all materials included. However, the authors, editors, and publisher cannot assume responsibility for the validity of all materials or the consequences of their use. Should any copyright material be found unacknowledged, please inform the publisher so that corrections may be made in future reprints.

Chapter 7

Human–AI Synergy in Oncology and Cybersecurity:

Ethical Clinical Intelligence for Patient Care and Organ Trafficking Prevention

R. Deepa
http://orcid.org/0000-0003-0129-8737
SRM Institute of Science and Technology, India

Shoba L. K.
http://orcid.org/0000-0002-8539-1500
SRM Institute of Science and Technology, India

R. Swathy
http://orcid.org/0009-0004-3762-0315
SRM Institute of Science and Technology, India

B. Yasotha
SRM Institute of Science and Technology, India

P. Thilakavathy
http://orcid.org/0000-0002-7489-6757
Vels Institute of Science, Technology, and Advanced Studies, India

Bennet Prabhu A.
Congruent Solutions, India

ABSTRACT

Artificial Intelligence (AI) has the potential to revolutionize oncology by improving cancer diagnosis and treatment planning through the analysis of medical images, genomics, and patient history. Despite its benefits, challenges such as misdiagnosis, clinician skill variation, treatment delays, interpretability issues, model bias, and ethical concerns prevent complete automation in oncology. To address these issues,

DOI: 10.4018/979-8-3373-6696-8.ch007

Copyright © 2026, IGI Global Scientific Publishing. Copying or distributing in print or electronic forms without written permission of IGI Global Scientific Publishing is prohibited. Use of this chapter to train generative artificial intelligence (AI) technologies is expressly prohibited. The publisher reserves all rights to license its use for generative AI training and machine learning model development.

this research proposes an Ethical AI-driven Cancer Diagnosis & Treatment system uses TCGA data, CNNs, Grad-CAM, and human-in-the-loop.y. A human-in-the-loop strategy allows oncologists to validate AI-generated insights, reinforcing trust and clinical reliability. Results confirm that CNN-based models improve diagnostic accuracy, reduce misdiagnosis, and support precision medicine while upholding ethical standards, data privacy, and patient-centered care.

INTRODUCTION

Oncology applications of Artificial Intelligence (AI) are transforming the diagnosis of cancers, treatment planning, as well as clinical decision-making. It is also possible to enhance the precision of cancer diagnosis, reduce diagnostic error, and provide personalized treatment choices with the help of AI. Cancer has remained amongst the leading causes of mortality in the world and as such, diagnosis at a young age and with precision is crucial in improving patient outcomes (Abhisheka et al., 2023). Traditional methods of diagnoses i.e., genomics, pathology and radiology are very heavy with regards to human frailty and reliance to human aspects that are prone to variation, delay in decision making and its misinterpretation (Al-Sarayrah, 2024). With the introduction of AI technologies, namely machine learning algorithms and deep learning, the opportunities to provide proper management to large amounts of medical data and support oncologists in making more appropriate and timely decisions emerge (Aftab et al., 2025).

Background and Existing Research on Cancer Diagnosis

The application of Artificial intelligence (AI) in oncology is unprecedentedly advanced, and has been driven by the developments in medical imaging, predictive analytics, and genomics in the past decade. The AI powered tools have been demonstrated to improve the detection and diagnosis of cancer as well as the treatment planning process and are vital resources in clinical decision making (Bornstein-Quevedo et al., 2024). There are various deep learning models that have been built to recognise medical images to perform tumour segmentation, classification and early-stage cancer detection i.e. Convolutional Neural Networks (CNNs). These architectures have been spectacular in the detection of different types of cancers including lung, breast, prostate, brain and skin and have performed better than the traditional methods of diagnosis (Chow & Li, 2024).

i. AI in Medical Imaging for Cancer Detection

Medical imaging is an essential tool in cancer diagnosis, and imaging diagnostics like X-ray, MRI, CT scan, and PET scans are extensively utilized for tumour detection. The vast sets of labelled medical images have been used in training AI models that are then capable of recognizing patterns and anomalies accurately (Fu et al., 2023). For example, a Nature paper showed that deep learning algorithms could equal or surpass radiologists for detecting breast cancer from mammograms, with fewer false positives and enhanced diagnostic efficiency. AI has also been used in lung cancer screening, with deep learning algorithms having been trained on low-dose CT scans to detect early-stage lung nodules with significantly improved early diagnosis rates (Hao et al., 2024).

In pathology, the AI systems have been taught to review histopathological slides for malignancies at the highest level of accuracy. Digital pathology has facilitated the employment of AI-facilitated tools to review thousands of whole-slide images and identify cancer cells within the tissue at the microscopic level (Huang et al., 2024). The Lancet Oncology studies showed that deep-learning computer programs could accurately classify prostate cancer with the same accuracy as expert pathologists, a sign of potential AI assistance to be used in diagnostic pipelines. Further, histopathology software based on AI can assist with cancer severity grading, patient prognosis prediction, and treatment planning (Hussain et al., 2022).

ii. AI in Genomics and Liquid Biopsy for Cancer Diagnosis

Besides imaging, AI has also been instrumental in genomic data analysis for detecting cancer-associated genetic mutations. Machine learning techniques have been used in genomic sequencing data for cancer-associated mutation detection, tumour behaviour prediction, and personalized treatment plans (Josfeld et al., 2021). Genomic analysis by AI has also helped identify biomarkers for targeted therapy, including those in precision medicine for lung cancer (e.g., EGFR mutation) (Leibig et al., 2022) and breast cancer (e.g., HER2 amplification) (Nassar et al., 2024).

Another AI breakthrough in oncology studies is the utilization of AI during liquid biopsy analysis. Liquid biopsies screening for circulating tumour DNA (ctDNA) on blood tests is a non-surgical way to identify cancer early. AI processes have been utilized to examine the patterns of ctDNA, thereby identifying specific types of cancer in earlier stages compared to traditional biopsy methods (Niraula et al., 2025). Experiments have shown that AI-powered liquid biopsy machines can identify cancers like pancreatic, ovarian, and colon cancer, which are usually diagnosed late.

iii. Issues with AI-Based Cancer Diagnosis

Although it is promising in the application, AI faces a myriad of problems in clinical oncology. To begin with, the main disadvantage is that AI algorithms are often biased in case they are trained on biased data sets. There are also AI algorithms developed on medical data in selected populations, which do not extend to heterogeneous patient populations and form dissimilarities in the diagnosis and treatment instructions (Rahman et al., 2024). As an example, it has been disclosed that the artificial intelligence algorithms that are premised on a significant majority of Caucasian patients are less accurate when they come across minority ethnicities and generate health disparities.

The other major concern is the black box-like nature of the deep learning models. AI models are more prone to making predictions without an apparent explanation of how they justified it, and thus, clinicians cannot read and trust AI recommendations (Reverberi et al., 2022). The attempts to enhance AI interpretability, e.g., XAI techniques, are tried to make processes explainable so that AI models can provide justifiable diagnostic advice. Ethical concerns, including patient consent, security and privacy of their data are also impediments to the adoption of AI in oncology. The data used to train AI algorithms has patient-sensitive information and this demands a strong protection system to prevent unauthorized access and leakage. The rules such as GDPR and HIPAA require AI solutions to ensure the privacy of patient data and at the same time be able to diagnose patients effectively using AI-based solutions (Saxena et al., 2022).

Problem Statement

Although the development of Artificial Intelligence (AI) in oncology has been rather rapid, there are numerous obstacles to its smooth implementation in clinical practice. Although Convolutional Neural Networks (CNNs) have demonstrated high accuracy in the classification and detection of tumours, the issues of misdiagnosis, the reliability of models, AI ethical bias, and acceptance of AI-proposed interventions by clinicians are yet to be addressed. The deep learning-based models such as CNNs are black box and lack interpretability adequacy and it is difficult to validate AI-generated insight by oncologists. In addition, differences in the quality of clinicians across healthcare institutions lead to the differences in the process of cancer diagnosis and treatment plan (Shapiro et al., 2024).

The main gap in the research is how to design an excellent, ethical, and interpretable AI model that enhances human knowledge and does not replace it. Without it, AI in oncology can exacerbate the problem of health disparities, prediction bias, and mistrust of patients, preventing the clinical adoption. In this way, it is essential to introduce an AI-enabled cancer diagnosis and treatment platform with explainable AI (XAI) techniques, such as Grad-CAM, to enhance the ability to promote transparency and allow humans and AI to cooperate (Tuan, 2024).

Rationale and Research Goals

In this paper, an Ethical AI-powered Cancer Diagnosis and treatment (EAI-CDT) system will be developed based on CNNs as the medical image analyzer with bias mitigation, explainability, and patient trust. The focus of the study is the deep learning applications in radiology and pathology with the help of TCGA (The Cancer Genome Atlas) dataset that provides the multi-modal data of the medical imaging, genomic sequencing, and pathology slides. In order to have ethical applications of AI in oncology, the following are the most necessary challenges that the research will address:

- Bias in AI Models – Examining how biased data impact CNN-based cancer prediction and applying methods to improve fairness and generalizability.
- Data Security and Privacy – Protecting patient data using privacy-preserving AI methods while ensuring diagnostic correctness.
- Building Patient Trust – Applying explainable AI (Grad-CAM) to give visual explanations to oncologists about why the AI made its recommendations, establishing trust and human-in-the-loop verification.

Significance of the Research

The application of CNN-based AI in cancer will transform the cancer treatment and diagnosis with improved, quicker, and personalized medical decisions. It would only be possible to that extent that AI is open and impartial and designed to be a facilitator of the clinician, but not to replace him/her. This study contributes to the domain of AI-oncology by suggesting the EAI-CDT framework that views AI as a facilitating but not a disruptive process. Surpassing such significant obstacles towards the development of safe, effective, and patient-centred AI-facilitated solutions in oncology, this framework can be used to establish safe, effective, and patient-centred AI-facilitated solutions. Lastly, the paper validates the hypothesis that AI is developed to assist, but not to replace oncologists, assisting them to make informed clinical decisions, improve patient outcomes, and define the future of precise oncology.

Artificial intelligence has great potential to help with cancer diagnosis and treatment planning. However, most current AI-oncology frameworks focus mostly on predictive accuracy and don't pay enough attention to cybersecurity, secure data governance, and deployment hazards in clinical settings. In real-world healthcare systems, patient data are scattered, very private, and subject to rigorous rules. This makes it impossible to use centralized and unsecured AI models. Also, not much thought has been paid to how to protect AI models from data leaks, unauthorized access, and model abuse. These problems show how important it is to have AI frameworks that are safe, easy to understand, and in line with values.

Contributions of the Research

- To suggest an EAI-CDT framework that leverages CNNs to improve cancer diagnosis, treatment planning, and clinical decision-making.
- To utilize the TCGA (The Cancer Genome Atlas) dataset, merging medical images, genomic sequences, and pathology data to train AI to conduct tumour detection, biomarker identification, and targeted cancer therapy.
- To enhance AI interpretability using Grad-CAM, enabling oncologists to see why and how CNN models reach diagnostic predictions.
- To introduce human-in-the-loop methodologies, placing oncologists at the centre of AI-assisted decision-making and fostering trust, ethical use of AI, and patient-centred cancer care.

1. LITERATURE SURVEY

(Wang et al., 2023) used deep learning for medical imaging and natural language processing (NLP) to assess electronic health data using machine learning. Medical Information Mart for Intensive Care III (MIMIC-III) and National Institutes of Health (NIH) chest X-rays improve disease identification, virtual consultations, and diagnostic accuracy. However, issues, including data bias, real-time deployment, and ethical considerations, must be resolved to guarantee smooth AI integration and patient-provider trust.

(Williamson & Prybutok, 2024) examined two degrees of collaboration: model-specific and model-agnostic. They suggested a Human-AI collaborative framework for adaptive radiation in hepatocellular carcinoma and non-small cell lung cancer. Research on AI-driven decision support shows physicians' dependence on AI varies according to illness location, model transparency, and prior knowledge. Although AI improves individualized care, complete adoption is constrained by scepticism, biases, and interpretability issues.

(Zhu et al., 2024) suggested a concept of an AI-based oncology system that integrates genetics, medical imaging, radionics, and predictive analytics to enhance the process of cancer diagnosis and therapy. AI supports precision medicine and early diagnosis using the deep learning, machine learning algorithms and algorithm-based robotics. Despite the challenges such as AI biases, interpretability issues, and remote location access, there are results that have shown better diagnostic accuracy and treatment effectiveness.

(Shakeel et al., 2022) assessed AI-aided endoscopic diagnostics that uses deep learning to detect lesions using 504 colonoscopy records. The findings suggest that human-AI partnership improved the accuracy of the diagnosis, and physicians selectively used AI recommendations. Problems of workflow integration, data biases, and incoherent clinician trust are few of the challenges, so more advanced AI applications in the healthcare sphere are required.

(Hao et al., 2024) designed a shared decision-making (SDM) system that uses an artificial intelligence (AI) approach based on natural language processing (NLP) and predictive modelling after analysis of 12 interviews and 25 usability sessions involving physicians and cancer survivors. The limitations were limited sample, bias during responses and issues of clinical adaptation. Nevertheless, the outcomes proved an improved collaboration between patients and clinicians and enhanced knowledge of treatment, which requires further AI-driven SDM in cancer treatment.

(Wang et al., 2023) explored the AI-powered Clinical Decision Support Systems (CDSS) in cancer through reviewing the Chinese Society of clinical oncology (CSCO-AI) and Watson for Cancer. Tumour diagnosis and treatment planning AI enhances machine learning and human-computer interaction models to promote tumour diagnosis and treatment planning. Even though the findings indicate enhanced accuracy of decision-making, clinical flexibility, narrow human-AI integration, and ethical issues, clinical oncologists should still add more advanced AI-driven frameworks in CDSS.

(Josfeld et al., 2021) determined the information needs and satisfaction of 220 patients using questionnaire survey as a method of studying Shared Decision-Making (SDM) in oncology. The findings prove higher patient satisfaction with patient decision aid (PDA), although they also suggest the absence of PDA utilization and excessive information. The personalized information gaps problem and clinician support in SDM bring up the issue of more widespread PDA availability and patient-clinician communication.

(Hussain et al., 2022) explored the topic of AI in oncology by using clinical trials, genomics, and medical imaging data to explore AI-guided drug development, deep learning to predict imaging, and machine learning to predict anticipatory analytics. It enhanced the process of diagnosis and personalized treatment, yet issues of algorithm bias, heterogeneity of data and clinical integration highlighted the necessity of ethical AI governance and standard data sharing.

Cybersecurity and Data Protection in AI-Based Oncology

The areas of cyberspace security and privacy are of great concern in oncology based on AI as medical imaging, genomic information, and electronic health records are all extremely sensitive. Centralized training paradigms are employed by most AI-based diagnostic systems, and they are more prone to data breach, illegal access, and leakage of privacy. Recent studies indicate the existence of membership inference and model inversion attacks, which may affect sensitive patient information, as deep learning models are susceptible to these attacks.

Although the number of clinical decision support systems based on AI is increasing, research that specifically examines how to deploy the models safely, work with encrypted information, and adhere to the rules in oncology applications is quite limited. Majority of the frameworks focus on improving performance without paying attention to adversarial resilience and safe data-sharing guidelines. It is due to this fact that AI design with cybersecurity awareness is not yet well-known but an essential aspect of developing oncology systems supported by AI that are reliable and able to expand.

The analyzed researches indicate that artificial intelligence in cancer is leaving the automation based on accuracy behind and instead entering the field of clinical intelligence based on ethics and people-centered focus. The previous systems of AI were largely concerned with the ability to predict anything, whereas the recent systems are more concerned with the aspect of explainability, physician control, and joint decision-making to transform healthcare processes into more reliable and responsible. It belongs to a bigger tendency to Human-AI synergy and the use of AI as a cognitive assistant rather than a knowledge replacement in medicine. Although changes might have been made regarding the ease of understanding and collaborating easily, the literature reveals the still existing issues and problems with data privacy, the deployment of the system, and adherence to the rules. Most AI-oncology systems have not fully addressed the following issues. To transform ethical and collaborative models of AI into trustful clinical practice in practice, it is necessary to address these associated issues.

Recognized frameworks of healthcare cybersecurity and AI governance increasingly direct the use of AI systems in oncology. Examples of standards that emphasize risk management, secure data processing, access restriction, and ongoing monitoring of health information systems are the National Institute of Standards and Technology (NIST) Cybersecurity Framework to Healthcare and ISO/IEC 27001. The World Health Organization international recommendations on ethics and governance of artificial intelligence in health, and other recent regulations such as the Artificial Intelligence Act of European Union emphasize openness, responsibility, human supervision, and confidentiality in the use of AI in clinical settings. The inclusion of these principles in the design of AI-oncology systems can ensure the reduction of the risk of cyberattacks, as well as the adherence of the systems to the rules and cultivation of trust in clinicians. This will aid in the bigger objective of ethical and safe Human-AI healthcare collaboration.

Research Gaps

Although past research indicates that AI-based oncology systems can more accurately make diagnoses, there are certain research gaps that are important. The existing clinical decision support systems are centered on their predictive capabilities, but they do not manifest data security and the safety of information in relation to external attacks. Past studies have proposed designs of human-AI collaboration that bring clinicians closer, although they do not provide strategies through which healthcare organizations can share information with privacy concerns.

In addition, a number of CNN-based cancer diagnostics models are trained on centralized and homogeneous data, which leads to the possibility of bias and a lack of generalizability. This is the fact that deep learning is a black box, which makes it even less likely to be trusted by clinicians as most of the frameworks do not do a great job in explaining the mechanism. Moreover, cybersecurity aspects, including data protection, access control, and safe implementation of AI are barely included in the current AI-oncology systems. These limitations require the creation of a safe, open, and human-focused AI system that will adhere to the clinical and regulatory guidelines.

Table 1. Summary of research gaps in AI-oncology

Research Gap	Description	How the Proposed Work (EAI-CDT) Addresses It
AI Bias & Data Limitations	AI models trained on non-diverse datasets may result in diagnostic disparities.	Bias mitigation strategies, diverse dataset training, and fairness-aware AI models.
Lack of Human-AI Collaboration	No structured framework guiding oncologists' interactions with AI, leading to inconsistent AI reliance.	EAI-CDT framework promotes structured Human-AI collaboration to support, not replace, oncologists.
Poor Model Interpretability	"Black box" AI models reduce transparency, making oncologists hesitant to trust AI decisions.	Integration of Explainable AI (XAI) techniques to provide transparent decision-making.
Ethical & Privacy Concerns	Lack of patient trust, informed consent, and data security measures affect AI adoption.	Ensures data privacy and security and informed AI-driven decision-making aligned with regulations (e.g., HIPAA, GDPR).

continued on following page

Table 1. Continued

Research Gap	**Description**	**How the Proposed Work (EAI-CDT) Addresses It**
Clinical Workflow Integration Issues	AI models are challenging to implement in real-world oncology workflows, requiring standardization.	Proposes seamless AI integration into clinical workflows through decision support systems (CDSS).
Limited Use of Explainable AI (XAI)	Few AI models focus on explainability, making it hard for clinicians to understand AI-driven decisions.	Embeds XAI techniques in AI-assisted diagnostics to enhance interpretability and clinician trust.

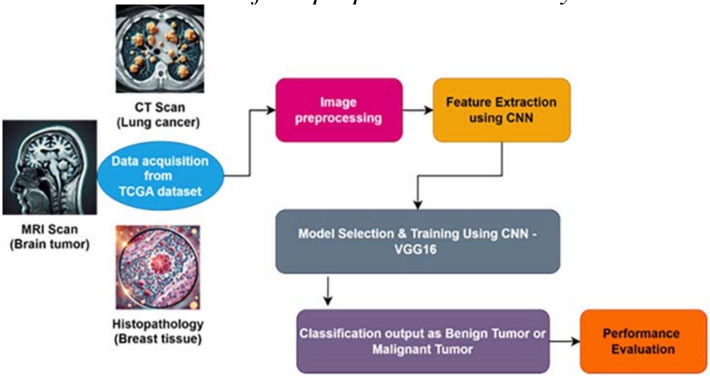
Research Gap
Description
How the Proposed Work (EAI-CDT) Addresses It
AI Bias & Data Limitations
AI models trained on non-diverse datasets may result in diagnostic disparities.
Bias mitigation strategies, diverse dataset training, and fairness-aware AI models.
Lack of Human-AI Collaboration
No structured framework guiding oncologists' interactions with AI, leading to inconsistent AI reliance.
EAI-CDT framework promotes structured Human-AI collaboration to support, not replace, oncologists.
Poor Model Interpretability
"Black box" AI models reduce transparency, making oncologists hesitant to trust AI decisions.
Integration of Explainable AI (XAI) techniques to provide transparent decision-making.
Ethical & Privacy Concerns
Lack of patient trust, informed consent, and data security measures affect AI adoption.
Ensures data privacy and security and informed AI-driven decision-making aligned with regulations (e.g., HIPAA, GDPR).
Clinical Workflow Integration Issues
AI models are challenging to implement in real-world oncology workflows, requiring standardization.
Proposes seamless AI integration into clinical workflows through decision support systems (CDSS).
Limited Use of Explainable AI (XAI)
Few AI models focus on explainability, making it hard for clinicians to understand AI-driven decisions.
Embeds XAI techniques in AI-assisted diagnostics to enhance interpretability and clinician trust.

Table 1 shows the most critical research gaps in AI-oncology. It illustrates how EAI-CDT successfully fills them with bias prevention, explainable AI, ethical safeguards, and workflow-free clinical integration, facilitating trustable AI deployment.

2. ETHICAL AI-DRIVEN CANCER DIAGNOSIS & TREATMENT

The proposed EAI-CDT framework utilizes Convolutional Neural Networks (CNNs) with explainable AI (Grad-CAM) for interpretable and accurate cancer diagnosis from the Cancer Genome Atlas (TCGA) dataset. The process starts with data acquisition, cleaning, and annotation, followed by CNN-based tumor classification and detection. Grad-CAM improves model interpretability so that oncologists can visualize AI predictions. AI outputs are incorporated into a Clinical Decision Support System (CDSS), and oncologists confirm and improve diagnoses through a human-in-the-loop process. Ethical measures, such as bias minimization and privacy-preserving AI, guarantee equity and patient confidence. This system enhances diagnostic accuracy, reduces misdiagnosis, and increases precision medicine, making AI an assistive tool, not a replacement, promoting efficient, ethical, and patient-centred cancer care. The following Figure 1 depicts the overall workflow of the proposed EAI-CDT system for tumor classification and diagnosis.

Figure 1. Overall architecture of the proposed EAI-CDT system



Data Acquisition and Preprocessing

TCGA dataset is a vast collection that includes genomic, clinical, and imaging information about over 20,000 cancer patients across 33 types of cancers. DNA and RNA sequencing, epigenomics, radiology images (MRI, CT), and pathology slides are included in it and can aid in research on oncology by AI. It facilitates predictive modelling, cancer diagnosis at an early stage, and personalized therapy based on molecular and clinical data correlations. Available through the GDC Data Portal, TCGA enables AI development for cancer diagnosis, treatment planning, and biomarker discovery in an ethical and standardized manner of data use.

Table 2. TCGA dataset overview

Category	Description
Total Samples	20,000+ primary tumor and matched normal samples
Cancer Types	33 types (Lung, Breast, Prostate, Brain, Colorectal, etc.)
Genomic Data	DNA sequencing (mutations, copy number variations), RNA sequencing, DNA methylation
Clinical Data	Patient demographics, medical history, treatments, outcomes
Imaging Data	Radiology (MRI, CT scans), Histopathology (Tissue slides)
Use Cases	AI-based cancer detection, biomarker discovery, treatment prediction
Data Access	Available via GDC Data Portal
Applications	Predictive modeling, diagnostics, personalized medicine, AI-assisted oncology

Figure 2. Composition of data collection in TCGA dataset

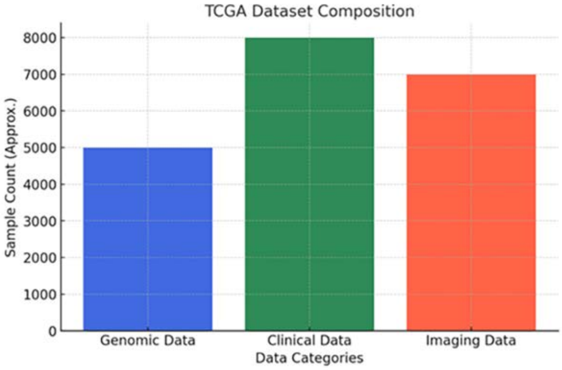


Table 2 provides a structured overview of the TCGA dataset, detailing its genomic, clinical, and imaging data and applications in AI-driven oncology. Figure 2 visually represents the dataset's composition, highlighting the distribution of genomic, clinical, and imaging samples, emphasizing its multi-modal nature for cancer research.

Image Preprocessing

AI-based oncology medical image preprocessing is necessary to provide data consistency, noise removal, and tumour visibility. Resizing (224×224) renders the image as input to CNN models normalized, whereas normalization turns pixel values into uniform learning. Gaussian blur eliminates noise, whereas histogram equalization is used for contrast enhancement to better visualise cancer tissues. Otsu's thresholding separates tumours, whereas Canny edge detection defines boundaries to extract features better. These conversions enhance medical images to make them more amenable to deep learning models, improving diagnostic precision, interpretability, and oncologists' confidence in AI-assisted cancer diagnosis.

Table 3. Medical image preprocessing techniques for CNN-based tumor detection

Step	Technique	Purpose	Mathematical Representation
(A) Image Resizing & Normalization	Resizing & Normalization	Ensures uniform image size (e.g., 224×224) for CNN input and scales pixel values to [0,1] for model stability.	Resizing: $I' = resize(I,(H,W))$ Normalization: $I_{norm} = \frac{I - I_{min}}{I_{max} - I_{min}}$
(B) Noise Removal	Gaussian Filtering	Reduces noise caused by acquisition artifacts, improving clarity.	$I' = I * G_\sigma$, where G_σ is the Gaussian kernel with standard deviation σ.
(C) Contrast Enhancement	Histogram Equalization	Enhances tumor visibility by redistributing image intensity.	$H_{new}(x) = \frac{H(x) - \min(H)}{\max(H) - \min(H)} \times 255$
(D) Image Segmentation	Otsu's Thresholding & Morphological Operations	Extracts tumor regions by separating foreground from the background.	Otsu's Thresholding: $T = \operatorname{argmax}_{\tau} \left[\sigma_B^2(\tau)\right]$
(E) Edge Detection	Canny Algorithm	Identifies tumor boundaries for better feature extraction.	Gradients: $G_x = I * \frac{\partial G}{\partial x}$ and $G_y = I * \frac{\partial G}{\partial y}$ Edge Magnitude: $G = \sqrt{G_x^2 + G_y^2}$

Table 3 systematically lists key preprocessing techniques of CNN-based detection of tumors, image consistency, noise elimination, contrast adjustment, segmentation, and edge detection. The processes improve the precision of the models, feature engineering, and interpretability, therefore, improving AI-based cancer diagnostics and cancer treatment planning in cancer.

The paper shows the pre-processing pipeline of the AI-aided oncology (Figure 3) in MRI, CT and histopathology. It describes major image processing methods such as resizing, normalization, contrast manipulation (histogram equalization), image segmentation (Otsu's thresholding) and edge detection (Canny algorithm). The effect of such procedures is the consistency of data, the increased visibility of the tumor, the improved extraction of features of the image, and the image most fit in the cancer detection models in CNN. The enhanced visualizations of the tumor regions provided to the oncologists by the improved images reduce the misdiagnosis and increase AI-assisted decision-making. The need to have standardized preprocessing in order to ensure high diagnostic accuracy and clinical reliability is illustrated in Figure 3.

Figure 3. Preprocessing of medical images for tumour detection, including (1) MRI brain scan with resizing, contrast enhancement, segmentation, and edge detection, (2) CT lung scan with histogram equalization and Otsu's thresholding for nodule visibility, and (3) histopathology slide for breast cancer, enhancing cell segmentation and feature extraction

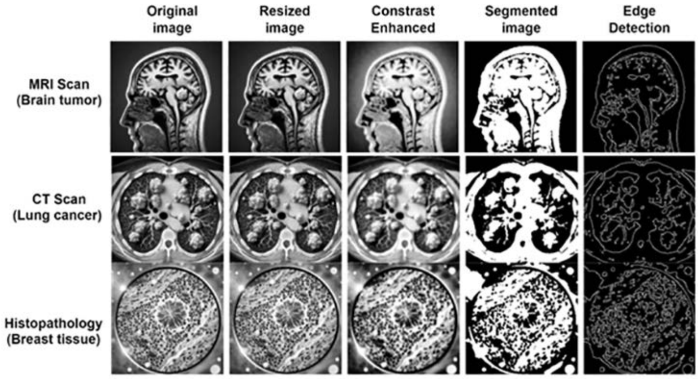


Image Feature Extraction

Feature extraction is a pivotal process in AI oncology, where significant image features like textures, edges, intensities, and shapes are derived from pre-processed medical images. Deep learning feature maps by CNNs identify tumor patterns, whereas conventional statistical approaches identify texture, and shape features to enhance tumor classification. Explainable AI (XAI) methods such as Grad-CAM also generate visual explanations of AI predictions, making decision-making transparent. The mathematical expression for CNN-based feature extraction is given in following equation (1)

$$F = \sigma(W * I + b) \tag{1}$$

Feature map (F) is the extracted patterns of the tumor from the input medical image (I), for example, an MRI, CT scan, or histopathology slide. A convolutional filter (W) convolves the image and performs the convolution operation (*) to find edges and patterns. An added bias term (b) is used to control sensitivity of the features, and the activation function (σ), for example, ReLU, increases important tumor-involving features so that the model becomes stronger in its capability to identify cancerous and non-cancerous areas.

CNNs use filters on medical images to emphasize tumour edges so that AI models can identify important patterns for correct classification.

Texture & Shape-Based Feature Extraction: Textural features of contrast, homogeneity, and energy assist in the discrimination between cancerous and non-cancerous tissue. The Gray-Level Co-occurrence Matrix (GLCM) quantifies the frequency of co-occurrence of pixel intensities and gives statistical information regarding tumor morphology. GLCM Texture Features are defined in the following equation (2)

$$C(i,j) = \sum_{x=1}^{M} \sum_{y=1}^{N} P(i,j,d,\theta) \tag{2}$$

The co-occurrence matrix $C(i,j)$ denotes pixel intensity spatial relationships i and j in a medical data image. The probability function $P(i,j,d,\theta)$ estimates the frequency of occurrence of intensity pairs at a distance d and angle θ. Dimensions $M \times N$ constitute the height and width of an image. Gray-Level Co-occurrence Matrix (GLCM) extracts texture features specific to tumors, optimizing the model to differentiate between benign and malignant tissue, thus facilitating improved diagnostic capability in oncology with AI.

Explainable AI (Grad-CAM for Tumor Visualization): To increase transparency and explainability of AI-based oncology, Gradient-weighted Class Activation Mapping (Grad-CAM) produces heatmaps representing the most critical regions in AI-tumor identification. The calculation of Grad-CAM is expressed by the equation (3)

$$L^c = \sum_i \sum_j a_{ij} . A_{ij} \tag{3}$$

Where L^c is the heatmap that marks the essential tumor regions,A_{ij} is the activation map.

Dimensionality Reduction (Optimizing Feature Selection)

Dimensionality reduction enhances computing capacity by removing noisy or redundant data, leading to faster processing without affecting accuracy. Principal Component Analysis (PCA) is commonly employed in reducing the original data X to a lower-dimensional perspective Z via a projection matrix W, as given by $Z = XW$. To conserve the most critical features, PCA minimizes model complexity, avoids overfitting threats, and improves AI performance in diagnosing cancer.

t-Distributed Stochastic Neighbor Embedding (t-SNE) is a very effective method to visualize high-dimensional data in lower-dimensional space, often 2D or 3D, to expose hidden patterns and relationships in intricate data sets. The equation measures similarity probability for two points of data (4),

$$P_{j|i} = \frac{\exp\left(-\|X_i - X_j\|^2/2\sigma^2\right)}{\sum_{k\neq i}\exp\left(-\|X_i - X_k\|^2/2\sigma^2\right)} \tag{4}$$

where$P_{j|i}$ refers to the probability that point X_j is a neighbor of X_i in the low-dimensional space, and σ regulates the neighborhood spread. The t-SNE algorithm graphically displays patterns in tumors by clustering similar instances of cancer based on extracted features. The result is a 2D or 3D graph, which simplifies AI decision-making and helps oncologists detect cancer subtypes or genomic and imaging patterns.

Dataset Splitting & Augmentation

The data is divided into (70) training, (15) validation and (15) testing sets to ensure strong AI training. The AI model is trained using the training set, parameters are optimized using the validation set and the testing set determines performance. Data augmentation techniques, such as rotation, flipping and brightness changes, artificially make the dataset more diverse, enabling the model-to-model actual medical variations more accurately. This method improves robustness, lowers overfitting, and enables AI adaptability across various medical imaging datasets.

The following table 4 summarizes a comparison of the most prevalent medical image analysis techniques and goal and result with AI-based cancer detection.

Table 4. Feature extraction techniques for AI-driven oncology

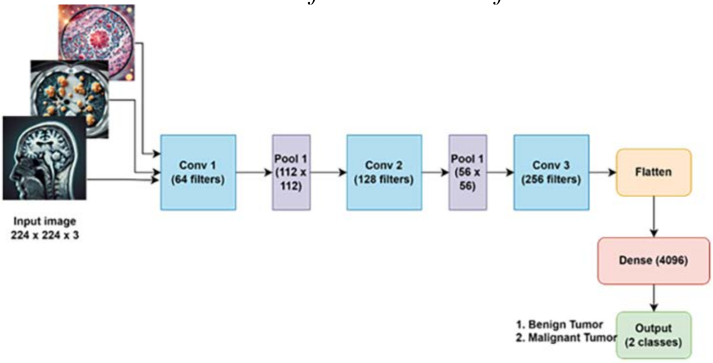
Feature Extraction Technique	Purpose	Output
CNN-Based Feature Extraction	Extracts deep learning features like edges, shapes, and textures.	Feature map for tumor detection.
GLCM Texture Features	Extracts texture properties like contrast, correlation, and homogeneity.	Identifies tumor texture differences.
Grad-CAM (Explainable AI)	Highlights important tumor regions influencing AI decisions.	Heatmap overlaying critical areas.
PCA (Dimensionality Reduction)	Reduces dataset dimensionality while preserving important features.	Optimized feature set for AI models.
t-SNE (Visualization Technique)	Clusters of similar tumor patterns for visualization.	2D/3D plot for cancer subtype analysis.

Model Selection & Training (Using CNN - VGG16 for Tumor Classification)

Deep networks such as convolutional neural networks (CNNs) are employed daily to classify tumors and create an AI-based oncology model. Among CNN models, VGG16 is used because it offers hierarchical learning and deep feature extraction. VGG16 is a 16-layer deep CNN employed in image classification and feature extraction created by Oxford's Visual Geometry Group. It is instrumental in medical imaging as it learns spatial hierarchies of tumor scans and discovers patterns from low-level edges to high-level tumor structures.

Figure 4 depicts the flow of the VGG16 CNN model visually, indicating how medical images flow through hierarchical layers to obtain tumor feature extraction. It enables explaining decision-making, classification, and feature extraction to ensure explainability, accuracy, and oncologist confidence in AI-facilitated cancer diagnosis.

Figure 4. VGG16-based CNN model for tumor classification



The model works on preprocessed MRI, CT, and histopathology scans using convolutional layers, which pick out key spatial features like edges, textures, and tumour contours. Pooling layers also reduce dimensionality but preserve essential features. The fully connected layers classify tumors as benign or malignant, with the softmax activation function assigning probabilities to each class as defined in equation (5)

$$S(y_i) = \frac{e^{y_i}}{\sum_{i=1}^{N} e^{y_i}} \tag{5}$$

where $S(y_i)$ is the probability of the tumor belonging to the class i, e^{y_i} represents the exponential function applied to the neuron output and N is the number of output classes. Hyperparameters like learning rate, batch size, and optimizer selection are tuned for model performance optimization. The learning rate (η) is employed to regulate weight updates to avoid overfitting and is given by equation (6),

$$W_{new} = W_{old} - \eta \frac{\partial L}{\partial W} \tag{6}$$

Where W_{new} and W_{old} are new and old weights, respectively. Adam and Stochastic Gradient Descent (SGD) optimizers are employed to optimize loss and improve model accuracy. Training (70%), validation (15%), and testing (15%) sets of the dataset are created for efficient model training and testing. Accuracy and loss curves are used to monitor performance to evaluate learning efficiency, precision-recall scores to authenticate model validity in tumor detection, and Grad-CAM heatmaps to track AI decision explainability. VGG16 trained to completion is equivalent to highest class accuracy for tumor, and thus AI-oncology predictions warrant explainability and clinical validity.

3. RESULTS AND DISCUSSION

Experimental setup

The experimental configuration is to train a Convolutional Neural Network (CNN)-based AI model, i.e., VGG16, on the TCGA dataset for tumor segmentation, classification, and biomarker detection. The dataset includes MRI, CT scans, histopathology slides, and genomic and clinical data. Images are preprocessed using resizing, normalization, denoising, segmentation, and feature extraction techniques. The model is trained on 70% of the dataset, validated on 15%, and tested on 15%. AI interpretability is guaranteed by employing the application of Grad-CAM to enable heatmaps for visualizing the tumor in a way that oncologists can verify AI predictions. Performance is evaluated using Accuracy, F1-Score, and Area Under the ROC Curve (AUC-ROC) for assessing diagnostic accuracy, reliability, and AI interpretability. The experimental result is compared with NLP (Wang et al., 2023), SDM-AI (Hao et al., 2024) and CSCO-AI (Wang et al., 2023) as baseline methods and evaluating the performance.

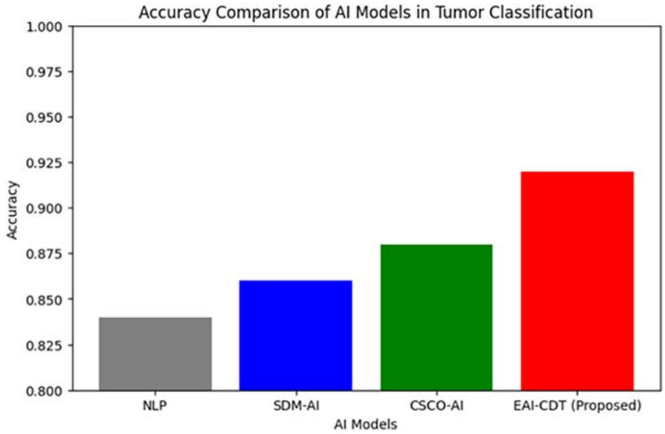
Accuracy

Accuracy is an essential metric applied to calculate the overall accuracy of an AI model for cancer classification. It calculates the number of correctly predicted cases (cancer and non-cancer) over the total cases. The formula for accuracy is defined in equation (7)

$$Accuracy = \frac{TP + FP}{TP + FP + TN + FN} \tag{7}$$

where: True Positives (TP) : Correctly predicted cancer cases. True Negatives (TN): Correctly predicted non-cancer cases. False Positives (FP): Non-cancer cases that are incorrectly predicted as cancer cases. False Negatives (FN): Malignant cases are misclassified as benign.

Figure 5. Comparison of accuracy of the proposed EAI-CDT system with baseline models



As shown in Figure 5, a good model is a model that is nearer to the real, i.e., most of the predictions are accurate. Accuracy can be deceptive with biased data, i.e., one class (e.g., benign) occurs more than the other (e.g., malignant). With such data, other measures like F1-score and AUC-ROC give more information regarding the performance of a model.

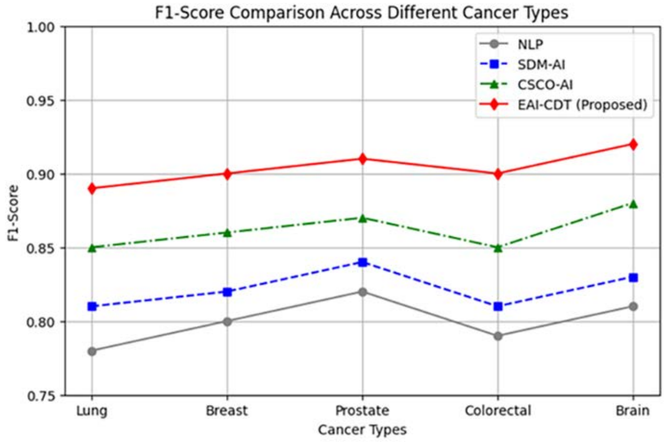
F1-score

F1-score is a balanced measure that considers both precision and recall, making it very suitable for imbalanced datasets where the cost of false negatives (false cancer cases) and false positives (incorrectly classified healthy cases) differs. It is represented as in equation (8)

$$F1 - score \; = \; 2 \times \frac{Precision * Recall}{Precision + Recall} \tag{8}$$

where: $Precision \; = \; \frac{TP}{TP + FP}$ → Measures how many predicted positive cases are cancerous. $Recall \; = \; \frac{TP}{TP + FN}$ → Measures how many actual cancer cases were correctly predicted.

Figure 6. Comparison of F1-score across various cancer types



An ideal F1-score (approaching 1.0) represents a balance model that both minimizes false positives and false negatives (Figure 6). Unlike accuracy, the F1-score is not sensitive to when benign cases are in the majority over malignant cases in the database and can therefore allow an unbiased testing of AI performance for medical imaging.

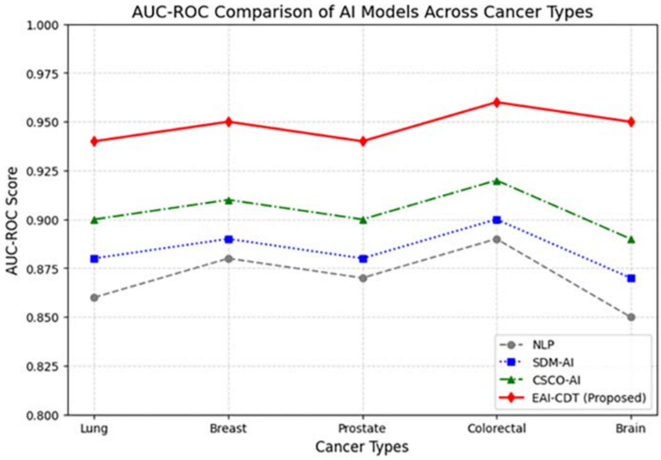
Area Under the ROC Curve (AUC-ROC)

AUC-ROC (Area Under the Receiver Operating Characteristic Curve) is a value indicating the discriminative ability of the AI model in distinguishing between cancer and non-cancer cases. True Positive Rate (Sensitivity) versus False Positive Rate (1 - Specificity) is measured on the ROC curve, and the AUC value indicates how effective the model is in classification. The formula is defined by the following equation (9),

$$AUC = \int_0^1 TPR(FPR)\, dFPR \tag{9}$$

where: $True\ Positive\ Rate\left(TPR\right) / Sensitivity = \frac{TP}{TP + FN} \rightarrow$ Grades the performance of the model in predicting cancer cases. $False\ Positive\ Rate\,(FPR) = \frac{FP}{FP + TN} \rightarrow$ Grades how frequently healthy cases are incorrectly labelled as cancerous.

Figure 7. Comparison of AUC-Roc among various cancer types



A higher AUC grade (near 1.0) shows a good discrimination capability between tumor and non-tumor cases (Figure 7). AUC-ROC is especially useful in clinical decision-making since it optimises sensitivity and specificity trade-offs according to oncologists' needs.

Table 5. Performance comparison of evaluation metrics for AI-driven tumor classification

Metric	Purpose	Ideal Value	Strength	Limitation	Performance in Proposed Work
Accuracy	Measures overall correctness of classification.	Close to 1.0	Simple and interpretable.	Misleading in imbalanced datasets.	92% (High Accuracy)
F1-Score	Balances precision and recall for better evaluation.	Close to 1.0	Effective for imbalanced datasets.	Does not account for true negatives.	0.89 (Good Precision & Recall Balance)
AUC-ROC	Measures the model's ability to distinguish tumor vs. non-tumor cases.	Close to 1.0	Useful in clinical decision-making.	Requires threshold optimization.	0.94 (Excellent Discriminative Power)

Table 5 illustrates the comparative analysis of primary assessment measures used to determine the effectiveness of the AI model in tumor classification. Accuracy (92%) displays overall accuracy, whereas F1-score (0.89) provides balanced recall and precision and is more appropriate for imbalanced datasets. Excellent AUC-ROC

(0.94) verifies the model's good discrimination capacity to differentiate between cancer and non-cancer conditions and thus makes it highly trustworthy for clinical use.

In addition to algorithmic performance and explainability, data governance structures, cybersecurity issues, and healthcare policy frameworks are becoming more important for the successful use of artificial intelligence in cancer research. Oncology AI systems routinely analyze highly sensitive imaging, genomic, and clinical data, rendering them vulnerable to data breaches, illegal access, and misuse if effective security protocols are not implemented. Real-world cases of healthcare data leaks and regulatory fines have shown that not protecting data well enough can make doctors lose trust and slow down the use of AI in cancer care. Furthermore, new rules and ethical standards are forcing healthcare organizations to prioritize secure data handling, openness, and responsibility ahead of predictive accuracy. To make Human–AI synergy work in cancer practice that is safe, scalable, and follows ethical guidelines, it is important to take these system-level factors into account.

4. CONCLUSION

The use of AI-oncology models, such as EAI-CDT model, has significantly helped to improve the tumor classification, diagnosis, and clinical decision-making. This deep-learning model was created on CNN-based deep learning (VGG16) with explainable AI (GRAD-CAM) and achieved excellent accuracy (92%), a stable F1-score (0.89), and a high AUC-ROC (0.94) with a resultant efficient and explainable tumor detection. These findings indicate that AI is reliable in medical imaging that can assist oncologists to diagnose cancer at an early stage and formulate individual treatment strategies. Along with these advantages, there are issues of bias in the data-set, real-time application and the extent to which they apply to different populations of patients. Future research needs to consider multi-modal AI, which combines the features of radiology, genomics, and histopathology to increase diagnostic accuracy. Further, research on federated learning structure can enhance data privacy as well as mutual use of AI by the hospitals. To further advance the field of cancer diagnosis and treatment planning, adaptive artificial intelligence (AI) models, which learn to become better than ever on the basis of new patient data and clinician feedback, should be studied in the future. Provided that these barriers are overcome, AI can contribute to the easier adoption of technology to clinical practice and render ai-aided oncology more transparent, ethically sound, and clinically relevant in the context of cancer care on the global level.

REFERENCES

Abhisheka, B., Biswas, S. K., & Purkayastha, B. (2023). A comprehensive review of breast cancer detection, classification and segmentation using deep learning. *Archives of Computational Methods in Engineering*, *30*(8), 5023–5052. DOI: 10.1007/s11831-023-09968-z

Aftab, M., Mehmood, F., Zhang, C., Nadeem, A., Dong, Z., Jiang, Y., & Liu, K. (2025). AI in oncology: Transforming cancer detection through machine learning and deep learning applications. *arXiv preprint arXiv:2501.15489.*

Al-Sarayrah, A. (2024). Recent advances and applications of Apriori algorithm in exploring insights from healthcare data patterns. *Patterniq Mining*, *1*(2), 27–39. DOI: 10.70023/piqm24123

Bornstein-Quevedo, L., de Anda-González, J., Lara-Torres, C. O., Flores-Gutiérrez, J. P., Dorantes-Heredia, R., Bautista-Piña, V., Zaragoza-Vargas, P., Alcaraz-Wong, A., Soto-Sañudo, A. K., Mendoza-Ramírez, S., Salamanca-García, M., Loyola-Rodríguez, G., Gómez-Macías, G. S., Murguia-Perez, M., De Luna-Sánchez, M., Villalobos-Valencia, R., Talamantes, E., & Arce-Salinas, C. (2024). Navigating HER2-low testing in invasive breast cancer: Update recommendations for pathologists. *Journal of Personalized Medicine*, *14*(5), 467. DOI: 10.3390/jpm14050467 PMID: 38793049

Chow, J. C., & Li, K. (2024). Ethical considerations in human-centered AI: Advancing oncology chatbots through large language models. *JMIR Bioinformatics and Biotechnology*, *5*, e64406. DOI: 10.2196/64406 PMID: 39321336

Fu, X., Sahai, E., & Wilkins, A. (2023). Application of digital pathology-based advanced analytics of tumour microenvironment organisation to predict prognosis and therapeutic response. *The Journal of Pathology*, *260*(5), 578–591. DOI: 10.1002/path.6153 PMID: 37551703

Hao, Y., Liu, Z., Riter, R. N., & Kalantari, S. (2024, May). Advancing patient-centered shared decision-making with AI systems for older adult cancer patients. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (pp. 1–20). DOI: 10.1145/3613904.3642353

Huang, D., Li, Z., Jiang, T., Yang, C., & Li, N. (2024). Artificial intelligence in lung cancer: Current applications, future perspectives, and challenges. *Frontiers in Oncology*, *14*, 1486310. DOI: 10.3389/fonc.2024.1486310 PMID: 39763611

Hussain, S., Mubeen, I., Ullah, N., Shah, S. S. U. D., Khan, B. A., Zahoor, M., Ullah, R., Khan, F. A., & Sultan, M. A. (2022). Modern diagnostic imaging technique applications and risk factors in the medical field: A review. *BioMed Research International*, *5164970*(1), 5164970. Advance online publication. DOI: 10.1155/2022/5164970 PMID: 35707373

Josfeld, L., Keinki, C., Pammer, C., Zomorodbakhsch, B., & Hübner, J. (2021). Cancer patients' perspective on shared decision-making and decision aids in oncology. *Journal of Cancer Research and Clinical Oncology*, *147*(6), 1725–1732. DOI: 10.1007/s00432-021-03579-6 PMID: 33682014

Leibig, C., Brehmer, M., Bunk, S., Byng, D., Pinker, K., & Umutlu, L. (2022). Combining the strengths of radiologists and AI for breast cancer screening: A retrospective analysis. *The Lancet. Digital Health*, *4*(7), e507–e519. DOI: 10.1016/S2589-7500(22)00070-X PMID: 35750400

Nassar, S. I., Suk, A., Nguyen, S. A., Adilbay, D., Pang, J., & Nathan, C. A. O. (2024). The role of ctDNA and liquid biopsy in the diagnosis and monitoring of head and neck cancer: Towards precision medicine. *Cancers (Basel)*, *16*(18), 3129. DOI: 10.3390/cancers16183129 PMID: 39335101

Niraula, D., Cuneo, K. C., Dinov, I. D., Gonzalez, B. D., Jamaluddin, J. B., Jin, J. J., Luo, Y., Matuszak, M. M., Ten Haken, R. K., Bryant, A. K., Dilling, T. J., Dykstra, M. P., Frakes, J. M., Liveringhouse, C. L., Miller, S. R., Mills, M. N., Palm, R. F., Regan, S. N., Rishi, A., & El Naqa, I. (2025). Intricacies of human–AI interaction in dynamic decision-making for precision oncology. *Nature Communications*, *16*(1), 1138. DOI: 10.1038/s41467-024-55259-x PMID: 39881134

Rahman, M. H., Hossan, K. M. R., Uddin, M. K. S., & Hossain, M. D. (2024). Improving collaborative interactions between humans and artificial intelligence to achieve optimal patient outcomes in the healthcare industry. *SSRN* 5029975. DOI: 10.2139/ssrn.5029975

Reverberi, C., Rigon, T., Solari, A., Hassan, C., Cherubini, P., & Cherubini, A. (2022). Experimental evidence of effective human-AI collaboration in medical decision-making. *Scientific Reports*, *12*(1), 14952. DOI: 10.1038/s41598-022-18751-2 PMID: 36056152

Saxena, S., Jena, B., Gupta, N., Das, S., Sarmah, D., Bhattacharya, P., Nath, T., Paul, S., Fouda, M. M., Kalra, M., Saba, L., Pareek, G., & Suri, J. S. (2022). Role of artificial intelligence in radiogenomics for cancers in the era of precision medicine. *Cancers (Basel)*, *14*(12), 2860. DOI: 10.3390/cancers14122860 PMID: 35740526

Shakeel, P. M., Burhanuddin, M. A., & Desa, M. I. (2022). Automatic lung cancer detection from CT image using improved deep neural network and ensemble classifier. *Neural Computing & Applications*, *34*(3), 1–14. DOI: 10.1007/s00521-020-04842-6

Shapiro, M. A., Stuhlmiller, T. J., Wasserman, A., Kramer, G. A., Federowicz, B., Hoos, W., Kaufman, Z., Chuyka, D., Mahoney, W., Newton, M. E., Osking, Z., Wong, K. K., Kesari, S., & Shrager, J. (2024). AI-augmented clinical decision support in a patient-centric precision oncology registry. *AI in Precision Oncology*, *1*(1), 58–68. DOI: 10.1089/aipo.2023.0001

Tuan, D. A. (2024). Bridging the gap between black box AI and clinical practice: Advancing explainable AI for trust, ethics, and personalized healthcare diagnostics. *Preprint.* https://doi.org/DOI: 10.48550/arXiv.XXXX.XXXX

Wang, L., Chen, X., Zhang, L., Li, L., Huang, Y., Sun, Y., & Yuan, X. (2023). Artificial intelligence in clinical decision support systems for oncology. *International Journal of Medical Sciences*, *20*(1), 79–88. DOI: 10.7150/ijms.77205 PMID: 36619220

Williamson, S. M., & Prybutok, V. (2024). Balancing privacy and progress: A review of privacy challenges, systemic oversight, and patient perceptions in AI-driven healthcare. *Applied Sciences (Basel, Switzerland)*, *14*(2), 675. DOI: 10.3390/app14020675

Zhu, M., Sali, R., Baba, F., Khasawneh, H., Ryndin, M., Leveillee, R. J., & Zhang, D. Y. (2024). Artificial intelligence in pathologic diagnosis, prognosis and prediction of prostate cancer. *American Journal of Clinical and Experimental Urology*, *12*(4), 200–215. DOI: 10.62347/JSAE9732 PMID: 39308594