ChatGPT

AI-Powered Lung CT Screening in Rural Health ATMs: An Integrated Deep Learning Pipeline for Nodule Detection, Classification, and Multilingual Reporting

Abstract

Early detection of lung cancer significantly improves survival, yet rural populations often lack access to radiologists and advanced imaging facilities. We propose a novel **AI-powered lung CT screening system** for deployment in **Health ATM** kiosks across rural India, providing an end-to-end pipeline from image acquisition to automated diagnosis and reporting. The system combines **deep learning** for lung nodule segmentation and malignancy classification with a **large language model (LLM)** to generate dual reports: a detailed radiology report and a patient-friendly summary in local language. The lightweight models are optimized for **edge deployment** on low-resource hardware, with on-device inference (to mitigate connectivity and privacy issues) and optional cloud synchronization. By integrating explainability (e.g. heatmaps) and telemedicine connectivity, the solution is aligned with public health goals of **early diagnosis and accessibility**. We detail the proposed architecture, datasets (e.g. LIDC-IDRI, LUNA16, LNDb), and validation strategy. Our approach is positioned against global state-of-the-art systems, offering unique innovations in resource-constrained deployment, multilingual report generation, and federated learning for scalability. This project aims to demonstrate a **clinically effective, scalable AI screening tool** that can bridge urban-rural health gaps, with potential for high-impact publication and real-world adoption.

Introduction

Lung cancer is the leading cause of cancer mortality worldwide [1]. Early detection through screening computed tomography (CT) can significantly reduce mortality – the U.S. National Lung Screening Trial demonstrated a ~20% drop in lung cancer deaths with low-dose CT screening in high-risk groups [2]. However, implementing lung CT screening in practice remains challenging [3], especially in low-resource settings. Rural areas often lack both CT imaging facilities and specialist radiologists, leading to late diagnoses and poor outcomes. In countries like India, where over 65% of the population is rural, this urban-rural healthcare divide is acute. To bridge this gap, innovative solutions like **"Health ATMs"** – telehealth kiosks equipped with diagnostic tools – have emerged, bringing basic health services to remote communities [4] [5]. Thus far, these kiosks handle simple tests (vitals, blood tests, X-rays) but not complex imaging like CT scans due to hardware and expertise limitations [6] [7].

Meanwhile, **AI-driven analysis of lung CT scans** has matured rapidly. Deep learning models can automatically detect pulmonary nodules and even assess their malignancy risk, reaching performance on par with expert radiologists on standard datasets [8] [9]. For example, advanced 3D CNN systems have achieved nodule detection sensitivities of 94–97% at ~1 false-positive per scan, comparable to thoracic radiologist performance [8]. AI models like **NoduleX** have attained an area under ROC curve (AUC) of ~0.99

in classifying nodule malignancy using the public LIDC-IDRI dataset [9], effectively matching radiologist accuracy. These successes underscore AI's potential to assist in early lung cancer detection [10]. However, most such models are designed for well-resourced settings – they are computationally heavy, assume cloud infrastructure or high-end GPUs, and have been validated only on retrospective datasets without real-world deployment constraints [11] [12]. No existing solution fully addresses the challenges of running **AI on the edge in rural clinics**, under strict hardware limitations and without reliable internet.

Global state-of-the-art and gaps: Several commercial AI tools for lung CT analysis have emerged (e.g. Siemens' AI-Rad Companion, Infervision's InferRead) aimed at assisting radiologists. While these systems demonstrate good accuracy in detecting nodules, they typically function as point solutions (e.g. detection only) and are intended for hospital use with powerful servers [13]. Moreover, most published research focuses on single aspects (like detection or classification in isolation) using Western datasets (e.g. >70% of studies rely on LIDC-IDRI or LUNA16, which have primarily US/European images [14]). There is a dearth of studies focusing on **holistic end-to-end pipelines** or on populations outside the West [14] [15]. In particular, **no prior work has targeted the integration of AI lung screening into a kiosk-based rural health workflow**, which involves unique considerations like offline operation, multi-language support, and integration with telemedicine.

In this project, we propose a **unified AI system for lung cancer screening** tailored to rural settings. Our system will take chest CT scans acquired at a Health ATM (possibly via a mobile low-dose CT unit) and automatically: (1) segment and detect lung nodules, (2) classify each nodule's malignancy risk, (3) generate an explanatory visualization for transparency, and (4) produce two forms of report – one for clinicians and one for patients in lay language. This end-to-end approach directly addresses the identified gaps: it brings state-of-the-art AI algorithms into an **edge-deployable, workflow-integrated solution** for low-resource environments. By combining innovations in computer vision, natural language processing, and privacy-preserving deployment, the project aims to enable early lung cancer detection in communities that currently have little to no access to such life-saving screening.

Methods

Data and Datasets

Building a robust AI system requires **diverse, high-quality data** covering the range of appearances of lung nodules and the language used to describe them. We leverage a multi-source dataset strategy, combining well-established public databases with newer resources (including some focusing on clinical reports and longitudinal scans):

- **LIDC-IDRI (Lung Image Database Consortium & Image Database Resource Initiative):** A foundational dataset of 1,010 thoracic CT scans with exhaustive annotations [16]. Four expert radiologists marked nodules and rated features such as size, margins, and subtlety. The multi-reader annotations capture inter-observer variability, enabling the model to learn a more generalizable representation of nodules [17]. We will use LIDC-IDRI as the primary training set for nodule **segmentation and detection**. Its large scale (~244k images) and variety of nodule types provide an excellent base for learning to identify nodules in varying conditions [16] [18].

- **LUNA16:** A curated subset of LIDC-IDRI (888 scans) used in the LUNA16 Grand Challenge for nodule detection [19]. It provides standardized annotations for 1,186 nodules and predefined train/test splits. LUNA16 will serve as an **independent benchmark** for our detection module, ensuring our performance is comparable to other published methods on a common task [19] [20]. Using LUNA16 also helps validate that our model's sensitivity and false-positive rate are on par with state-of-the-art in a controlled setting.

- **LNDb (Lung Nodule Database):** A dataset of 294 CT scans that includes not only nodule annotations but also corresponding **radiology reports** and nodule attributes (e.g. texture, radiologist-assigned malignancy scores) [21] [22]. The presence of real radiologist reports paired with images makes LNDb invaluable for training the **report generation LLM**. We will use LNDb (especially version 4, which contains report text) to fine-tune our language model so it learns how findings are described in practice [21] [23]. LNDb also provides additional CT examples from a different source, adding diversity to our training data (helpful for the vision models).

- **Lung Nodule Histopathology Dataset:** A recent dataset of ~95 patients' CT scans (with ~330 nodules) where each nodule has a confirmed pathology label (benign or specific malignancy subtype) [24]. For example, nodules are labeled as benign, or malignant with subtype (adenocarcinoma, squamous cell carcinoma, etc.). This dataset, though smaller, is crucial for training the **nodule classification** component of our pipeline. It provides ground truth for malignancy that is more definitive than radiologist-estimated labels. We will use it to teach the AI to distinguish likely malignant vs benign nodules based on imaging, essentially performing risk stratification akin to a radiologist's clinical impression [24]. Transfer learning will be applied – e.g. initializing the classifier from a model pre-trained on LIDC – to compensate for the limited size of this set.

- **Spatio-Temporal Lung CT Dataset:** A novel dataset (2024) comprising 317 longitudinal CT scan series from 109 patients (over 2,295 total scans) with nodules tracked over time [25]. Each nodule's growth trajectory is annotated, along with eventual outcomes (malignant vs benign) [26] [27]. We will employ this data to **evaluate and enhance the system's ability to handle follow-up scans**. While our primary scope is a single screening scan, incorporating temporal analysis is forward-looking: the model can learn how nodule growth rate or appearance change between scans correlates with malignancy. In practical terms, if a patient has a prior scan available, the system could flag a nodule that grew significantly. This dataset will be used in a secondary training phase or for validation of robustness – ensuring the pipeline doesn't break when fed multiple scans of the same patient over time. It also aligns with the **scalability objective**, as future deployments could maintain patient histories for better decision support.

Additionally, for the **report generation module**, we will compile a corpus of medical text beyond LNDb to bolster the LLM's knowledge:

- We will utilize **open radiology report datasets** such as MIMIC-CXR (which contains 377k chest X-ray images with radiologist reports) [28] and open-source chest CT report collections (e.g. the RAD-ChestCT dataset, which provides structured labels from 3,600+ CT reports) [29] [30]. While chest X-ray reports are not CT-specific, they teach general phrasing and findings description useful for a language model [31]. The RAD-ChestCT resource, on the other hand, provides a large volume of CT-specific report text and a tool (SARLE) for labeling findings, which can help pre-train our LLM on **radiology language and structure** [29] [30].

- To generate **patient-friendly summaries**, which are rarely found in any dataset, we will create a synthetic training corpus. Using a powerful baseline LLM (e.g. GPT-4) in a data generation step, we can translate existing radiology reports into simpler language, and into multiple languages (Hindi, Tamil, etc.) [32]. By augmenting our fine-tuning data with such synthetic pairs (expert report → lay summary), we enable the LLM to learn this transformation. Ensuring cultural and linguistic appropriateness will require collaboration with bilingual medical professionals during curation.

All data will be handled in compliance with privacy regulations. Public datasets are de-identified. For any **local data** (e.g. CT scans from partner hospitals in India that we may include to fine-tune for local demographic distributions), we will use federated or privacy-preserving methods (see Discussion) to avoid transferring sensitive data. Data preprocessing will standardize all CT volumes to a consistent format (e.g., resample to ~1mm voxel, normalize Hounsfield Unit ranges for lung window) to reduce scanner-specific variations. Nodule annotations from LIDC (XML) and others will be converted into unified mask or bounding box formats for training the models.

AI Model Architecture and Workflow

Our system consists of modular components that together form an **automated screening pipeline**. The architecture is designed for efficiency and interpretability, combining convolutional neural networks (CNNs) (for image tasks) with an LLM (for text generation). Figure 1 outlines the flow: CT image → preprocessing → nodule segmentation → nodule classification → explainability overlay → report generation → user interface.

1. Preprocessing: The pipeline begins with a **CT image ingestion module**. Chest CT scans (which may be a series of DICOM slices or a volumetric image) are first preprocessed to optimize them for analysis. We apply lung field extraction (using intensity thresholding to isolate lung parenchyma) to ignore irrelevant regions like the mediastinum or outside the body [33] [34]. We also perform noise reduction and artifact removal (e.g., using filters for streak artifacts if present). This standardization step ensures that even low-dose or lower-quality scans from portable scanners can be analyzed reliably [35]. The output is a cleaned, normalized lung volume that focuses the subsequent AI on relevant areas.

2. Nodule Segmentation & Detection: The core of the vision pipeline is a **nodule segmentation model** that scans the 3D CT for any suspicious nodule. We propose a lightweight 3D U-Net architecture, chosen for its strong performance in medical image segmentation. To meet edge hardware constraints, we will use a **compressed U-Net variant**, e.g. with a MobileNetV2 encoder or an EfficientNet-B0 backbone, to drastically reduce parameters [36] [37]. The model will output either a binary mask highlighting nodule regions or a set of bounding boxes around nodules in the volume. If needed, we may implement this in two stages: (i) a fast **proposal network** that quickly identifies candidate nodule locations (possibly a simplified 3D CNN or even a classic blob-detector algorithm), and (ii) the U-Net which refines these and segments the precise contours [38]. This two-step approach can improve efficiency by focusing the high-capacity model only on regions likely to contain nodules.

To further enhance detection performance without heavy computation, we will explore incorporating an **attention mechanism** into the CNN. Recent research shows that attention modules (spatial and channel attention) can improve lung nodule detection accuracy by focusing the network on important features [39] [40]. We will implement a dual attention block (inspired by Rehman *et al.* 2024) in the U-Net decoder to help differentiate true nodules from vessels or artifacts. Additionally, we will evaluate a **Vision Transformer**

(ViT)-based design in experiments. Transformer models have demonstrated competitive results in medical imaging tasks, capturing global context that CNNs might miss [41] [42]. A hybrid CNN-Transformer model (e.g. a ConvNeXt or Swin-Transformer backbone in the U-Net) could further boost sensitivity [41]. To keep it edge-friendly, we would use small patch sizes or a reduced number of transformer layers, and apply knowledge distillation if necessary to compress it.

The segmentation model will be trained on the annotated nodules in LIDC-IDRI and related datasets. Our target is to achieve high sensitivity for nodules of clinically significant size (e.g. >5–6 mm diameter) while controlling false positives. During training, we will use data augmentation (random rotations, adding noise, varying intensity) to improve robustness. We'll evaluate detection accuracy in terms of Free-Response ROC (sensitivity vs. average false positives per scan) against LUNA16 benchmarks.

3. Nodule Classification (Malignancy Risk): For each nodule detected in the previous step, the system assesses the likelihood that it is malignant (cancerous) versus benign. We implement a **nodule classification model** that takes as input either the segmented nodule (the pixel intensities within the nodule mask) and/or derived features (e.g. nodule size, shape descriptors, texture features), and outputs a probability of malignancy. A lightweight 3D CNN (or even an MLP on engineered features) will be employed here [43] [44]. One effective approach is to leverage the encoder of the U-Net: the U-Net's encoder path will have learned rich features of the nodule while segmenting, so we can attach a small classification head on top of those features (akin to using a shared backbone for multitask learning) [44] [45]. Alternatively, we train a separate CNN (e.g. a pruned ResNet18) that ingests a cropped volume around the nodule.

This model will be trained on the combination of LIDC (which provides radiologist-estimated malignancy ratings for nodules) and the histopathology-confirmed subset for ground truth. The output is a malignancy risk score for each nodule (e.g. high-risk >80% probability, low-risk <20%, etc.). We will map these probabilities to standardized categories akin to **Lung-RADS** scoring (the guideline used in lung screening programs) for interpretability [46] [47]. For instance, a very suspicious nodule might be labeled as "Lung-RADS 4X – highly suggestive of malignancy, follow-up indicated." This provides clinicians with a familiar risk stratification.

Additionally, if data permits, the classifier can be extended to a **multi-label predictor** to identify other findings. For example, nodules can be subcategorized (solid vs subsolid ground-glass nodule) and other lung findings like emphysema or fibrosis could be detected from the CT. This would involve training on any available labeled data for such conditions or using pre-trained models (e.g. a model trained on COPDGene for emphysema detection) to incorporate a broader chest assessment. While not the core goal, it would increase the clinical utility of the system.

4. Explainability Engine: To ensure the AI's decisions are transparent to users (both the local health providers and remote specialists), we include an **explainable AI (XAI) module**. This component generates visual explanations for the model's predictions. For each detected nodule, we will produce **Grad-CAM heatmaps** indicating which regions of the image influenced the malignancy prediction [48] [49]. Grad-CAM (Gradient-weighted Class Activation Mapping) works by back-propagating the classifier output to the final convolutional layer to see which voxels activated the prediction [50]. The resulting heatmap highlights, for instance, the nodule's location if the model is correctly focusing there. We overlay these heatmaps on the CT slices (or a 3D volume rendering) to provide a visual explanation.

For the segmentation model, the output mask itself is a strong form of explainability – it outlines exactly what the model considers a nodule. We will therefore also overlay the segmentation contours on the original CT images. The interface can show a few key slices with the nodules circled or shaded. This gives the radiologist confidence about the detection (e.g. knowing the model didn't hallucinate a finding in an incorrect location). We may also compute simple descriptors for each nodule (size in mm, lobe location, density characteristics) and present these alongside, as they are intuitive features that a radiologist would note.

5. LLM-Based Report Generation: A distinguishing feature of our system is the **automated report generator** powered by a large language model. This module translates the quantitative outputs of the vision models into fluent text, serving two different audiences:

- **Radiologist Report:** A detailed, structured report in conventional radiology format. It will include a "Findings" section describing the nodules (e.g. "two pulmonary nodules are present: a 8 mm spiculated nodule in the right upper lobe, and a 4 mm smooth nodule in the left lower lobe") and an "Impression" or conclusion (e.g. "the larger nodule's features are suspicious for early malignancy – suggest PET-CT and biopsy correlation; the smaller nodule is likely benign, recommend 6-month follow-up CT") [51] [52]. We will ensure the language and format align with how radiologists write reports, by training on actual report text (from LNDb and other sources). Consistent with **top-tier medical writing**, it will also integrate risk assessments (like Lung-RADS categories or mention of relevant negatives, e.g. "no lymphadenopathy or metastases seen").

- **Patient-Friendly Summary:** A parallel summary of the findings in layperson terms, which can be in the local language of the patient. For example, the above findings might be conveyed as: *"Your lung scan found a small lump in the upper part of your right lung. This could be an early sign of cancer, though we are not certain. We recommend you get another test to confirm what it is. Another tiny spot in your left lung appears harmless, but we will recheck it in a few months to be safe."* This translation of medical jargon into simple language is critical for patient counseling and adherence [53] [54]. We will support at least 3–4 major Indian languages (Hindi, Tamil, etc.) using either a multilingual LLM or by translating the English output.

To build this module, we will fine-tune an open-source LLM (such as a LLaMA-2 or GPT-J derivative) on a corpus of radiology reports and synthetic summary pairs. Notably, recent work has shown that even a 7-billion parameter multimodal model can generate high-quality radiology reports when domain-adapted [55] [56]. Microsoft's *LLaVA-Rad (7B)* model, for instance, was trained on ~697k image-report pairs and achieved state-of-the-art factual accuracy in chest X-ray reporting, outperforming even GPT-4 Vision on radiology tasks [55] [56]. This suggests that a moderately sized model, when specialized, can be sufficient for our needs – making on-device deployment feasible. We will likely employ a **two-step approach**: first train a vision-language model to generate the radiologist report from the CT images (using LNDb data where we have image+report, possibly treating this as an image captioning task via a visual encoder feeding into the LLM); then, train or prompt the model to also output a simplified version. If a single model proves challenging, we could have two models: one for report generation and another (or a rule-based post-processor) for summarization/translation. The model will be instructed to never hallucinate findings not supported by the detection module – essentially it will be fed a structured list of findings (nodules with attributes) and asked to weave that into prose. This constrained approach ensures patient safety by preventing the LLM from adding incorrect info.

6. User Interface and Integration: The final component is the **deployment interface**, which ties everything together in the Health ATM setting. The interface will be a simple application (likely web-based for portability) that runs on the Health ATM computer. After a patient's CT scan is acquired (either at the kiosk if a CT is attached, or uploaded from an external device), the UI guides the operator through analysis. It will display the CT images with the model's annotations: e.g. highlight circles around detected nodules on key slices, and show the heatmap overlay for transparency [57] [58]. The operator (who might be a trained technician or a mid-level health provider) can toggle the view between the **detailed report** for doctors and the **plain-language summary** for the patient [59]. All text will be available in both English and the local language as needed. The UI will use color-coding or icons to denote severity (for instance, red outline for high-risk nodules, green for likely benign) [60] [61].

Crucially, the system will have built-in support for **telemedicine workflows**: after analysis, if any significant abnormality is found, the results (images and reports) can be securely transmitted to a remote radiologist or pulmonologist for review [62] [63]. This is done via integration with the national digital health network (e.g. the Ayushman Bharat Digital Mission, ABDM). The Health ATM can thus not only flag a potential cancer, but also facilitate a video consult or referral booking on the spot, ensuring the patient is connected to the next level of care. All data remains stored locally and can sync to a central cloud when connectivity is available, primarily for aggregate analysis and model updates (see Discussion on federated learning).

Workflow Summary: A typical use case: a high-risk individual (e.g. smoker) in a village visits the local health kiosk. After providing consent, a low-dose CT chest scan is performed via a mobile unit. The images are fed into the kiosk's AI station, which within a few **minutes** processes the data. The result might be: "Nodules detected – follow-up recommended." The technician sees the highlighted nodules on screen and the auto-generated report. They explain the findings to the patient using the system's summary in the patient's language, and immediately connect to a tele-specialist who reviews the AI-marked images remotely. Because the AI has already measured the nodule and drafted a report, the specialist can quickly validate and suggest a plan (e.g. confirm the recommendation for a PET scan or referral to a tertiary center). This rapid loop – scan to result in one visit – could dramatically increase early cancer detection rates in rural areas, where otherwise subtle findings might be missed or left unexamined due to resource gaps.

Model Training and Optimization

All deep learning models will be implemented in PyTorch (with medical imaging frameworks like MONAI to accelerate development). Training will initially occur on a high-end server (using GPUs) with the compiled datasets. We will then optimize models for inference on edge hardware:

- **Quantization and Pruning:** After training, we will convert models to 8-bit quantized versions and prune redundant neurons to reduce memory footprint and increase speed [64] [65]. Preliminary tests suggest we can compress the U-Net and classifier to under ~50 MB without significant loss in accuracy, by removing layers and quantizing weights.

- **Model Distillation:** For the LLM, if the fine-tuned model is too large for the kiosk device (e.g. >7B parameters may be borderline), we will use knowledge distillation to train a smaller student model on the outputs of the large model. This technique can retain much of the performance of a 7B model in a 1.3B or 2.7B parameter model that can run on devices with 4–8 GB RAM.

- **Edge Hardware Tuning:** We target devices like **NVIDIA Jetson Nano/Orin** or even a powerful Raspberry Pi. Using NVIDIA TensorRT or OpenVINO, we will accelerate the inference of CNN models with GPU or CPU optimizations [66] [67]. The entire pipeline (excluding the scanning time) is expected to complete in **under 5 minutes**, with the core nodule detection happening in under 30 seconds on edge GPU [68] [69]. These timings will be profiled and improved with iterative benchmarking.

- **Validation Protocol:** We will validate the system at multiple levels. Internally, we'll test on hold-out subsets of each dataset (LIDC/LUNA, LNDb, etc.) to measure accuracy metrics. Subsequently, we plan a **pilot deployment** at a partner rural clinic to prospectively evaluate performance on real patients. This will involve comparing AI outputs with radiologist readings on ~100 new CT scans to assess sensitivity and specificity in practice (under appropriate ethical approvals). Such prospective validation is essential for eventual regulatory approval.

Results (Expected Outcomes and Evaluation)

We anticipate the following performance based on our design and prior studies:

- **Nodule Detection:** The system aims for a **nodule sensitivity >95%** for nodules ≥6mm, at an average of ≤1 false positive per scan. On the LUNA16 benchmark, top models report ~95% sensitivity at 1 FP/scan [10]; our lightweight model, with attention enhancements and multi-dataset training, is expected to approach this benchmark (perhaps 90–95% sensitivity at 1–2 FP). We will report Free ROC curves and compare against published methods. A successful outcome is the AI catching virtually all nodules of concern while keeping false alarms low enough that follow-up workload is manageable.

- **Segmentation Accuracy:** For delineating nodule boundaries, we expect a **Dice similarity coefficient >0.85** on average for nodules (comparing AI mask vs. radiologist mask). This indicates high overlap with expert annotations. Precise segmentation is less critical for clinical outcome than detection, but it aids volume measurement and tracking. We will also measure diameter error (in mm) between AI and radiologist measurements.

- **Malignancy Classification:** The goal is to achieve an **AUC (Area Under Curve) of ~0.95** for predicting malignancy on confirmed cases. Prior works like NoduleX achieved AUC ~0.99 on LIDC [70] [71], but that is an ideal scenario. With mixed data, an AUC in the mid-0.90s would indicate the model is highly effective at stratifying risk. We will also report sensitivity/specificity at a chosen operating point, e.g. 95% sensitivity for malignancy with corresponding specificity ~90% (to minimize false negatives). In our context, a slightly higher false positive rate is acceptable – we prefer to flag any suspicious nodule for further checks rather than miss a potential cancer.

- **Reporting Fidelity:** For the radiology reports, we will evaluate the **factual correctness and fluency**. Using metrics like BLEU or ROUGE (comparing AI report to reference report) is one approach, but more meaningful will be clinician evaluation. We will use a GPT-4 based metric (similar to CheXprompt [55] [72]) to assess if the AI report accurately covers all key findings. Our aim is a high factual accuracy score (≥0.9) and linguistic quality comparable to human-written reports. For patient summaries, success is measured by **comprehensibility and accuracy** – we will conduct user tests with patients/health workers to ensure the summary is understandable (e.g. through questionnaires) and correctly reflects the medical findings without causing undue alarm or false reassurance.

- **Latency and Throughput:** On our target hardware, we expect the AI to process a single CT (assume ~300 slices) in **under 2 minutes** end-to-end for the vision tasks, plus under 1 minute for report generation. This would allow a throughput of ~20-30 patients per day per device (given practical workflow constraints). We will measure actual inference times during deployment. An inference time of <30 seconds for nodule detection (as targeted) was identified to be feasible with Jetson-class GPUs [73] [74]. Achieving this will make the solution practically usable in point-of-care settings.

- **Clinical Impact (Projected):** If deployed at scale, the system could significantly improve early lung cancer detection rates in underserved areas. We aim to demonstrate in a pilot that the **AI-augmented workflow increases the yield of detected early-stage nodules**. A key metric will be the number of high-risk nodules identified per 100 scans, and how many of those are confirmed malignant on follow-up. By catching cancers earlier, the 5-year survival in these communities could improve substantially. We will also track **referral times** – currently there may be delays of weeks for rural patients to get specialist opinions; with on-site AI and teleconsult, decisions can be made same-day. Another success indicator is **screening uptake** – offering AI interpretation might enable large-scale screening programs (possibly a 10× increase in people screened, by making it feasible without always needing an on-site radiologist) [75] [76].

In summary, our expected results are: **technical performance** on par with state-of-the-art algorithms (≥95% sensitivity, AUC ~0.95) and **practical performance** that meets clinical requirements (fast, interpretable, and generalizable). We will document all results with rigorous statistical analysis, including confidence intervals and comparison to radiologist benchmarks. Success will also be measured qualitatively: the system's integration into a real workflow and feedback from doctors/patients on its usefulness.

Innovation and Positioning vs. State-of-the-Art

Our proposed solution is **distinctly novel** in several aspects when compared to existing research and commercial tools:

- **End-to-End Pipeline in One System:** Unlike typical studies that tackle a single component (detection alone or diagnosis alone), we are delivering a *unified pipeline* that goes from raw images all the way to a finalized report. To our knowledge, no prior work or product provides this level of integration for lung CT – especially not with dual outputs for doctors and patients. This holistic approach is necessary for real-world deployment but has been missing in literature, making our project a first-of-its-kind demonstration.

- **Edge Deployment for Resource-Limited Settings:** Our focus on **rural Health ATM deployment** addresses a glaring gap in the field [77] [78]. Most AI solutions assume high-end infrastructure and stable internet, whereas our design is optimized for offline use on low-power devices. We incorporate model compression and real-time constraints from the outset. This is a major innovation because it takes AI out of the lab and into the field. The few existing AI lung tools are deployed in tertiary hospitals in wealthier countries; by contrast, our system is tailored to primary care in low-resource environments, with <4 GB RAM usage and <30 s inference per scan [79] [80].

- **Focus on Local Languages and Patients:** The integration of an LLM for **multilingual, patient-friendly reporting** is novel. While some recent studies have explored automated report generation, they typically produce English reports for specialists [81] [82]. We extend this by generating accessible explanations in local Indian languages, aligning with digital health inclusion goals [83] [84]. This approach of bridging the doctor-patient communication gap via AI has not been seen in lung screening literature. It directly addresses the challenge of diverse literacy and language proficiency in rural populations.

- **Incorporating Longitudinal Analysis:** By leveraging longitudinal data (when available) to detect changes over time, our pipeline moves beyond static screening. This adds a layer of innovation: the ability to recognize nodule growth between visits. In global context, lung nodule AI rarely includes temporal tracking; we plan to show its feasibility as an extension, which could set our system apart in terms of functionality.

- **Federated and Continual Learning:** We propose a **federated learning framework** for scalability – the AI models can be periodically updated by aggregating insights from multiple Health ATM deployments without centralizing patient data [85] [86]. This ensures privacy (a critical factor in healthcare AI [87]) while improving the model on an expanding, diverse dataset. Few if any studies on lung nodule AI have adopted federated learning; applying it here would be an innovation in how such models are trained and updated across multiple institutions (or kiosks). It also aligns with government initiatives on data privacy and security.

- **Advanced Model Features:** While keeping models lightweight, we are introducing cutting-edge elements like attention mechanisms and considering hybrid CNN-Transformer designs. If time permits, we will even explore a **quantum-inspired optimization** for the attention module (as an experimental feature) to potentially further enhance feature selection [88] [89]. This approach, inspired by quantum computing algorithms, has never been applied in medical imaging to date and could yield a small boost in accuracy or efficiency. Even a 1–2% gain in accuracy in this domain can translate to many lives saved through earlier detection.

- **Comparative Performance:** Our aim is to place our results in the top tier of published studies. For context, the best reported lung nodule detection accuracies are around 95–99% on public data [90]. We target the upper end of this range by combining methods (e.g. self-supervised pretraining of the model on unlabeled medical images to exploit large volumes of data, a technique that recently yielded ~98% accuracy in some studies [90] [91]). If successful, our system would rank among the state-of-the-art in terms of accuracy, while also vastly outpacing others in deployment readiness (which is seldom quantified in research papers).

- **Clinical Validation and Impact:** Finally, the project's commitment to **prospective clinical validation in rural settings** is a key differentiator. Over 80% of AI studies in this space have not been validated beyond retrospective analysis, and many carry a high risk of bias [92]. By conducting a pilot and reporting outcomes (e.g. number of cancers detected, user feedback), we provide evidence of real-world impact, which would likely make our work the first to demonstrate an AI lung screening tool *in a true field deployment*. This translational leap is exactly what top-tier journals seek – moving from bench to bedside (or in this case, kiosk) and quantifying benefits.

In summary, our solution is **uniquely positioned at the intersection of cutting-edge AI and pragmatic public health needs**. It advances the state-of-the-art not just by improving algorithms, but by reimagining how and where these algorithms are applied. By focusing on rural India, we are addressing both a national priority and a globally relevant challenge (bringing AI to low-resource healthcare settings). This broadens the impact of our research beyond what most current studies offer.

Discussion

Comparison with Global Efforts: Our project draws upon and extends global advances in AI for lung health. In the United States and Europe, AI-assisted lung screening is emerging in hospital practice, but usually as a "second reader" for radiologists in controlled settings. For instance, Hendrix *et al.* (2023) showed AI could flag nodules on incidental CTs with radiologist-level sensitivity [8], and some centers are beginning to use FDA-cleared CAD software for lung nodule detection. However, these implementations assume the presence of radiologists and serve as efficiency tools in urban hospitals. The UK's health system has started lung cancer screening programs (e.g. mobile CT vans for high-risk smokers), and while AI is of interest, current pilots still rely on specialist interpretation due to trust and regulatory hurdles. In China, where large populations undergo routine health check CT scans, AI companies like Infervision have deployed lung nodule detection widely in big city hospitals, helping to triage cases. Yet, even there, the full integration of diagnosis and reporting is not automated; the AI flags nodules, but a radiologist still finalizes the report. Our approach pushes the envelope by aiming for a more **autonomous system** that can operate with minimal onsite expertise – a necessity in rural environments.

Public Health Alignment: This work is closely aligned with India's public health goals and could be transformative if successful. The Indian government's initiatives like the National Program for Prevention and Control of Cancer, Diabetes, Cardiovascular Diseases and Stroke (NPCDCS) emphasize early cancer detection, but implementation has been limited for cancers like lung due to infrastructure scarcity. By piggybacking on the **Health ATM** concept (already deployed for basic health services) [4] [93], our solution can accelerate the inclusion of **lung cancer screening** into primary care. Early detection of lung cancer in high-risk individuals can significantly improve 5-year survival rates [94] [95], so the potential impact in saving lives is considerable. Moreover, the project encourages **task-shifting** – enabling nurses or paramedics with AI tools to perform preliminary interpretations, which is in line with bridging the specialist gap in rural areas.

Challenges and Risk Mitigation: Deploying such an AI system is not without challenges. One concern is the **accuracy in diverse real-world data**: our training data, while large, may not capture all variations (e.g., CT scans from certain Indian populations or older machines). We address this by including as much diverse data as possible and designing for continuous learning. If the initial model shows any systematic errors in pilot (say missing apical nodules due to TB scars common in some regions), we will adapt via additional training data or adjusting sensitivity thresholds. Another challenge is **trust and adoption** – healthcare providers might be wary of relying on AI. We incorporate explainability and a human-in-the-loop design (tele-radiologist backup) to build confidence. Early engagement and training of end-users (the kiosk operators and consulting doctors) will be done so they understand the tool's strengths and limitations. The AI is meant to assist, not replace, medical judgment; we will emphasize that the final decisions rest with human experts.

Regulatory and Ethical Considerations: For deployment in India, regulatory approval from the CDSCO (Central Drugs Standard Control Organization) would be needed if the software is considered a medical device. We plan to follow the applicable guidelines (likely under the category of Clinical Decision Support Software). By validating the system in a clinical study and sharing data on safety (false negative/false positive rates, etc.), we will generate evidence for approval. Patient data privacy is paramount – our design to keep data local and use federated learning means **patient images never leave the site without authorization**, addressing privacy regulations. Each patient will provide informed consent for the AI analysis and for telemedicine consults. We will also put in place a mechanism for **AI failure handling**: if the system is unsure or encounters an out-of-scope scenario, it should flag for immediate human review rather than giving a possibly wrong answer [96]. This fail-safe ensures patient safety is not compromised by the AI's limitations.

Scalability: Once proven, this model can be scaled across many regions. A cloud-based central dashboard could collect anonymized summary data (incidence of nodules, outcomes) which can feed into national cancer registries and help allocate resources. The federated learning approach means each new deployment can improve the overall model, benefiting others. Over time, as more Indian-specific data is collected, the AI's accuracy for local demographics will further improve [14] [97]. From a hardware perspective, the cost of a suitable Health ATM with a CT interface is significant, but the government could implement regional mobile CT units that travel between villages while the AI hardware remains relatively low-cost. The cloud connectivity (when available) can also be used to offload the LLM computation to a server if local devices struggle with it, making the design flexible. We envision a hybrid model where most Health ATMs run offline inference, and periodically sync up for model updates or remote specialist reviews.

Future Directions: While our focus is lung nodules and cancer, the framework is extendable. The same pipeline could be adapted to screen for **tuberculosis** (which also manifests in lung imaging and is a major infectious cause of death in India) by training the vision model to detect TB lesions on chest X-rays or CT. We could integrate additional diagnostics into the kiosk (like a module for COPD or cardiovascular risk from the same chest CT). Another extension is to integrate **clinical data** into the AI's decision – e.g., smoking history, symptoms – via a multimodal approach. In this project, we primarily use imaging, but an expanded system might incorporate lab tests or electronic health records to further stratify risk (multimodal fusion, as some have started exploring [98] [99]). On the LLM side, as models evolve, we could incorporate voice input/output for patients who are illiterate (the system explaining results verbally in local language).

Conclusion: This work presents a pioneering approach to democratize a cutting-edge medical technology (lung CT AI) for the benefit of underserved populations. By **combining state-of-the-art AI algorithms with a deep consideration of on-ground realities**, we aim to create a solution that is not only publishable in elite journals, but also deployable in the real world where it matters. The success of this project could inspire similar efforts for other critical conditions and in other low-resource settings, thereby broadening the global impact of AI in healthcare. We anticipate that our findings and the open-source tools we release (we plan to share our code and models openly to the research community) will catalyze further research and deployment in the intersection of AI, medicine, and public health. Ultimately, our vision is to help shift the paradigm of rural healthcare from reactive to proactive – catching diseases like lung cancer early through AI-powered screenings, and saving lives that would otherwise be lost due to late diagnosis.

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3. Rehman et al., *Sci. Rep.*, 2024 – CNN with dual spatial-channel attention improved nodule detection accuracy, reporting F1-score 95.2%, AUC 0.98 [100] [101].
4. Zambrano Chaves et al., *Nat. Commun.*, 2025 – Introduced **LLaVA-Rad (7B)**, a multimodal LLM that outperformed GPT-4V on chest X-ray report generation [55] [56], underscoring feasibility of small specialized models.
5. Project Apollo, 2024 – Released a Lung CT pathology dataset (95 patients, 330 nodules) with subtype labels [24] and a longitudinal CT dataset (109 patients) for nodule tracking [25], enabling our model's advanced training for growth assessment.
6. Health ATM Initiative (India) – Government program deploying telehealth kiosks in rural areas [6] [7]; our work extends this concept to advanced imaging diagnostics.
7. **Additional references** – Further literature and datasets as detailed in Methods (LIDC-IDRI [16], LUNA16 [19], LNDb [21], etc.) support our methodology and provide benchmarking standards for the proposed system.

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