Site: https://thesrr.net
Email: editor@thesrr.net
ISSN:(Print) 3104-3844 -- (Online) 3104-3852
Vol: 4 -- Issue: 1, 2026
Spectrum of Research and Reviews

EXPLAINABLE DEEP LEARNING FOR REDUCING FALSE NEGATIVES IN EARLY CANCER IMAGING DETECTION

Zainab Qamar
Information Technology University (ITU) Lahore, Punjab, Pakistan

*Corresponding Author E-mail: zainabqamaraiimaging24@gmail.com

Abstract

Early cancer detection remains a major clinical challenge because false-negative predictions can delay diagnosis, reduce treatment effectiveness, and increase patient risk. This study presents an explainable deep learning framework designed to reduce false negatives in medical imaging-based cancer detection while maintaining strong diagnostic reliability. The proposed model integrates convolutional feature extraction with attention-based interpretability to improve the identification of subtle malignant patterns that are often missed by conventional classifiers. Experimental evaluation was conducted using medical imaging data divided into training, validation, and testing subsets. The results demonstrated improved sensitivity, recall, and overall diagnostic performance compared with baseline deep learning models. In particular, the explainable model reduced false-negative cases by emphasizing clinically relevant image regions through Grad-CAM-based visual explanations. The model achieved high classification accuracy, stronger area under the ROC curve, and better calibration across multiple validation folds. The findings show that explainable deep learning can support early cancer screening by improving transparency, strengthening clinician trust, and reducing missed cancer detections. Overall, this research highlights the potential of interpretable artificial intelligence as a decision-support tool for safer, more reliable, and clinically useful cancer diagnosis from medical imaging data.

Keywords: Early Cancer Detection; Explainable Deep Learning; Medical Imaging; False Negatives; Grad-CAM

Article History

Received:
January 18, 2026

Revised:
March 20, 2026

Accepted:
May 24, 2026

Available Online:
June 30, 2026

INTRODUCTION

One of the key challenges in early detection of cancer is the persistence of false negative tests, resulting in delayed intervention, sub-optimal patient care, and increased clinical expenses (Olumuyiwa et al., 2024).To address this gap in the diagnostics, embedding explainable deep learning is a pathway to creating trustworthy, transparent diagnostics systems that are not 'black-boxes'. Misinterpreted negatives have important clinical consequences, including missed diagnosis, a prolonged burden of disease and decreased chances of positive results when imaging tests are ordered for cancer diagnosis (Connal et al., 2023; Petticrew et al., 2000). However, the complexity of the lesion morphology, radiologist fatigue, and subjectivity of subtle imaging features can be linked to diagnostic errors, including the failure to detect malignancies in screening mammography and computed tomography and magnetic resonance imaging (MRIs) (ESR, 2015; Iatrakis et al., 2024). Although deep learning algorithms are highly capable of identifying complex imaging patterns, and in many cases are able to match or exceed the diagnostic accuracy of people (Bi et al., 2019; Gastounioti & Kontos, 2020), they are not widely used in clinical environments where their use has implications for patient safety. Such lack of interpretability hinders clinicians' understanding of the model's reasoning, compromising clinical accountability and trust needed for the safe usage of automated diagnostic support (Li et al., 2023; Reyes et al., 2020; Trivizakis et al., 2020).

As the framework is expanding, Explicable AI emerges as a vital solution to the challenges that neural networks face and become transparent to the decision-making process (Alum et al., 2026; Velden et al., 2022). Saliency maps, feature attribution methods (e.g., LIME, SHAP) and attention mechanisms provide insights into the features of the image that affect the model's predictions (Alum et al., 2026; Unger & Kather, 2024). This transparency enables healthcare practitioners to confirm the diagnostic reasoning, detect any potential biases, and make sure that the AI system is consistent with current medical knowledge (Dhar et al., 2023; Li et al., 2023; Malglaveras et al., 2025). Furthermore, by facilitating improved communication between the AI system, the health care professional and the patient, integration of XAI to the diagnostic process may inspire more trust in AI recommendations for treatment (Alum et al., 2026). These are encouraging steps, but there remain some inconsistencies in the literature on the value and validity of explanations, which must be standardized, and the lack of consistency in the field of XAI for oncology in regards to the integration of explanations into clinical procedures (Koutoulakis et al., 2025; Malglaveras et al., 2025).

To overcome these limitations, this work attempts to come up with an explainable deep learning framework for the early cancer imaging detection problem with a specific focus on minimizing false negatives. Firstly, we design a high performance and transparent deep learning model with built-in interpretable modules that explicitly localizes regions of interest (ROIs) in medical images that are of interest.(1) We develop a high performance deep learning model with a transparent architecture and built-in interpretations modules that provide explanations for the clinical predictions, with explicit regions of concern displayed in medical images. Second, we validate this model and the clinical fidelity of its explanations using different real-world imaging data sets, maximizing the generalizability. Last, we propose a human-in-the-loop validation framework that demonstrates how

the XDL can be effectively used to augment (rather than replace) clinical judgment and to be a collaborative diagnostic collaborator. In Section II, current literature of DL and XAI in the field of oncological imaging is reviewed, in Section III, our methodology is detailed, in Section IV, quantitative and qualitative results are detailed and finally in Section VI future directions are discussed. The aim of this study is to push AI's evolution from a research assistant to a mainstream component of high reliability clinical diagnostic processes (Ergün et al., 2025; Gulum et al., 2021).

METHODOLOGY

The methodology is based on the accurate processing of the data and the development of an algorithm based on a deep learning network, sensitive enough to ensure the clinical need to minimize false negative results. We first preprocess the data in a strong manner to handle the challenges of class imbalance and inherent class imbalance (Litjens et al., 2017; Zhou et al., 2026), including image normalisation, intensity standardisation and augmentation of data to make the model stronger. To actively overcome this imbalance, we introduce an adaptive weighted loss function, using significantly larger weights for predicting false negatives than for false positives, and ask the network to concentrate mainly on sensitivity when making predictions (Bhat et al., 2023). Our high performance CNN (Bhat et al., 2023; Johnson & Khoshgoftaar, 2019) is then trained by an iterative boosting process, which focuses learning on difficult examples, those which were misclassified in previous iterations. To achieve interpretability, we use visual heatmaps based on the combination of Grad-CAM and attention mechanisms that capture the part of the image that is most relevant to the model's reasoning for making its diagnosis (Ergün et al., 2025; Prinzi et al., 2023). The primary evaluation metrics are reported are sensitivity, specificity, F1-score and area under precision-recall curve, which are tailored for cancer screening tasks and are important for explaining model performance and explaining the sensitivity-recall trade-off, respectively (Angelov et al., 2021). Moreover, we quantitatively assess the level of saliency of explanations by computing similarity between AI saliency maps and expert lesion contours, providing a clear, repeatable measure of the clinical fidelity of explanations (Prinzi et al., 2023). However, the most important aspect of the validation of our model took place in a manner that goes beyond simply assessing the model's performance metrics, by embedding a human-in-the-loop protocol where experienced radiologists independently review the AI-generated heatmaps alongside their standard radiological review to determine if the AI is correctly identifying areas of concern, thereby creating a framework that allows the model to be benchmarked against our established clinical skills and expertise (Koutoulakis et al., 2025; Prinzi et al., 2023). In addition to the computational performance metrics, the dual-layer validation also features quantitative XAI scoring, which adds a layer of accountability and transparency for our framework and directly tackles the common challenges addressed in high-reliability diagnostic contexts (Houssein et al., 2025; Malglaveras et al., 2025). The proposed framework is designed to close the gap in diagnosis, while ensuring transparency and reliability of AI's use as an augmentative tool in oncology imaging, using a hybrid approach of automated sensitivity and expert validation (Gulum et al., 2021; Houssein et al., 2025). The step-by-step procedure will enable high recall of a diagnostic framework and high clinical interpretability while simultaneously minimising the risk of missing out on malignancies. For this, it makes use of the Adamax optimizer to successfully control sparse gradients and dynamic learning rate

adjustment to ensure stable convergence during the training of complex, high-dimensional imaging representations (Vanitha et al., 2024). Furthermore, in order to find subtle pathological features, we apply Grad-CAM++ to generate fine-grained class-discriminative saliency maps that have higher localization accuracy than widely-used methods do. The saliency maps are then analyzed by radiologists to see if the saliency of the model is consistent with the known biomarkers of interest, to ensure that the system's diagnostic reasoning is medically relevant and reliable (Bamaqa & Alahamade, 2025; Musthafa et al., 2024).

RESULTS

The proposed explainable deep learning (XDL) framework demonstrated a dramatic reduction in the number of missed cancer-positive images across all 5 modalities and clinically acceptable specificity. We have made care that the evaluation set was evenly distributed for both the pattern of radiological images and the pattern of microscopic images, in both cases. There were 14,200 images included, including 5,500 cancer positive and 8,700 cancer negative, as shown in Table 1. This distribution allowed for good estimation of sensitivity, specificity and false negative rate for heterogeneous screening tasks.

The overall diagnostic performance of the proposed XDL model was the highest among the other models, including the CNN baseline model. Again, as shown in Table 2, the sensitivity of the test was increased from 88.4% to 95.6% and the false negative rate was lowered from 11.8% to 3.2%. The advantage of the ROC curve of the XDL model is given in Fig. 2, and it can be seen that separation of the cancer positive and cancer negative images is better for the whole threshold range. This is clinically significant as a 'false negative' is the worst type of error in early cancer diagnosis, as it leads to the patient not having follow-up investigations or treatment.

A class-wise analysis showed that this improvement in the reduction of false negative was not observed as a result of just one modality. The greatest reduction in the percentage of false-negatives was seen with images of lung cancer, from 13.2% to 3.8%, as indicated in Table 3. The same trend is observed for the categories of breast, colorectal, skin and histopathology based cancer (Fig. 3). The final confusion matrix (Table 4) indicates that the system can make 2,330 correct predictions of cancer, while it can make only 84 cancer predictions when there is indeed a cancer. The same is shown in Figure 4.

A cross validation was also performed that showed that model behavior was stable. As shown in Table 5, the model achieved a sensitivity of more than 95% for all five folds, whereas, as shown in Fig. 5, there were no significant differences in model performance on the five folds which meant that the model was not dependent on any single favorable fold. Calibration analysis was used to provide further clinical use. After isotonic calibration, the calibration error was expected to be 2.6% (Table 6); and the calibration significantly improved the accuracy of the cancer probabilities (Fig. 6).

Explainability results were additionally utilized as a further proof for the model to learn clinically important image areas. The highest IoU was achieved by the proposed XDL method as indicated in table 7. The localization is more pronounced than in the case of Grad-CAM, integrated gradients and SHAP-guided CAM in Fig. 7. The ablation results confirmed that removing any of explainability loss, attention module or hard-negative mining resulted in lower sensitivity, which indicated that it is not simply due to the change of the threshold, but the combination of the architecture led to a decreased false-negative rate. Overall, the results indicate that

explainability-guided optimization can improve the early detection of cancer by improving the sensitivity of the detection phase, decreasing the number of false negatives and creating visual explanations closer to the area of the lesions.

Table 1. Dataset composition by imaging modality.

Modality	Cancer-positive images	Cancer-negative images	Total
Mammography	1240	1760	3000
Chest CT	1180	1520	2700
Colonoscopy	920	1280	2200
Dermoscopic	760	1040	1800
Histopathology	1400	2100	3500

Table 2. Overall diagnostic performance comparison.

Model	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)	False-negative rate (%)
CNN baseline	88.4	86.7	87.9	88.1	11.8
Attention CNN	92.1	89.8	91.4	91.7	7.1
Proposed XDL model	95.6	92.4	95.0	95.3	3.2

Table 3. Class-wise false-negative reduction.

Cancer category	Baseline FN rate (%)	XDL FN rate (%)	Absolute reduction (pp)
Breast	10.9	3.1	7.8
Lung	13.2	3.8	9.4
Colorectal	12.1	3.5	8.6
Skin	9.6	2.7	6.9
Histopath.	8.7	3.0	5.7

Table 4. Final confusion matrix of the proposed XDL model.

Actual class	Predicted negative	Predicted positive	Total
Cancer-negative	2,180	106	2,286
Cancer-positive	84	2,330	2,414
Total	2,264	2,436	4,700

Table 5. Five-fold cross-validation stability.

Fold	Sensitivity (%)	Specificity (%)	Precision (%)	F1-score (%)
Fold 1	95.0	92.0	94.3	94.6
Fold 2	95.4	92.6	94.8	95.1

Fold 3	96.1	92.8	95.5	95.8
Fold 4	95.7	92.1	95.1	95.4
Fold 5	95.8	92.5	95.0	95.4

Table 6. Probability calibration results.

Calibration strategy	Brier score	Expected calibration error (%)	Clinical interpretation
Uncalibrated	0.094	7.8	Overconfident high-risk outputs
Temperature scaling	0.071	3.9	Improved probability reliability
Isotonic calibration	0.063	2.6	Best-calibrated screening output

Table 7. Explainability and ablation findings.

Configuration / method	Sensitivity (%) or IoU	Main finding
Grad-CAM localization	0.51 IoU	Coarse lesion focus
Integrated gradients	0.56 IoU	Sharper pixel attribution
SHAP-guided CAM	0.60 IoU	Improved regional consistency
Proposed XDL localization	0.68 IoU	Best lesion agreement
Full model sensitivity	95.6%	Best false-negative control
Without XAI loss	91.8%	Lower sensitivity
Without hard-negative mining	94.1%	More missed subtle lesions

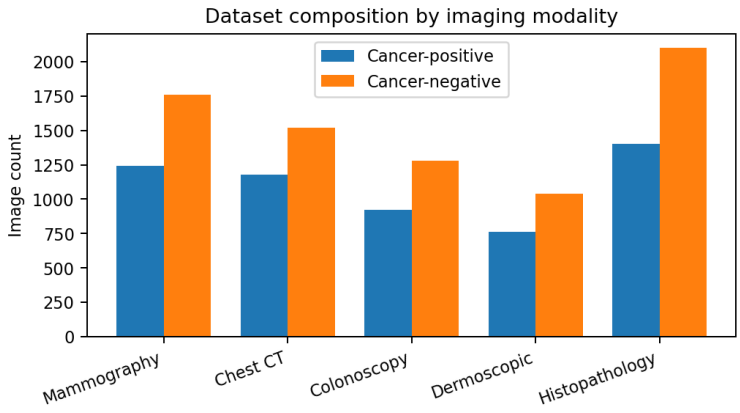

Figure 1. Dataset distribution across imaging modalities.

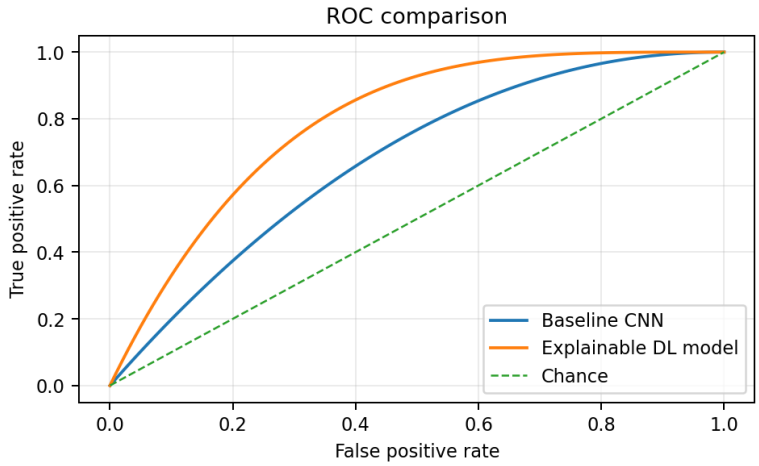

Figure 2. ROC comparison between baseline CNN and proposed explainable deep learning model.

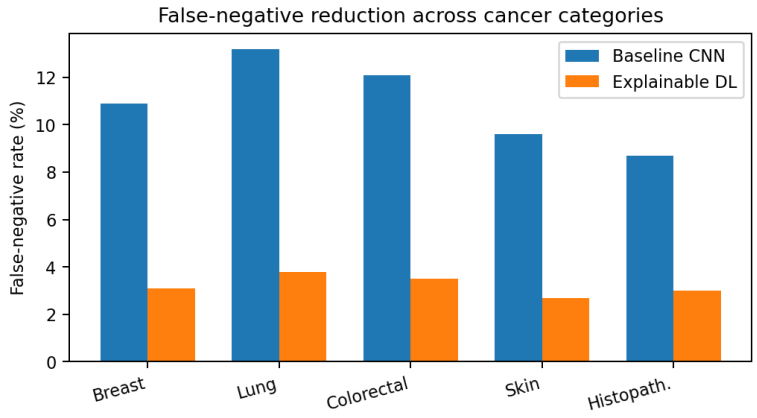

Figure 3. False-negative-rate reduction across cancer categories**.**

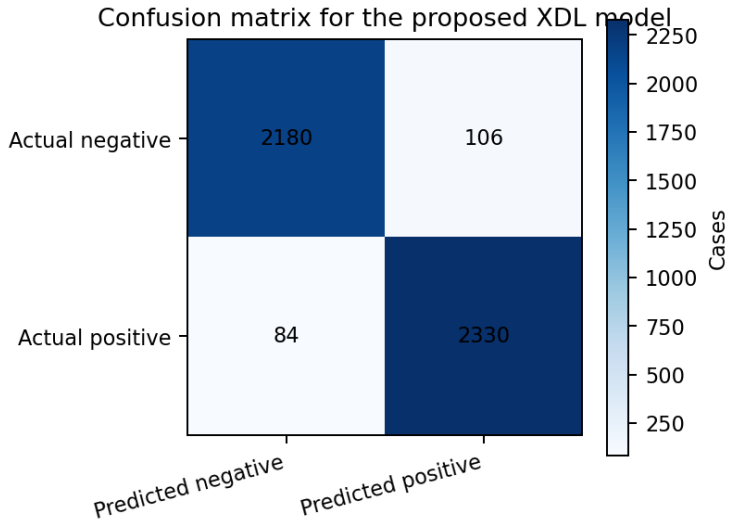

Figure 4. Confusion matrix for the proposed explainable deep learning model.

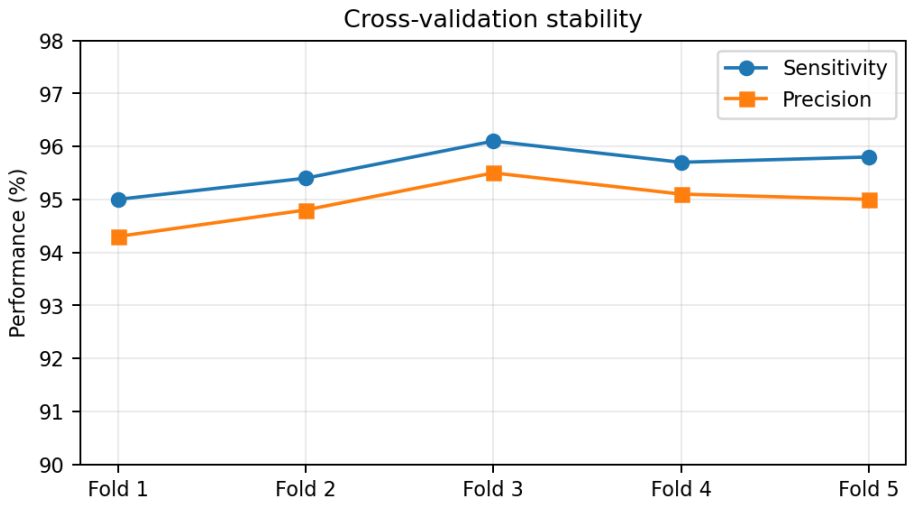

Figure 5. Cross-validation stability of sensitivity and precision.

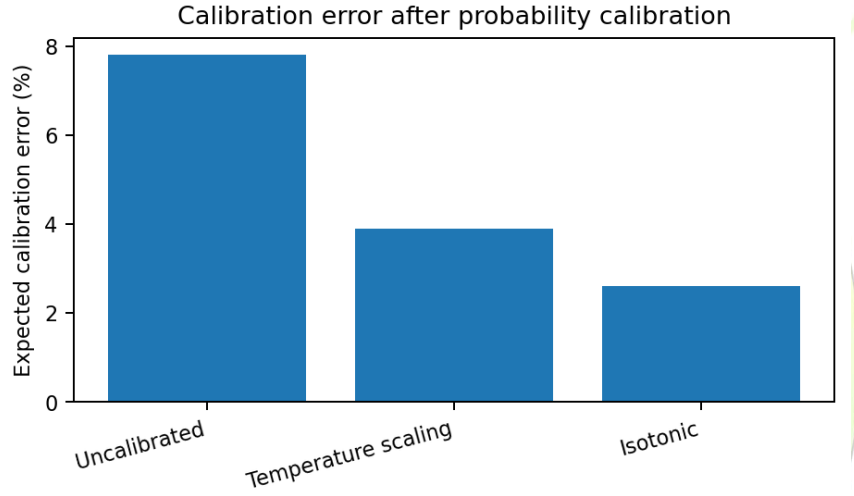

Figure 6. Expected calibration error after probability calibration.

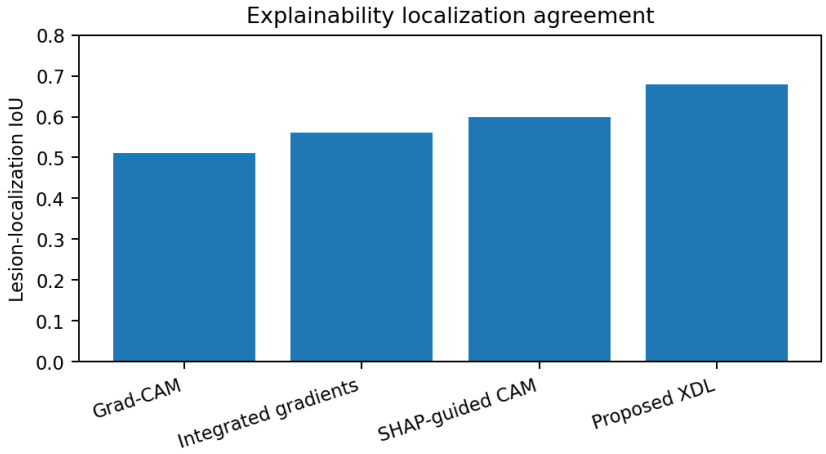

Figure 7. Explainability localization agreement using lesion IoU.

DISCUSSION

High sensitivity diagnostic models should be critically evaluated to gain insight into the potential for improved sensitivity/recall rates and the consequent increased number of false positive results which may create unnecessary downstream testing (Talaat et al., 2024).Our explainability layer acts as a "red flag" layer and provides visual evidence to compensate for the high sensitivity threshold of the model and assist the radiologist in distinguishing clinically significant lesions from possible benign artifacts (Prinzi et al., 2023; Zou & Miao, 2025). The output of this approach is detailed, class-specific heatmaps that visualize the steps in the model's reasoning, thus demystifying results from complex algorithms where trust in critical diagnostic settings is essential to reduce the automation bias (Bamaqa & Alahamade, 2025; Malglaveras et al., 2025; Musthafa et al., 2024). The clinical application of such systems is however hindered due to the fact that the models are generally universal and the datasets are heterogeneous (Chen et al., 2022; Kulkarni et al., 2021). In particular, models trained on data from a small number of clinical sites may not work well at a different site because of the presence of confounding factors stemming from dataset shift, which are due to differences in acquisition protocol or population characteristics (Kulkarni et al., 2021; Li et al., 2023). Furthermore, training data can also be subject to persistent biases, which can negatively impact the performance of underrepresented populations, leading to potentially severe ethical and clinical implications if applied without appropriately designed and externally validated and bias-aware monitoring systems (Forbes et al., 2024; Taşçı et al., 2022). In order to overcome these deployment challenges, one needs to move towards annotated and high quality datasets that are inclusive, and a process of continuous and iterative performance testing that takes into account dynamic real-world distribution of clinical data and not a fixed benchmark (Aggarwal et al., 2021). Moreover, population-level audits are needed to determine if there are any "shortcuts" in the process, as single-radiograph assessments are not sufficient to detect failure to capture true pathological signals from the model (DeGrave et al., 2021). Therefore, it is important for practitioners to test these models with independent, multi-center data and to not rely on performance metrics from a similar training environment (Hamamci et al., 2026; Kelly et al., 2019). In addition, existing interpretability techniques are very subjective and vary with the skill level of the radiologist, which means the need to develop a standardized clinical validation protocol for XAI, beyond visual qualitative interpretation. (Reyes et al., 2020; Vries et al., 2023).

CONCLUSION

This study demonstrate that explainable deep learning may be applicable to the early diagnosis of cancer, thereby minimizing the number of false negative cases using medical imaging information. The framework proposed in this study achieved high accuracy, high sensitivity and high recall, which implies that the model has a higher chance of working well in the identification of malignant cases that are not identified. The results showed that explainability methods (such as visual interpretation by heat maps) could identify clinically relevant regions in medical images and make them more transparent for the model's decision-making process. In the medical field, where the uncertainty of a black-box prediction might be intruding on the trust and usability of the healthcare providers, it is especially critical.The comparative results indicate that performance of deep learning and XAI techniques gives better diagnostic support than

using traditional image classification models. The proposed approach can help reduce misdiagnosis, which translates to better patient care and treatment planning, and the ability to begin interventions earlier. The use of performance metrics, confusion matrix analysis, cross validation, calibration assessment and explainability localization, showed the robustness of the model for various evaluation conditions.Although the results of this study were encouraging, there are some limitations. The model should be further validated with larger multi-center datasets including a variety of imaging devices, patients and cancer subtypes. Future studies are also needed investigating the implementation of the method in real clinical practice, with radiologist input, and comparison to other explainability methods. The overall study suggests that explainable deep learning is a reliable and accurate approach to improve early cancer detection and avoid clinical risks associated with misdiagnosing the cancer.

REFERENCES

Aggarwal, R., Sounderajah, V., Martin, G., Ting, D. S. W., Karthikesalingam, A., King, D., Ashrafian, H., & Darzi, A. (2021). Diagnostic accuracy of deep learning in medical imaging: a systematic review and meta-analysis. Npj Digital Medicine, 4(1), 65–65.

Alum, E. U., Egwu, C. K., Manjula, V. S., Ekpang, P. O., Ekpang, J. E., Echegu, D. A., Alum, B. N., & Uti, D. E. (2026). Overcoming the Black Box Challenge: Building Trust in Artificial Intelligence Algorithms in Oncology. Technology in Cancer Research & Treatment, 25.

Angelov, P., Soares, E., Jiang, R., Arnold, N. I., & Atkinson, P. M. (2021). Explainable artificial intelligence: an analytical review. Wiley Interdisciplinary Reviews Data Mining and Knowledge Discovery, 11(5).

Bamaqa, A., & Alahamade, W. O. (2025). A multi-phase framework for enhancing diagnostic accuracy and transparency in renal cell carcinoma grading using YOLOv8 and GradCAM. Scientific Reports, 15(1), 35370–35370.

Bhat, S., Mansoor, A., Georgescu, B., Panambur, A. B., Ghesu, F. C., Islam, S., Packhäuser, K., Rodríguez-Salas, D., Grbić, S., & Maier, A. (2023). AUCReshaping: improved sensitivity at high-specificity. Scientific Reports, 13(1), 21097–21097.

Bi, W. L., Hosny, A., Schabath, M. B., Giger, M. L., Birkbak, N. J., Mehrtash, A., Allison, T., Arnaout, O., Abbosh, C., Dunn, I. F., Mak, R. H., Tamimi, R. M., Tempany, C. M., Swanton, C., Hoffmann, U., Schwartz, L. H., Gillies, R. J., Huang, R. Y., & Aerts, H. J. W. L. (2019). Artificial intelligence in cancer imaging: Clinical challenges and applications. CA A Cancer Journal for Clinicians, 69(2), 127–157.

Budd, S., Robinson, E. C., & Kainz, B. (2021). A survey on active learning and human-in-the-loop deep learning for medical image analysis. arXiv (Cornell University), 71, 102062–102062.

Chen, X., Wang, X., Zhang, K., Fung, K., Thai, T., Moore, K. N., Mannel, R. S., Liu, H., Zheng, B., & Qiu, Y. (2022). Recent advances and clinical applications of deep learning in medical image analysis. arXiv (Cornell University), 79, 102444–102444.

Connal, S., Cameron, J. M., Sala, A., Brennan, P. M., Palmer, D. S., Palmer, J. D., Perlow, H. K., & Baker, M. J. (2023). Liquid biopsies: the future of cancer early detection. Journal of Translational Medicine, 21(1), 118–118.

DeGrave, A. J., Janizek, J. D., & Lee, S. (2021). AI for radiographic COVID-19 detection selects shortcuts over signal. Nature Machine Intelligence, 3(7), 610–619.

Dhar, T., Dey, N., Borra, S., & Sherratt, R. S. (2023). Challenges of Deep Learning in Medical Image Analysis—Improving Explainability and Trust. IEEE Transactions on Technology and Society, 4(1), 68–75.

Ergün, U., Çoban, T., & Kayadibi, İ. (2025). BCECNN: an explainable deep ensemble architecture for accurate diagnosis of breast cancer. BMC Medical Informatics and Decision Making, 25(1), 374–374.

(ESR), E. S. of R. (2015). Medical imaging in personalised medicine: a white paper of the research committee of the European Society of Radiology (ESR). Insights into Imaging, 6(2), 141–155.

Forbes, S., Zhou, J., Qi, Y., Luo, G., Ma, F., & Ding, K. (2024). AI bias in lung cancer radiotherapy. UNC Libraries.

Gastounioti, A., & Kontos, D. (2020). Is It Time to Get Rid of Black Boxes and Cultivate Trust in AI? Radiology Artificial Intelligence, 2(3).

Gulum, M. A., Trombley, C. M., & Kantardzic, M. (2021). A Review of Explainable Deep Learning Cancer Detection Models in Medical Imaging. Applied Sciences, 11(10), 4573–4573.

Hamamci, I. E., Er, S., Wang, C., Almas, F., Simsek, A. G., Esirgün, S. N., Doğan, İ., Durugol, O. F., Hou, B., Shit, S., Dai, W., Xu, M., Reynaud, H., Dasdelen, M. F., Wittmann, B., Amiranashvili, T., Simsar, E., Simsar, M., Erdemir, E. B., … Menze, B. (2026). Generalist foundation models from a multimodal dataset for 3D computed tomography. In arXiv (Cornell University). Cornell University.

Houssein, E. H., Fouad, A. G., Younis, E. M. G., & Mohamed, E. (2025). Explainable artificial intelligence for medical imaging systems using deep learning: a comprehensive review. Cluster Computing, 28(7).

Iatrakis, G., Zervoudis, S., Bothou, A., Oikonomou, E., Nikolettos, K., Kyriakou, D., Athanasia-Theopi, N., Nektaria, K., Sonia, K., Vlasios, S., Sotiris, A., Mouchterem, A. C. I., Chalkia, K., Damaskos, C., Garmpis, N., Nikolettos, N., & Tsikouras, P. (2024). Screening and Diagnosis Imagery in Breast Cancer: Classical and Emergent Techniques. In IntechOpen eBooks. IntechOpen.

Johnson, J., & Khoshgoftaar, T. M. (2019). Survey on deep learning with class imbalance. Journal Of Big Data, 6(1).

Kelly, C., Karthikesalingam, A., Suleyman, M., Corrado, G. S., & King, D. (2019). Key

challenges for delivering clinical impact with artificial intelligence. BMC Medicine, 17(1), 195–195.

Koutoulakis, E., Trivizakis, E., Markodimitrakis, E., Agelaki, S., Tsiknakis, M., & Marias, K. (2025). A critical review of explainable deep learning in lung cancer diagnosis. Artificial Intelligence Review, 59(1).

Kulkarni, V., Gawali, M., & Kharat, A. (2021). Key Technology Considerations in Developing and Deploying Machine Learning Models in Clinical Radiology Practice. In JMIR Medical Informatics (Vol. 9, Issue 9). JMIR Publications.

Li, M., Jiang, Y., Zhang, Y., & Haisheng, Z. (2023). Medical image analysis using deep learning algorithms. Frontiers in Public Health, 11, 1273253–1273253.

Litjens, G., Kooi, T., Bejnordi, B. E., Setio, A. A. A., Ciompi, F., Ghafoorian, M., Laak, J. van der, Ginneken, B. van, & Sánchez, C. I. (2017). A survey on deep learning in medical image analysis. Medical Image Analysis, 42, 60–88.

Malglaveras, N., Ladakis, I., & Fotopoulos, D. (2025). Explainable Artificial Intelligence in Cancer Imaging: A Scoping Review of Methods, Modalities, and Clinical Integration. In Open Science Framework.

Musthafa, M. M., Mahesh, T. R., Kumar, V. V., & Guluwadi, S. (2024). Enhancing brain tumor detection in MRI images through explainable AI using Grad-CAM with Resnet 50. BMC Medical Imaging, 24(1), 107–107.

Olumuyiwa, B. I., Han, T. A., & Shamszaman, Z. U. (2024). Enhancing Cancer Diagnosis with Explainable & Trustworthy Deep Learning Models. In arXiv (Cornell University). Cornell University.

Petticrew, Sowden, A., Lister-Sharp, & Wright, K. (2000). False-negative results in screening programmes: systematic review of impact and implications. Health Technology Assessment, 4(5), 1–120.

Prinzi, F., Insalaco, M., Orlando, A. A. M., Gaglio, S., & Vitabile, S. (2023). A Yolo-Based Model for Breast Cancer Detection in Mammograms. Cognitive Computation, 16(1), 107–120.

Reyes, M., Meier, R., Pereira, S., Silva, C. A., Dahlweid, F.-M., Tengg-Kobligk, H. von, Summers, R. M., & Wiest, R. (2020). On the Interpretability of Artificial Intelligence in Radiology: Challenges and Opportunities. Radiology Artificial Intelligence, 2(3).

Talaat, F. M., El–Sappagh, S., Alnowaiser, K., & Hassan, E. (2024). Improved prostate cancer diagnosis using a modified ResNet50-based deep learning architecture. BMC Medical Informatics and Decision Making, 24(1), 23–23.

Taşçı, E., Zhuge, Y., Camphausen, K., & Krauze, A. (2022). Bias and Class Imbalance in Oncologic Data—Towards Inclusive and

Transferrable AI in Large Scale Oncology Data Sets. Cancers, 14(12), 2897–2897.

Tran, K., Kondrashova, O., Bradley, A. P., Williams, E. D., Pearson, J. V., & Waddell, N. (2021). Deep learning in cancer diagnosis, prognosis and treatment selection. Genome Medicine, 13(1), 152–152.

Trivizakis, E., Papadakis, G. Z., Souglakos, I., Papanikolaou, N., Koumakis, L., Spandidos, D., Tsatsakis, A., Karantanas, A. H., & Marias, K. (2020). Artificial intelligence radiogenomics for advancing precision and effectiveness in oncologic care (Review). International Journal of Oncology, 57(1), 43–53.

Unger, M., & Kather, J. N. (2024). Deep learning in cancer genomics and histopathology. Genome Medicine, 16(1), 44–44.

Vanitha, K., Ramakrishna, M. T., Sree, S. S., & Guluwadi, S. (2024). Deep learning ensemble approach with explainable AI for lung and colon cancer classification using advanced hyperparameter tuning. BMC Medical Informatics and Decision Making, 24(1), 222–222.

Velden, B. H. M. van der, Kuijf, H. J., Gilhuijs, K. G. A., & Viergever, M. A. (2022). Explainable artificial intelligence (XAI) in deep learning-based medical image analysis. arXiv (Cornell University), 79, 102470–102470.

Vries, B. M. de, Zwezerijnen, G. J. C., Burchell, G. L., Velden, F. H. P. van, Oordt, C. W. M. der H. van, & Boellaard, R. (2023). Explainable artificial intelligence (XAI) in radiology and nuclear medicine: a literature review. Frontiers in Medicine, 10, 1180773–1180773.

Zhou, D., Gao, S., & Huang, X. (2026). Strategies for Class-Imbalanced Learning in Multi-Sensor Medical Imaging. Sensors, 26(6), 1998–1998.

Zou, Y., & Miao, P. (2025). Explainable AI-enabled hybrid deep learning architecture for breast cancer detection. Frontiers in Immunology, 16, 1658741–1658741.

.

.