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A multi-cancer detection framework using deep learning and hybrid machine learning approaches

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ABSTRACT

The diagnostic solutions offered by the present artificial intelligence (AI) solutions suffer from non-generalizability and heavy reliance on complex models. In an attempt to solve these issues, we propose a lightweight yet versatile method consisting of a combination of ResNet50 transfer learning and hybrid machine learning. Image features are extracted from dermoscopic, MRI, and histopathological images. These are subjected to principal component analysis (PCA) dimensionality reduction followed by classification using support vector machine (SVM), random forest (RF), logistic regression (LR), and XGBoost algorithms. This segregation of the two processes improves efficiency. The hybrid approach using ResNet50 + LR yielded an accuracy of 91.01% in the case of breast cancer detection compared to 86.26% of a baseline convolutional neural network (CNN). Also, ResNet50 gave an accuracy of 96.61% in diagnosing skin cancer. Custom CNN provided an accuracy of 99.42% for lung cancer and 96.33% for brain tumor detection.

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1. INTRODUCTION

Cancer causes close to 10 million deaths each year, which makes it vital to have fast and reliable means of diagnosis [1]. Deep learning (DL) has automated cancer detection. However, existing systems are often siloed, focusing on single cancer types, and require high computational resources limiting clinical deployment. In this regard, we propose a hybrid framework that merges ResNet50 feature extraction with classical machine learning (ML). This exploits the robustness of DL [2] and reduces computational costs for scalable multi-cancer screening.

Various DL and hybrid approaches for cancer detection have been studied recently as summarized in Table 1. Nugroho *et al.* [3] used convolutional neural network (CNN) to classify skin lesion on HAM10000 but they did not do proper preprocessing and achieved 78% accuracy. Nahata and Singh [4] achieved 91% accuracy using InceptionResNet on ISIC datasets, but faced class imbalance. Ahmed *et al.* [5] used 3D CNN on LUNA16 dataset for lung cancer classification with an accuracy of 80%. GS-PCANet with principal component analysis (PCA), support vector machine (SVM), Ram *et al.* [6] - 90.8%. Ramamoorthy *et al.* [7] used ResNet50/Xception in Moroccan datasets of breast cancer but the results were not generalized.

Asri *et al.* [8] used traditional ML models like KNN, SVM, and decision tree (DT) on WBCD dataset and achieved 86.9%. Cheng *et al.* [9] and Afshar *et al.* [10] used CNN and capsule networks respectively for brain tumor classification with accuracy of 84-86%. However, these promising approaches are mostly restricted to individual cancer types and lack a unified multi-cancer framework [11].

Table 1. Literature survey analysis for cancer detection

Reference	Cancer type	Model(s) used	Dataset	Metrics	Key insights	Limitations
Nugroho *et al.* [3]	Skin	CNN	HAM 10000	Accuracy: 78	CNN classifies skin photos well	No model comparison; few metrics; no preprocessing and validation.
Nahata and Singh [4]	Skin	Inception ResNet	ISIC 2018 + ISIC 2019	Accuracy: 91	High accuracy with DL, transfer learning, and augmentation.	Class imbalance, less interpretable, lacks practical validation.
Ahmed *et al.* [5]	Lung	Vanilla 3D CNN	LUNA16	Accuracy: 80	3D CNN preserves spatial context.	Lower accuracy; few test slices; simple CNN used.
Ram *et al.* [6]	Lung	GS- PCANet	HE stained slides from K-rasG12D model	Accuracy: 90.8	GS-PCANet with reduced PCA and SVM for lesion detection.	False positives; noise-sensitive; computationally expensive.
Ramamoorthy *et al.* [7]	Breast	ResNet50, Xception	Private Moroccan	Accuracy: 88	Xception better than ResNet50; both have clinical promise.	Sparse data, no validation; poor generalizability.
Asri *et al.* [8]	Breast	KNN, SVM, DT	Wisconsin Breast Cancer (WBCD)	Accuracy: 86.9	Basic ML algorithms; DT best.	No DL; low accuracy; no hybrid model.
Cheng *et al.* [9]	Brain	CNN	3064 MRI images	Accuracy: 84.19	Region augmentation improves CNNs on small datasets.	Accuracy limited; complex model.
Afshar *et al.* [10]	Brain	Capsule Network	3064 T1-weighted MRI images	Accuracy: 86.56	Capsule networks handle spatial relationships better.	Lower accuracy than CNNs; hyperparameter sensitive; compute intensive.

Though DL has automated the process of diagnosis, current methods work independently with one cancer type at a time and have high computational cost hindering their applicability in the clinic setting. We propose a novel methodology incorporating ResNet50 features extraction and traditional ML to exploit the advantages of DL technology with minimized computational expenses for multiple cancers detection. Research gap: despite extensive research, existing studies generally lack:

- A unified framework for a common DL-ML pipeline for multiple cancer type detection.
- Cross-modality generalization: testing the models on dermoscopic, MRI, and histopathological images.
- A comparative hybrid benchmark that systematically combines ResNet50 with classical ML classifiers.

To address this, we propose Health-Buddy, a unified framework that combines ResNet50 [12] for feature extraction, PCA dimensionality reduction, and hybrid classifiers (SVM [13], RF [14], LR [15], and XGBoost [16]), benchmarked against a custom CNN [17].

To contextualize the datasets and clinical importance, the following cancer types are addressed:

- Skin cancer: dermoscopic examination of different lesions.
- Lung cancer: detection of malignant tumors in histopathology.
- Breast cancer: microscopic differentiation of benign and malignant tissue.
- Brain tumor: MRI-based detection of glioma, pituitary, and meningioma.

This diversity confirms the model's ability to generalize across visually disparate data types, offering a scalable, lightweight alternative to complex end-to-end models.

2. METHOD

HealthBuddy employs a consistent multi-stage pipeline that includes data collection, pre-processing, custom CNNs, transfer learning with ResNet50, and hybrid classification.

2.1. Data collection

Table 2 lists the datasets utilized in this study, along with their description and size for each cancer type. These datasets offer diversity across imaging modalities for the assessment of model generalizability.

Table 2. Datasets used for each cancer type

Cancer	Dataset	Description	Size
Skin	HAM10000 [18]	Dermatoscopic images classified into seven lesion types	10,000
Lung	LC25000 [19]	Histopathological images of healthy and cancerous tissues	15,000
Breast	Breast Cancer-AE [20]	Microscopic breast tissue images labeled benign / malignant	8,000
Brain	Brain MRI [21]	MRI scans of glioma, meningioma, pituitary, or no tumor	7,000

2.2. Data preprocessing and augmentation

The images were resized to 224×224 with 3 RGB channels. For evaluation, to have equal number of images from each class, stratified sampling was performed to divide the dataset into 70%, 15%, and 15% train, validate and test respectively. Data augmentation of training images included scaling $(1/255)$, $\pm 20^{\circ}$ rotation, horizontal flipping and shear zooming ($\leq 10\%$) by nearest neighbor interpolation. No data augmentation was performed on validation and test images.

2.3. Custom CNN architecture

A custom CNN model was developed to perform multiclass classification of multiple cancer types. The proposed architecture, illustrated in Figure 1, is designed to automatically extract hierarchical features from input images and classify them into their respective cancer categories. The architecture consists of three convolutional blocks for feature extraction, followed by a flatten layer, a fully connected layer with dropout regularization, and a SoftMax output layer for final classification.

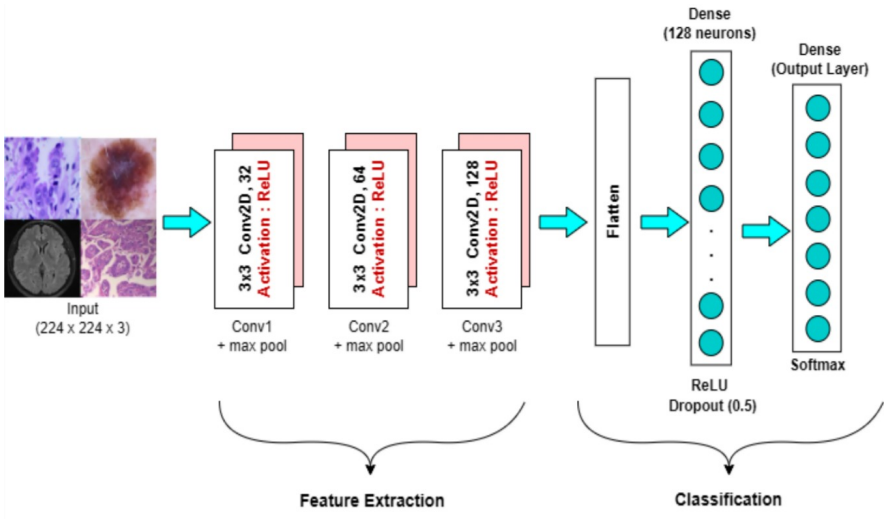

Figure 1. Custom CNN architecture used for all cancer types

2.3.1. Convolutional blocks (feature extraction)

Three Conv2D layers (3×3 kernels with 32, 64, 128 filters) were used to capture hierarchical features. Each convolution is immediately followed by:

- ReLU activation: introduces non-linear functions to model intricate relationships. ReLU(x) = max(0, x)
- Batch normalization: stabilizes the learning process and helps it converge faster.
- Max pooling (2×2): downsamples the input feature maps to decrease computations.

2.3.2. Classification head

- Flattening: once features have been extracted, the 2D feature maps are flattened to become 1D.
- Fully connected layer: the 1D vector is passed through a fully connected layer (128 units) with applying L2 regularization ($\lambda = 0.001$) and dropout (rate=0.5) to prevent overfitting.
- Classification: the output layer employs SoftMax function activation to provide class probabilities specific to cancer types (e.g., 7 classes for skin cancer, 4 for brain cancer).

$$\text{SoftMax}(z_i) = \frac{e^{z_i}}{\sum_{j=1}^{K} e^{z_j}}, \quad \text{for } i = 1, 2, \ldots, K \tag{1}$$

2.3.3. Training configuration

- Optimizer: Adam with a learning rate of 1×10^{-4}
- Loss function: categorical crossentropy
- Epochs: trained for up to 50 epochs
- Callbacks: to improve the convergence, early stopping (with patience = 10) and learning rate reduction (factor = 0.5, patience = 5) were used.

2.4. Transfer learning with ResNet50

ResNet50 pre-trained on ImageNet was used taking advantage of its 50 residual layers to get robust hierarchical features. Figure 2 shows the ResNet50 modified architecture used for joint detection of all four cancer classes.

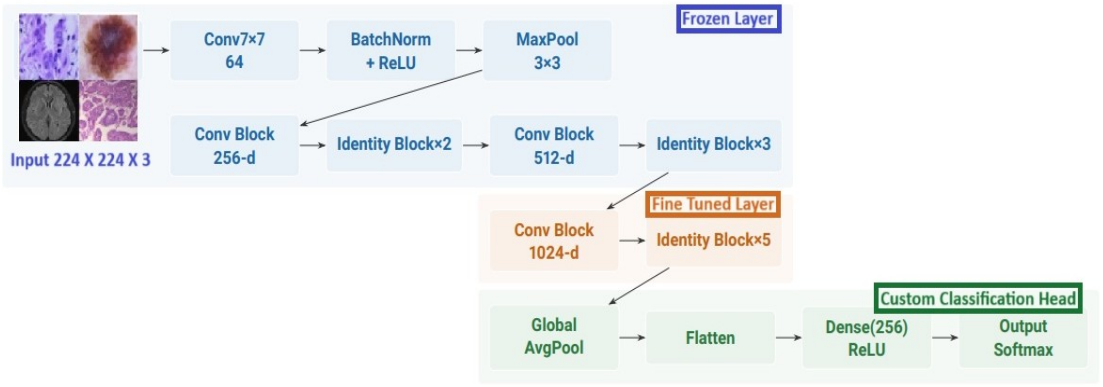

Figure 2. Transfer learning architecture: modified version of ResNet50 having frozen layers, fine tuned layers, and a customized classification head

2.4.1. Feature extraction (frozen base)

Initially, convolutional layers were frozen to preserve low and mid level features. After that, a custom classification head was created, which consisted of GlobalAveragePooling2D, Dense (256 units, ReLU), BatchNormalization and Dropout ($rate = 0.5$) to reduce overfitting. The classification head was trained for 30 epochs.

2.4.2. Fine-tuning phase

Then the last 20 layers were fine-tuned for 20 epochs using Adam optimization (learning rate $= 1 \times 10^{-5}$). For better convergence and dealing with class imbalance, class weights, EarlyStopping (patience=10), and ModelCheckpoint were used.

2.4.3. Hybrid model justification

The selected features are reduced using PCA [22] before being classified with SVM, RF, LR, or XGBoost. Compared to computationally intensive vision transformers (ViTs), this lightweight approach reduces training complexity and memory usage during inference. Previous studies have shown that such hybrid models can outperform standalone CNNs in liver disease detection [23] and skin cancer classification [24].

2.5. Deployment via flask

To evaluate its practical applicability, the models were deployed through a flask-based web application [25], enabling real-time image analysis and interactive clinical testing [26].

3. RESULTS AND DISCUSSION

We evaluated the custom CNN, ResNet50, and hybrid architectures (SVM, RF, LR, and XGBoost) across four cancer types using standard metrics: accuracy, precision, recall, and F1-score.

3.1. Accuracy

The comparison is shown in Table 3. Although the ResNet50 model was the best performer on skin cancer dataset (96.61%), hybridization of ResNet50 and LR achieved better results than just CNN (86.26%) in breast cancer.

Table 3. Accuracy of various models on different cancers

Model	Skin	Lung	Breast	Brain
CNN	93.22%	99.42%	86.26%	96.33%
ResNet	96.61%	92.31%	86.26%	93.44%
ResNet + SVM	93.89%	91.24%	88.63%	93.82%
ResNet + RF	95.06%	91.60%	85.68%	93.82%
ResNet + LR	95.50%	91.24%	91.01%	94.36%
ResNet + XGB	93.94%	91.96%	90.04%	93.75%

3.2. Precision

Table 4 demonstrates the capability of the proposed model to reduce the number of false positives. The hybrid models that used LR and XGBoost achieved precision scores of ($\geq 91\%$) on the lung, breast, and brain datasets.

Table 4. Precision of various models on different cancers

Model	Skin	Lung	Breast	Brain
CNN	94%	99%	84%	94%
ResNet	97%	92%	84%	93%
ResNet + SVM	95%	91%	92%	94%
ResNet + RF	96%	92%	85%	94%
ResNet + LR	96%	91%	94%	94%
ResNet + XGB	94%	92%	91%	94%

3.3. Recall

Table 5 demonstrates the sensitivity towards positive cases. The custom CNN had almost perfect recalls on both lung and breast cancer (99%), whereas the hybrid models presented better balance of sensitivity and specificity.

Table 5. Recall of various models on different cancers

Model	Skin	Lung	Breast	Brain
CNN	94%	99%	99%	92%
ResNet	97%	92%	99%	93%
ResNet + SVM	94%	91%	91%	93%
ResNet + RF	95%	91%	98%	93%
ResNet + LR	96%	91%	93%	94%
ResNet + XGB	94%	91%	95%	93%

3.4. F1-score

As can be seen from Table 6, hybrid approaches retain good precision-recall balance regardless of dataset imbalance. This observation supports the reliability of the feature extraction process based on ResNet50 network [27].

Table 6. F1-score of various models on different cancers

Model	Skin	Lung	Breast	Brain
CNN	92%	99%	91%	94%
ResNet	95%	92%	91%	93%
ResNet + SVM	95%	91%	92%	93%
ResNet + RF	95%	91%	90%	93%
ResNet + LR	95%	91%	93%	94%
ResNet + XGB	95%	91%	93%	93%

3.5. Training and validation accuracy and loss curves

Figures 3-6 illustrate the learning curves for the best-performing models. Across all cancer types, the graphs show consistently rising accuracy and decreasing loss, indicating effective convergence. The lung cancer CNN Figure 4, in particular, demonstrates stable learning with minimal overfitting, validating the efficacy of the chosen hyperparameters.

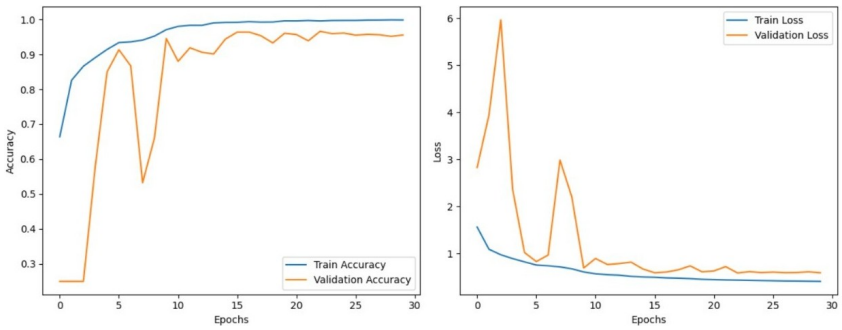

Figure 3. Skin cancer (ResNet50)

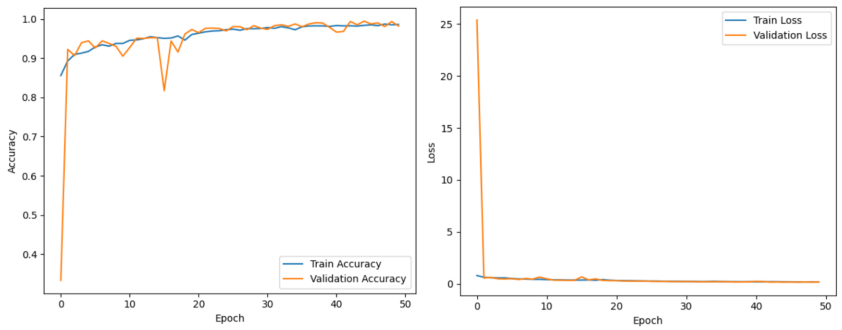

Figure 4. Lung cancer (CNN)

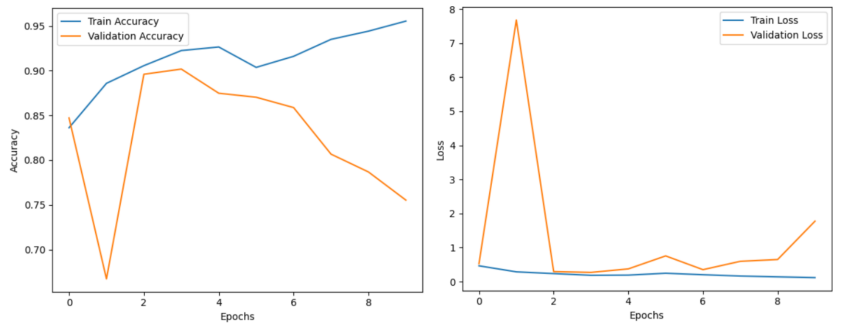

Figure 5. Breast cancer (ResNet50+LR)

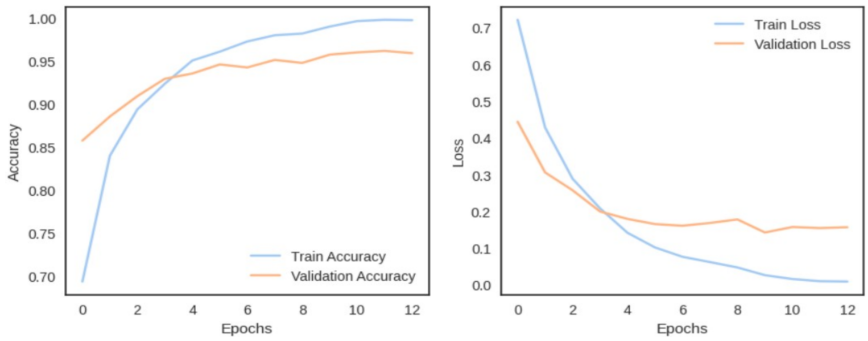

Figure 6. Brain cancer (CNN)

3.6. Confusion matrix analysis

Figure 7 confirms high classification reliability. The brain CNN Figure 7(a) achieves high sensitivity for meningioma, despite minor overlap between glioma and pituitary classes. Breast Figure 7(b) and lung Figure 7(c) models demonstrate clear separation between malignant and benign/healthy tissues. Skin ResNet50 Figure 7(d) exhibits a strong diagonal trend, effectively isolating melanoma from benign lesions.

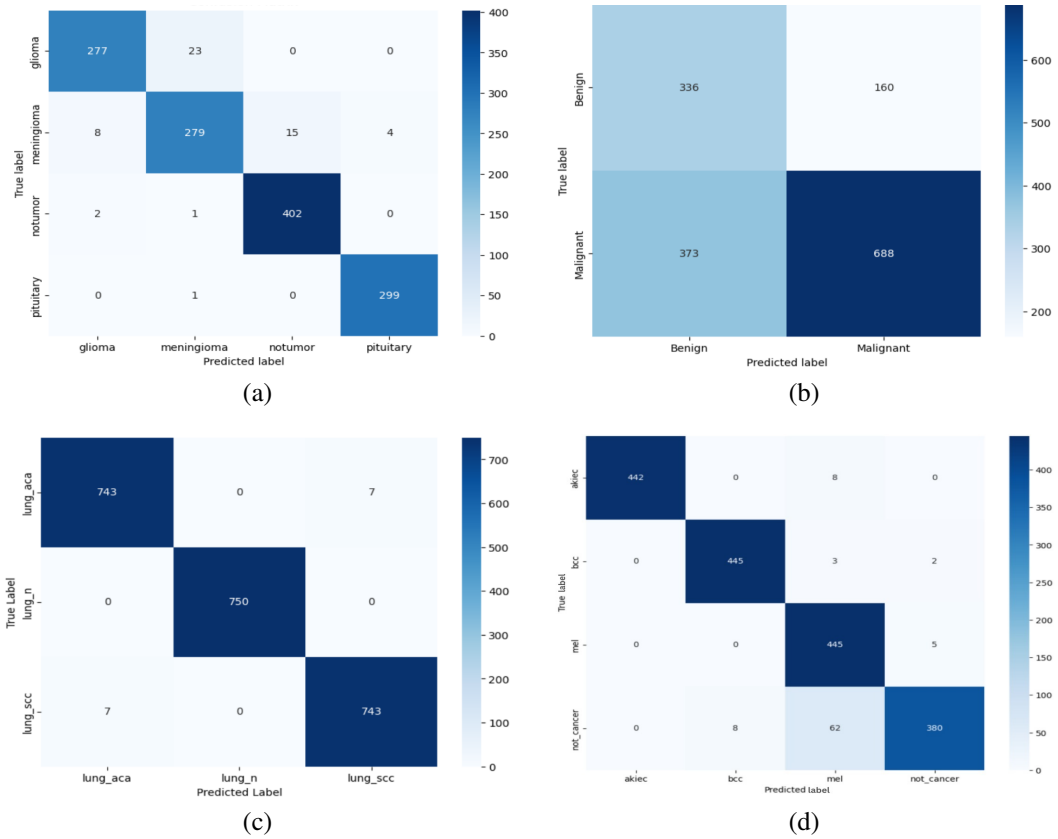

Figure 7. Confusion matrices of the best performing model for each cancer type; (a) CNN for brain, (b) ResNet50+LR for breast, (c) CNN for lung, and (d) ResNet50 for skin

3.7. Comparative analysis and discussion

Figure 8 confirms that optimal architecture relies on the imaging modality. Consistent with literature [10], [14], our custom CNN excelled in high-contrast lung (99.42%) and brain (96.33%) tasks. Conversely, the hybrid ResNet50+LR achieved superior performance for breast histopathology (91.01%) [11], [21].

Error analysis reveals specific challenges, such as MRI intensity overlaps between Glioma and Pituitary tumors. However, compared to resource-intensive ViTs, our hybrid approach offers a strategic trade-off. It achieves competitive accuracy (e.g., 96.61% for Skin) with a significantly lighter computational footprint, validating its suitability for rapid, resource-constrained screening.

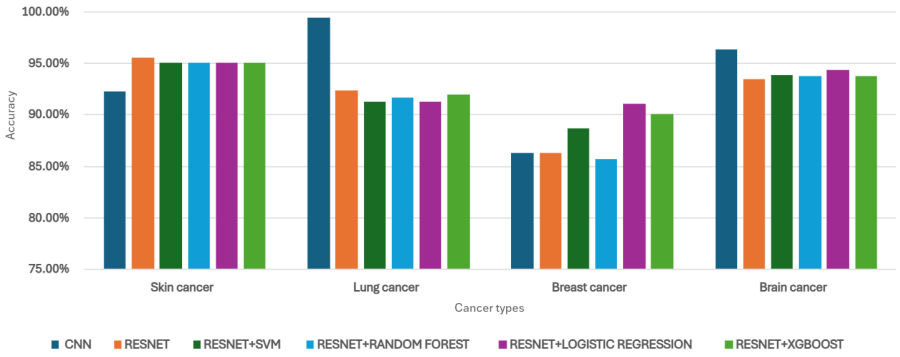

Figure 8. Comparative accuracy of deep learning and hybrid models across different cancers

3.8. Ethical and clinical deployment challenges

The clinical application needs to deal with the demographic bias in the dataset (for example, HAM10000). In order to solve the problem related to the "black box" system, we used an interpretable classifier like logistic regression in our hybrid layer. In addition, our light model allows inference from device-level Edge AI.

4. CONCLUSION

The current study creates a unified framework for multi-cancer screening, demonstrating the effectiveness of the same hybrid model (ResNet50 + ML) in different imaging techniques. It is clear from our results that although CNN works well when there is a need for high contrast (lung/brain), hybrid approaches outperform the former when it comes to dealing with complicated textures (breast). Combining high accuracy (up to 96.61%) with reduced costs, the framework becomes applicable in clinical practice.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal Analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject Administration
Fu : **Fu**nding Acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets supporting the findings of this study are publicly available and have been referenced appropriately within the manuscript. Specifically, four open-access datasets were used for skin, breast, brain, and lung cancer classification tasks. All dataset sources are cited in the References section.

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