

SilicoSafe

AI-Powered Diagnostic Triage for Silicosis in Dust-Exposed Workers

GLOBAL AI SAFETY HACKATHON

Project	SilicoSafe — AI Diagnostic Triage System
Team	Team SilicoSafe
Members	Utkarsh Raj (Team Lead) Garv Gupta
Organization	Maharaja Agrasen Institute of Technology
Submission Date	22 June 2026

Clinical risk scoring · DenseNet121 chest X-ray analysis · TB misdiagnosis safeguard · bilingual referral generation · compensation-awareness support

Executive Summary

Silicosis is an irreversible, progressive occupational lung disease caused by prolonged inhalation of crystalline silica dust. It affects an estimated tens of millions of stone-crushing, mining, sandblasting, and construction workers worldwide, the majority of whom live in low-resource regions with little access to pulmonologists or radiologists. Because early symptoms overlap heavily with tuberculosis, silicosis is routinely misdiagnosed or detected only at an advanced, irreversible stage — delaying treatment and blocking workers from compensation they are legally entitled to.

SilicoSafe is a web-based clinical triage system that equips frontline and community health workers — not specialists — with an AI-assisted screening tool. It fuses a structured occupational and symptom risk score with a DenseNet121 deep-learning model that analyses chest X-rays for radiological patterns associated with silicosis, while explicitly flagging features that may indicate TB instead of replacing clinical judgement. The system never issues a diagnosis: it produces a transparent, explainable risk tier and routes the worker to the right level of care, in the worker's own language.

Key Innovations

- Composite risk engine combining rule-based occupational/clinical scoring with AI image analysis, rather than relying on imaging alone.
- Explicit TB-confusion safeguard that surfaces overlapping radiological features instead of silently suppressing them.
- Human-in-the-loop design: every output is a referral recommendation, never an automated diagnosis.
- Bilingual, low-literacy-friendly referral and compensation guidance for last-mile usability.
- Lightweight, web-based architecture accessible from any browser-enabled device in rural deployment.

Expected Impact

Outcome Area	Current State	With SilicoSafe
Time to triage	Weeks (referral-dependent)	Minutes, at point of contact
TB confusion risk	High, often undetected	Flagged explicitly for review
Specialist dependency	Required for first screen	Needed only for confirmation
Compensation access	Frequently missed	Guided documentation support

By shifting the first screening step from a scarce specialist to any trained frontline worker with a phone, SilicoSafe targets the single largest bottleneck in occupational lung health: getting a worker in front of any qualified assessment at all.

1. The Problem

1.1 Occupational exposure. Mining, stone-crushing, sandblasting, and construction expose millions of workers to respirable crystalline silica. Chronic exposure scars lung tissue, producing progressive, incurable fibrosis. The disease is entirely preventable but, once advanced, cannot be reversed — making early detection the only effective intervention.

1.2 Diagnostic bottleneck. Reading a chest X-ray for silicosis requires a trained radiologist, who is rarely available in rural or informal-sector settings. Workers travel long distances, wait weeks, and are frequently misdiagnosed with tuberculosis because early-stage radiological patterns overlap. A missed or delayed diagnosis means continued exposure, irreversible progression, and loss of eligibility for compensation schemes tied to timely medical certification.

1.3 Problem statement. Frontline health workers in dust-exposed regions need a fast, low-cost, explainable way to identify which workers are at meaningful risk of silicosis and need urgent specialist referral — without overstepping into unsupervised diagnosis.

2. The SilicoSafe Solution

SilicoSafe combines four layers into a single web-based workflow usable by a community health worker in under ten minutes per worker:

Layer	Function
Occupational & symptom intake	Structured questionnaire on exposure years, dust type, protective equipment, cough, breathlessness, chest pain.
Rule-based clinical risk score	Weighted scoring of exposure duration, intensity, and symptom severity, producing a baseline risk band.
AI chest X-ray analysis	DenseNet121 model (via TorchXRyVision) estimates probabilities for silicosis-associated and TB-associated radiological patterns.
Composite risk & referral engine	Merges clinical and imaging scores into a single explainable risk tier and generates a bilingual referral with compensation guidance.

Crucially, the AI model output is never shown as a standalone verdict. It is one weighted input into a composite score that a health worker reviews alongside the clinical questionnaire, preserving human judgement at every step.

3. System Architecture

SilicoSafe uses a lightweight three-tier architecture optimized for low-bandwidth, web-based deployment accessible via any device with a browser.

1. User (Frontline Health Worker, Web Browser)
2. React + Vite Frontend — intake forms, X-ray capture/upload, results dashboard
3. FastAPI Backend — request orchestration, risk-engine logic, SQLite storage
4. DenseNet121 / TorchXRayVision Model — chest X-ray feature & pathology extraction
5. Composite Risk Analysis Engine — merges clinical + AI scores into a risk tier
6. Bilingual Referral & Results Dashboard — worker-facing recommendation and next steps

Figure 1. Data flow from worker intake through AI-assisted risk analysis to referral.

3.1 Implementation Stack

Layer	Technology
Frontend	React, Vite
Backend	FastAPI (Python)
AI / Imaging	PyTorch, TorchXRayVision, DenseNet121, Pillow, NumPy
Storage	SQLite

3.2 AI Model Pipeline

Input X-ray → Preprocessing & normalization → DenseNet121 convolutional layers → Pathology probability vector (incl. silicosis-associated and TB-associated features) → Composite Silicosis Risk Score.

DenseNet121's densely-connected layers reuse feature maps across the network, which improves gradient flow and performs well on the comparatively small, high-resolution datasets typical of medical imaging — making it a practical transfer-learning backbone for this task.

4. Composite Risk Scoring Model

Factor	Weight	Clinical Impact
Years of silica exposure	High	Strongest single predictor of fibrotic change
Use of protective equipment	Medium	Modifies effective exposure intensity
Chronic cough / breathlessness	Medium	Core symptomatic indicator
AI silicosis-pattern probability	High	Radiological corroboration
AI TB-pattern probability	Safeguard	Triggers differential-diagnosis flag

Scores are combined into three referral tiers — **Low**, **Elevated**, and **Urgent** — each mapped to a specific recommended action (routine monitoring, district hospital referral, or urgent specialist referral with compensation-documentation support).

5. AI Safety & Responsible Design

SilicoSafe is deliberately positioned as a **triage support tool, not a diagnostic device**. This framing drives every design decision below.

Principle	How SilicoSafe Applies It
Human-in-the-loop	Health workers review and confirm every AI-assisted score before any referral is issued.
Transparency	Risk tier breakdown shows the contribution of clinical vs. AI components, not a single black-box number.
Explainability	Pathology probabilities are surfaced per-feature so workers see what drove the score.
Error handling	Low-confidence or ambiguous AI outputs are flagged for mandatory specialist review rather than auto-resolved.
TB-confusion safeguard	TB-associated probability is shown alongside silicosis probability whenever both are elevated.
Data privacy	Worker data and images are stored locally (SQLite) with minimal retention by default.
Non-diagnostic positioning	UI language consistently uses “risk indication” and “referral recommendation,” never “diagnosis.”

6. Societal Impact, Limitations & Future Work

6.1 Societal Impact

- Extends specialist-grade first-line screening to rural and informal-sector workers with no radiologist access.
- Strengthens worker access to legally mandated compensation through earlier, better-documented detection.
- Reduces public-health misallocation caused by silicosis cases wrongly treated as tuberculosis.

6.2 Known Limitations

- Model trained/validated on available chest X-ray datasets; large-scale clinical validation is still required before any regulatory claim.
- False positives/negatives are possible — mitigated by the human-in-the-loop referral design, not eliminated.
- Current architecture assumes intermittent internet connectivity for model inference and sync.

6.3 Future Work

- Integration with India's Ayushman Bharat digital health ecosystem for continuity of care.
- On-device / offline inference for fully connectivity-independent rural deployment.
- Genuine Grad-CAM visual explainability overlays on X-ray images.
- Expanded regional-language support and aggregate occupational-health dashboards for policymakers.

7. Conclusion

Silicosis is a preventable disease that continues to disable and kill workers primarily because early detection cannot reach the people who need it. SilicoSafe addresses this not by replacing clinicians but by extending a transparent, explainable, human-supervised first screen to the point of contact — the worksite and the community clinic. By combining structured clinical risk scoring with AI-assisted imaging analysis under a strict triage-not-diagnosis design philosophy, SilicoSafe offers a deployable, safety-conscious path to earlier intervention, better referral quality, and improved access to compensation for some of the world's most under-served workers.

References

- [1] World Health Organization, “Silicosis,” WHO Fact Sheets, Geneva, Switzerland.

- [2] International Labour Organization, "Occupational Lung Diseases: Prevention and Control," ILO Report, Geneva.
- [3] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely Connected Convolutional Networks," in Proc. IEEE CVPR, 2017.
- [4] J. P. Cohen et al., "TorchXRyVision: A Library of Chest X-ray Datasets and Models," MIDL, 2022.
- [5] P. Rajpurkar et al., "CheXNet: Radiologist-Level Pneumonia Detection on Chest X-rays with Deep Learning," arXiv preprint, 2017.
- [6] National Institute for Occupational Safety and Health (NIOSH), "Silicosis Surveillance," CDC, USA.
- [7] V. Gulshan et al., "Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy," JAMA, 2016 (reference architecture for clinical AI screening).