MediScan AI

Early Disease Detection From Medical Imaging

Empowering Healthcare In Resource-Limited Settings

DA-IICT Hackathon 2026

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The Healthcare Crisis

Why Early Disease Detection Matters

10M+
TB Cases Annually

2.5M
Pneumonia Deaths

60%
Lack Expert Care

The Reality : In Resource-Limited Healthcare Settings, Access To Skilled Radiologists And Advanced Diagnostic Tools Is Severely Restricted. Manual Analysis Of Medical Images Is Slow, Requires Specialized Expertise, And Often Leads To Delayed Diagnosis.

Critical Challenges

- Limited Access To Trained Radiologists In Rural And Remote Areas
- Time-Consuming Manual Interpretation Of X-Rays And CT Scans
- High Risk Of Misdiagnosis Due To Human Error And Fatigue
- Delayed Treatment Leading To Disease Progression And Mortality

Our Solution : MediScan AI

AI-Powered Early Disease Detection

An Intelligent System That Processes Medical Images To Automatically Detect Early Signs Of Tuberculosis, Pneumonia, And Bone Fractures With Explainable AI Reasoning.

Core Capabilities

Automated Detection : Real-Time Analysis Of X-Rays And CT Scans With High Accuracy

Contour Mapping : Visual Overlays Highlighting Abnormal Regions For Easy Interpretation

Explainable AI : Clear Reasoning Behind Every Diagnostic Decision

Multi-Disease Support : Detection Of TB, Pneumonia, And Fractures In A Single System

Resource-Efficient : Designed To Work On Limited Computational Infrastructure

System Architecture

End-To-End AI Pipeline

Image Upload (X-Ray/CT) → Preprocessing & Enhancement → CNN Model Analysis

Contour Mapping ← Disease Classification ← Feature Extraction

Explainable Results + Visual Feedback

Pipeline Features : The System Uses Advanced Deep Learning Architectures With Attention Mechanisms, Processes Images Through Multiple Stages Of Enhancement, And Generates Human-Interpretable Outputs With Highlighted Regions Of Concern.

Technology Stack

Cutting-Edge AI & Computer Vision

TensorFlow / PyTorch

Deep Learning Framework For CNN Model Development And Training

OpenCV

Image Preprocessing, Contour Detection, And Visualization

ResNet / DenseNet

Pre-Trained CNN Architectures For Feature Extraction

Grad-CAM

Explainable AI For Visualizing Model Decision Regions

Flask / FastAPI

Backend API For Model Inference And Result Delivery

React.js

Interactive Frontend For Image Upload And Result Visualization

Why These Technologies ? Our Stack Combines State-Of-The-Art Deep Learning With Proven Computer Vision Techniques, Ensuring Both High Accuracy And Interpretability While Maintaining Computational Efficiency For Deployment In Resource-Constrained Environments.

Deep Learning Model Architecture

Multi-Task Learning For Disease Detection

Hybrid CNN Architecture

Input Layer → Image (512x512 Grayscale)

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ResNet-50 Backbone → Feature Extraction

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Attention Module → Focus On Relevant Regions

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Multi-Head Classification → TB / Pneumonia / Fracture

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Segmentation Branch → Contour Mapping

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Output → Class Probability + Heatmap + Contours

Model Innovations

Transfer Learning : Pre-Trained On ImageNet, Fine-Tuned On Medical Datasets

Attention Mechanism : Focuses On Diagnostically Relevant Image Regions

Multi-Task Learning : Simultaneous Classification And Segmentation

Contour Mapping Technology

Precise Localization of Abnormalities

What Is Contour Mapping ? Advanced Image Processing Technique That Creates Visual Overlays On Medical Scans, Clearly Delineating Abnormal Regions Such As Lesions, Infiltrates, And Fractures.

Technical Implementation

U-Net Segmentation : Pixel-Level Classification Of Abnormal Tissue

Edge Detection : Canny And Sobel Operators For Precise Boundaries

Morphological Operations : Noise Reduction And Contour Refinement

Color-Coded Overlays : Red For High-Risk, Yellow For Moderate Concern

Visualization Pipeline :

Raw Image → Probability Heatmap → Threshold Application → Contour Detection → Overlay Generation → Final Annotated Image

Clinical Impact : Healthcare Workers Can Instantly Identify Problem Areas Without Extensive Radiology Training, Reducing Diagnostic Time From Hours To Seconds.

Explainable AI (XAI)

Building Trust Through Transparency

"Black Box" Models Are Not Acceptable In Healthcare. Our System Explains Every Decision It Makes.

XAI Techniques Implemented

Grad-CAM

Gradient-Weighted Class Activation Mapping Highlights Which Regions Influenced The Diagnosis

LIME

Local Interpretable Model-Agnostic Explanations For Feature Importance

Attention Maps

Visual Representation Of Where The Model "Looks" During Analysis

Feature Attribution

Quantifies The Contribution Of Each Image Region To Final Prediction

Why It Matters : Explainability Increases Clinician Trust, Enables Validation Of Model Decisions, Facilitates Learning For Healthcare Workers, And Ensures Regulatory Compliance For Medical AI Systems.

Datasets & Training Strategy

High-Quality Medical Image Databases

1. ChestX-ray14 (NIH Dataset)

https://nihcc.app.box.com/v/ChestXray-NIHCC

112,120 Frontal-View X-Ray Images From 30,805 Patients With 14 Disease Labels Including Pneumonia And Tuberculosis

2. TBX11K Dataset

https://mmcheng.net/tb/

11,200 Chest X-Rays With Bounding Box Annotations For Tuberculosis Detection

3. RSNA Pneumonia Detection Challenge

https://www.kaggle.com/c/rsna-pneumonia-detection-challenge

30,000 Chest X-Ray Images With Pneumonia Annotations And Bounding Boxes

4. MURA (Musculoskeletal Radiographs)

https://stanfordmlgroup.github.io/competitions/mura/

40,561 Radiographic Images For Bone Fracture Detection Across Multiple Body Parts

Data Processing Pipeline

Ensuring Robustness Across Image Qualities

Preprocessing Techniques

CLAHE : Contrast Limited Adaptive Histogram Equalization For Enhanced Visibility

Normalization : Standardizing Pixel Intensity Across Different Imaging Devices

Denoising : Gaussian And Bilateral Filtering To Remove Artifacts

Resizing & Padding : Uniform Input Dimensions While Preserving Aspect Ratio

Data Augmentation for Generalization

Rotation : ±15 Degrees To Simulate Different Patient Positioning

Zoom & Scale : 0.9-1.1x To Handle Varying Distances

Brightness & Contrast : Simulating Different X-Ray Machine Settings

Elastic Deformation : Mimicking Anatomical Variations

Result : Our Model Remains Robust To Variations In Image Quality, Resolution, Noise Levels, And Acquisition Parameters—Critical For Deployment In Resource-Limited Settings With Diverse Equipment.

Expected Performance Metrics

Clinical-Grade Accuracy Standards

95%+
Accuracy

93%+
Sensitivity

94%+
Specificity

Disease-Specific Performance Goals

Tuberculosis Detection

AUC: 0.96 | Sensitivity: 94% | Specificity: 95%

Pneumonia Detection

AUC: 0.95 | Sensitivity: 92% | Specificity: 94%

Fracture Detection

AUC: 0.97 | Sensitivity: 95% | Specificity: 96%

Processing Speed

< 3 Seconds Per Image On Standard Hardware

Benchmark Comparison: Our Target Metrics Match Or Exceed Performance Of Radiologists In Similar Settings, With The Added Advantage Of 24/7 Availability And Zero Fatigue.

Real-World Impact

Transforming Healthcare Delivery

Access to Care

Bringing Expert-Level Diagnostics To Rural Clinics And Remote Healthcare Facilities Where Radiologists Are Unavailable

Speed & Efficiency

Reducing Diagnostic Time From Hours To Seconds, Enabling Faster Treatment Decisions And Better Patient Outcomes

Cost Reduction

Eliminating The Need For Expensive Specialist Consultations And Reducing Misdiagnosis Costs By Up To 70%

Global Scalability

Deployable Across Diverse Populations And Healthcare Systems, From Urban Hospitals To Mobile Health Units

Estimated Impact: 50,000+ Patients Could Receive Timely Diagnosis Annually In A Single District, Potentially Saving Thousands Of Lives Through Early Intervention

Phase 1 : Foundation (Hours 0-8)

Data Pipeline Setup : Download And Preprocess Datasets (NIH, TBX11K, RSNA, MURA)

Environment Configuration : Setup TensorFlow/PyTorch Environment With GPU Support

Base Model Development : Implement ResNet-50 Backbone With Transfer Learning

Phase 2 : Core Development (Hours 8-24)

Model Training : Train Multi-Task Learning Model On Combined Datasets

Contour Mapping : Implement U-Net Segmentation And OpenCV Contour Detection

XAI Integration : Add Grad-CAM And Attention Visualization

Backend API : Develop Flask/FastAPI Endpoints For Inference

Phase 3 : Integration & Polish (Hours 24-36)

Frontend Development : Build React.js Interface With Image Upload And Visualization

Testing & Validation : Evaluate Model Performance On Test Sets

Demo Preparation : Create Compelling Demonstration Scenarios

Meet Our Team

Passionate Innovators Driving Change

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Team Leader | AI/ML Architect

🧑‍💻 Rajan Parmar

Deep Learning Engineer

🧑‍💻 Deep Parmar

Computer Vision Specialist

🧑‍💻 Hemakshi Rathod

Backend & API Developer

🧑‍💻 Hetvi Parmar

Frontend & UI/UX Designer

Our Mission : To Leverage Cutting-Edge AI Technology To Democratize Healthcare Access And Save Lives In Underserved Communities Worldwide.

Together, We Bring Expertise In Machine Learning, Computer Vision, Full-Stack Development, And A Shared Passion For Healthcare Innovation.

Let's Save Lives Together

MediScan AI : Bringing World-Class Diagnostics
To Every Corner Of The Globe

95%+
Diagnostic Accuracy

<3s
Processing Time

3
Disease Types

Ready To Transform Healthcare?

Join Us In Making Expert Medical Diagnosis Accessible To All

Team MediScan AI | DA-IICT Hackathon 2026

Nishant • Rajan • Deep • Hemakshi • Hetvi

"AI That Cares, Technology That Heals, Innovation That Saves Lives"