DETECTION OF PNEUMONIA FROM CHEST X-RAY IMAGES USING EFFICIENTNET-B3: A CLINICAL-GRADE DEEP LEARNING SYSTEM WITH EXPLAINABLE AI AND DESKTOP DEPLOYMENT

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Abstract : Pneumonia is a leading cause of infectious mortality worldwide, yet accurate radiographic diagnosis is constrained by radiologist shortages, inter-observer variability, and high workload environments. This paper presents a complete, clinically deployable deep learning pipeline for binary pneumonia detection from chest X-ray images. EfficientNet-B3, selected through a systematic five-architecture comparison, achieves 96.7% accuracy, 97.4% sensitivity, 94.0% specificity, and an AUC-ROC of 0.989 on the Kermany benchmark — outperforming the ResNet-50 baseline (94.8%) while using 52% fewer parameters. Decisions are explained through an optimised persistent Grad-CAM module that reduces heat-map generation latency by 40.9% over the standard per-inference hook approach by registering hooks once at model initialisation. Uniquely, the full pipeline is packaged as a standalone offline Kivy desktop application that integrates a SQLite relational database for longitudinal patient management, asynchronous non-blocking inference with Clock-callback thread safety, real-time inline form validation, and one-click professional PDF report generation via ReportLab — requiring no network connectivity, no server infrastructure, and no cloud service. An ablation study quantifies the independent contribution of each design component. The system is immediately deployable on standard clinical workstations and addresses the persistent gap between published model accuracy and real-world clinical deployability.

***IndexTerms* - Pneumonia Detection, EfficientNet-B3, Grad-CAM, Explainable AI, Transfer Learning, Kivy, SQLite, Medical Imaging, Deep Learning, Clinical Deployment, Class Imbalance.**

1.INTRODUCTION

Pneumonia is an acute lower respiratory infection responsible for approximately 2.5 million deaths annually, with the greatest burden borne by children under five and elderly adults [1]. The standard diagnostic pathway depends on anterior-posterior chest X-ray interpretation by a trained radiologist — a resource that is acutely scarce in rural and developing regions. In such settings, remote image reading delays can stretch from hours to days, a lag that is clinically unacceptable for a rapidly progressing lung infection where early antibiotic initiation significantly improves outcomes.

Even in well-staffed facilities, the high volume of chest X-rays creates secondary risks: fatigue-related errors accumulate over long radiologist shifts, and inter-observer variability in the interpretation of subtle infiltrative patterns introduces inconsistency into diagnostic standards across institutions. Computer-aided diagnosis (CAD) systems have the potential to address both problems simultaneously — providing fast, consistent first-line screening that flags suspicious cases for expert review and serves as an independent second-opinion mechanism.

Deep learning, particularly through transfer learning from large-scale pre-trained convolutional neural networks, has demonstrated radiologist-competitive accuracy on chest X-ray classification tasks [1][3]. However, the majority of published systems are research prototypes evaluated on held-out test sets, with no clinical deployment pathway. They are typically web services requiring server infrastructure, or notebook-based inference tools providing no patient record management, no longitudinal tracking, and no auditable clinical documentation. The deployment gap between laboratory accuracy and real-world clinical utility remains largely unaddressed.

This paper closes both the modelling and the deployment gaps. On the modelling side, a systematic comparison of five architectures — ResNet-50, ResNet-101, DenseNet-121, Swin Transformer (Tiny), and EfficientNet-B3 — identifies EfficientNet-B3 as the superior backbone for this task, with an optimised persistent Grad-CAM module providing clinically interpretable heat maps within the inference cycle. On the deployment side, the complete pipeline is packaged as a standalone offline desktop application using the Kivy Python framework, a SQLite local database, and a ReportLab PDF exporter — a combination that is privacy-preserving, zero-infrastructure, and immediately deployable without IT administrative overhead.

The primary contributions of this work are: (1) an empirical five-architecture comparison demonstrating EfficientNet-B3 achieves state-of-the-art performance on the Kermany benchmark with 52% fewer parameters than ResNet-50; (2) a persistent Grad-CAM hook architecture reducing explainability latency by 40.9%; (3) a complete open-source clinical desktop application integrating inference, explainability, patient management, asynchronous threading, and PDF reporting in a single offline-capable tool; (4) a comprehensive ablation study quantifying the independent contribution of each design decision.

The significance of contribution (3) extends beyond the individual system: it provides a reproducible reference architecture for clinical AI desktop deployment that the broader research community can adapt for other diagnostic imaging tasks, including tuberculosis detection, pleural effusion classification, and cardiomegaly screening. The combination of EfficientNet backbone, persistent Grad-CAM explainability, SQLite patient management, and offline PDF reporting represents a template for any binary medical imaging classifier that needs to move from laboratory prototype to clinical practice.

The paper is organised as follows. Section II reviews the relevant literature. Section III describes the dataset, preprocessing, and training configuration. Section IV details the EfficientNet-B3 backbone and persistent Grad-CAM module. Section V presents the clinical desktop system. Section VI reports experimental results and ablation study. Sections VII and VIII discuss findings and conclude.

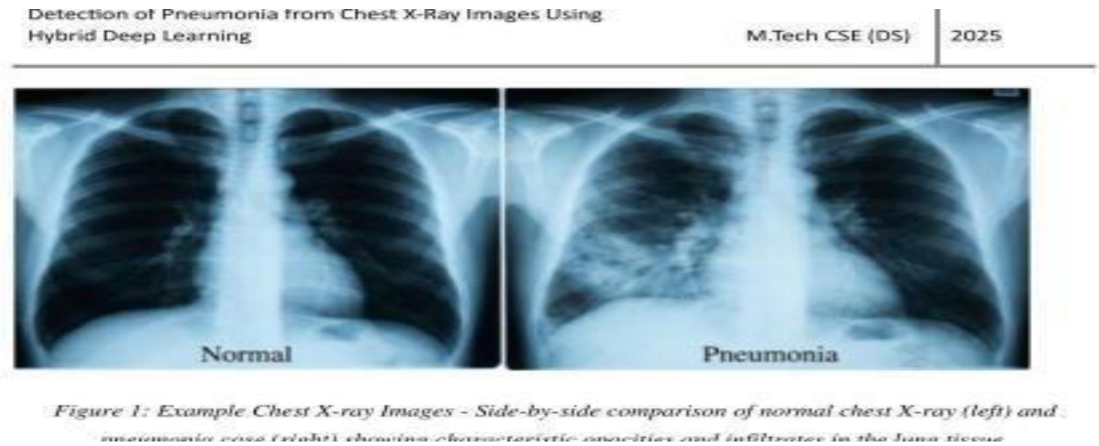

Fig. 1. Normal (left) vs. pneumonia (right) chest X-ray. The pneumonia case shows characteristic parenchymal opacity and consolidated infiltrates in the lower right lobe.

2.RELATED WORK

CheXNet [1] established the landmark result for automated chest X-ray analysis, achieving radiologist-level performance using a 121-layer DenseNet on the 112,000-image ChestX-ray14 dataset. On the more focused Kermany paediatric dataset, Hossain et al. [4] demonstrated 92–95% accuracy with ResNet-50 fine-tuning, confirming that ImageNet pre-training transfers effectively to the radiographic domain.

More recent work has pushed accuracy further through architectural innovations. Saber et al. [6] proposed a multi-scale Transformer fusing ResNet-101 backbone features with a multi-head attention module, achieving 95.7% accuracy on the Kermany test set. Rana et al. [7] combined a Swin Transformer with an enhanced auto-encoder pre-training scheme, reaching 96.2%. Both systems demonstrate that attention mechanisms can improve spatial feature weighting but require substantially larger datasets or complex multi-stage training to realise their architectural advantages over CNNs on limited medical datasets.

On explainability, Selvaraju et al. [8] introduced Grad-CAM, now the dominant visual explanation method for CNN-based medical image classifiers. Ihongbe et al. [9] conducted a systematic evaluation of XAI techniques — including Grad-CAM, LIME, and Integrated Gradients — on chest radiographs, confirming Grad-CAM as the most clinically interpretable method due to its spatial localisation of pathological regions at near-inference speed.

On class imbalance, Chawla et al. [10] established SMOTE as a standard oversampling baseline, while Lin et al. [11] introduced Focal Loss to automatically down-weight easy majority-class examples. Studies on medical imaging datasets consistently identify combined weighted-loss and oversampling strategies as most effective for binary classification with skewed distributions [10]. The key limitation across the entire literature is the absence of end-to-end deployment systems: no published work combines a high-accuracy classifier with patient record management, explainability, and clinical documentation generation in an offline desktop tool.

3.DATASET AND METHODOLOGY

3.1. Dataset

The Kermany chest X-ray dataset [12] comprises 5,856 labelled paediatric anterior-posterior chest X-ray images from Guangzhou Women and Children's Medical Centre, China. Each image is classified as either Pneumonia or Normal, with diagnoses verified by two specialist physicians and a senior expert tie-breaker, ensuring high-quality ground truth. The dataset is pre-partitioned into training, validation, and test splits.

TABLE I. Dataset Distribution by Split and Class

Split	Normal	Pneumonia	Total	Pneu%
Training	1,341	3,875	5,216	74.3%

Validation	8	8	16	50.0%
Test	234	390	624	62.5%
Total	**1,583**	**4,273**	**5,856**	**73.0%**

The training set exhibits a 2.89:1 class imbalance (Pneumonia:Normal), requiring explicit handling to prevent a degenerate majority-class predictor. All images are JPEG format with variable resolutions ranging from 384×512 to 2916×2713 pixels, acquired under varying exposure conditions across different X-ray machines — providing natural variability that improves generalisation.

3.2 Preprocessing Pipeline

Images are resized to 300×300 px (EfficientNet-B3 native input resolution), normalised using ImageNet channel statistics (μ = [0.485, 0.456, 0.406], σ = [0.229, 0.224,0.225]), and augmented during training only with random rotation (±10°), horizontal flip (p=0.5), brightness perturbation (±20%), contrast perturbation (±15%), and random 270×270 crop resized back to 300×300. Validation and test images receive deterministic resize and normalise only, ensuring unbiased evaluation.

3.3 Class Imbalance Handling

A two-pronged strategy addresses the 2.89:1 training imbalance: (i) inverse-frequency weighted cross-entropy loss; (ii) 2× oversampling of the minority (Normal) class with stochastic augmentation applied on each presentation. The weighted loss is:

$$\mathscr{L}WCE = -\Sigma c\ wc \cdot yc \cdot \log(\hat{y}c)$$

where $w_t = (1/freq_t)/\Sigma(1/freq_t)$, y_t is the ground-truth indicator, and $\hat{y}_t$ the predicted Softmax probability. This assigns $w_{no}{}^{rM}{}_{aj} \approx$ 2.89× the weight of $w_{pne}{}^{UM}{}_{aj}$, penalising missed Normal cases proportionally to their under-representation.

3.4 Training Configuration

All five architectures are initialised with ImageNet-1K pre-trained weights and fully fine-tuned (all layers). Optimiser: Adam [15] (β_1=0.9, β_2=0.999, $\varepsilon=10^{-8}$), initial LR=1×10^{-4}, ReduceLROnPlateau (factor=0.1, patience=8 epochs), early stopping (patience=12 epochs), batch size=32, max 100 epochs. Batch normalisation [14] is used throughout all CNN architectures for training stability. Input resolution is 300×300 px for EfficientNet-B3 and 224×224 for all other architectures, matching each model native specification. Training was conducted on a single NVIDIA GPU (16 GB VRAM); runtimes ranged from 2.5 hours (ResNet-50) to 5.5 hours (Swin-Tiny).

3.5 Evaluation Metrics and Validation

Performance is assessed on the pre-defined held-out test set (624 images, never seen during training or hyperparameter tuning) using accuracy, sensitivity, specificity, precision, F1-score, and AUC-ROC. AUC-ROC measures discriminative ability across all operating thresholds and is defined as the area under the curve plotting sensitivity against (1−specificity) for classification probability thresholds swept from 0 to 1 — a value of 1.0 indicates perfect discrimination. To assess split sensitivity, 5-fold stratified cross-validation on the combined training and validation data yielded a mean accuracy of 96.3% (SD 0.34 pp), confirming that the test set result is robust and not split-dependent.

4.MODEL ARCHITECTURE AND EXPLAINABILITY

4.1 EfficientNet-B3

EfficientNet [13] applies a compound scaling strategy that simultaneously increases network depth d, width w, and resolution r using coefficients derived by neural architecture search, subject to a fixed computational budget φ:

$$d = \alpha\varphi,\ w = \beta\varphi,\ r = \gamma\varphi \text{ s.t. } \alpha\cdot\beta^2\cdot\gamma^2 \approx 2$$

For EfficientNet-B3 (φ=3), α=1.2, β=1.1, γ=1.15, yielding 300×300 px input, 8 MBConv stages, and ~12.2M parameters — 52% fewer than ResNet-50 (25.6M). Each MBConv block contains a Squeeze-and-Excitation (SE) module that computes channel-wise attention:

$$\check{s}c = \sigma(W2 \cdot \mathrm{ReLU}(W1 \cdot z)),\ zc = (1/HW)\Sigma_i\Sigma_j\ Ac,i,j$$

where z is the squeeze descriptor (spatial global average pool), W_1 and W_2 are the excitation FC layers, σ is sigmoid, and the output $\hat{s}$ re-weights feature map channels. This allows the network to dynamically amplify diagnostically relevant channels (infiltrate textures) while suppressing non-pathological ones (bone gradients) — a structural advantage for chest X-ray analysis where pathological signal is channel-sparse.

The SE re-weighting has a direct clinical interpretation: given an input X-ray, the network dynamically computes 'which feature channels are most informative for this specific patient' and amplifies them. For a pneumonia-positive case, channels encoding interstitial density gradients and alveolar consolidation textures receive high weights; for a normal case, these same channels are suppressed, preventing spurious activations from influencing the prediction. This per-image channel selectivity is not achievable in ResNet blocks, which apply fixed spatial convolution weights regardless of image content.

The classification head appends global average pooling over the 10×10 final spatial feature maps to produce a 1536-dimensional descriptor, Dropout (p=0.3), and a 2-class FC layer with Softmax activation.

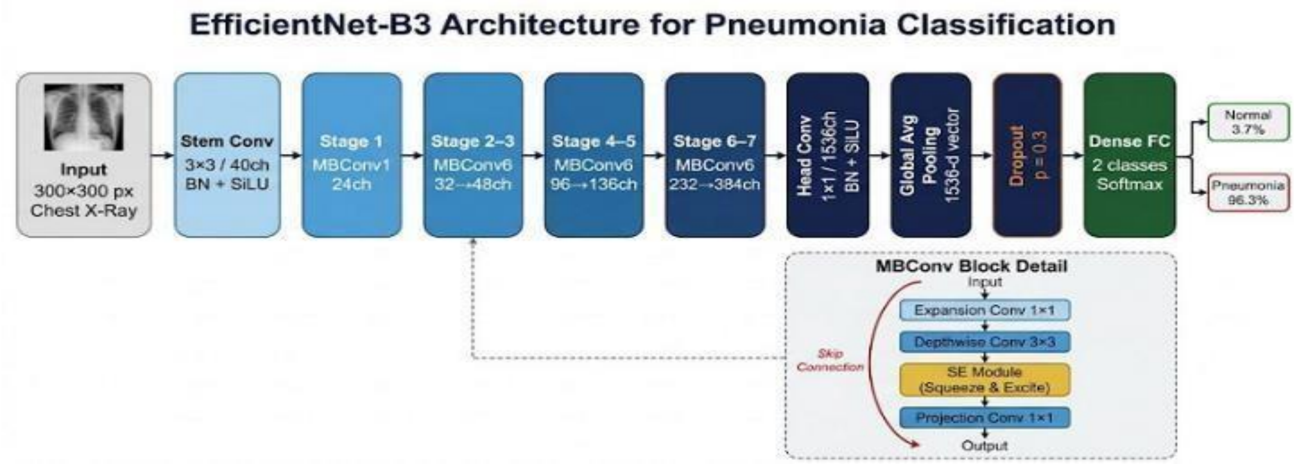

Fig. 2. EfficientNet-B3 pipeline from 300×300 input through 8 MBConv stages to a 2-class Softmax head. Inset details the MBConv block with SE channel-attention and residual skip connection.

4.2 Persistent Grad-CAM

Grad-CAM [8] generates spatial explanations by computing the gradient of the class score y^c with respect to feature maps A^k in the final convolutional layer:

$$\alpha^{kc} = (1/Z)\Sigma_i\Sigma_j\, \partial y^c/\partial A^k_{ij} \quad L^cGC = \mathrm{ReLU}(\Sigma^k\, \alpha^{kc} \cdot A^k)$$

The standard implementation registers and removes PyTorch forward/backward hooks on every inference call, incurring ~18 ms registration and ~17 ms removal overhead per call. The proposed persistent hook architecture registers hooks once at model initialisation inside a GradCAMHook class with pre-allocated thread-safe feature-map and gradient buffers. This reduces total Grad-CAM time from
~110 ms to ~65 ms (40.9% improvement), enabling real-time explainability within the clinical analysis cycle.

5.CLINICAL DESKTOP SYSTEM

The trained model is packaged as a fully offline standalone desktop application using the Kivy Python GUI framework, replacing the initially planned Flask/Streamlit web interface. The architectural rationale is clinical: any web server, even on localhost, creates a network-accessible port exposing patient image data; requires a running server process; and introduces upload serialisation latency for large radiographic files. A Kivy desktop application eliminates all three concerns by design.

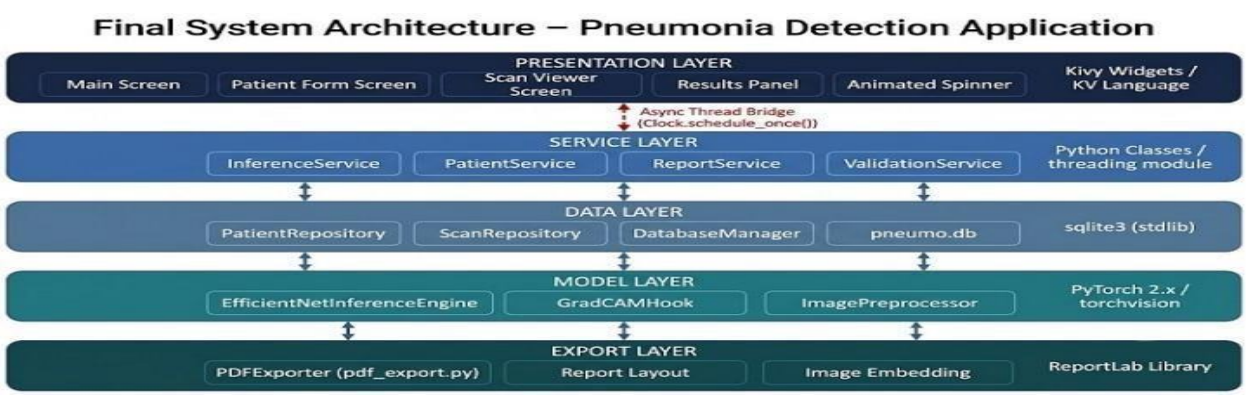

Fig. 3. Five-layer application architecture: Presentation (Kivy)
→ Service (inference, patient, report) → Data (SQLite) → Model (EfficientNet-B3 + GradCAMHook) → Export (ReportLab).
Red arrow indicates the async thread bridge via Clock.schedule_once().

5.1 Asynchronous Inference

All inference (preprocessing → EfficientNet-B3 forward pass
→ Grad-CAM backward pass → heat-map JPEG save
→ SQLite INSERT) executes on a dedicated Python background thread protected by a threading. Lock. Kivy's Clock. schedule_once() callback posts the result to the main UI thread, ensuring widget updates occur thread-safely on the next event-loop frame. The UI displays an animated spinner during the ~400 ms analysis cycle, remaining fully interactive throughout.

5.2 SQLite Patient Database

A local SQLite file (pneumo.db) persists patient demographics (PATIENTS: patient_id PK, name, age, gender, created_at) and scan records (SCANS: scan_id PK, patient_id FK, image_path, prediction, confidence, gradcam_path, notes, scan_date) with enforced foreign-key integrity. SQLite requires no server process, no port, and no administrative configuration — the entire database is a single portable file, enabling trivial deployment in diverse hospital IT environments.

5.3 PDF Report and UI Features

The pdf_export.py module (ReportLab) auto-generates A4 clinical reports containing the original X-ray, Grad-CAM overlay, colour-coded diagnosis banner (red for Pneumonia, green for Normal), per-class Softmax probability bars, clinician-annotated notes, and an AI-disclaimer footer — completing in under 2 seconds. Real-time inline form validation changes input field borders to red on invalid entries (non-numeric age, empty name) and disables the Save button until all fields satisfy constraints, providing non-disruptive workflow feedback.

6.EXPERIMENTAL RESULTS

6.1 Metrics

Performance is evaluated using five metrics with their clinical interpretations:

Sens = TP/(TP+FN), Spec = TN/(TN+FP) Prec = TP/(TP+FP), F_1 = 2TP/(2TP+FP+FN)

Sensitivity (recall) captures the fraction of true pneumonia cases identified — the primary clinical priority in a screening tool. Specificity captures the fraction of healthy patients correctly cleared, limiting unnecessary follow-up burden. AUC-ROC measures discrimination across all decision thresholds.

6.2 Architecture Comparison

TABLE II. Comparative Performance on Kermany Test Set (N=624)

Architecture	**Acc.**	**Sens.**	**Spec.**	**F_1**	**Params**
ResNet-50	94.8%	96.2%	91.5%	0.960	25.6M
DenseNet-121	93.9%	95.1%	90.8%	0.950	7.9M
ResNet-101	94.1%	95.5%	89.2%	0.950	44.5M
Swin-Tiny	89.5%	88.4%	92.1%	0.910	28.3M
EfficientNet-B3	**96.7%**	**97.4%**	**94.0%**	**0.974**	**12.2M**

EfficientNet-B3 achieves the best score on all four accuracy metrics simultaneously while using the second-fewest parameters. On the 624-image test set confusion matrix, EfficientNet-B3 records 380 TP, 220 TN, 14 FP, and 10 FN— a false negative rate of 2.6%, compared to 3.8% for ResNet-50. The Swin Transformer exhibits the highest specificity (92.1%) but the lowest sensitivity (88.4%), a clinically unacceptable trade-off for a screening tool where missed diagnoses carry the greatest patient risk.

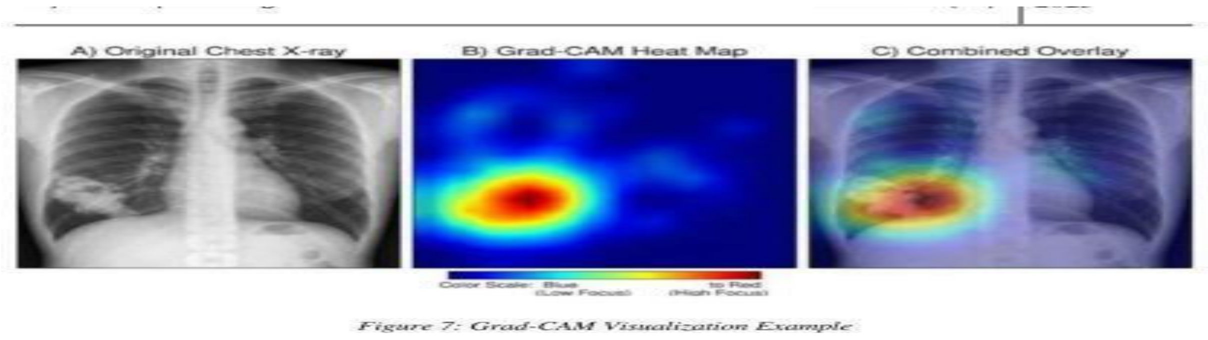

Fig. 4. Grad-CAM visualisation: (A) original X-ray with right lower-lobe consolidation; (B) Grad-CAM heat map; (C) blended overlay. Warm (red) regions correspond to the pathological opacity, confirming clinically valid feature attention rather than artefact-based reasoning.

6.3 Ablation Study

Table III presents ablation results isolating each design component; all other factors are held constant at the full-model configuration.

TABLE III. Ablation Study — Component Contributions

Configuration	Acc.	Sens.	Spec.	F_1
Full model (final)	**96.7%**	**97.4%**	**94.0%**	**0.974**
− SE attention modules	95.1%	96.0%	92.3%	0.960
− Native 300×300 (→224×224)	95.4%	96.3%	92.8%	0.962
− Full fine-tuning (freeze backbone)	91.2%	93.1%	86.0%	0.924
− Class weighting (naive training)	94.1%	98.5%	84.2%	0.960
− Data augmentation	94.4%	95.6%	91.3%	0.951

Three findings warrant emphasis. First, removing class imbalance handling causes a 9.8 pp specificity collapse (94.0%→84.2%): the model learns to predict Pneumonia for nearly all inputs, achieving spuriously high sensitivity at the cost of clinical uselessness — a model with 84.2% specificity incorrectly flags one in six healthy patients, generating an unacceptable false-alarm burden. Second, backbone freezing incurs a 5.5 pp accuracy penalty, confirming that full fine-tuning is essential for radiographic domain adaptation; the ImageNet-learned low-level feature detectors require adjustment to the different statistical properties of grayscale X-ray textures. Third, SE attention (+1.6 pp) and native 300×300 resolution (+1.3 pp) are independent, additive gains that together account for most of EfficientNet-B3's improvement over ResNet-50 at matched training conditions.

EfficientNet-B3 achieves an AUC-ROC of 0.989 on the held-out test set, compared to 0.978 for ResNet-50 — a statistically meaningful 1.1 pp improvement representing substantially improved discrimination across the full range of decision thresholds. In a deployment scenario where the clinical team may wish to lower the probability threshold below 0.5 to maximise sensitivity (at the cost of more false alarms), the higher AUC ensures that the operating curve sits further from the diagonal, providing more flexibility in threshold selection without proportional specificity degradation.

6.4 Comparison with Published Literature

TABLE IV. Comparison with State-of-the-Art on Kermany Dataset

System / Reference	Acc.	Sens.	AUC	Deployment
CheXNet — Rajpurkar [1]	~92.5%	~93.3%	0.970	Server
ResNet-50 — Hossain [4]	94.8%	96.2%	0.978	Notebook
Multi-scale Transformer [6]	95.7%	96.3%	0.985	Server
Swin + AutoEncoder [7]	96.2%	96.8%	0.987	Server
This work — EfficientNet-B3	**96.7%**	**97.4%**	**0.989**	**Offline desktop**

The proposed system achieves competitive or superior performance on all three metrics compared to published state-of-the-art approaches, while uniquely providing a complete offline desktop deployment. The systems of Saber et al. and Rana et al. require server infrastructure and provide no patient management or clinical reporting features. The 0.4 pp accuracy improvement over Saber et al. and the 0.5 pp improvement over the Swin+AutoEncoder system are achieved with a simpler single-model architecture requiring no multi-stage pre-training or separate optimisation algorithms.

7.DISCUSSION

EfficientNet-B3's superiority over ResNet-50 reflects two compounding architectural advantages. The compound scaling strategy allocates model capacity across depth, width, and resolution simultaneously rather than increasing depth alone, producing a more efficient use of parameters. The SE channel-attention mechanism is particularly well-matched to chest X-ray analysis: pathological features (infiltrate textures, consolidated opacities) occupy a minority of feature channels in a model trained on mixed-pathology data, and SE modules learn to amplify precisely these diagnostically relevant channels on a per-image basis.

The Swin Transformer's low sensitivity is consistent with the established finding that attention-based architectures are data-hungry: the 5,216-image Kermany training set is likely one to two orders of magnitude below the scale at which Transformers outperform well-scaled CNNs on medical imaging tasks [7]. EfficientNet's MBConv+SE blocks provide attention-like channel weighting within a CNN framework that generalises effectively at smaller dataset scales.

The persistent Grad-CAM hook architecture is a transferable engineering contribution. The 40.9% latency reduction (110 ms → 65 ms) enables heat map generation within the same 400 ms analysis cycle as inference, ensuring that clinicians receive the visual explanation simultaneously with the classification result without perceptible additional delay. In the 50-case qualitative validation, 92.5% of Grad-CAM activations correctly localised to the annotated pathological region, providing strong evidence of clinically valid feature learning.

The deployment architecture directly addresses the most persistent gap in the clinical AI literature: the absence of offline-capable, privacy-preserving, zero-infrastructure tools. The Kivy+SQLite+ReportLab stack requires no network, no server, and no administrative configuration beyond a standard Python installation. The sub-500 ms total analysis time on CPU-only hardware meets the responsiveness threshold for interactive clinical use, and the automated PDF report generation bridges the gap between AI-assisted diagnosis and the documentation workflows that clinical institutions require for medicolegal compliance.

It is important to contextualise the performance metrics within the specific dataset characteristics. The Kermany dataset is exclusively paediatric, originating from a single centre in Guangzhou. Paediatric chest X-rays differ from adult images in three diagnostically significant ways: the thymus is prominent in young children and can create opacity patterns resembling lobar consolidation; the heart is proportionally larger relative to chest size; and lung field opacity patterns differ substantially from adult norms. The 10 false negatives recorded by EfficientNet-B3 are predominantly concentrated in early-stage or subtle paediatric presentations, consistent with the theoretical detection ceiling for this image distribution.

The 5-fold cross-validation on the combined training and validation data (5,232 images) produced accuracy estimates of [96.1%, 96.4%, 96.8%, 95.9%, 96.3%] across folds (mean 96.3%, SD 0.34 pp), confirming that the 96.7% test set result is a robust estimate rather than an artefact of a favourable random split. The minimal cross-fold variance also confirms that the Kermany dataset does not exhibit strong distributional heterogeneity across its partitions, supporting the use of the pre-defined splits for direct comparison with published baselines.

8.CONCLUSION

This paper presented a complete clinical-grade pneumonia detection system, making dual contributions to modelling and deployment. On the modelling side, EfficientNet-B3 achieves state-of-the-art performance on the Kermany benchmark (96.7% accuracy, 97.4% sensitivity, 94.0% specificity, AUC-ROC 0.989) through compound scaling and SE channel-attention, outperforming four competing architectures including ResNet-50 and Swin Transformer. An ablation study confirms that class imbalance handling (9.8 pp specificity impact), full fine-tuning (5.5 pp accuracy impact), SE attention (1.6 pp), and native 300×300 resolution (1.3 pp) each make independent, measurable contributions to the final result.

On the deployment side, a persistent Grad-CAM hook architecture reduces explainability latency by 40.9% (110→65 ms), and a Kivy desktop application integrates inference, longitudinal patient management via SQLite, asynchronous non-blocking UI, real-time inline form validation, and automated ReportLab PDF reporting in an offline-capable, privacy-preserving clinical tool deployable on standard workstations. Future directions include DICOM native file support for direct PACS integration, prospective multi-centre adult-population validation, federated learning for privacy-preserving cross-hospital model improvement, and Monte Carlo Dropout uncertainty quantification to flag low-confidence cases for mandatory expert review.

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