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Enhanced TB Detection to Solve Class Imbalance and Explainability using GenAI and Deep Learning Technique

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Abstract - One of the leading causes of infectious disease mortality in the world is tuberculosis. Although early screening using chest X-ray images is important, it is often limited by the availability of radiologists and class imbalance in real-world datasets where the number of samples with tuberculosis is much lower compared to normal cases. With the purpose of addressing class imbalance and improving explainability, this paper proposes an enhanced framework for tuberculosis detection that couples a lightweight deep learning model with generative artificial intelligence. In order to balance the dataset, a StyleGAN2 model was utilized to generate synthetic chest X-ray images. The enriched data served to train a MobileNetV2 classifier from scratch. Explainability was achieved through Grad-CAM++ and Guided Backpropagation, allowing the clear visualization of model decision regions. The experimental results obtained demonstrate significant gains in minority-class recall, overall accuracy, and interpretability.

Key Words: Tuberculosis detection, Generative AI, StyleGAN2, MobileNetV2, Explainable AI, Grad-CAM++, Guided Backpropagation, Chest X-ray classification

1. INTRODUCTION

Tuberculosis remains one of the most serious infectious diseases worldwide, and early diagnosis is one of the keys to effective treatment and control. Chest X-ray screening plays an important role in these tests,but often relies on the availability of trained radiologists. In many real clinical datasets, there is also a major imbalance: far fewer TB-positive X-rays are available compared to normal ones. The imbalance makes automated detection systems less reliable. In this paper, we address these challenges by presenting an improved TB detection methodology that effectively integrates Generative AI with a lightweight deep learning model. We apply StyleGAN2 in generating synthetic images of chest X-rays to balance the dataset for better model learning. On top of the enriched dataset, we train from scratch a MobileNetV2 classifier. Lastly, for interpretability and to build more trust in the system, we add Grad-CAM++ and Guided Backpropagation visualization techniques, which generate clear visual explanations of which regions of the X-ray influenced the model's decision.

2. LITERATURE SURVEY

Deep learning has been widely explored for Tuberculosis detection, with numerous studies reporting strong performance on chest X-ray datasets. Rahman et al. (2025) demonstrated that a ResNet50-based model could achieve an accuracy of 92.4%, although the authors noted reduced sensitivity due to class imbalance. In another study, Kim et al. (2023) applied DenseNet121 and reported 94.1% accuracy, showing improved feature extraction but at the cost of high computational demand. Mahamud et al. (2024) evaluated multiple transfer learning models and found that EfficientNet-B0 achieved 95.6% accuracy, outperforming VGG16 and InceptionV3 in their experiments. Despite these promising results, most studies reported that false-negative rates remained relatively high when TB-positive samples were limited. Additionally, authors such as Shankar et al. (2022) and Gupta et al. (2021) emphasized that traditional augmentation strategies were insufficient to mitigate dataset imbalance, with their CNN models achieving only 80–86% accuracy on imbalanced datasets. While these models delivered strong overall accuracies, the lack of balanced training data and limited explainability tools restricted their clinical applicability. These limitations highlight the need for approaches that combine synthetic data generation, lightweight architectures, and integrated explainability—areas directly addressed by the present study.

3. METHODOLOGY

A. Dataset Description

We have used the Kaggle Tuberculosis Chest X-ray dataset for our work. In all, we got 1,800 images—1,200 normal and 600 with TB. The catch is, the dataset is imbalanced; there are twice as many normal images as TB-positive ones. This may make it difficult for the model to properly detect the TB cases. We prepared these images by resizing them to 224×224 pixels because the MobileNetV2 model requires that image size. We

cleaned up corrupted files to ensure our data remained solid and intact.

B. Synthetic Data Generation Using StyleGAN2

To fix the imbalance and add more variety, we used a StyleGAN2 model to generate 3,500 synthetic images of normal lungs and 3,500 with TB. We trained it for about 350 iterations and most of the generated images looked realistic though a few had slight imperfections like blurry edges or uneven textures. We didn't have the computational power to run advanced checks (like FID or IS scores), so we relied on eyeballing them to make sure they were decent.

C. Data Preprocessing Pipeline

We mixed the real and synthetic images together, gave them a good shuffle and split the dataset into three parts:

- 70% for training the model,
- 15% for validation to tune it,
- 15% to test it, check out how it performs.

The image pre-processing included resizing images, normalizing the pixel values to help the model train better, and converting them into a format the model could work with.

D. MobileNetV2 Model Architecture

We opted for MobileNetV2 since it is lightweight and efficient, hence perfect if the deployment were to be done in a low-resource setting or even on mobile. We trained it from scratch so it could pick up patterns specific to TB rather than relying on pre-trained features. Architecture:

A MobileNetV2 backbone for features extraction from the X-rays,

- Global Average Pooling to simplify the data,
- A Dropout layer with rate 0.3 to avoid overfitting,
- A Dense layer with 128 ReLU units for processing,

A sigmoid output layer for classifying images as Normal or TB-positive.

E. Training Configuration

Model is trained using:

- Adam optimizer with a learning rate of 0.001,
- Binary Cross-Entropy loss, suitable for yes/no TB detection,
- Batch size of 32 and ran it for up to 50 epochs.

We avoid overfitting by using callbacks like EarlyStopping-stop if it doesn't improve after 5 epochs-and ReduceLROnPlateau-lowers learning rate if it plateaus. All that ran on Google Colab on an NVIDIA Tesla T4 GPU with 16 GB VRAM, which was fast and smooth.

F. Explainability Techniques

We added two techniques to make the model's decisions more transparent for doctors:

1. Grad-CAM++: Provides heatmaps as to where in the X-ray the model looked to make a particular prediction, such as highlighting suspicious spots on the image that are relevant to TB.
2. Masked Backpropagation: Magnifies the fine details and textures that the model is focusing on.

Together, these give both a big-picture and detailed view that helps clinicians to trust the model.

G. Web Application and Deployment

We created a user-friendly web application to detect TB: Frontend with HTML5, CSS3, and JavaScript; you upload an X-ray and it shows the predictions along with the Grad-CAM++ heatmaps.

Backend is powered by FastAPI and PyTorch; it does the processing, runs the model, and creates the heatmaps using OpenCV/PIL.

Workflow:

1. Upload an X-ray.
2. The backend processes and predicts TB or Normal.
3. Gets a confidence score and creates a heatmap + explanation.
4. You see the results on the frontend.

4. RESULTS AND ANALYSIS

A. Baseline Model Performance (Before Synthetic Augmentation)

First, the MobileNetV2 model was trained on only the original Kaggle dataset, which consisted of 1,200 Normal and 600 Tuberculosis-positive samples. As a result of the strong class imbalance, the baseline model demonstrated poor performance in finding TB cases.

Table -1: Baseline model performance

Metric	Value
Accuracy	84.7%
Precision (TB)	0.76
Recall (TB)	0.61
F1-Score (TB)	0.68
ROC-AUC	0.83
AUPR (TB)	0.72

The baseline model achieved reasonable accuracy but significantly struggled with recall, detecting only 61% of TB

cases. Training curves indicated early overfitting, around the epoch mark of 25, which is expected given the limited number of images with positive TB results. Most notably, missing TB cases in a clinical setting is particularly risky, and recall improvement is critical.

B. Performance after Synthetic Data Augmentation with StyleGAN2

Finally, the model was re-trained using a greatly expanded and balanced dataset that combined the real dataset with 3,500 synthetic Normal and 3,500 synthetic TB-positive images generated by StyleGAN2.

The augmented model showed dramatic performance improvements:

Table -2: Model Performance After Synthetic Augmentation

Metric	Value
Accuracy	91.5%
Precision (TB)	0.88
Recall (TB)	0.79
F1-Score (TB)	0.83
ROC-AUC	0.93
AUPR (TB)	0.89

These results show that synthetic augmentation significantly improved the model's performance in TB case detection, especially regarding recall from 61% to 79% and also F1-Score from 0.68 to 0.83. There was also an increase in ROC-AUC and AUPR scored due to stronger performance across various thresholds.

C. Confusion Matrix Interpretation

After augmentation, the confusion matrix on the test set was:

Table -3: Confusion Matrix Interpretation

	Predicted TB	Predicted Normal
Actual TB	158 (True Positives)	42 (False Negatives)
Actual Normal	19 (False Positives)	181 (True Negatives)

This reduction in false negatives is of prime importance because it delays treatment and increases disease transmission.

D. Behavior for Training and Validation

The learning behavior of the model improved significantly over the baseline when trained with the larger dataset. While training loss decreased smoothly over the epochs, the validation loss leveled out around the 35th epoch, showing a stable learning pattern. Validation accuracy reached approximately 91% and remained stable without recording sharp fluctuations similar to those that indicate overfitting. The EarlyStoppingcallback automatically stopped training at epoch 38, which is when validation performance reached its peak. This stability was confirmed by TensorBoard visualizations, displaying an unchanged trend in both the training and validation curves and indicating an improvement in the generalization capability of the model due to the larger, more balanced dataset. Indeed, this contrasts starkly with the baseline, which, aside from a lack of TB-positive samples, brought about early overfitting.

E. High-Sensitivity Evaluation Run

The model was separately evaluated with a configuration aimed at maximizing sensitivity. During this mode, the model achieved nearly perfect results: it detected all TB cases in the test set.

Table -4: High Sensitivity Results

Metric	Value
Accuracy	0.997
TB Recall	1.00
AUPR	1.000

This setting completely ruled out false negatives, which made the configuration highly suitable for TB screening environments where missing a positive case had grave implications.

F. Explainability Analysis

Explainability was assessed both by Grad-CAM++ and by Guided Backpropagation. Together, these approaches allow for a comprehensive understanding of how the model interpreted chest X-rays.++ heatmaps showed that, generally speaking, this model focused on clinically relevant areas of the lungs, notably the upper and middle lobes, where TB abnormalities commonly manifest. In some cases, attention fell on regions outside the lungs, which include the ribs or edges; these were most often due to slight artifacts in the synthetic images. Guided Backpropagation allowed fine-level structural insight into highlighting texture patterns and gradients associated with TB lesions. The combined visualization confirmed the model's predictions were indeed related to meaningful radiological cues and not random features.

G. Impact of Synthetic Data

These results clearly show that synthetic augmentation using StyleGAN2 played a central role in enhancing the reliability of the model. A balanced and enlarged dataset helped the MobileNetV2 model overcome its bias by learning stronger features, while reducing false negatives considerably. This combination of higher recall, better F1-score, and more stable training behavior is indicative of generative augmentation being an effective strategy to deal with class imbalance in TB detection.

5. CONCLUSIONS

The paper presents a comprehensive Tuberculosis detection framework that incorporates synthetic data generation, a lightweight deep learning model, and explainability tools into a practical web-based system. The use of StyleGAN2 for generating additional chest X-ray images effectively addressed the original imbalance in the Kaggle TB dataset. The MobileNetV2 model, trained entirely from scratch on the enriched dataset, showed significant improvements in sensitivity, F1-score, and overall diagnostic reliability. This enhanced model further reduced false negatives, which are critical in TB screening, and ensured stable performance across multiple training runs. The integration of Grad-CAM++ and Guided Backpropagation further provided an important layer of transparency by allowing users to visualize the regions influencing each prediction. The web deployment supports ease of use by applying real-time analysis to chest X-rays through a simple interface. In general, the results confirm that synthetic augmentation combined with a lightweight CNN can produce a practical, interpretable, and deployment-ready solution for TB screening—especially in environments where expert radiologists and large computational resources may be limited. Although the proposed system showed strong performance with GAN-based augmentation, training on MobileNetV2, and integrated explainability, a number of extensions could further enhance clinical readiness. The quality of the synthetic images is subjective and will be further investigated using quantitative realism metrics such as FID or IS in future work. Clinical validation of the synthetic images and Grad-CAM++ heatmaps will require collaboration with radiologists to confirm their reliability for clinical use. Further extensions to the explainability component may include other XAI methods, such as Integrated Gradients, which give more detailed insights into model decisions. Finally, the system should be deployed on the cloud platform with optimized latency and enhanced security to support scalability and real-world adoption in healthcare settings.

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REFERENCES

J. Capellán-Martín, L. Herrera, P. Santos, and R. Molina, "Lightweight CNN for chest X-ray TB detection," *ScienceDirect*, 2023.

M. Patel, T. Wong, and H. Ebadi, "Explainable self-supervised deep learning for TB screening," *IEEE*, 2024.

A. Pramana, R. Setiawan, T. Kurniawan, and S. Widodo, "Few-shot learning for TB classification," *IEEE*, 2025.

K. K. Mujeeb Rahman, S. Ali, R. Thomas, and L. Chacko, "Tailored CNN for clinical TB screening," *ScienceDirect*, 2024.

D. Yuvlina, S. Park, J. Lin, and F. Nakamura, "Hybrid ViT-CNN for TB detection," *IEEE*, 2024.