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Original Research Article

AI-Assisted Tuberculosis Detection on Chest X-Rays in Resource-Limited Settings

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Abstract:

Background: Tuberculosis (TB) remains a major public health challenge in low- and middle-income countries, with India alone accounting for nearly 27% of the global burden. Although chest radiography is a frontline screening tool, many resource-limited areas lack trained radiologists. While AI-based diagnostic tools show promise, their adoption is limited by cost, infrastructure, and technical barriers.

Objective: This study evaluated the diagnostic accuracy and feasibility of a no-code AI model built using Google Teachable Machine (GTM) to classify chest X-rays (CXRs) as TB-positive or normal in resource-limited settings.

Methods: A balanced open-source dataset of 1,400 CXRs (700 TB-positive, 700 normal) was used. GTM, leveraging transfer learning (MobileNet), enabled model training without coding or specialized hardware. The dataset was split 85:15 for training and testing. Evaluation metrics included accuracy, sensitivity, specificity, precision, F1 score, and training curve analysis.

Results: The GTM model achieved an accuracy of 98.57% (95% CI 95.9–99.5), sensitivity of 99.05% (95% CI 94.8–99.8), and specificity of 98.10% (95% CI 93.3–99.5) Only three misclassifications occurred in the 210 test images. The model was trained in under 10 minutes on a consumer laptop using browser-based Google Teachable Machine.

Conclusion: The no-code GTM model while being accessible, fast, and deployable in rural or low-resource settings, demonstrated diagnostic performance within the range of previously reported performance for deep learning and commercial CAD systems; external validation is needed to confirm these findings. Its offline capability and ease of use make it a promising first-line screening tool for TB control in India and other high-burden regions. Further research should explore external validation, integration with explainability tools, and real-world implementation via PHCs and mobile units.

Keywords: Tuberculosis, Artificial Intelligence, Google Teachable Machine, No-code AI, Chest X-ray, Rural Health, CAD, TB Screening, Resource-limited Settings, Public Health.

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Introduction

Tuberculosis (TB) remains among the top ten global causes of death and the leading cause from a single infectious agent, surpassing HIV/AIDS. As per the WHO Global TB Report 2024, approximately 10.8 million people contracted TB in 2023, with over 1.09 million deaths among HIV-negative individuals and 161,000 additional deaths among those with HIV. Low- and middle-income countries bear the brunt of this burden, with Southeast Asia contributing over 45% of global cases. India alone reported over 2.8 million notified TB cases in 2023, representing 27% of the global burden [1].

Despite national initiatives like the National Tuberculosis Elimination Programme (NTEP), India faces persistent challenges in timely and accurate TB diagnosis, particularly in rural and resource-constrained areas. Chest X-ray (CXR) remains a first-line screening tool due to its speed and accessibility, but interpreting CXRs accurately requires skilled radiologists—often unavailable in India's rural and tier-2/tier-3 healthcare infrastructure—leading to diagnostic delays and under-detection [2,3].

Artificial intelligence (AI)-based solutions, especially convolutional neural networks (CNNs), have shown diagnostic capabilities comparable to human experts in interpreting CXRs. Models such as CAD4TB, qXR, and Lunit INSIGHT CXR report high sensitivity and AUROC values of 0.94–0.96 in TB detection [4–6]. However, their dependence on expensive software, high-performance computing, and complex deployment pipelines limits their use in primary healthcare centers.

To bridge this gap, interest has grown in developing accessible, no-code, and browser-based AI tools suitable for low-resource settings. Google Teachable Machine (GTM) is one such platform, enabling image classification using a drag-and-drop interface without coding or ML expertise. GTM employs transfer learning, typically with lightweight CNNs like MobileNet, and supports real-time inference on basic consumer devices [7].

Recent studies have demonstrated GTM's applicability in medical image analysis. For instance, Abraham et al. (2024) reported >94% accuracy for brain tumor classification using MRI scans [8]. GTM has also been used in skin lesion detection, dental imaging, and diabetic retinopathy screening. However, large-scale validation for TB detection in national programs is still lacking.

To our knowledge, this is among the first structured evaluationsof a GTM-based, no-code AI model for classifying TB-positive and normal CXRs using a public dataset. It assesses the model's diagnostic accuracy and feasibility for deployment in low-resource Indian settings, supporting India's TB elimination efforts under the National Strategic Plan and Sustainable Development Goals (SDGs) [9].

Materials and Methods

This retrospective diagnostic performance evaluation study was conducted using an open-source chest radiograph dataset to assess the feasibility and accuracy of a no-code machine learning model built on Google Teachable Machine (GTM). The primary goal was to determine whether GTM—a browser-based platform requiring no programming—could effectively classify chest X-rays (CXRs) into tuberculosis (TB) and normal categories, mimicking real-world deployment in resource-limited healthcare settings such as rural primary health centers (PHCs) and mobile screening units. All experiments were performed on a standard consumer laptop (Intel i5, 8 GB RAM, no GPU) with only a web browser, reflecting infrastructural constraints typical in many Indian healthcare environments.

The study utilized a publicly available dataset compiled by Rahman et al. [10], comprising 1,400 de-identified posteroanterior-view CXRs, equally divided into 700 TB-positive and 700 normal cases. These grayscale images, standardized to 512×512 resolution, were used without any augmentation or enhancement to preserve clinical realism. GTM's drag-and-drop interface was used to upload the images into two custom classes (TB and Normal), and the platform internally handled preprocessing such as resizing (to 224×224), normalization, and batch loading.

GTM uses a pre-trained MobileNet architecture optimized for edge devices and supports browser-based training without external scripts or coding. For this study, a standard image project was configured for binary classification and trained for 50 epochs with a batch size of 32 and a learning rate of 0.0001. The platform automatically split the dataset into training (85%, 1,190 images) and test (15%, 210 images) sets in a stratified manner. Model performance metrics—including accuracy, sensitivity (recall), specificity, precision, F1 score, and confusion matrix—were obtained from GTM's internal dashboard and cross-verified manually using the confusion matrix outputs. Training curve plots (accuracy and loss vs. epochs) were used to visually assess model learning stability.

No patient-identifiable information was involved in the study. The dataset was publicly available under appropriate research-use licensing, and no human participants were recruited, hence ethical approval was not required.

Results

The AI model developed using Google Teachable Machine (GTM) was trained on 1,190 chest X-ray images and tested on 210 images. Training and validation accuracy curves showed smooth convergence, with the model reaching above 95% test accuracy by epoch 20 and stabilizing thereafter. A slight divergence in the loss curves after epoch 30 suggested early signs of overfitting, although test accuracy remained consistently high.

Performance on the test set is summarized in **Table 1**, which presents the confusion matrix. The model correctly classified 207 of 210 test images, with only one false negative (missed TB case) and two false positives (normal cases misclassified as TB).

Table 1: Confusion Matrix

Actual / Predicted	Normal	Tuberculosis	Total
Normal	103	2	105
Tuberculosis	1	104	105
Total	104	106	210

Based on the confusion matrix, class-wise precision, recall (sensitivity), and F1 scores were calculated and are shown in Table 2. Both classes demonstrated excellent performance with F1 scores of 0.985, indicating balanced classification across TB and non-TB images.

Table 2: Class-Wise Performance Metrics

Class	Precision	Recall (Sensitivity)	F1 Score
Normal	0.990	0.981	0.985
Tuberculosis	0.981	0.990	0.985

The model achieved an accuracy of 98.57% (95% CI 95.9–99.5), sensitivity of 99.05% (95% CI 94.8–99.8), and specificity of 98.10% (95% CI 93.3–99.5). This symmetry across metrics highlights the model's reliability and lack of class bias—critical for tuberculosis screening, where both missed diagnoses and false positives can carry clinical and public health consequences.

Visual outputs from the GTM dashboard supported these findings. The final training accuracy reached 100%, while the test accuracy plateaued around 98.5% (Figure 1). Training loss dropped to near-zero by epoch 50, and test loss stabilized at approximately 0.12, suggesting good generalization with minimal overfitting (Figure 2).

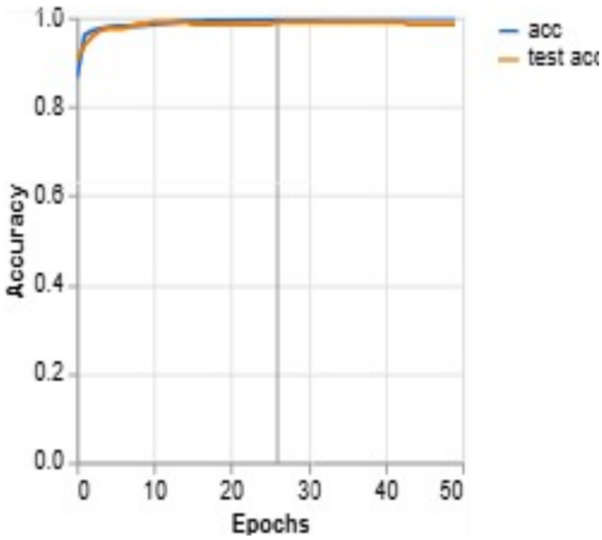

Figure 1: Accuracy per Epoch Plot

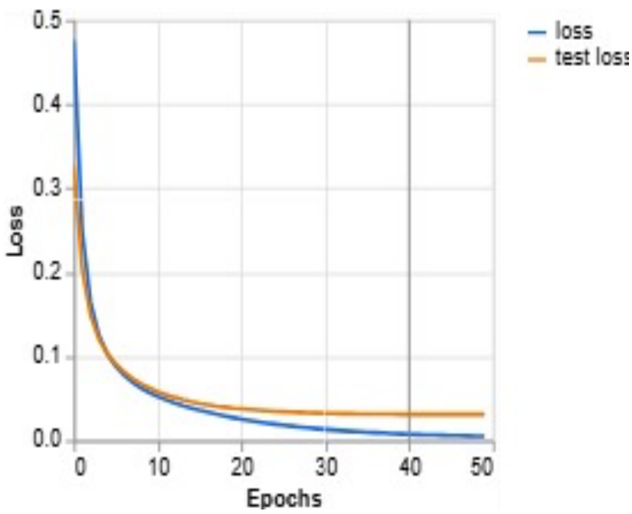

Figure 2: Loss per Epoch Plot

Discussion

This study demonstrates that a no-code, browser-based AI platform—Google Teachable Machine (GTM)—can deliver high diagnostic accuracy for tuberculosis (TB) detection from chest X-rays in resource-constrained environments. The model achieved 98.6% accuracy, with 99.0% sensitivity and 98.1% specificity, misclassifying only three out of 210 test images. These results highlight GTM's consistency and diagnostic balance, making it a viable screening tool where radiologists are unavailable and infrastructure is minimal.

When compared with conventional deep learning models and commercial CAD systems, GTM's performance is notably competitive. Studies using CNNs on large datasets (e.g., Nijiati et al., 9,628 images) have reported 93.2–95.5% sensitivity and 95.8–98.1% specificity [11], while Susanto et al. reported 94.1% accuracy using a YOLO-CNN hybrid [12], and Nafisah and Muhammad achieved 99.1% using explainable AI [13]. Commercial tools like CAD4TB v6 reported 90% sensitivity with specificity up to 98% [14,15], and qXR achieved 74.3% specificity at 90% sensitivity in a comparative Bangladesh study [15]. Meta-analyses have consistently shown pooled sensitivities above 88% and specificities near 87% across commercial and academic AI systems [16]. Despite being trained on a smaller dataset, our GTM model matches these benchmarks, affirming its value as a lightweight alternative to resource-intensive systems.

A standout advantage of GTM is its ease of use and suitability for low-resource settings. Unlike cloud-based CAD tools that demand DICOM preprocessing and external computing, GTM operates entirely within a web browser using TensorFlow.js. It requires no programming, runs on basic laptops or tablets, and can function offline—making it ideal for PHCs, outreach programs, or mobile diagnostic vans. Previous studies in hematopathology using GTM have shown over 97% accuracy in white blood cell classification [9], and this study extends its application to radiological imaging, reinforcing its versatility across medical domains.

Importantly, the model also maintained robustness on heterogeneous chest X-ray inputs.

Nonetheless, several limitations warrant attention. GTM's default input resolution of 224×224 pixels may fail to capture fine-grained radiological features. The platform lacks integrated explainability tools like Grad-CAM, hindering model transparency for clinical interpretation. The dataset used was relatively small and homogeneous, emphasizing the need for external validation across diverse populations and imaging conditions. Additionally, GTM currently supports only binary classification, excluding differentiation from other lung pathologies. A mild divergence in loss curves after epoch 30 suggests potential overfitting, warranting further tuning and generalizability checks in future studies.

Despite these challenges, GTM offers substantial promise. Its offline compatibility, simplicity, and speed align well with WHO and NTEP goals for early TB detection in under-resourced settings. It could also serve as an educational resource, improving AI literacy and building clinician confidence in deploying machine learning tools in public health workflows. Future directions should explore model explainability integration, multi-class extension, and real-world deployment in partnership with PHCs and mobile units.

Conclusion

This study demonstrates that Google Teachable Machine, a no-code AI platform, can achieve high diagnostic accuracy in TB detection on chest X-rays, making it especially suitable for rural and resource-limited settings in India. Its ease of use, low infrastructure demands, and potential for decentralized deployment empower local healthcare workers to participate in AI-driven screening. While further validation and integration are needed, GTM offers a practical, scalable solution aligned with India's TB elimination goals, supporting early diagnosis and promoting equitable access to AI in public health.

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