TB Screening Kit for Rural Area

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***Abstract*—** Tuberculosis (TB) continues to be a major public health concern, particularly in rural areas where access to diagnostic facilities and trained medical professionals is limited. Early detection plays a critical role in reducing transmission and improving treatment outcomes. This project proposes the design and development of a cost-effective, portable TB screening kit tailored for rural healthcare settings. The system integrates simple diagnostic techniques with user-friendly interfaces, enabling frontline health workers to conduct rapid preliminary screening without the need for advanced laboratory infrastructure. Unlike conventional diagnostic approaches that require laboratory microscopy or molecular testing, the proposed kit emphasizes affordability, portability, and ease of use, making it suitable for resource-constrained environments. The study highlights the potential of such screening solutions to bridge the urban rural healthcare divide, support timely referrals, and strengthen community-level disease surveillance. Future directions include integrating IoT-based data collection for centralized monitoring, exploring AI-driven analysis for enhanced accuracy, and evaluating large-scale deployment feasibility in public health programs

***Index Terms*—** Tuberculosis, Screening Kit, Rural Healthcare, Early Diagnosis, Public Health.

I. INTRODUCTION

Early and scalable screening for Tuberculosis (TB) remains challenging due to limited diagnostics in low resource settings, variable data quality, and the need for quick, non-invasive assessments. Recent research cough-sound analysis, multimodal fusion with explainability, hardware/IOT health monitoring, edge acceleration (FPGA), and bioinformatics for anti-TB peptides.

This survey critically reviews representative works across these themes, highlighting approaches, datasets, algorithms, strengths, and limitations, and maps them to our proposed IOT + AI multimodal TB Screening Kit (cough + saliva database + cloud inference).

II. BACKGROUND

Tuberculosis (TB) remains a pressing health concern in India, especially in rural areas where access to medical facilities and early diagnosis is limited. To address this gap, the project introduces an affordable, portable TB screening kit that leverages AI and IOT technologies to support early-stage diagnosis and streamlined data management. The kit captures multimodal inputs such as cough sounds and saliva strip readings, enabling on-the-spot screening by field health workers. Designed to be battery-operated and offline compatible, it securely stores data in the cloud for access by doctors and healthcare authorities. By improving diagnostic reach and closing the gap in digital health records, this solution supports timely treatment and enhances public health planning.

i. Diagnostic Context for TB

Traditional TB diagnosis relies on sputum microscopy/CBNAAT/culture and chest imaging. These methods, while accurate, can be invasive, time-consuming, infrastructure-heavy, and hard to scale in rural settings.

ii. AI and IOT for Screening

AI-enabled analysis of CXR and cough audio has shown promise for fast, low-cost pre-screening. IOT provides portable data capture, connectivity, and cloud inference, enabling deployment beyond clinical centers. Yet, dataset shift, noise, and model interpretability remain open challenges Units

iii. Strengths and Limitations

Strengths across the field include high accuracy on curated datasets, lightweight models for edge/cloud, and promise of multimodality. Limitations include small or biased datasets, single modality reliance, heavier/complex models not fit for the field, lack of real-time IoT integration, and limited validation in rural use-cases.

III. LITERATURE SURVEY

Over the past decade, Artificial Intelligence (AI) and Internet of Things (IoT) technologies have gained significant attention in healthcare as low-cost, portable solutions for disease screening. These approaches have opened new opportunities for early detection of Tuberculosis (TB), especially in rural and resource-limited areas

i Cough-Audio Based TB (and Respiratory) Screening.

- Paper 7 (DMRNet – Cough TB Screening): Uses a deep CNN-like model on Mel spectrograms of cough audio; it is non-invasive and mobile-ready, but is sensitive to noise, requires diverse audio for robustness, and remains single modality.
- Paper 6 (Survey of AI on Cough): Reviews classical ML (SVM/RF/kNN/LR) and deep learning (CNN/RNN/LSTM/HMM) on MFCC/Mel features, sometimes combined with vitals or symptoms; it demonstrates scalable, non-invasive, low-cost feasibility, yet faces challenges with dataset quality (noise, imbalance), privacy concerns, and heterogeneous recording devices.

- Paper 14 (Generic exemplar: SVC/DT/MLP on cough): Employs lightweight ML on MFCC features, offering fast inference and a simple pipeline; however, it has a lower performance ceiling than CNNs when handling complex audio patterns.
- Key Insight: Cough AI is well-suited for field triage but achieves more stable accuracy when supported by noise handling, data augmentation, and fusion with other signals.

ii Chest X-Ray (CXR)–Based AI for TB

- Paper 10 (MobileNetV2 / ResNet18, Transfer Learning): Uses lightweight CNNs with transfer learning on Shenzhen/Montgomery datasets (~800+ CXRs), achieving good accuracy; limitations include small datasets, single modality dependence, and generalization risk.
- Paper 8 (Improved DenseNet for TB, CXR): Employs an enhanced DenseNet architecture for higher accuracy with strong image performance; requires good-quality X-rays and may be computationally heavier for edge deployment.
- Paper 1 (Ensembled CNNs + ML: DenseNet201, Xception, InceptionResNetV2 + SVM/KNN): Performs feature extraction with deep CNNs and classifies using classical 4 ML with ensembling, yielding high accuracy and resource efficiency; constrained to static images without multimodality.
- Paper 4 (EfficientNet-B0 + SVM, CT slices): Applies transfer learning on CT slices with an SVM classifier to improve performance on small datasets, delivering high accuracy under data scarcity; CT is less accessible than CXR and the dataset is small.
- Key Insight: Transfer learning with lightweight CNNs (e.g., MobileNet, EfficientNet) is effective when data is limited, but image-only pipelines omit complementary signals that could improve real-world robustness

iii Multimodal Fusion & Explainability (XAI)

- Paper 2 (Fusion Network + EAMSO + XAI/Grad-CAM): Uses features from ResNet 50/InceptionV3/EfficientNet-B4 feeding an ANN with PCA and optimized fusion; explainability provided via Grad-CAM. Strengths include very high accuracy (~98.8%) and interpretability; limits are complexity/heavy compute, making it less suited for low power field devices.
- Paper 12 (TrioFusionNet + EAMSO exemplar): Employs are advanced multi-stream fusion with heavy optimization. Strengths are accuracy gains from complementary features; limits computational intensity and harder edge deployment.
- Key Insight: Fusion improves accuracy and trust (with XAI), but model complexity must be balanced against deployment constraints in rural settings.

iv Domain Shift & Generalization

- Paper 3 (Unsupervised Domain Adaptation, DIFL, on CXR) employs ResNet-50 with adversarial learning to learn domain invariant features across TBX11K, Shenzhen, New Delhi, and Montgomery datasets, aiming to tackle population and device shifts and improve generalization. Its strengths lie in addressing cross-geometry/machine variability and enhancing real-world robustness, while its limitations include training instability and higher resource demands.
- Key Insight: Domain adaptation is essential for robustness across geographies and imaging devices, but it introduces additional training complexity

v Hardware/IoT Health Monitoring & Cloud

- Papers 11 and 12 present IoT vital monitoring systems built on Arduino/ESP8266 with Firebase/Blynk and GSM/GPS, focusing on real-time vitals, cloud dashboards, and alerting without AI-based diagnosis. Their strengths are a practical low-cost IoT stack with remote visibility, while limitations include the absence of disease prediction and dependence on connectivity.
- Paper 13 demonstrates an IoT + AI pattern using a Decision Tree for diabetes with Firebase, combining simple machine learning and cloud integration for prediction and monitoring; it effectively showcases AI–IoT integration but is not TB specific, and simple models may underperform on complex tasks.
- Key Insight: Although not tailored to TB, these works directly inform the ESP32 + Wi-Fi + cloud architecture, dashboards, and alert mechanisms planned for the screening kit.

vi Edge Acceleration / Hardware-Aware AI

- Paper 9 describes an FPGA implementation of a trained DCNN for CXR-based TB/pneumonia screening, deploying the model on hardware to achieve fast, efficient inference. Its strengths include low latency, energy efficiency, and offline capability, while limitations involve higher development complexity and reduced flexibility compared to cloud-based approaches.
- Key Insight: Edge acceleration is appealing for connectivity limited settings but introduces engineering complexity, whereas cloud deployment remains simpler for iterative development.

vii Bioinformatics (Anti-TB Peptides)

- Paper 5 presents a hybrid stacked ensemble for anti-TB peptide prediction, combining RF and ERT as base learners with a logistic regression meta-classifier, built on hybrid feature encoding and DT-RFE feature selection to achieve high accuracy. Its strengths include strong generalization and availability via a public web server, while its limitations stem from being a computational biology approach rather than a field screening solution.
- Key Insight: The ensemble-learning and feature-selection methodology is excellent and conceptually informative, but it falls outside the scope of the proposed sensor-based TB screening kit.

IV. COMPARATIVE ANALYSIS OF SELECTED SYSTEM

Below is a clean, plain-text table with aligned columns. You can paste it into a text editor or Word and it will keep the column structure. If you need a Markdown version, say ―Markdown‖.

Table 1 Comparison Of The Selected System

System / Paper	Technology	Key Features	Limitations
DMRNet (Paper 7)	CNN on Mel spectrograms (audio)	Non-invasive cough TB screening	Noise sensitivity; single modality
Cough AI Survey (Paper 6)	ML/DL MFCC/Mel on	Broad methods and devices	Data quality; privacy
MobileNetV2/ResNet 18 (Paper 10)	Transfer learning privacy on CXRs	Light-weight; good accuracy	Small datasets; single modality
Improved DenseNet (Paper 8)	Deep CNN on CXR	Higher image accuracy	Heavier; image quality dependent
Ensemble CNN+ML (Paper 1)	Deep features + SVM/KNN	High accuracy; resource efficient	Still only image
EfficientNet + SVM (Paper 4)	TL on CT + SVM High	accuracy on small data	CT access limited; small set
XAI Fusion + EAMSO (Paper 2/12)	Multi-stream fusion + XAI	Very high accuracy; explainable	Complex; heavy
Domain Adaptation DIFL (Paper 3)	Adversarial domain adaptation	Handles dataset shift	Training instability; high compute
FPGA DCNN (Paper 9)	Edge acceleration (FPGA)	Fast; energy efficient	Developme nt complexity
IoT Vital Monitors (Papers 11/12)	Aduino/ESP826 6 + Cloud	Real-time cloud dashboard	No AI; connectivity dependency
Peptide Ensemble (Paper 5)	RF/ERT → LR stacking	High accuracy; robust	Not field screening
SVC/DT on Cough (Paper 14)	Classical ML	Light-weight	Lower ceiling vs CNN

V. TRENDS AND OBSERVATIONS

Accuracy improves when moving from single to multimodal inputs, such as combining CXR with additional cues, but deployments must remain lightweight and explainable. In imaging, transfer learning with MobileNet, EfficientNet, or ResNet on small medical datasets is standard practice, and using SVM on deep features helps when data is limited. Cough is a non invasive, low-cost signal, yet it should be denoised and ideally fused with saliva strip or CXR inputs for reliability. Practical studies demonstrate IoT + cloud readiness using ESP/Arduino with Wi-Fi and Firebase/AWS for dashboards and alerts, which is directly applicable to the proposed kit. Generalization remains a known risk, making domain adaptation important for real world robustness, albeit with added training complexity. Edge acceleration via FPGA or similar hardware can reduce latency and long-term cost, but it is more complex to build and maintain, so a cloud-first approach is pragmatic initially

VI. SYNTHESIS OF FINDINGS.

Multimodal sensor fusion is motivated by the limitations of single signals: cough-only or CXR only approaches have blind spots, whereas combining audio, saliva strip, and optional CXR can reduce false positives and false negatives. While complex fusion architectures and transformers may achieve top accuracy, they often exceed rural hardware constraints, so lightweight, explainable models are preferable for field deployment. Under data scarcity, transfer learning with pretrained CNNs, targeted augmentation, and simple SVM or logistic heads are effective. Mature IoT patterns—ESP32 with cloud dashboards and HTTP/MQTT workflows—support portable kits with both offline and online flexibility.

VII. RESEARCH GAPS AND FUTURE DIRECTIONS

Addressing dataset diversity and shift requires ethically expanding and augmenting data, alongside exploring lightweight domain adaptation for cough and CXR to improve robustness. To mitigate single-modality fragility, employ rule-based or logistic fusion of cough, saliva strip, and optional CXR for more reliable triage. Improving model interpretability in field tools calls for XAI techniques—such as saliency maps, Grad-CAM, and audio saliency—to build trust with health workers. Given the mismatch between heavy models and edge constraints, prioritize MobileNet/EfficientNet-lite with quantization, and consider FPGA or Edge TPU in later phases. Ensuring operational IoT reliability involves resilient uploads, store-and-forward on ESP32, and simple dashboards with alerts.

CONCLUSION

The reviewed literature shows strong progress in CXR AI, cough-based screening, fusion with explainability, IoT/cloud integration, and hardware acceleration. However, single modality dependence, small or biased datasets, deployment complexity, and generalization risks persist. Our project addresses these gaps with a low-cost, portable, multimodal kit—ESP32 captures cough (denoised) and strip color (RGB), cloud AI (lightweight CNN + simple fusion) returns risk scores, and a web dashboard logs patient records for rural health workers. By combining transfer learning, explainable outputs, and practical IoT/cloud patterns, the system aims for scalable, real time, and trustworthy TB pre-screening in underserved communities.

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