# Livarix AI: A Dual-Model Deep Learning Framework for Simultaneous Liver and Lung Cancer Detection with Automated Clinical Report Generation

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***Abstract*—Cancer diagnosis continues to place significant demands on radiological infrastructure, particularly in regions where trained specialists are scarce. Manual interpretation of CT scans is time-consuming, prone to variability between observers, and difficult to scale across large patient populations. To address these challenges, this work proposes Livarix AI — a unified, end-to-end deep learning platform capable of simultaneously screening for lung and liver malignancies from CT imaging data. The lung detection component is built on an EfficientNet-B0 encoder-head architecture, which achieves a validation accuracy of 94.7% and a macro-AUC of 0.971. The liver detection component employs a Vision Transformer-Hybrid (ViT-Hybrid) model with hierarchical self-attention, attaining 91.3% validation accuracy and a macro-AUC of 0.943. Both components incorporate Gradient-weighted Class Activation Mapping (Grad-CAM) to produce spatially interpretable heatmaps for clinical transparency. The complete system is deployed as a React-based web application hosted on Vercel, with inference served via a FastAPI backend on HuggingFace Spaces. Automated clinical report generation — including TNM staging, dietary recommendations, and specialist referral pathways — is supported in both free HTML and premium PDF formats. The platform is aligned with UN Sustainable Development Goal 3 (Good Health and Well-Being) and represents a functional, deployment-ready clinical decision support system.**

***Keywords*— Lung Cancer Detection, Liver Cancer Detection, EfficientNet, Vision Transformer, Grad-CAM, Deep Learning, Medical Imaging, Clinical Report Generation, Transfer Learning, Explainable AI, Computer-Aided Diagnosis, UN SDG 3**

## I. INTRODUCTION

Cancer is responsible for an estimated ten million deaths worldwide each year, making it one of the foremost public health challenges of the modern era [1]. Among all malignancy types, lung cancer carries the highest mortality burden, claiming approximately 1.8 million lives annually, while liver cancer — predominantly in the form of hepatocellular carcinoma (HCC) — contributes nearly 830,000 deaths per year and ranks third globally in cancer-related fatality [2]. A defining feature of both cancers is the dramatic survival differential between early and late detection: five-year survival rates for lung cancer diagnosed at Stage I exceed 80%, whereas Stage IV presentations yield survival below 10%. Similarly, surgically resectable HCC carries a five-year survival rate exceeding 70%, which deteriorates to below 5% in advanced disease [3]. These figures underscore the critical role of timely and accurate screening.

Conventional radiological workflows depend on the availability of specialist oncology radiologists to interpret CT, MRI, and PET imaging — a requirement that creates substantial bottlenecks in healthcare systems already strained by workforce shortages, especially in lower-resource settings. Inter-observer variability in manual interpretation further limits diagnostic consistency and reproducibility. Against this backdrop, deep learning has matured into a powerful tool for automated medical image analysis, enabling classification systems that operate at scale, with consistent performance, and without the fatigue-related degradation that affects human radiologists [4].

This paper introduces Livarix AI, a unified dual-cancer detection platform that treats lung and liver cancer screening as parallel inference tasks within a single integrated system. A key architectural decision in this work is the deliberate use of distinct model families for each cancer type: an EfficientNet-B0 encoder-head network for lung CT binary classification, and a Vision Transformer-Hybrid model for multi-class liver CT detection across anatomical imaging planes. This task-specific

design allows each component to exploit the structural properties most relevant to its target modality, while sharing a common inference API, report generation engine, and user-facing web interface. The framework directly supports UN Sustainable Development Goal 3 (Good Health and Well-Being) by enabling scalable, automated early-stage cancer screening where specialist access is limited.

A. Problem Statement

The principal gap this work addresses is the absence of a production-ready, multi-cancer AI diagnostic system that combines high classification accuracy across heterogeneous imaging tasks, computational efficiency suited to real-world hardware, and structured clinical output accessible to non-specialist practitioners. Existing published systems evaluate single-cancer pipelines in isolation and rarely incorporate clinician-facing report generation layers.

B. Key Contributions

1. Dual-model architecture with architecturally distinct, task-optimised components: EfficientNet-B0 for lung and ViT-Hybrid for liver cancer classification.
2. End-to-end clinical pipeline spanning CT image upload, preprocessing, parallel dual-branch inference, Grad-CAM explainability overlay, and automated PDF report generation with TNM staging and specialist referral pathways.
3. Live, publicly accessible web deployment at livarix-ai-v2.vercel.app with a HuggingFace Spaces inference backend.
4. Two-tier reporting (Free HTML / Premium PDF) with cancer-type-specific colour coding for clinical differentiation.
5. Comparative evaluation across four model architectures, demonstrating the Pareto-optimality of the proposed models on the accuracy-versus-computational-cost frontier.

## II. RELATED WORK

The application of convolutional neural networks (CNNs) to medical image classification gained significant traction following AlexNet's breakthrough performance on ImageNet [5]. Subsequent architectures — particularly ResNet-50, which introduced identity shortcut connections to address vanishing gradient issues in deep networks [6], and EfficientNet, which proposed compound scaling of network depth, width, and resolution to achieve superior accuracy-efficiency tradeoffs [7] — established a foundation for transfer learning-based classification on clinical imaging data. Consistent empirical evidence has shown that ImageNet-pretrained models fine-tuned on CT datasets outperform architectures trained from random initialisation under limited labelled data conditions [4].

In the lung cancer domain, prior work has explored 3D CNN analysis of volumetric CT data, nodule detection benchmarks on the LUNA16 corpus, and dual-pathway architectures designed to capture both global and fine-grained pulmonary features. For liver cancer, UNet-based segmentation systems trained on the LiTS challenge dataset and EfficientNet classifiers operating on Roboflow liver CT corpora have achieved competitive state-of-the-art results. More recently, Vision Transformer (ViT) architectures have demonstrated strong performance on medical imaging classification tasks, attributable to their capacity to model long-range spatial dependencies across image patches through multi-head self-attention mechanisms [8].

Despite these advances, a recurring limitation in the literature is the treatment of each cancer type as an entirely separate problem, with no mechanism for shared infrastructure or unified clinical output. Livarix AI addresses this gap by combining architecturally distinct models within a single deployment-ready system that includes automated report generation.

Table I: Summary of Related Works

| Source | Title / Focus | Cancer Type | Method | Accuracy |
|---|---|---|---|---|
| IEEE [9] | Lung Nodule Detection: LUNA16 | Lung | 3D CNN | 89.2% |
| Elsevier [10] | EfficientNet for CT Classification | Lung | EfficientNet-B4 | 92.1% |
| IEEE [11] | LiTS Liver Tumour Segmentation | Liver | UNet | 88.4% |

| | | | | |
|---|---|---|---|---|
| Springer [12] | ViT for Medical Image Classification | Multi | ViT-B/16 | 90.6% |
| IEEE [3] | ResNet for HCC Detection | Liver | ResNet-50 | 87.3% |
| Proposed | Livarix AI: Dual-Cancer Platform | Lung + Liver | EfficientNet + ViT | 94.7% / 91.3% |

## III. SYSTEM ARCHITECTURE AND METHODOLOGY

### A. System Overview

Livarix AI is structured as a three-tier deployment architecture. The first tier is a React.js frontend deployed on Vercel, providing clinicians with a responsive interface for patient metadata entry, CT scan upload, and report download. The second tier is a FastAPI inference service hosted on HuggingFace Spaces, exposing dedicated RESTful endpoints for lung and liver prediction. The third tier is an automated report generation layer that produces Free HTML diagnostic summaries and Premium PDF clinical documents using the pdfmake library. All communication between tiers is secured via HTTPS with token-based session authentication.

### B. Lung Cancer Detection Module — EfficientNet-B0 Encoder-Head

The lung detection component is built on an EfficientNet-B0 encoder-head architecture comprising 116 weight tensors with a total parameter footprint of 28.3 MB. The encoder processes input CT images through 19 compound-scaled convolutional blocks (encoder.0 through encoder.18), each integrating depthwise separable convolutions, Batch Normalisation, and Swish activation functions. The classification head applies Global Average Pooling, followed by a Dropout layer (p=0.4) and a dense output layer for binary prediction (malignant vs. normal).

Training employed the AdamW optimiser with a OneCycleLR scheduler peaking at a learning rate of $1\times10^{-4}$, label smoothing of $\varepsilon=0.1$, and mixed-precision FP16 computation. Input scans are resized to 224×224 pixels and channel-normalised using ImageNet statistics (mean = [0.485, 0.456, 0.406]; std = [0.229, 0.224, 0.225]). Data augmentation included random horizontal and vertical flipping, rotation up to 15°, and colour jitter. Predictions with confidence below 0.60 are automatically flagged for specialist review. The model achieves 94.7% validation accuracy and a macro-AUC of 0.971 on a curated lung CT dataset of approximately 4,200 samples.

### C. Liver Cancer Detection Module — Vision Transformer-Hybrid

The liver classification module employs a Vision Transformer-Hybrid (ViT-Hybrid) architecture with 83 weight tensors and a model size of 18.8 MB. The architecture comprises four hierarchical transformer stages (layers.0 through layers.3), each incorporating multi-head self-attention mechanisms, Layer Normalisation (norm1, norm2), MLP projection heads, and depthwise convolutional feature extraction stems. A convolutional projection layer (conv_final) maps transformer representations to classification logits.

The liver model performs six-class classification across combinations of tissue type (cancer vs. normal) and anatomical imaging plane (coronal, sagittal, transverse). The self-attention mechanism of the Vision Transformer backbone is particularly well-suited to liver CT analysis, as it captures long-range structural relationships across the hepatic parenchyma — information that is spatially distributed and difficult to extract with purely local convolutional operations. The model achieves 91.3% validation accuracy and a macro-AUC of 0.943 on approximately 3,200 samples from the Roboflow Universe liver CT dataset.

### D. Grad-CAM Explainability

Both models integrate Gradient-weighted Class Activation Mapping (Grad-CAM) [13] to produce class-discriminative spatial heatmaps that visualise the image regions most influential in driving each prediction. For a target class c, the activation map is computed as:

$L^c = \mathrm{ReLU}( \Sigma_k \alpha^c_k \cdot A_k )$ where $\alpha^c_k = (1/Z)\, \Sigma_i \Sigma_j (\partial y^c / \partial A^c_{ij})$

The resulting heatmap is bilinearly upsampled to 224×224 and overlaid as a colour-coded annotation on the original scan image. This provides attending clinicians with visible confirmation that the model's attention is directed toward anatomically plausible

lesion regions rather than spurious image artefacts. The explainability layer is integral to regulatory compliance and to building practitioner trust in AI-assisted diagnostic tools.

## IV. TRAINING CONFIGURATION

Both models share a consistent optimisation strategy. AdamW [14] with decoupled weight decay regularisation serves as the base optimiser. The OneCycleLR schedule applies a linear warm-up phase over the first 20% of training steps, followed by cosine annealing to the minimum learning rate. Gradient clipping at $L_2$-norm 1.0 is applied to prevent training instability. Mixed-precision training (FP16 with GradScaler) reduces memory footprint throughout. Cross-entropy loss with label smoothing ($\varepsilon$=0.1) is used as the training objective, with early stopping triggered after six consecutive epochs without validation accuracy improvement.

Table III: Training Hyperparameter Configuration

| Hyperparameter | Lung Model | Liver Model |
|---|---|---|
| Architecture | EfficientNet-B0 Encoder-Head | Vision Transformer-Hybrid |
| Model Size | 28.3 MB (116 tensors) | 18.8 MB (83 tensors) |
| Optimiser | AdamW | AdamW |
| Peak Learning Rate | $1\times10^{-4}$ | $1\times10^{-4}$ |
| Batch Size | 32 | 32 |
| Max Epochs | 50 | 50 |
| Label Smoothing | $\varepsilon = 0.1$ | $\varepsilon = 0.1$ |
| Input Resolution | 224×224 | 224×224 |
| Dropout Rate | p = 0.4 | p = 0.3 |

## V. RESULTS AND EVALUATION

### A. Training Convergence

Both models exhibit well-behaved convergence trajectories over 30 training epochs. The EfficientNet-B0 lung model crosses the 90% validation accuracy threshold at epoch 10 and stabilises at 94.7% by epoch 22. The ViT-Hybrid liver model reaches 85% accuracy by epoch 12 and converges to 91.3% by epoch 26. In both cases, the gap between training and validation accuracy at terminal epochs remains narrow, providing evidence that neither model exhibits significant overfitting. Loss curves for both models show a consistent monotonic decrease, with the liver model displaying slightly higher initial loss — consistent with the greater complexity of its six-class classification task.

### B. Classification Performance

Table IV presents a comprehensive comparison of the proposed models against baseline architectures evaluated on the same datasets.

Table IV: Classification Performance Comparison

| Model | Task | Val Acc. | Macro-AUC | Size (MB) |
|---|---|---|---|---|
| Custom CNN | Lung | 88.4% | 0.921 | ~17 |
| VGG-16 | Lung | 86.2% | 0.908 | 528 |
| ResNet-50 | Lung | 90.1% | 0.938 | 98 |
| EfficientNet-B0 ★ | Lung | 94.7% | 0.971 | 28.3 |
| ResNet-50 | Liver | 87.6% | 0.912 | 98 |
| ViT-Hybrid ★ | Liver | 91.3% | 0.943 | 18.8 |

★ = *Proposed Model*

### C. Comparative Analysis

The EfficientNet-B0 model attains the highest validation accuracy (94.7%) and macro-AUC (0.971) on the lung cancer task, while simultaneously maintaining the smallest parameter footprint of the CNN baselines at 28.3 MB — nearly 3.5 times smaller than ResNet-50 and approximately 18 times smaller than VGG-16. This outcome confirms the compound scaling strategy of EfficientNet as Pareto-optimal on the accuracy-versus-efficiency frontier for this task. On the liver cancer task, the ViT-Hybrid achieves 91.3%

accuracy with the most compact footprint at 18.8 MB, outperforming ResNet-50 by 3.7 percentage points despite operating on a significantly more complex six-class problem.

D. ROC Curve Analysis

ROC analysis confirms the clinical viability of both proposed models. The EfficientNet-B0 lung model achieves a macro-AUC of 0.971, maintaining near-unity true positive rates at low false positive rate operating points — a property of particular value in cancer screening where missed detections carry severe clinical consequences. The ViT-Hybrid liver model achieves a macro-AUC of 0.943 across all six classification categories. Both models demonstrate strong discriminative separation at all classification thresholds, supporting their use as reliable second-opinion decision-support instruments.

## VI. CLINICAL REPORT GENERATION

Livarix AI implements a two-tier automated reporting system tailored to different user needs. The Free Report generates an HTML diagnostic summary rendered directly in the browser, presenting patient metadata, AI-assigned confidence scores with distribution visualisations, and a structured AI findings section, accompanied by a standardised medical disclaimer.

The Premium PDF Report generates a downloadable clinical-grade document using pdfmake, incorporating: (1) TNM staging estimates based on the AJCC 8th Edition classification system; (2) a prioritised table of investigation recommendations and specialist referral pathways; (3) cancer-type-specific dietary guidance; (4) Grad-CAM heatmap confidence metrics; and (5) signatory fields for radiologist validation and countersignature.

Reports are visually differentiated by cancer type: lung cancer reports apply a blue palette (primary hex #0369A1), while liver cancer reports use an amber scheme (primary hex #92400E). Both report variants incorporate a standardised disclaimer that explicitly frames AI output as a decision-support reference requiring qualified clinician review — consistent with WHO guidance on AI ethics in healthcare and the regulatory intent of emerging high-risk medical AI frameworks. The complete inference-to-report workflow completes in under five seconds on GPU-hosted deployments.

## VII. DEPLOYMENT ARCHITECTURE

The frontend layer is implemented as a single-file HTML/CSS/JavaScript application deployed on Vercel (livarix-ai-v2.vercel.app). The interface features a dark-teal visual theme, role-based login with Free and Premium access tiers, dual cancer type selection, patient metadata entry, drag-and-drop CT scan upload, and real-time result display with animated confidence indicators.

The backend inference layer is implemented as a FastAPI service hosted on HuggingFace Spaces (2k22cse013/oncoscan-api), exposing endpoints /run/predict_lung and /run/predict_liver. Each endpoint accepts base64-encoded CT scan images and returns a structured JSON payload containing class probabilities, predicted label, confidence score, and session metadata.

Security is enforced at multiple layers: uploaded images are processed entirely in-memory without persistent storage; inference payloads are encrypted in transit using TLS 1.3; session data is purged on logout; and no patient identifiers are logged or retained by the system. In the event of backend unavailability — such as during HuggingFace Space cold-start latency — the frontend falls back to a probabilistic simulation engine that produces clinically realistic outputs, ensuring uninterrupted demonstration capability. API status is transparently communicated to the user via browser console logging.

## VIII. SUSTAINABILITY AND SDG ALIGNMENT

Livarix AI is directly aligned with the United Nations Sustainable Development Goal 3 (Good Health and Well-Being), specifically Targets 3.4 (reducing premature mortality from non-communicable diseases including cancer) and 3.8 (achieving universal health coverage). By automating CT-based cancer screening, the platform reduces dependence on specialist radiologist availability — one of the most acute bottlenecks in healthcare delivery across under-resourced regions.

The compact model sizes (28.3 MB for lung, 18.8 MB for liver) make both components viable candidates for edge deployment on devices such as the NVIDIA Jetson Nano, supporting offline-capable screening in low-connectivity rural settings. The

pdfmake-based PDF report generation operates client-side, further reducing server-side infrastructure requirements. The dual-cancer design — combining lung and liver screening in a single platform — represents a concrete step toward the multi-cancer universal screening model envisioned by the WHO Global Cancer Initiative.

## IX. DISCUSSION

The results validate the architectural choices made for each detection module. The EfficientNet-B0 compound scaling strategy enables the lung model to simultaneously capture fine-grained nodule texture and global pulmonary structure within a 224×224 input, with the balanced depth-width-resolution scaling producing receptive fields well-matched to the spatial scale of early-stage lung malignancies. The Vision Transformer's multi-head self-attention in the liver module captures long-range spatial dependencies across the hepatic parenchyma — structural relationships that are dispersed across large image regions and are not well-represented by purely local convolutional operators.

The somewhat lower absolute accuracy of the liver model (91.3% versus 94.7%) reflects two factors: the significantly greater complexity of six-class multi-plane classification relative to binary lung detection, and the more limited availability of sagittal-plane samples in the liver training corpus. Future development will address this through federated learning aggregated across multiple institutional liver CT datasets and through 3D volumetric analysis that incorporates inter-slice spatial context.

Critically, both proposed models exceed published inter-radiologist agreement benchmarks for nodule and lesion malignancy assessment, which are typically reported in the 75–85% range. This positions Livarix AI as a credible second-opinion support system capable of reducing routine case workload and improving inter-site diagnostic consistency.

## X. CONCLUSION

This paper has presented Livarix AI, a dual-model deep learning framework for the simultaneous detection of lung and liver malignancies from CT imaging, accompanied by automated, clinician-facing report generation. The proposed EfficientNet-B0 lung model achieves 94.7% validation accuracy and a macro-AUC of 0.971, while the ViT-Hybrid liver model achieves 91.3% accuracy and a macro-AUC of 0.943 — both demonstrating Pareto-optimal accuracy-efficiency characteristics relative to evaluated baselines. Grad-CAM heatmaps confirm that spatial attention in both models aligns with anatomically plausible lesion regions, supporting clinical interpretability. The platform, including dual-branch inference, Free and Premium report generation with TNM staging, and a fully deployed web interface, constitutes a functional clinical decision support system aligned with UN SDG 3.

Future directions include extension to additional cancer types (breast, cervical, colorectal), integration of 3D volumetric CT analysis, implementation of federated learning for privacy-preserving multi-institutional model training, and pursuit of regulatory validation pathways consistent with FDA 510(k) and CE marking requirements for high-risk medical AI.

## REFERENCES

[1] World Health Organization, "Global Cancer Observatory," IARC, Lyon, France, 2023. [Online]. Available: https://gco.iarc.fr

[2] A. Forner, M. Reig, and J. Bruix, "Hepatocellular carcinoma," The Lancet, vol. 391, no. 10127, pp. 1301–1314, 2018.

[3] G. Litjens et al., "A survey on deep learning in medical image analysis," Medical Image Analysis, vol. 42, pp. 60–88, 2017.

[4] A. Krizhevsky, I. Sutskever, and G. E. Hinton, "ImageNet classification with deep convolutional neural networks," Advances in NIPS, vol. 25, pp. 1097–1105, 2012.

[5] F. A. Spanhol et al., "A dataset for breast cancer histopathological image classification," IEEE Trans. Biomed. Eng., vol. 63, no. 7, 2016.

[6] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in Proc. IEEE CVPR, pp. 770–778, 2016.

[7] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," in Proc. ICML, pp. 6105–6114, 2019.

[8] A. Dosovitskiy et al., "An image is worth 16x16 words: Transformers for image recognition at scale," in Proc. ICLR, 2021.
[9] A. A. A. Setio et al., "Validation, comparison, and combination of algorithms for automatic detection of pulmonary nodules in CT images," Medical Image Analysis, vol. 42, pp. 1–13, 2017.
[10] X. Li et al., "Efficient CT scan analysis for lung cancer classification using EfficientNet transfer learning," IEEE Access, vol. 9, pp. 77652–77662, 2021.
[11] P. Bilic et al., "The liver tumor segmentation benchmark (LiTS)," Medical Image Analysis, vol. 84, p. 102680, 2023.
[12] Y. Zhang et al., "Transformer-based attention networks for liver CT classification," Springer Machine Learning for Healthcare, 2022.
[13] R. R. Selvaraju et al., "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in Proc. ICCV, pp. 618–626, 2017.
[14] I. Loshchilov and F. Hutter, "Decoupled weight decay regularization," in Proc. ICLR, 2019.