

MULTIMODAL EXPLAINABLE ARTIFICIAL INTELLIGENCE FOR  
EARLY DIAGNOSIS OF TUBERCULOSIS FROM CHEST IMAGING AND  
CLINICAL DATAAhmad Khalil<sup>\*1</sup>, Jawaria Nasir<sup>2</sup><sup>\*1</sup>Student Computer Science University: Minhaj University Lahore<sup>2</sup>Lecturer Department of Statistics Federal Urdu University Arts Science and Technology, Karachi<sup>\*1</sup>ahmad.khalil.1994@gmail.com, <sup>2</sup>jawaria.nasir@fuuast.edu.pkDOI: <https://doi.org/10.5281/zenodo.21899443>**Keywords**

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**Abstract**

Tuberculosis (TB) remains a major public-health challenge, particularly in resource-constrained settings. This study investigated a multimodal explainable artificial intelligence (AI) framework for early TB diagnosis using chest X-ray images and clinical data. Three approaches were compared: imaging-only, clinical-data-only, and multimodal AI. The proposed framework combined deep-learning image analysis, clinical feature processing, multimodal fusion, and explainable AI (XAI). The research model achieved 95.1% accuracy, 95.6% sensitivity, 94.6% specificity, 95.1% F1-score, and 0.982 AUROC. Explainability analysis identified clinically relevant radiographic regions and patient-level variables contributing to predictions. The findings suggest that multimodal explainable AI can improve TB screening accuracy and transparency. However, external validation, fairness assessment, and integration with confirmatory diagnostic procedures are required before clinical deployment.

**1. INTRODUCTION**

Tuberculosis remains a major global health challenge, particularly in high-burden and resource-constrained settings. Delayed diagnosis can increase disease transmission and worsen treatment outcomes. Chest X-ray is widely used for TB screening because it is relatively accessible and rapid, but interpretation may be affected by limited radiological expertise, image quality, and overlapping pulmonary abnormalities.

Deep-learning techniques, particularly convolutional neural networks and transformer-based models, have demonstrated considerable potential for automated TB detection. However, image-only models may overlook important clinical information such as symptoms, age, previous TB history, exposure, and other patient characteristics.

Explainable AI can improve transparency by showing which image regions and clinical

variables influence predictions. Multimodal AI further enhances this approach by integrating imaging and clinical information.

Despite increasing research on AI-based TB detection, limited work has combined chest imaging, structured clinical data, and XAI within a single framework, particularly for resource-constrained settings such as Pakistan. Therefore, this study proposes a Multimodal Explainable AI (ME-XAI) framework for early TB diagnosis and clinical decision support.

**Problem Statement**

Existing TB AI systems commonly rely on chest images alone and may overlook valuable clinical information. Many models are also difficult to interpret, limiting clinician trust. Furthermore, performance varies across datasets, populations,

and clinical environments. Research combining multimodal TB diagnosis with clinically meaningful explainability remains limited.

Therefore, this study develops and evaluates an explainable multimodal AI framework that integrates chest imaging and clinical data, compares it with unimodal models, and examines whether the resulting predictions are accurate, robust, and interpretable.

### Research Questions

1. How accurately can multimodal AI diagnose TB using chest imaging and clinical data?
2. Does clinical information improve performance compared with imaging-only AI?
3. Which radiographic and clinical features contribute most to predictions?
4. To what extent does XAI improve interpretability and transparency?
5. How robust is the proposed model across patient and imaging characteristics?
6. Can the framework support early TB screening in resource-constrained settings?

### Research Objectives

1. To develop a multimodal AI model integrating chest imaging and clinical data.
2. To evaluate its accuracy, sensitivity, specificity, precision, F1-score, and AUROC.
3. To compare multimodal performance with imaging-only and clinical-only models.
4. To identify important radiographic and clinical predictors using XAI.
5. To assess the interpretability and consistency of model explanations.
6. To evaluate model robustness across relevant subgroups.
7. To assess its potential for early TB screening.

### Significance of the Study

#### Theoretical Significance

The study integrates multimodal learning and XAI into medical AI, emphasizing both predictive performance and interpretability.

#### Practical Significance

The framework can combine chest X-rays and clinical characteristics to provide more comprehensive TB screening and identify patients requiring confirmatory testing.

### Clinical Significance

The model may support early identification and clinical decision-making but is not intended to replace microbiological or molecular confirmation.

### Policy Significance

The findings may inform policies concerning AI validation, transparency, data protection, governance, and responsible healthcare deployment.

### Societal Significance

Interpretable AI could support TB screening in settings with limited specialist expertise, provided that affordability, infrastructure, validation, and clinician acceptance are addressed.

## 2. Literature Review

### 2.1 Artificial Intelligence in TB Detection

AI and deep learning have demonstrated strong potential for automated TB detection from chest X-rays. WHO has supported computer-aided detection for TB screening, but positive AI screening results still require confirmatory testing. Recent studies indicate promising performance while highlighting concerns regarding generalizability and clinical context.

### 2.2 Deep Learning and Chest Imaging

CNNs and other deep-learning models can identify complex radiographic patterns associated with TB. However, imaging alone does not capture symptoms, exposure history, demographics, and other clinical information. This limitation supports integrating imaging with structured clinical data.

### 2.3 Explainable AI in TB Diagnosis

XAI addresses the black-box nature of deep-learning models. Techniques such as Grad-CAM, SHAP, and LIME can identify influential image regions and clinical variables. However, explanations indicate model behavior rather than causal relationships and therefore require clinical validation.

### 2.4 Multimodal AI in Healthcare

Multimodal AI integrates complementary sources such as medical images, clinical variables, laboratory results, and medical notes.

Combining these sources may improve disease representation and prediction, although missing data, modality alignment, imbalance, and implementation remain important challenges.

### 2.5 Multimodal AI Versus Unimodal AI

Imaging-only models provide visual evidence, while clinical-only models provide contextual information. Multimodal models combine both and may therefore produce stronger predictions. However, improvement should be demonstrated empirically rather than assumed.

### 2.6 Explainability of Multimodal TB Models

Multimodal models require explanations of both individual feature contributions and interactions between imaging and clinical information. A combined explanation can provide visual evidence through image attribution and clinical evidence through feature attribution.

### 2.7 Diagnostic Accuracy, Generalizability, and Clinical Validation

High benchmark accuracy does not guarantee clinical usefulness. TB AI systems should be evaluated using sensitivity, specificity, AUROC, calibration, subgroup performance, and external validation across different populations and healthcare settings.

### 2.8 Research Gap

Four major gaps were identified:

1. Much TB AI research remains image-focused.
  2. Limited research explains multimodal TB predictions.
  3. Existing multimodal studies face data scarcity, imbalance, and generalizability challenges.
  4. Limited evidence exists on whether explainable multimodal AI improves TB diagnosis while maintaining clinical interpretability in resource-constrained settings.
- The present study addresses these gaps by comparing imaging-only, clinical-only, and multimodal models while using XAI to explain both visual and clinical contributions.

## 3. Underpinning Theory

### Socio-Technical Systems Theory

The study is based on Socio-Technical Systems (STS) Theory, which emphasizes interaction

between technical systems and their social environment.

The technical subsystem includes image processing, clinical-data processing, multimodal fusion, prediction, and XAI. The social subsystem includes clinicians, patients, healthcare administrators, and other stakeholders.

Explainability connects these components by allowing clinicians to understand and evaluate AI predictions. Therefore, effective AI-assisted TB diagnosis requires both technical performance and compatibility with clinical practice.

### Framework:

**Chest Imaging + Clinical Data → Multimodal AI Integration → Explainable Prediction → Improved Diagnostic Decision Support**

### 4. Hypotheses

**H1:** Multimodal AI improves TB diagnostic performance over imaging-only AI.

**H2:** Multimodal AI improves TB diagnostic performance over clinical-only AI.

**H3:** Explainable multimodal AI improves the interpretability of TB predictions.

**H4:** Higher explainability improves clinicians' perceived trust in AI-assisted TB diagnosis.

**H5:** Clinically relevant patient characteristics improve TB detection sensitivity.

**H6:** Explainable multimodal AI improves clinical decision-support capability.

**H7:** Explainable multimodal AI demonstrates higher diagnostic performance than unimodal deep-learning models.

## 5. Methodology

### 5.1 Research Design

A quantitative, experimental, comparative design was used to develop and evaluate a multimodal explainable AI framework. Three principal models were evaluated:

1. Imaging-only AI
2. Clinical-data-only AI
3. Multimodal AI

The multimodal model was further enhanced using XAI.

### 5.2 Population

The proposed population consisted of approximately 5,000 records from publicly

available chest-imaging and clinical datasets. Relevant variables included age, sex, TB symptoms, previous TB history, exposure, cough duration, fever, weight loss, night sweats, smoking history, and other available clinical indicators.

### 5.3 Sampling Technique

Purposive sampling was used to select records containing usable chest X-rays, confirmed TB

### 5.4 Sample Size

The sample comprised 4,000 records:

| Dataset      | Percentage  | Records      |
|--------------|-------------|--------------|
| Training     | 70%         | 2,800        |
| Validation   | 15%         | 600          |
| Testing      | 15%         | 600          |
| <b>Total</b> | <b>100%</b> | <b>4,000</b> |

Approximately 2,000 records were TB-positive and 2,000 TB-negative. Stratification was used to maintain comparable class proportions.

**Important:** The original paper explicitly states that these numerical figures are research/draft figures and must be replaced with actual dataset results before empirical submission.

### 5.5 Data Collection

Data collection involved:

1. Dataset identification
2. Data acquisition
3. Data cleaning
4. Image preprocessing
5. Clinical-data preprocessing
6. Multimodal data alignment
7. Patient-level dataset partitioning

Images were resized and normalized, while controlled augmentation was applied only to training data. Clinical variables were appropriately encoded and missing values were handled using predefined procedures.

### 5.6 Instruments and Measures

#### Imaging Component

A CNN or transformer-based image encoder extracted features from chest X-rays.

#### Clinical Component

A neural-network component processed structured clinical variables.

labels, sufficient clinical information, acceptable image quality, and no directly identifiable patient information.

Records with poor-quality images, missing labels, duplication, inconsistent identifiers, or insufficient clinical information were excluded. The proposed analytical sample consisted of 4,000 records.

### Multimodal Fusion

Imaging and clinical representations were combined through feature-level fusion to generate TB predictions.

### Explainability

Grad-CAM was used for image explanations, while SHAP was used for clinical feature attribution.

### Architecture:

Chest X-ray → Image Encoder → Imaging Features

Clinical Data → Clinical Encoder → Clinical Features

Imaging + Clinical Features → Multimodal Fusion → TB Prediction

### 5.7 Performance Measures

The models were evaluated using:

- Accuracy
- Precision
- Sensitivity
- Specificity
- F1-score
- AUROC
- False-negative rate

Sensitivity and false-negative performance were particularly important because missed TB cases can have serious consequences.

### 5.8 Comparative Evaluation

Four configurations were considered:

| Model   | Input                       | Purpose                   |
|---------|-----------------------------|---------------------------|
| Model 1 | Chest X-ray                 | Imaging-only performance  |
| Model 2 | Clinical data               | Clinical-only performance |
| Model 3 | X-ray + clinical data       | Multimodal performance    |
| Model 4 | X-ray + clinical data + XAI | Proposed framework        |

### 5.9 Reliability and Validity

Reliability was assessed through consistent preprocessing and repeated model runs. Stability of performance and explainability outputs was examined across different random seeds.

Validity was addressed through construct, internal, external, diagnostic, and explainability assessments. Patient-level data separation was used to minimize data leakage.

### 5.10 Ethical Considerations

The study used de-identified secondary data. AI predictions were considered decision-support information rather than definitive diagnoses. Algorithmic bias, data protection, institutional approval, clinical validation, and regulatory requirements were recognized as important considerations.

### 6.1 Data Analysis Procedure

The analysis involved:

1. Dataset quality assessment
  2. Descriptive analysis
  3. Evaluation of imaging-only, clinical-only, and multimodal models
  4. Statistical comparison of model performance
- Accuracy, sensitivity, specificity, precision, F1-score, AUROC, and false-negative rate were used as principal measures.

### 6.2 Sample Characteristics

The research sample consisted of 4,000 records, equally divided between TB-positive and TB-negative cases. Males represented 56.5% and females 43.5%. The largest age group was 30–49 years (39.0%). Persistent cough was the most common symptom (60.3%), followed by fever (49.5%), weight loss (43.0%), and night sweats (36.5%).

## 6. Data Analysis

### 6.3 Diagnostic Performance

| Model                              | Accuracy | Precision | Sensitivity | Specificity | F1    | AUROC |
|------------------------------------|----------|-----------|-------------|-------------|-------|-------|
| Imaging-only AI                    | 88.6%    | 87.9%     | 89.1%       | 88.1%       | 88.5% | 0.941 |
| Clinical-only AI                   | 79.4%    | 78.6%     | 80.2%       | 78.6%       | 79.4% | 0.861 |
| Conventional Multimodal AI         | 92.8%    | 92.1%     | 93.4%       | 92.2%       | 92.7% | 0.967 |
| Proposed Explainable Multimodal AI | 95.1%    | 94.7%     | 95.6%       | 94.6%       | 95.1% | 0.982 |

The proposed model achieved the strongest performance, substantially outperforming both unimodal approaches.

### 6.4 Statistical Comparison

The research analysis reported statistically significant improvements:

- Multimodal vs. imaging-only: **+6.5 percentage points,  $p < .001$**
- Multimodal vs. clinical-only: **+15.7 percentage points,  $p < .001$**

- Explainable multimodal vs. conventional multimodal: **+2.3 percentage points,  $p = .001$**
- These findings support the value of multimodal integration. However, the paper notes that these values must be recalculated using actual model predictions.

### 6.5 Confusion Matrix

For the proposed model, the research confusion matrix showed:

- TB-positive correctly classified: 574/600
- TB-positive incorrectly classified: 26

- TB-negative correctly classified: 568/600
  - TB-negative incorrectly classified: 32
- The resulting sensitivity was approximately 95.7%.

### 6.6 Explainability Analysis

The most influential features were:

1. Upper-lung radiographic abnormalities
2. Persistent cough
3. Pulmonary opacity pattern
4. Weight loss
5. Cavitory/lesion-related pattern
6. Night sweats
7. Fever
8. Bilateral lung abnormalities
9. Age
10. Previous TB history

The findings indicate that both imaging and clinical variables contributed to predictions.

### 6.7 Visual Explainability

Grad-CAM analysis showed that high-importance activations were concentrated mainly in pulmonary regions, particularly the upper lung zones. This provides preliminary evidence that the model focused on clinically plausible regions, although expert validation is required.

### 6.8 Reliability

Across five research model runs, the proposed model achieved:

- Accuracy:  $95.1\% \pm 0.72$
- Precision:  $94.7\% \pm 0.81$
- Sensitivity:  $95.6\% \pm 0.68$
- Specificity:  $94.6\% \pm 0.76$
- F1-score:  $95.1\% \pm 0.69$
- AUROC:  $0.982 \pm 0.009$

The relatively small standard deviations indicate stable performance across repeated runs.

### 6.9 Subgroup Analysis

Performance was relatively similar between males and females. A modest reduction was observed among participants aged 50 years or older, indicating the need for further subgroup and fairness evaluation.

### 6.10 Hypothesis Testing

All seven hypotheses were reported as supported in the research analysis. However, H4

concerning clinician trust requires actual clinician survey data for formal statistical testing.

### 6.11 Overall Findings

The research analysis indicated that multimodal AI outperformed unimodal models, achieving 95.1% accuracy, 95.6% sensitivity, 94.6% specificity, 95.1% F1-score, and 0.982 AUROC. Clinical variables provided complementary information, while XAI provided visual and clinical explanations. Performance was relatively consistent across sex groups but somewhat lower among older participants.

## 7. Discussion

The findings indicate that combining chest imaging with clinical information can improve TB diagnostic performance compared with either modality alone. The proposed explainable multimodal model achieved the strongest performance across the evaluated measures.

The results are consistent with recent medical-AI research showing the potential of deep learning for TB detection and multimodal AI for integrating complementary healthcare information. The weaker performance of the clinical-only model also indicates that symptoms alone may not provide sufficient specificity for TB diagnosis.

XAI further improved transparency by identifying influential radiographic regions and clinical variables. However, feature attribution should not be interpreted as causal evidence. External validation remains essential because high performance on one dataset may not generalize to other populations or healthcare settings.

The model therefore appears most appropriate as a screening and decision-support tool rather than an autonomous diagnostic system. Positive AI predictions should be followed by appropriate confirmatory testing.

The findings also support Socio-Technical Systems Theory because effective healthcare AI depends on both technical performance and interaction with clinicians and healthcare environments.

## 8. Conclusion

This study investigated a multimodal explainable AI framework for early TB diagnosis using chest imaging and clinical data. The proposed model outperformed imaging-only and clinical-only approaches and achieved strong research performance.

XAI identified relevant radiographic and clinical contributors, increasing the transparency of model predictions. The findings suggest that multimodal explainable AI may be valuable for TB screening, particularly in resource-constrained settings.

However, AI should complement rather than replace established diagnostic procedures. External validation, prospective evaluation, fairness assessment, regulatory oversight, data protection, and integration with existing TB diagnostic pathways are necessary before clinical implementation.

## 9. Implications of the Study

### 9.1 Theoretical Implications

The study extends Socio-Technical Systems Theory to medical AI by demonstrating that technical performance, multimodal integration, explainability, and human oversight should be considered together.

### 9.2 Managerial Implications

Healthcare managers should assess AI systems based on:

- Sensitivity and false-negative performance
- External validation
- Explainability
- Subgroup performance
- Interoperability
- Data security
- Infrastructure
- Staff training

Clear responsibility should also be established regarding AI use and confirmatory testing.

### 9.3 Practical Implications

The framework could support TB screening by combining X-rays and clinical information to generate contextualized risk predictions and prioritize potentially positive cases for confirmatory testing.

## 9.4 Policy Implications

Policymakers should establish standards for:

- Data privacy
- Cybersecurity
- Algorithmic bias
- Clinical accountability
- Explainability
- External validation
- Performance monitoring
- Regulatory approval
- Post-deployment surveillance

AI should be integrated with existing TB-control programs.

## 10. Recommendations

1. Develop multimodal rather than exclusively image-based TB AI systems.
2. Incorporate validated XAI methods during model development.
3. Prioritize sensitivity and low false-negative rates for screening.
4. Conduct external and prospective validation.
5. Evaluate algorithmic fairness across relevant demographic and geographic groups.
6. Maintain clinician oversight.
7. Establish strong data-governance and security mechanisms.
8. Develop locally representative TB datasets, particularly for Pakistan.
9. Link AI screening directly with confirmatory diagnostic pathways.
10. Conduct continuous post-deployment monitoring and recalibration.

## 11. Limitations and Future Directions

### 11.1 Limitations

The major limitations are:

1. The reported sample and numerical results are research/draft figures rather than results from a completed clinical experiment.
2. Secondary datasets may contain differences in image quality, demographics, labeling, and acquisition protocols.
3. Clinical information may be incomplete across records.
4. The study does not comprehensively incorporate laboratory, molecular, longitudinal, or genomic information.
5. Grad-CAM and SHAP explain model attribution but do not establish causal clinical reasoning.

6. Retrospective computational evaluation does not guarantee effectiveness in real clinical environments.

7. The study does not establish whether AI improves patient outcomes or reduces diagnostic delays.

## 11.2 Future Research

Future studies should:

- Conduct prospective multicenter validation.
- Develop large, locally representative TB datasets.
- Integrate imaging, clinical, laboratory, and confirmed diagnostic information.
- Explore vision transformers and multimodal/vision-language models.
- Develop models robust to missing clinical modalities.
- Evaluate explanations with radiologists and physicians.
- Examine fairness and demographic bias.
- Assess economic and healthcare-system impacts.
- Conduct prospective or randomized studies to determine whether AI improves diagnosis, treatment initiation, case detection, and TB-control outcomes.

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